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From Buzz to Bust: How Fake News Shapes the Business Cycle

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From Buzz to Bust:
How Fake News Shapes the Business Cycle *

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Abstract

The proliferation of fake news poses significant challenges for policymakers and raises concerns about its potential impact on economic stability. This paper explores this question, focusing on the macroeconomic effects of technology related fake news in the US for the period 2007–2022. Utilizing a novel dataset of fact-checked statements from PolitiFact, we construct a binary indicator to build a proxy for the exogenous variation in fake news issuance. Adopting a proxy-VAR approach, we show that technology fake news increases macroeconomic uncertainty, exacerbates unemployment, and depresses industrial production. Similar effects are observed for fake news related to the supply side, such as tax rates or the price of gas. On the contrary, fake news related to government finance, market regulation, or the labor market does not impact economic stability. Furthermore, fake news that conveys negative information about technological developments exhibits stronger depressive impacts than positive ones.

Keywords: Fake news, business cycle, proxy-VAR.

JEL Classification: C32, E32

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"Nothing can now be believed which is seen in a newspaper. Truth itself becomes suspicious by being put into that polluted vehicle. The real extent of this state of misinformation is known only to those who are in situations to confront facts within their knowledge with the lies of the day."

Thomas Jefferson

Letter to John Norvell, 14 June 1807

Introduction

The late 19^{th} century witnessed a significant transformation in the American media landscape with the emergence of sensationalist journalism. This reporting style, pioneered by *New York World* and *Hearst's New York Journal*, engaged in a readership competition, prioritized captivating headlines and emotionally charged narratives over factual accuracy and investigative depth. This phenomenon, dubbed "yellow journalism" by contemporaries, bears a striking resemblance to the challenges presented by the proliferation of fake news in the 21^{st} century. The critical importance of discerning truth from falsehood, emphasized back then, remains a major concern for modern democracies and policymakers. As Christine Lagarde, 4^{th} President of the European Central Bank, stated in a November 2019 speech, *"The task of separating truth from falsehood has plagued policymaking for centuries [. . .] Today, this task of distilling the truth is more urgent than ever."* Likewise, the 2024 World Economic Forum ranked fake news as the most severe global risk[1] anticipated over the next two years.[2] However, as concerning as it is perceived, the macroeconomic impact of fake news remains unexplored.[3] This paper attempts to fill this gap by addressing the simple question: *Does fake news shape aggregate fluctuations?*

This paper investigates the effects of fake news shocks on business cycle dynamics and their contribution to overall business cycle volatility. A key challenge of this paper is to identify the fake news shock. This is achieved by constructing a novel dataset of fact-checked statements compiled from PolitiFact, a Pulitzer Prize winning independent fact-checking organization operating since 2007. PolitiFact provides a six-level rating of fact-checked statements covering various topics (politics, health, crime, . . . , and economic issues), ensuring a comprehensive analysis of the impact of factual and misleading information across various economic and non-economic domains.

[1]"Global risk is defined as the possibility of the occurrence of an event or condition, which, if it occurs, would negatively impact a significant proportion of GDP, population, or natural resources" (WEF, 2024).

[2]Fake news also induce potentially worrying effects on societal and political polarization, and rising of populism. Funke et al. (2023) point to significant medium- and long-term economic costs of populism. While Acemoglu et al. (2019) and Papaioannou and Siourounis (2008) suggest that populism corrodes the economic advantages of democratic institutions. These effects are beyond the scope of this paper.

[3]To our knowledge, only a handful of papers study the impact of fake news on the financial markets—by investigating the effect of fake news on the stock returns of firms, e.g. Arcuri et al. (2023), Karppi and Crawford (2016), Kogan et al. (2022) and Clarke et al. (2021).

First, we convert this rating to a binary indicator, classifying each statement as true or fake. We then use this indicator, available on a daily basis, to build a proxy that captures exogenous variations in fake news issuance at a monthly frequency.[4]

We identify the dynamic causal effect of fake news shocks on business cycle dynamics in a Vector AutoRegression (VAR) model. This is achieved by employing a proxy-VAR (see Stock and Watson, 2012; Mertens and Ravn, 2013; Gertler and Karadi, 2015; Lagerborg et al., 2022; Baker et al., 2023) estimated on US monthly data for the period ranging from January 2007 to December 2022, which features, in its baseline version, the unemployment rate, industrial production, and the first business cycle factor identified by McCracken and Ng (2021). Importantly, our benchmark VAR also includes the 1-month ahead macroeconomic uncertainty index (Jurado et al., 2015). This index plays a key role in unraveling the propagation mechanisms of fake news shocks, as we hypothesize that by adding noise to the system, they increase the uncertainty faced by the agents in the economy.

Our results suggest that a technology-related fake news (hereafter fake technology news) shock increases macroeconomic uncertainty and the unemployment rate, depresses production, and contributes significantly to the overall volatility of the business cycle. The validity of our instrument is key in drawing causal conclusions. We first assess and verify its exogeneity with respect to fundamentals. Furthermore, we performed two sanity checks to assess its relevance beyond the standard weak instrument test. First, we show that "true" news and "fake" news lead to distinct responses of the economy, supporting the instrument's ability to capture the unique impact of "fakeness." Second, we rely on a placebo experiment that uses scrambled news events to strengthen the claim that model artifacts or spurious correlations do not drive the observed effects.

We then explore the broader impact of fake technology news shocks beyond core economic indicators, delving into critical parts of the economic system, such as consumption, labor, and finance. Expanding our benchmark VAR to consumption expenditures reveals that fake technology news shocks *(i)* explain a sizeable share of both durables and non-durables and services and that *(ii)* consumers do cut on their expenditures in the aftermath of the shock. Fake news also harms the labor market —both hours worked and job openings fall after the shock— and financial markets —stock prices decrease with rising volatility. Inflation and inflation expectations initially dip, as does the monetary policy interest rate, but quickly revert to their long-run value. Finally, credit spread and risk premium increase, suggesting market confusion and higher investor risk aversion. In all cases, fake technology news shocks explain a sizeable share of the volatility of these variables.

Expanding beyond technology, we investigate how the economy reacts to fake news targeting other economic domains, including taxes, gas prices, government, labor markets, and financial

[4] Conversion to monthly frequency is required to match macro aggregates frequency.

regulation. Interestingly, fake news related to taxes and gas prices, traditionally considered supply-side phenomena in the economic literature, significantly influence key economic indicators in a manner similar to fake technology news. This finding suggests that supply-side fake news may indeed have a substantial impact. In contrast, we find no statistically significant impact of fake news related to labor markets, government finances, or financial regulations on the economy.[5]

To gain a more nuanced understanding of the impact of fake technology news, we focus on agent disagreement. We replace the macroeconomic uncertainty measure of Jurado et al. (2015) with a cross-sectional volatility measure derived from the Survey of Consumer Expectations. Our analysis reveals that fake technology news shocks explain over 90% of short-term volatility in disagreement, emphasizing their role as key drivers of confusion and divergent expectations among economic agents. Similarly to macroeconomic uncertainty, disagreement translates into an economic downturn: the shock explains approximately 60% of the volatility of unemployment and industrial production at the one-quarter horizon. These findings suggest that the economic influence of technology related fake news extends beyond traditional uncertainty measures, directly impacting the coordination of economic agents and contributing to greater business cycle volatility.

We further analyze the impact of the sentiment of technology related fake news by comparing macroeconomic responses to shocks derived from mixed, positive-only, and negative-only news. Notably, negative sentiment fake technology news shocks account for a significantly larger share of the volatility in unemployment, production, and macroeconomic uncertainty. Furthermore, when the proxy-VAR includes a confidence index, negative fake news demonstrates a significant impact, while positive news does not. These findings are consistent with previous research suggesting a stronger economic influence of negative news versus positive news. This may be attributed to a "negativity bias" in information processing, leading to increased uncertainty when people perceive potential threats.

The remainder of the paper is structured as follows. Section 1 discusses the empirical methodology and the construction of the instrument we rely on to identify the fake news shock. Section 2 presents our main results, and Section 3 presents robustness exercises. The last section offers some concluding remarks.

1 Methodology

The identification of the fake news shock relies on the hypothesis that fake news issuance creates some form of confusion/noise that adds to the uncertainty faced by economic agents.

[5]This result does not necessarily indicate that these types of fake news do not impact the economy. It rather suggests that their effect does not go through the mechanism we highlight in this paper—that of macroeconomic uncertainty.

For instance, in a survey of 1,002 U.S. adults conducted from December 1 to 4, 2016, by the Pew Research Center, about two in three U.S. adults say fabricated news stories cause a great deal of confusion about the basic facts of current issues and events.[6] Pomerance et al. (2022) study how the "double-whammy" of COVID-19 and fake news influenced households' consumption/saving behavior. They show that COVID-19 created uncertainty and that fake news made that uncertainty even worse. In the stock market, Hong et al. (2023) show that the concern for fake news affected the extreme stock market risk domestically and abroad. Hinging on this idea, our identification strategy relies on a proxy-VAR, in which we instrument a measure of macroeconomic uncertainty (Jurado et al., 2015) —and later a measure of disagreement— with a proxy for fake news. As will become clear in Section 1.2, we will exploit the exogenous variation in the change in the number of fake news as identified by a fact-checking organization.

1.1 The Proxy-VAR Approach

This section describes our approach to identifying fake news shocks through a proxy-VAR approach (see Stock and Watson, 2018; Kilian and Lütkepohl, 2018). We consider the following Vector-AutoRegressive (VAR) process

$$A(L)X_t = u_t, \tag{1}$$

where X_t is a $n_x \times 1$ vector of second order stationary endogenous variables, L denotes the lag operator ($L^i X_t = X_{t-i}$) and $A(L) = I - \sum_{i=1}^{p} A_i L^i$ is a matrix polynomial where A_i a $(n_x \times n_x)$ matrix, $p \in \mathbb{N}$ denotes the number of lags in the VAR.[7] u_t is a $(n_x \times 1)$ vector of canonical innovations such that $\mathbb{E}[u_t] = 0$ and $\mathbb{E}[u_t u_t'] = \Sigma$ and $\mathbb{E}[u_t u_{t-j}'] = 0$ for any $j > 0$. These innovations are assumed to be linear combinations of n_x mutually orthogonal structural shocks, ε_t such that

$$u_t = S\varepsilon_t, \tag{2}$$

where S is a non-singular $(n_x \times n_x)$ matrix. The structural shocks satisfy $\mathbb{E}[\varepsilon_t] = 0$ and $\mathbb{E}[\varepsilon_t \varepsilon_t'] = \Omega$ where $\Omega_{ij} = 0$ for $i \neq j$. The structural Wold decomposition of the process is then given by

$$X_t = C(L)\varepsilon_t, \tag{3}$$

where $C(L) = A(L)^{-1}S$. In this paper, we are only interested in identifying a single structural shock, the fake news shock. By convention and for convenience of notation, this shock is ordered first in vector ε_t and will hence be denoted as $\varepsilon_{1,t}$. Our approach to identifying the dynamics causal effects of this shock follows the instrumental variable strategy employed by Stock and Watson (2012, 2018).

[6] The results are reported to be robust across incomes, education levels, partisan affiliations, and most other demographic characteristics, see Pew (2016).

[7] Without loss of generality we omit constant terms.

Let Z_t be the (uni-dimensional) proxy variable —the instrument— for $\varepsilon_{1,t}$, which shall satisfy

$$\mathbb{E}[\varepsilon_{1,t} Z_t'] = \theta \neq 0, \tag{Relevance}$$

$$\mathbb{E}[\varepsilon_{j,t} Z_t'] = 0 \;\; \forall j > 1. \tag{Exogeneity}$$

The relevance condition ensures that the instrument correlates with the shock of interest. The exogeneity condition guarantees orthogonality between the instrument and the remaining shocks. Leveraging on (2) and the relevance and exogeneity conditions, we have

$$\mathbb{E}[u_t Z_t'] = S\mathbb{E}[\varepsilon_t Z_t'] = S \begin{pmatrix} \theta \\ 0 \end{pmatrix} = \begin{pmatrix} S_{11}\theta \\ S_{21}\theta \\ \vdots \\ S_{n_x 1}\theta \end{pmatrix}.$$

When the effect of the shock of interest on a reference variable (say the first appearing in the vector X_t) is normalized to unity ($S_{11} = 1$)[8], the last equality implies that in this case, S_{i1} can be directly recovered from the IV regression

$$u_{it} = S_{i1} u_{1t} + \sum_{j=2}^{n_x} \alpha_{i,j} \varepsilon_{j,t}.$$

However, innovations u_t are unobservable, making the direct estimation of this regression not possible. We follow the approach proposed by Stock and Watson (2018) and exploit the fact that $u_{i,t} = X_{i,t} - \mathbb{P}[X_{i,t}|X_{t-j}, j > 1]$, where $\mathbb{P}[Y|X]$ denotes the projection of Y onto X. In this case, the previous regression rewrites

$$X_{i,t} = S_{i1} X_{1,t} + \psi_i(L) X_{t-1} + \sum_{j=2}^{n_x} \alpha_{i,j} \varepsilon_{j,t} \;\; \text{for } i = 2, \ldots, n_x,$$

where $\psi_i(L)$ collects all the coefficients of the projection of $X_{i,t} - S_{i1}X_{1,t}$ in the space spanned by the past history of X_t. Subsequently, S_{i1} and $\psi_i(L)$ can be simply estimated using a two stage least square method, employing Z_t as an instrument for $X_{1,t}$. Applying this regression to each variable, we obtain the column vector $S_{\cdot,1}$ conditional on $S_{1,1} = 1$.

In the sequel, we will not impose a unit effect of the shock on the reference variable but will consider the effects of a unit shock. Therefore, we need to rescale $S_{\cdot,1}$ by $1/\sigma_{\varepsilon_1}$. The standard deviation σ_{ε_1} can be simply obtained by noting that, as long as (2) holds, we have $\varepsilon_{1,t} = \gamma' u_t$ where $\gamma = S_{\cdot,1}\Sigma^{-1}/(S_{\cdot,1}\Sigma^{-1}S_{\cdot,1}')$. Consequently, the volatility, σ_{ε_1}, of $\varepsilon_{1,t}$ can be computed as $\sigma_{\varepsilon_1}^2 = \gamma'\Sigma^{-1}\gamma = (S_{\cdot,1}\Sigma^{-1}S_{\cdot,1}')^{-1}$. Impulse responses and the associated forecast error variance decomposition can then be derived from (3). This final step is incorporated into the bootstrap procedure when standard errors are computed.

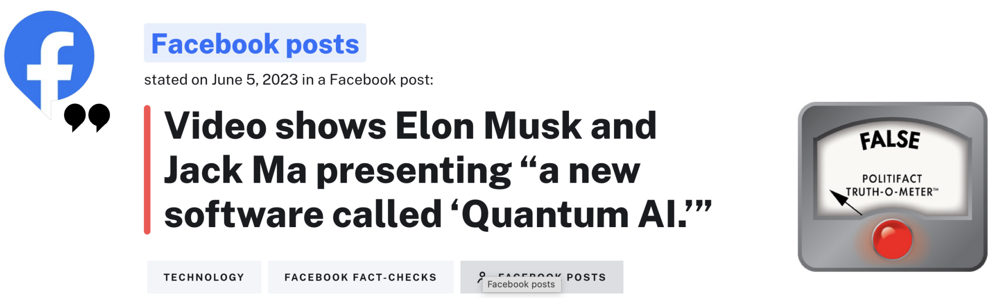
[8] In our case, the shock is the fake news shock and, as will become clear in the next section, the variable of interest is the Jurado et al.'s 2015 measure of macroeconomic uncertainty.

1.2 A Fake News Instrument

Our fake news data consist of fact-checked news compiled from the Assenza and Huber (2024) *Fake News Atlas* database. This database includes news items fact-checked by PolitiFact.[9] Established in 2007, PolitiFact is a non-profit fact-checking organization adhering to the principles of the International Fact-Checking Network. Its funding comes from content partnerships, online advertising, grants, and individual donations. We chose PolitiFact for several reasons. First, PolitiFact provides daily fact-checked news for the longest time horizon—compared to the other fact-checkers. Second, it is recognized for its quality, as witnessed by the Pulitzer Prize received in 2009. Third, to ensure transparency and independence in its fact-checking process, PolitiFact implemented strict disclosure policies to mitigate potential conflicts of interest. Collaborative efforts with social media platforms such as Meta and TikTok expand its reach in combating online misinformation. PolitiFact employs a meticulous fact-checking process that involves deep research, evidence verification, and multiple editorial reviews (see below). Last but not least, PolitiFact provides fact-checked news statements from a wide range of topics and various sources, such as social media, political speeches, media interviews, and newspaper articles. This section details the construction of this instrument, provides its essential properties, and discusses its exogeneity.

Figure 1 depicts a typical example of a fact-checked news item from the user's perspective. This example concerns a statement regarding a new AI software. The post clearly indicates the source of the news (i.e., Facebook post) and the date the news was first published. In addition, keywords that help classify the news are provided (in this technology, Facebook fact-checks, Facebook posts). The result of the fact-checking is presented visually and intuitively to the user by the "*Truth-O-Meter*".

Figure 1: Example of a Fact-Checked News Item



Source: https://www.politifact.com

PolitiFact relies on the "*Truth-O-Meter*" system to categorize the accuracy of news items. It

[9]Other fact checkers exist. We could also have considered e.g., http://www.factcheck.org, http://www.snopes.com or http://www.zebrafactcheck.com. The first one is, however, focused on politics, and the topics are very much related to the electoral cycle. Importantly, it does not provide a clear rating of the news. The second covers a broader range of topics and is as old as PolitiFact, but the rating methodology is unclear. The last one is much younger, and that would limit our sample to the 2012-2022 period.

includes six rating levels: *(i)* True, *(ii)* Mostly True, *(iii)* Half True, *(iv)* Mostly False, *(v)* False, *(vi)* Pants on Fire. The "True" and "Mostly True" ratings indicate factual accuracy with varying degrees of nuance. "Half True" acknowledges partial truth but highlights misleading elements. Ratings "Mostly False" and "False" denote significant misrepresentations of reality, and "Pants on Fire" highlights demonstrably false and egregious misinformation. This classification scheme aims to capture the varying degrees of truthfulness and misinformation in the news landscape. Importantly, news rating is not performed by an algorithm, but results from an investigation.[10] The news that needs to be checked is assigned to a reporter by an assigning editor. The reporter then conducts an investigation regarding the accuracy of the news and suggests a rating, which (s)he returns to the editor. The journalist and the assigning editor then discuss the rating to come to an agreement, and the rating is presented to two additional editors. The three editors and the journalist further discuss the rating, asking the following questions: *Is the statement literally true? Is there another way to read the statement? Is the statement open to interpretation? Did the speaker provide evidence? Did the speaker prove the statement to be true? How have we handled similar statements in the past? What is PolitiFact's "jurisprudence"?* The final decision is then submitted for a vote, and the rating is finally published. Errors can be easily reported to the website and are corrected very quickly. To avoid the possibility that our sample is contaminated by potential errors, we discarded the last available year (2023) from our sample.

Our identification does not require differentiating between disinformation (intentionally misleading) and misinformation (not intentionally misleading). In both cases, fake news creates noise in the system. Hence, we adopt a binary classification based on the "Truth-O-Meter" ratings. True news encompasses statements classified as "True", "Mostly True", and "Half True", recognizing that even "Half True" statements generally convey the core information accurately. On the contrary, fake news includes statements classified as "Mostly False", "False" and "Pants on Fire", representing varying degrees of disinformation and misinformation and the potential to mislead.[11]

The data cover the period running from January 1^{st}, 2007 to December 31^{st}, 2022. The entire data set includes 23,707 fact-checked statements. They are classified using the PolitiFact's rating system as "True" (11%), "Mostly True" (15%), "Half True" (16%) —a total of 32% that we classify as true—"Mostly False" (15%), "False" (30%), and "Pants on Fire" (13%) —a total of 68% fake.

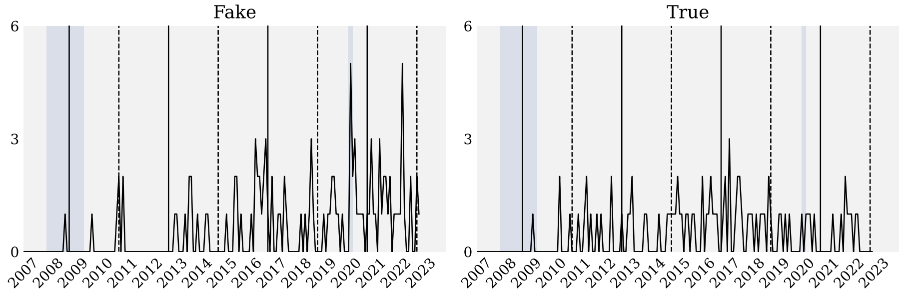
Fact-checked news regards a whole diversity of topics such as political debates, health issues, crimes, societal concerns, . . . , and economic issues. We focus on the latter. We collect fact-checked news on various economic topics including government finance (budget, deficit, debt), the labor market, financial regulation (including monetary policy), taxes, gas prices, and technology. This paper will devote most of its attention to the latter topic. According

[10]see https://www.politifact.com/ for additional details

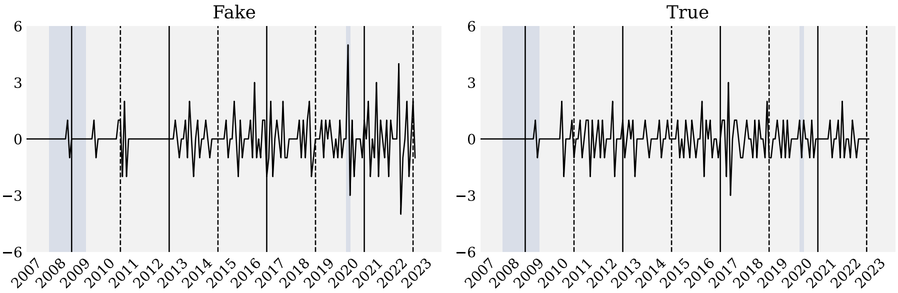
[11]We, however, assess the robustness of our results to the definition of fake news in Appendix C.

Figure 2: Fact Checked News (Technology)

(a) Number of Fact Checked News



(b) Change in Number of Fact Checked News



Notes. Monthly number and change in the number of fake and true news (related to technology). Shaded area: NBER Recessions, Vertical plain line: Presidential election, Vertical dashed line: Midterm election.

to our binary classification, 63% of the technology news is fake. 53% of fake technology news is anonymous and was first launched on one of the main social media platforms (X, former Twitter, Facebook, Instagram). The remaining 47% is attributed to politicians, journalists, or commentators on the societal environment. We collect the full set of fact-checked news for the various topics and then design a simple index that reports, for each month and each topic, the number of fake and true news as identified by PolitiFact fact checkers.

Panel (a) of Figure 2 reports for our sample the evolution of the number of true and fake technology news for each month.[12] As can be easily seen from the graph, this number is increasing, which is simply a manifestation of the increase in the number of news checked by the website. The share of fake technology news does not show any trend behavior. In order to avoid non-stationarity problems, we use as an instrument the *monthly change in the number of technological fake news* (see panel (b) of the figure). The series does not exhibit seasonality. Furthermore, no systematic increase or decrease in the production of fake news is observed during a recession relative to a boom, which seems to rule out any correlation with such events. Similarly, the production of fake news does not correlate with the production of true news (-0.08).

As pointed out in the previous section, to qualify as a valid instrument, our proxy (*monthly change in the number of fake technology news*) must satisfy an exogeneity condition and a

[12] The corresponding graphs for the other topics are reported in Appendix B.

relevance condition. In this section, we focus on the first condition and leave the analysis of the relevance condition to the next section. Figure 2 (b) suggests that the dissemination of fake technology news is unrelated to contemporary macroeconomic conditions; There does not appear to be more fake news during booms than during busts. More generally, macroeconomic conditions seem unlikely to generate the creation and sharing of fake technology news. While the literature is silent about the motivations to share fake technology news, general fake news creation and sharing is driven by self-promotion and the pursuit of (online) fame. Individuals driven by self-promotion are more likely to share fake news on social media (Islam et al., 2020). The goal is to gain as many followers, likes and shares as possible, boosting self-esteem and self-worth through being "popular" online.[13] It seems unlikely that the desire for self-promotion and online fame is related to macroeconomic conditions.[14]

The dissemination of fake news is very concentrated. Using data from the Twitter social media platform during the run up to the 2016 US election, Grinberg et al. (2019) found that only 0.1% of users were responsible for the sharing 80% of fake news. *Who are these spreaders?* Most recent findings in the psychology literature suggest that fake news spreaders are indeed special. Personality traits related to mental disorders are strong predictors of the creation and sharing of fake news. The psychology literature uses the Big5 character traits theory and the dark triad model to understand the psychological behavior of social media users. This line of research clearly shows that psychopathy is associated with high levels of online trolling (March et al., 2017), and narcissism is correlated with self-objection on social media (Fox and Rooney, 2015). Individuals with narcissistic or psychopathic personality traits are more likely to spread misinformation (Ahmed and Rasul, 2023). Given the somewhat random nature of personality traits such as narcissism, it is reasonable to take the monthly change in the number of fake technology news as exogenous with respect to macroeconomic factors. There is no evidence that these personality traits vary at the individual level over short time horizons or with the state of the business cycle.

As illustrative as the previous analysis may be, it remains largely anecdotal. We now delve into a more statistical approach and start by testing for the potential Granger causality running from business cycle conditions onto our proxy. In other words, we test for the non-predictability of the instrument with respect to the information set of the econometrician. To do so, we project each of our instruments on three lags of the variables included in our benchmark VAR (see next section)[15] — the Jurado et al. (2015) macroeconomic uncertainty index, the unemployment rate,

[13] For political fake news, the literature discusses two additional drivers. Political ideology is a strong motivation to share fake political news on social media platforms (e.g. Freiling et al., 2023). The sharing of fake news due to political ideology is driven mainly by the feeling of hate towards political opponents (Osmundsen et al., 2021). An additional mechanism that encourages the spread of political misinformation is simply "group pressure" (Lawson et al., 2023).

[14] According to Vosoughi et al. (2018) and contrary to conventional wisdom, robots accelerated the spread of true and false news at the same rate. Fake news spreads more because humans, not robots, are more likely to spread it.

[15] We use the same number of lags as in our VAR, as selected from the Bayesian Information Criterion.

the industrial production index, and the first business cycle factor identified by McCracken and Ng (2021) which summarizes key information about the business cycle and tests for the joint significance of the coefficients of the lagged variables. The p-value of the test is 0.94, which overwhelmingly rejects any form of Granger causality from the lagged variables on our proxy.[16] Importantly for our identification strategy, this implies that macroeconomic uncertainty does not predict greater fake news issuance the next month.

The political science literature argued that fake news issuance is potentially related to the political cycle. In order to address this potential issue, we run the following regression

$$z_t = \alpha + \rho z_{t-1} + \sum_{i=0}^{p} \phi_i d_{t-i} + \nu_t,$$

where z_t denotes our instrument, and d_t is a dummy variable equal to one in the month of either a presidential or a midterm election, and zero otherwise. If the electoral cycle plays a role in fake news issuance, then $\{\phi_i\}_{i=1}^{p}$ should differ significantly from zero. Recall that the election dates are perfectly known to the agents and are set exogenously. Hence, any significance of the ϕs would signal a causal effect of the electoral cycle on fake technology news issuance. In this regression, $p = 1$ as selected by a standard Bayesian Information Criterion. The test cannot reject the null of no effect (p-value=0.44). In other words, our technology instrument is exogenous with respect to the electoral cycle.

Since our analysis focuses on technology-related fake news, our chosen instrumental variable is likely to be endogenously influenced by technological shocks. To rule out this possibility, we run a simple VAR featuring changes in Total Factor Productivity (TFP) adjusted for utilization[17] and the unemployment rate. We identify the technology shock as the only shock that exerts a long-run effect on TFP (see Blanchard and Quah, 1989; Galí, 1999). Note that by using this decomposition, the technology shock combines expected (news shocks) and unexpected shifts in TFP. The correlation between our instrument and the technology shock is negligible (0.06), as illustrated in Figure 3 (a).

We then project our fake technology news instrument onto its own lagged values and the technology shock. We then test for the significance of the technology shock.[18] The test cannot reject the null of no effect overwhelmingly (p-value of 0.8).[19] We then expand this simple VAR by including our instrument.[20] We find that the contribution of the technology shock to the unforecastable volatility of the instrument is less than 2% at any horizon. This evidence strongly

[16]When applying the test to the other proxies we will consider in later sections, the test always rejects any form of Granger causality of the variables of the VAR on the proxy (see Appendix Table B1).

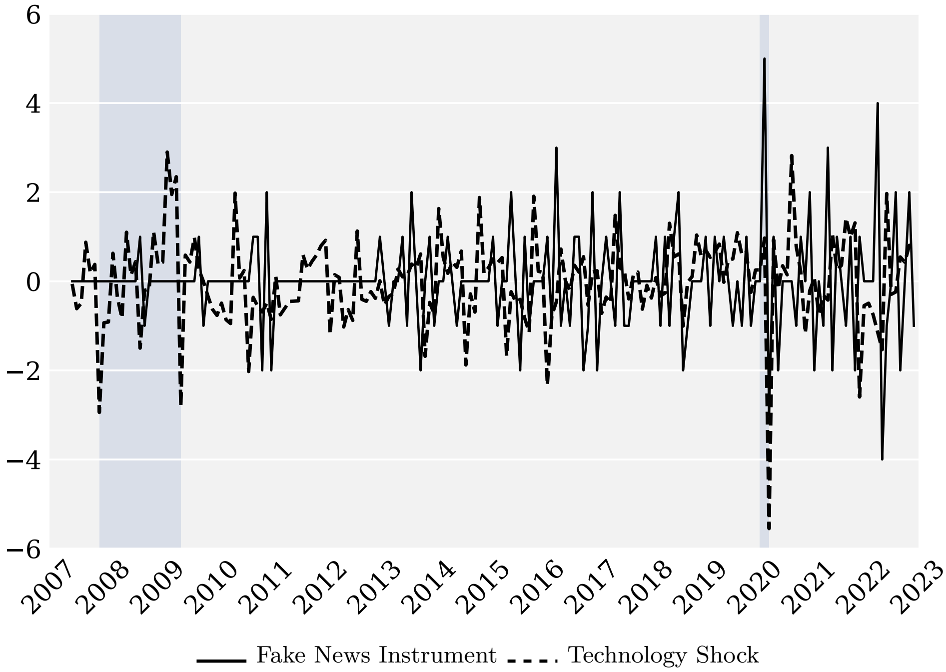
[17]Total Factor Productivity data are taken from Fernald (2012). Since these data are available on a quarterly basis, we used simple linear interpolation to convert the series to the monthly frequency. The results are robust to adopting the method of Chow and Lin (1971) using the growth rate of industrial production and unemployment as interpolation series. We also considered a quarterly version of the whole exercise, which led to the same conclusions.

[18]The distribution of the test is obtained from 1,000 bootstraps to accommodate for the generated regressor problem associated with the computation of the technology shock.

[19]In the quarterly version of the test, this p-value equals 0.49.

[20]We also considered a version of the VAR featuring the first factor of McCracken and Ng (2021) as a way

Figure 3: fake technology news Instrument vs Technology Shocks



Notes. The solid black line shows the monthly change in the number of fake news (related to technology), and the dashed line shows the change in Total Factor Productivity (TFP). The correlation between these two time series is equal to 0.06. Shaded areas represent NBER Recessions.

suggests that our instrument is exogenous with respect to technology shocks and, indeed, satisfies the exogeneity condition. This, however, leaves open the possibility that the production of fake news be explained by uncertainty surrounding technological conditions: greater uncertainty create a environment conducive to the production of fake news as a way to maintain confusion. In order to test for this possibility, we project our instrument onto its own lagged values and a measure of the volatility of technological conditions —the absolute value of the technology shock. The test cannot reject the null of no effect (p-value of 0.6), indicating that our instrument is also exogenous with regard to the volatility of technological conditions. In other words our identification strategy does not confound the effects of fake news issuance with the effects of uncertainty shocks.

2 Results

This section first presents our benchmark VAR, discusses the relevance of our fake news instrument, and derives the effects of fake technology news shocks for the economy. The VAR is then expanded to derive broader implications of fake news for the overall economy.

to avoid any omitted variable issue. In that case, the p-value of the test is 0.97, which further strengthens our exogeneity result.

2.1 Baseline Results and Relevance of Instrument

To capture the effects of fake technology news shocks on business cycle dynamics and their contribution to overall business cycle volatility, we begin by estimating a VAR model for the US economy using monthly data from January 2007 to December 2022.[21] The model includes the unemployment rate and the industrial production index (in logs, first difference)[22] obtained from the Federal Reserve Economic Database (https://fred.stlouisfed.org/).[23] Additionally, we incorporate the first business cycle factor identified by McCracken and Ng (2021) to capture any potential omitted information about the business cycle and avoid non-fundamentalness representation issues (see Forni and Gambetti, 2014; Beaudry et al., 2019). Finally and most importantly, the VAR includes the 1-month ahead macroeconomic uncertainty index Jurado et al. (2015). This index captures the conditional volatility of forecast errors obtained from a dynamic factor model applied to a broad set of macroeconomic aggregates. This approach has two key advantages. First, focusing on forecast errors ensures that the index measures genuine uncertainty, excluding predictable variations. Second, aggregating across multiple time series yields a comprehensive measure of macroeconomic uncertainty, compared to volatility measures based on a single indicator such as the VIX. The inclusion of this uncertainty index plays a crucial role in our identification strategy. By increasing the noise in the system, we hypothesize that fake news complicates economic agent forecasting, thereby raising macroeconomic uncertainty (measured by the Jurado et al. (2015) index).[24] This elevated uncertainty is then expected to propagate through the VAR to impact other macroeconomic variables. The VAR features three lags, selected by a standard Bayesian Information Criterion.

Importantly, for our proxy-VAR analysis to be valid, the fake technology news shock must be invertible. As shown by Plagborg-Møller and Wolf (2022), this is equivalent to saying that our instrument does not Granger cause the variables included in the VAR.[25] Plagborg-Møller and Wolf (2022) propose a simple test consisting of expanding the VAR with the instrument and testing for the Granger causality of the instrument on the other variables. In our case, we cannot reject the null of invertibility (p-value=0.14).

Figure 4 displays the Impulse Response Functions (IRFs) of the model variables to a one-standard deviation shock in the fake news. The shaded area represents the ± 1 standard deviation confidence band constructed from 1,000 replications of Kilian's (1998) bootstrap-after-bootstrap

[21] The sample size is limited by the availability of data on fake news.

[22] In order to ensure stationarity in our benchmark VAR, we estimated a specification in which the log of the industrial production index was introduced in difference in the VAR. Figure D1 and Appendix Table D1, show that performing the estimation relying on a level specification does not alter our results.

[23] Appendix A details the construction of the data.

[24] In Section 3.2, we will explore an alternative uncertainty measure based on disagreement among the forecasts and explore deeper the underlying mechanisms.

[25] Intuitively, if the shock is invertible, then the lags of the variables in the VAR capture all the forecasting power of lags of the fake technology news shock. In other words, lagged values of the instrument do not help predict the VAR variables.

procedure.[26] Our analysis uncovers a distinct impact of fake technology news shocks on business

Figure 4: Benchmark Reponses

Notes. The solid black line shows the IRF of the model variables to a fake technology news shock. Shaded areas represent ± 1 standard deviation around average response obtained from 1,000 Bootstrap replications.

cycles. The shock triggers a sustained surge in macroeconomic uncertainty, peaking at four months before gradually subsiding. This "hump-shaped" pattern suggests a powerful and gradual transmission mechanism, reflecting the spread of fake news, its gradual absorption by the public, and ultimately, heightened confusion and uncertainty. Interestingly, the initial response to the shock exhibits a counterintuitive pattern. We observe a slight decrease in unemployment (0.5 pp) and an increase in industrial production (0.35%). This may indicate that agents initially misinterpret fake news as additional information, leading to increased exploration and activity. However, this short-lived "boom" is swiftly followed by a sharp recession. After one month, the shock triggers a significant and persistent increase in unemployment (0.4 pp) and a decrease in industrial production (1%).

Table 1: Variance Contribution: Benchmark VAR

Variable	Impact	1 Month	1 Quarter	1 Year	2 Years	5 Years
Benchmark VAR						
Macro. Uncertainty	83.63	84.15	87.81	87.95	76.42	54.32
Unemployment	56.29	28.55	26.05	31.94	31.19	28.94
Ind. Production	13.33	9.38	37.70	54.59	54.81	27.19
True News						
Macro. Uncertainty	0.00	0.11	0.06	2.67	15.63	37.18
Unemployment	51.98	65.45	61.75	55.38	56.42	58.94
Ind. Production	26.88	33.43	21.35	9.92	7.75	44.68
Placebo						
Macro. Uncertainty	12.42	10.52	7.72	8.26	12.30	15.89
Unemployment	4.17	2.56	2.11	5.53	8.20	10.49
Ind. Production	2.48	2.27	1.84	2.18	2.36	2.69

The impulse response function reveals a strong propagation mechanism characterized by these hump-shaped dynamics. The initial uncertainty gradually builds up, leading to further depression in macroeconomic outcomes. Table 1 (first panel) quantifies these effects. The fake

[26] We abstract from the IRFs of the McCracken's factor as it possesses no clear economic interpretation *per se*.

technology news shock explains up to 88% of the 1-month-ahead macroeconomic uncertainty after a year. It explains 56% of the short-run volatility of the unemployment rate and still contributes 30% to its overall volatility after one year. Although the shock only explains 13% of the short-run volatility of the industrial production index, it accounts for about 55% of its volatility on the one-year horizon. This highlights the potential of fake technology news to act as a major driver of business cycles, particularly economic downturns.

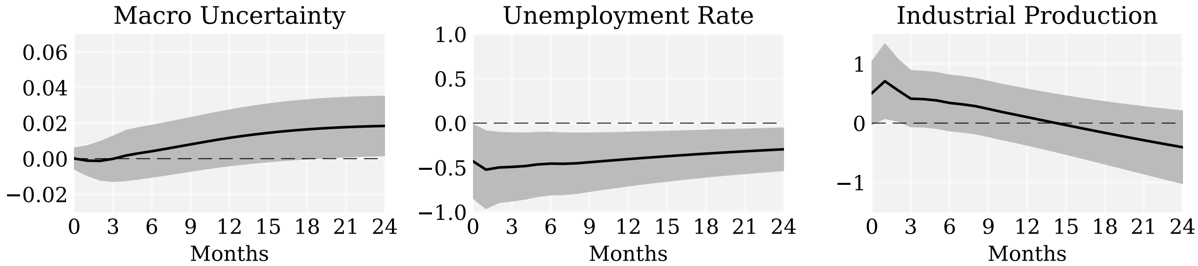
Our initial findings suggest that fake news events could trigger broader economic downturns. However, the validity of this conclusion hinges on the relevance of our chosen instrument to measure the impact of fake news. To ensure instrument reliability, we performed a standard weak instrument test based on Montiel Olea and Pflueger (2013). This test assesses whether the instrument significantly predicts macroeconomic uncertainty, accounting for lagged variables in the VAR. Our Fisher test statistic (10.6) exceeding the typical threshold of 10 suggests that the instrument is not weak and supports the link between fake news and economic fluctuations. While this result is indeed reassuring, we also want to check that it is not the fruit of a "*divine coincidence*". Therefore, we run two additional experiments.

In the first experiment, we replaced our "fake news" instrument with one based on fact-checked news classified as "true," "mostly true," and "half-true." This allows us to isolate the impact of "fakeness" from general news events. Figure 5(a) reveals stark differences. In contrast to fake news, the issuance of true news does not increase volatility, potentially even decreasing it. Although initially involved in the issuance of true news, its effect on industrial production is the opposite (initial decrease followed by an increase). These findings contradict empirical evidence (see e.g. Ludvigson et al., 2021; Baker et al., 2023), suggesting a negative comovement between uncertainty and aggregate activity. This inconsistency raises questions about the relevance of the instrument. Table 1 further strengthens these doubts. True news explains significantly less macroeconomic uncertainty compared to fake news: 0% initially, 0.1% after one quarter, and 2.5% after one year. Furthermore, the Montiel Olea and Pflueger (2013) test statistic for true news is 0.0, indicating virtually no power in the instrument. The combined evidence strengthens the argument that our findings are not driven by a "divine coincidence." The distinct responses to "true" and "fake" news highlight the specific role of "fakeness" in triggering negative economic consequences.

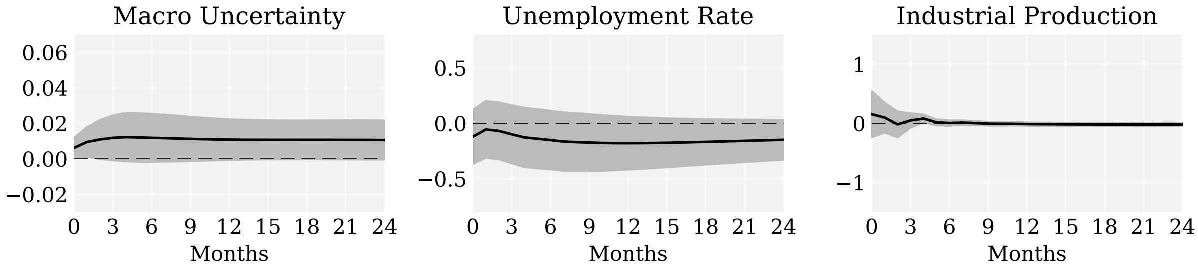
To further strengthen our confidence in the findings, we conducted a placebo experiment. This experiment aimed at verifying that the observed effects were genuinely driven by the "fakeness" of the news and not by spurious correlations or model quirks. We randomly selected a date within the sample period (January 2007-December 2022) and split our fake news instrument into two segments: the pre- and post-selected date. We then scrambled the instrument by flipping the order of these segments, essentially creating a fake timeline with the same number of news events but no chronological association with real events. We then estimated a new VAR model using this scrambled instrument and analyzed impulse responses (IRF) to a "placebo

Figure 5: Assessing Relevance

(a) True News



(b) Placebo



Notes. Panel a: the solid black line shows the IRFs of the model variables to a true technology news shock. Panel b: the solid black line shows the IRF to a placebo fake technology news shock. Shaded areas represent ± 1 standard deviation around average response obtained from 1,000 Bootstrap replications.

shock" We repeated this process 200 times, generating a total of 40,000 placebo IRFs (200 placebo × 200 bootstraps for each placebo).

Figure 5(b) and Table 1 reveal a crucial finding: placebo shock has no discernible impact on macroeconomic uncertainty or other economic variables. This result implies that our model is not fooled by random fluctuations in the instrument[27] and that the observed effects in our benchmark VAR are indeed attributable to the specific content and timing of actual fake news events. This placebo experiment strengthens the credibility of our findings by demonstrating that the observed effect of the fake technology news shock is not driven by artifacts of the instrument or the model or by some form of "divine coincidence". This evidence adds confidence to our conclusion that fake news events can trigger economic downturns.

2.2 Implications for the Broader Economy

Having established the instrument's validity and identified the impact of fake technology news shocks on core business cycle indicators, we now investigate their broader influence on critical parts of the economy. Specifically, we examine how fake news affects the goods, labor, and financial markets. We achieve this by progressively expanding our initial "benchmark" model with various economic activity measures, one at a time.[28]

Figure 6(a) illustrates how consumption expenditures react to fake technology news shocks.

[27]The average Montiel Olea and Pflueger (2013) statistics across the 200 placebo instruments is 0.

[28]In this section, we only reproduce the IRF of the extra variable we add in the VAR.

Although the initial impact is modest, it intensifies as the news spreads. After a month, spending on non-durables and services[29] drops by 0.7%, with durables experiencing a steeper decline of 2%— which also hints at investment behavior.[30] Even after a year, the effect persists, with non-durables and services still lagging by 0.4% and durables by 0.45%. Notably, these results align with the permanent income model, where uncertainty disproportionately affects durable goods (investment) compared to non-durables and services. Table 2 confirms this, showing that the impact on consumption steadily increases, reaching 39% for non-durables and services after a year and 42% for durables after three months. These substantial figures underscore the significant influence of fake technology news shocks on consumer behavior.

Panel (b) of Figure 6 focuses on additional business cycle indicators, namely capacity utilization and the Michigan consumer confidence index. Not surprisingly, the results pertaining to capacity utilization are very much in line with those for the industrial production index: capacity utilization increases (non-significantly) on impact to drop sharply in the following month and reach a trough after one quarter. The fake technology news shock is an important contributor to its variations, as it accounts for about one-third of its non-forecasted volatility after one quarter. Things are less clear for consumer confidence. While intuition suggests that fake news may impact consumer confidence, our results show a non-significant decline. In total, fake technology news shock accounts for less than 9.5% of the volatility of consumer confidence on any horizon. This suggests that fake news is not transmitted primarily to the economy through changes in consumer sentiment. One reason for this result is found in the definition of our instrument, which captures fake technology news regardless of how economic agents perceive them.[31]

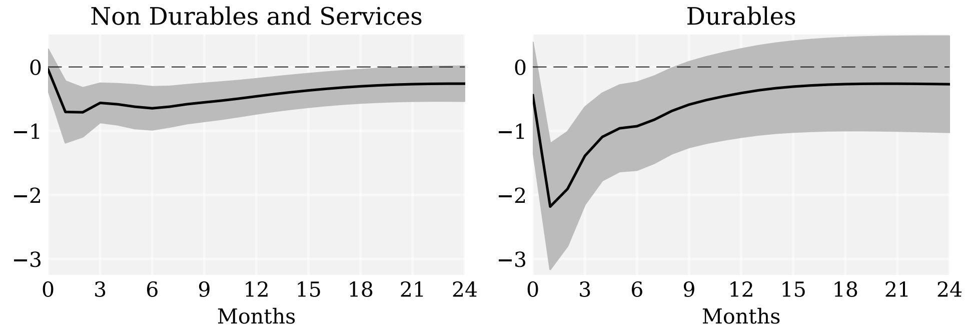
Panel (c) of Figure 6 shows that fake technology news shocks negatively impact the labor market, leading to persistent declines in average weekly hours in manufacturing and job openings (help-wanted index). Interestingly, as help-wanted drops, the unemployment rate increases (see Figure 4), suggesting that the fake technology news shock triggers movements along the Beveridge curve rather than displacements of the curve. This result, therefore, indicates that the shock does not act as a reallocation shock, which would generate a positive correlation between shifts in the unemployment rate and the vacancy rate, but rather as an aggregate shock. This shock contributes substantially to the overall volatility of both hours worked and help-wanted. For instance, while its contribution is mild in the very short run, it accounts for more than 50% of the volatility of hours and help wanted after one year.

Panel(d) finally shows that fake technology news shocks depress stock prices and increase volatility in the stock market. Interestingly, unlike macroeconomic uncertainty, the volatility response in the stock market lacks a "hump-shaped" pattern, exhibiting a faster response within one month. fake technology news shocks contribute the most to the stock market's volatility at

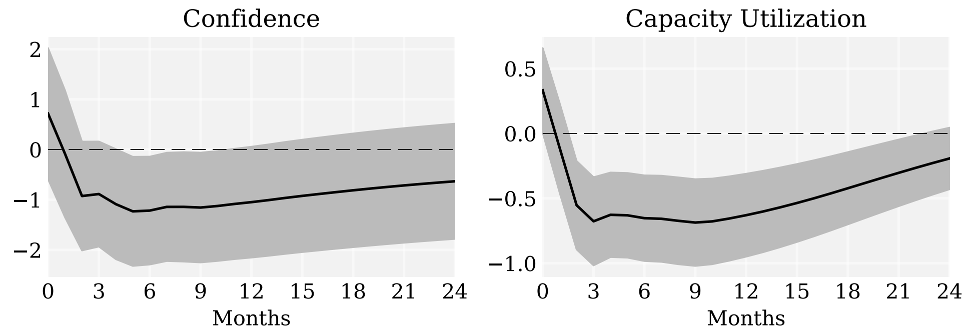
[29]See Appendix A for the exact construction of this variable.
[30]Unfortunately, we are not aware of aggregate investment time series at the monthly frequency.
[31]This point will be explored further in the next section.

Figure 6: Extra Variables (I)

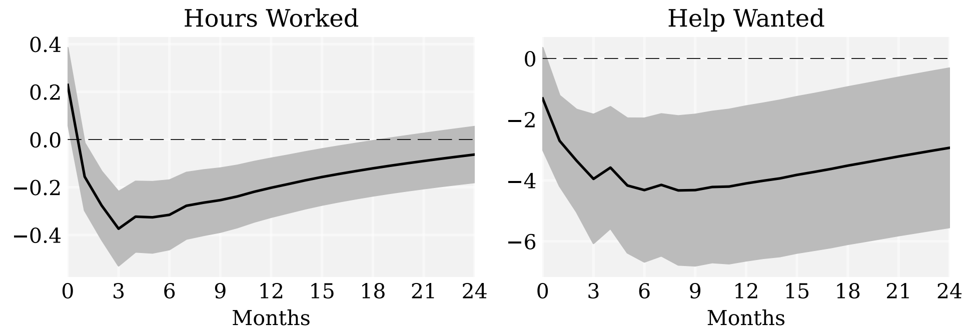
(a) Consumption



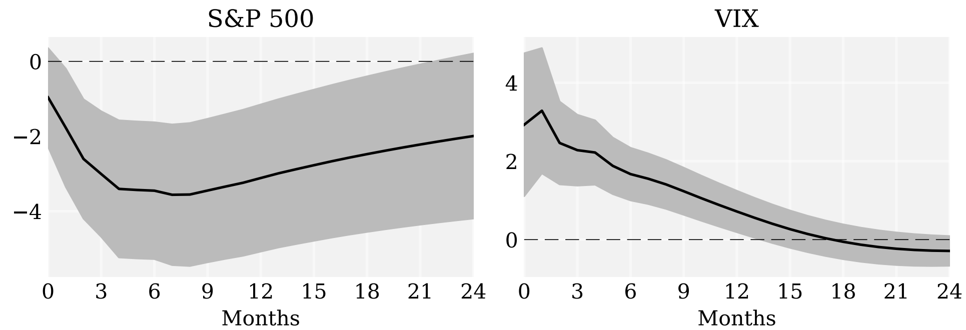
(b) Business Conditions



(c) Labor Market Conditions



(d) Financial Markets



Notes. The solid black line shows the IRFs of the extra model variables (added to the benchmark VAR) to a fake technology news shock. Shaded areas represent $\pm$ 1 standard deviation around average response obtained from 1,000 Bootstrap replications.

the one-year horizon (see Table 2).

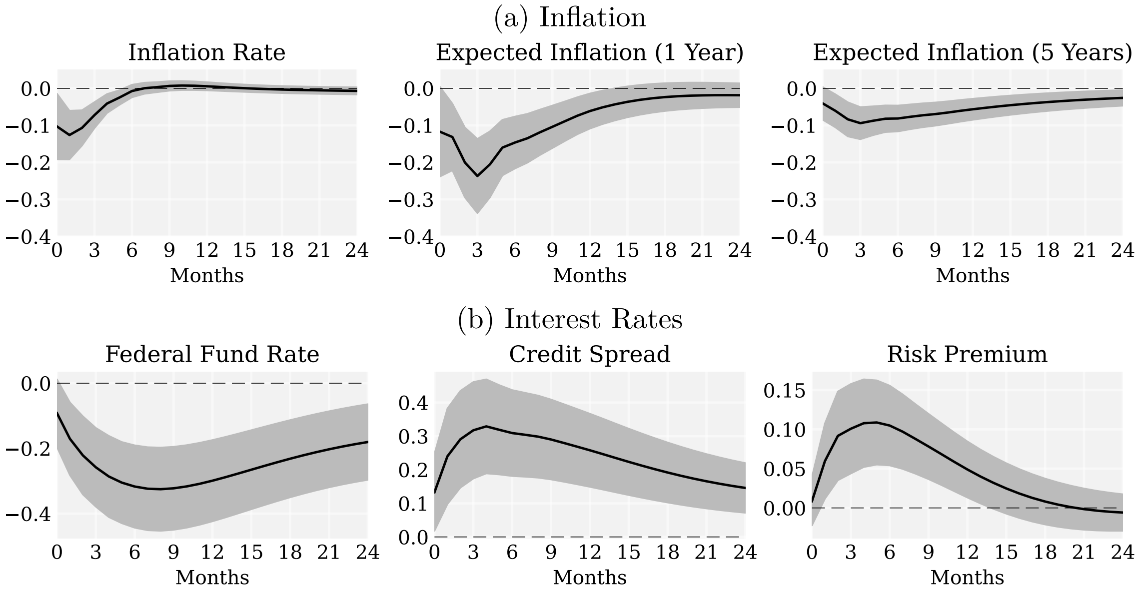
Table 2: Variance Contribution: Extra Variables

Variable	Impact	1 Month	1 Quarter	1 Year	2 Years	5 Years
Consumption						
Non Dur. and Serv.	0.29	26.55	38.25	45.20	37.15	18.93
Durables	3.52	34.78	41.65	29.03	19.22	10.95
Business Indicators						
Confidence	3.24	1.73	4.36	9.41	8.15	4.65
Capacity Util.	20.35	9.53	27.26	38.80	41.89	41.41
Labor Market						
Hours Worked	22.25	18.77	36.01	50.85	45.67	25.93
Help Wanted	7.47	24.06	44.36	54.48	49.72	29.15
Financial Markets						
S&P500	6.50	11.87	26.39	43.67	36.49	16.20
VIX	38.02	49.39	59.12	63.89	60.27	54.13
Inflation Rate						
Realized	12.46	25.14	34.76	35.71	34.93	33.32
Expected (1 Year)	9.12	14.11	35.46	48.57	45.71	40.59
Expected (5 Years)	10.60	17.32	34.17	53.22	53.80	47.82
Interest Rates						
Fed. Fund Rate	51.87	64.77	74.20	79.83	71.96	47.59
Credit Spread	22.16	32.17	44.85	60.76	60.54	53.40
Risk Premium	0.66	9.65	21.24	37.54	37.07	36.42

Panel (a) of Figure 7 sheds light on the impact of fake technology news shocks on the nominal side of the economy, focusing on inflation and inflation expectations (1-year ahead and 5-year ahead). Fake news initially lowers inflation, hitting a trough one month later with a 1% point decline. Our estimates suggest that the shock explains up to 35% of inflation volatility after one quarter (Table 2). Similarly, both short-term (1 year) and long-term (5 year) inflation expectations decrease, with short-term expectations showing a stronger initial response. In particular, the shock explains up to 50% of volatility in both after one year, suggesting significant impacts on beliefs. Despite fake news concerning technology, the observed decline in inflation alongside positive correlations with economic activity (production, capacity utilization, consumption) points towards a demand-side interpretation. This finding aligns with the literature showing that news shocks can have demand-side effects depending on the monetary policy environment. (see e.g. Lorenzoni, 2009; Blanchard et al., 2013)

Panel (b) of Figure 7 delves into how fake news affects monetary policy and financial markets. On the monetary policy front, similarly to inflation, the Federal Reserve's interest rate (federal fund rate) initially decreases after the shock, reaching its lowest point after nine months before gradual normalization. This suggests a smoothing strategy by the Fed in response to the volatile

Figure 7: Extra Variables (II)



Notes. The solid black line shows the IRFs of the extra model variables (added to the benchmark VAR) to a fake technology news shock. Shaded areas represent ± 1 standard deviation around average response obtained from 1,000 Bootstrap replications.

economic effects of fake news. In particular, fake technology news shocks explain up to 80% of the fed funds rate fluctuations within a year (Table 2), highlighting their significant influence on monetary policy, potentially compromising its effectiveness. All this shows how fake technology news shocks can significantly influence monetary policy, potentially reducing its effectiveness.

The figure also presents the responses of credit spread (BAA-AAA corporate bond rate difference) and risk premium (BAA corporate bond rate - fed funds rate). fake technology news shocks contribute significantly to their volatility. For example, after one quarter, they explain 45% of credit spread volatility and 21% of risk premium volatility, rising to 60% and 38%, respectively, after a year. The results suggest that fake technology news shocks create market confusion and increased volatility, leading to a higher risk premium demanded by investors. They exacerbate tensions in credit markets, potentially raising default risks and requiring higher premiums on risky loans.

We finally considered a version of the VAR featuring TFP.[32] In that case, the fake technology news shock explains less than 5% of TFP, therefore confirming the results of Section 1.2. The fake news shock is not a technology shock.[33]

[32] Monthly TFP data was obtained by simple interpolation (see footnote 17), so these results should be interpreted with caution.

[33] Replacing macroeconomic uncertainty by TFP makes our instrument completely irrelevant, which reinforces our result.

3 Discussion

This section provides additional insights into our identification strategy. It starts by investigating the effects of varying the fake news topics that are used to build our instrument. It also assesses the presence of a potential asymmetry in the response to negative versus positive fake news. Then, the analysis delves further into the mechanism by considering a measure of disagreement rather than uncertainty. Finally, we assess the robustness of our findings in relation to the methodology we use in this paper and the measure of uncertainty.

3.1 Alternative Instruments

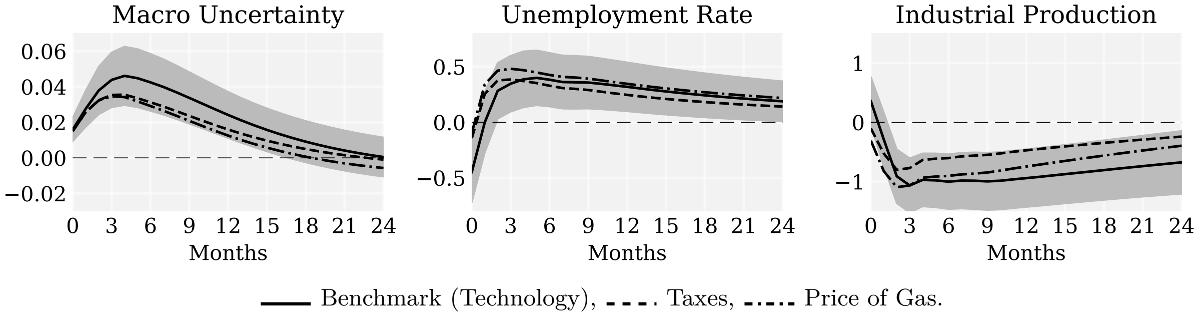
Our benchmark analysis focused on fake news related to technological advancements. This immediately prompts a broader question: *Does the economy react differently to fake news targeting other aspects of the economy?* This section tackles this question by considering other types of fake news, including fake news about the evolution of gas prices, taxes, labor market, financial regulation, and government finance.[34]

Figure 8 compares the response of the economy to a fake technology news shock in our benchmark VAR and in alternative VARs where the dynamic causal effect is identified using as a proxy the change in the number of fake news regarding taxes or the evolution of the price of gas. By tax fake news, we mean statements about either the evolution or the level of taxes. For example, during a debate on September 9, 2020, republican representative Bob Good stated "*82% of Americans [. . .] would experience a tax increase if Biden were elected.*" During a speech in Cleveland on the July 6^th, 2022, Joe Biden stated that "*The "average federal income tax" paid by the richest Americans is 8%. [. . .] If you're a cop, a teacher, a firefighter, union worker, you probably pay two to three times that*". In both cases, fact-checkers from PolitiFact proved these statements to be false. Gas price fake news refers to the state and evolution of the gas market that ought to affect gas prices. For example, on March 3, 2022, Donald Trump publicly said that "*The Strategic Petroleum Reserve has "been mostly empty" for decades.*" On October 27, 2022, during a Speech in Syracuse (NY), Joe Biden stated that the price of gas is "*down from over $5 when he [I] took office.*" Again fact checkers from PolitiFact proved these statements to be false. Both types of fake news are related to topics (taxes, gas prices) commonly viewed as supply-side phenomena in the literature.

Figure 8 and Table 3 compare and contrast the impact of fake technology news (benchmark) with the impact of fake news related to alternative supply-side topics (taxes, gas prices). Both tax and gas price fake news shocks have comparable overall impacts on key macroeconomic indicators such as unemployment, industrial production, and uncertainty. They trigger similar dynamics in these variables, suggesting a potentially common transmission mechanism for these

[34]Appendix C also investigates the robustness of our findings to the exact perimeter of the notion of fake news.

Figure 8: Alternative Instruments (I)



Notes. The solid black line shows the IRFs of the benchmark model variables to a fake technology news shock, the dashed line the IRFs to a fake tax news shock, and the dash-dotted line the IRFs to a fake gas price news shock. Shaded areas represent ± 1 standard deviation around average response in our Benchmark VAR obtained from 1,000 Bootstrap replications.

types of fake news.

The previous analysis focused on fake news related to the supply side. We now ask to what extent fake news about the functioning of labor markets, the government's financial stances, or financial regulation can impact the economy. Fake news about the labor market corresponds to statements regarding the institutional arrangement, the functioning of the labor market, the evolution of wages, or job creation/destruction. An example of fake news about the labor market is given by a statement made by Andrew Cuomo, former New York governor, on January 3rd, 2018, in which he said that "*A case before Washington's Supreme Court seeks to effectively end public labor unions.*" Financial regulation news regards the functioning of financial markets and any policy that affects financial stability (including monetary policy). An example of such fake news is given by a statement by Joe Biden on March 15th, 2020, during a debate. Because the Federal Reserve recently cut interest rates to near 0%, Joe Biden stated that "*the Fed will be of little consequence now. They've already used what leverage they have.*" Finally, government fake news regards the evolution of state and federal budgets, the size of the deficit, and the effects of a fiscal stimulus. An example of fake news related to the government is given by Lindsey Graham's —senator from South Carolina— interview on Fox News on December 12, 2021, in which he stated that "*the CBO says (the Build Back Better Act) is $3 trillion of deficit spending.*" As illustrated in Figure 9, the dynamic response of the economy to the fake news shock identified using labor market, government, or financial regulation news differ significantly from those in our benchmark VAR. Importantly, in all cases the instrument is found to be irrelevant, and, accordingly, the shock does not explain much of the macroeconomic uncertainty, the unemployment rate, and industrial production (see Table 3).

To shed more light on this result, let us consider the case of government fake news (see Appendix Figure B5). They differ from fake technology news in several aspects. Appendix Figure B5(b) suggests that larger spikes in the evolution of fake news issuance are observed during the Obama (2009:1-2016:12) and Biden (2021:1–2022:12) years compared to the Bush (2007:1-2008:12) and Trump (2017:1-2020:12) years. This observation is consistent when combining

Table 3: Variance Contribution: Alternative Instruments

Variable	Impact	1 Month	1 Quarter	1 Year	2 Years	5 Years
Technology (Benchmark)						
Macro. Uncertainty	83.63	84.15	87.81	87.95	76.42	54.32
Unemployment	56.29	28.55	26.05	31.94	31.19	28.94
Ind. Production	13.33	9.38	37.70	54.59	54.81	27.19
Taxes						
Macro. Uncertainty	75.74	73.82	64.19	51.07	43.03	30.97
Unemployment	5.73	12.17	24.42	24.69	22.13	19.83
Ind. Production	1.14	12.78	26.48	22.07	17.23	7.02
Price of Gas						
Macro. Uncertainty	74.64	73.74	62.89	45.23	37.28	32.94
Unemployment	2.64	17.98	37.28	41.54	39.96	38.10
Ind. Production	10.06	34.37	53.89	49.05	39.90	16.47
Labor Market						
Macro. Uncertainty	21.05	18.91	11.02	4.63	3.72	2.61
Unemployment	0.58	9.72	9.20	4.12	2.99	2.40
Ind. Production	31.99	33.02	23.26	11.87	9.19	4.73
Financial Regulation						
Macro. Uncertainty	23.18	25.99	24.72	14.88	18.82	44.93
Unemployment	9.29	41.53	69.91	85.63	88.88	91.05
Ind. Production	14.90	41.31	51.35	43.56	29.39	33.66
Government (Deficit, Budget, Debt)						
Macro. Uncertainty	2.93	3.61	7.52	13.14	12.09	8.12
Unemployment	0.28	0.15	1.85	3.60	3.06	2.54
Ind. Production	48.95	37.27	20.64	16.80	22.10	26.66

Figure 9: Alternative Instruments (II)

Benchmark (Technology), Labor Market, Government, Financial Regulation.

Notes. The solid black line shows the IRFs of the benchmark model variables to a fake technology news shock, the dashed line the IRFs to a fake labor market news shock, the dash-dotted line the IRFs to a fake government news shock, and the dotted line the IRFs to a fake financial regulation news shock. Shaded areas represent ± 1 standard deviation around average response in our Benchmark VAR obtained from 1,000 Bootstrap replications.

findings from psychology and political science. On the one hand, political ideology and partisan polarization provide strong motives for sharing fake political news on social media platforms (Freiling et al., 2023); the main one being the feeling of hatred toward political opponents (Osmundsen et al., 2021). On the other hand, spreaders of political fake news are reportedly Traditionalists/Conservatives (Srinivas et al., 2022) and Republicans are worse at discerning true and false news and are more likely to spread it than Democrats (see Osmundsen et al., 2021; Dobbs et al., 2023; Angelucci and Prat, 2024; Assenza et al., 2024). All these observations suggest that the issuance of fake news on government policies is more likely to be related to the electoral cycle. In order to test for this, we run the regression in the spirit of Section 1.2

$$g_t = \alpha + \rho g_{t-1} + \sum_{i=0}^{p} \phi_i d_{t-i} + \nu_t,$$

where g_t denotes the government fake news instrument, and d_t is a dummy variable that equals one in the month of either a presidential or a midterm election and zero otherwise. Shall the electoral cycle play a role in fake news issuance, then $\{\phi_i\}_{i=1}^{p}$ should differ significantly from zero. In this regression, $p = 3$ as selected by a standard Bayesian Information Criterion. The null of no effect is overwhelmingly rejected (p-value=0.00). In other words, government fake news issuance is fundamentally related to the (fixed) electoral cycle, which is totally predictable in the US and therefore, by construction, does not affect our macroeconomic uncertainty index much.

Taken together, these findings suggest that fake news primarily affects the economy through its impact on supply-side factors. This aligns with our initial focus on technology news.[35]

3.2 Disagreement rather than Uncertainty

Our identification rests on the idea that the issuance of fake news creates confusion that yields greater uncertainty in the economy and complicates the forecast of economic agents. Accordingly, we have used the macroeconomic uncertainty index developed by Jurado et al. (2015) to help identification of our fake news shock. In this section, we dive into another potential channel of transmission of fake technology news shocks: disagreement. By their very nature, fake news is controversial and can lead to increased disagreement among agents, regarding, among other things, future economic outcomes. To measure such disagreements, we make use of the Survey of Consumer Expectations (SCE) published by the New York FED. In particular, Question 4 of the survey (labeled `Q4new`) asks participants *What do you think is the percent chance that 12 months from now the unemployment rate in the U.S. will be higher than it is now?* We compute the cross-sectional volatility in the responses for each period in which this question was asked. We obtain a time series for this measure of disagreement that runs from June 2013 to December

[35]The fact that fake news related to other topics, such as the labor market, government spending, and financial regulations, have small or no impact does not entirely rule out that it can affect the economy. It rather suggests that such an effect is unlikely to go through the mechanism pushed in this paper.

2022.[36] We then estimate our benchmark VAR, replacing the Jurado et al. (2015) uncertainty measure by our disagreement measure.[37]

Figure 10: Disagreement VAR

Notes. The solid black line shows the IRFs of the model variables to a fake technology news shock. Instead of the 1-month ahead Jurado et al. (2015) macroeconomic uncertainty index, we include in the VAR a measure of disagreement (using micro-data from the Survey of Consumer Expectations, published by the New York Fed). Shaded areas represent ± 1 standard deviation around average response obtained from 1,000 Bootstrap replications.

The impulse response functions in Figure 10 closely resemble those of our benchmark VAR, reinforcing the notion that fake technology news shocks[38] sow confusion and disagreement among agents.

Crucially, Table 4 reveals that the fake technology news shock explains a sizeable portion of the unpredictable volatility in disagreement: over 90% in the short run. This not only underscores the significance of fake news as a source of agent disagreement, but also bolsters the relevance of our instrument.

Table 4: Variance Contribution: Disagreement

Variable	Impact	1 Month	1 Quarter	1 Year	2 Years	5 Years
Disagreement	94.06	92.94	86.56	74.82	70.62	69.17
Unemployment	11.58	54.06	64.69	66.60	65.09	64.48
Ind. Production	26.44	56.81	62.99	49.51	35.73	18.99

This amplified disagreement manifests itself as a decline in industrial production and a surge in unemployment. Paralleling our benchmark findings, the fake technology news shock accounts for a substantial share of business cycle volatility: approximately 65% for unemployment and 62% for industrial production at the one-quarter horizon. It is also worth noting that, despite

[36] A major advantage of this particular survey is that the quantitative microdata are readily available, and the construction of disagreement is straightforward. However, the shortness of the time series prevented us from basing our identification on this variable. In Appendix F, we also report results obtained from a different measure of disagreement that we constructed using data from the Michigan Survey. Although the Michigan Survey is available for the entire sample period, the qualitative nature of the relevant survey questions does not allow us to compute measures of disagreement straightforwardly; some parametric assumptions are needed. This complication makes our instrument suffer from a weakness problem for this particular measure of disagreement. Therefore, we do not base our analysis on the Michigan Survey.

[37] Appendix E shows that the results obtained from an LP-IV approach are very similar to those in the proxy-VAR.

[38] In this and the following sections, we are back to our benchmark fake technology news instrument.

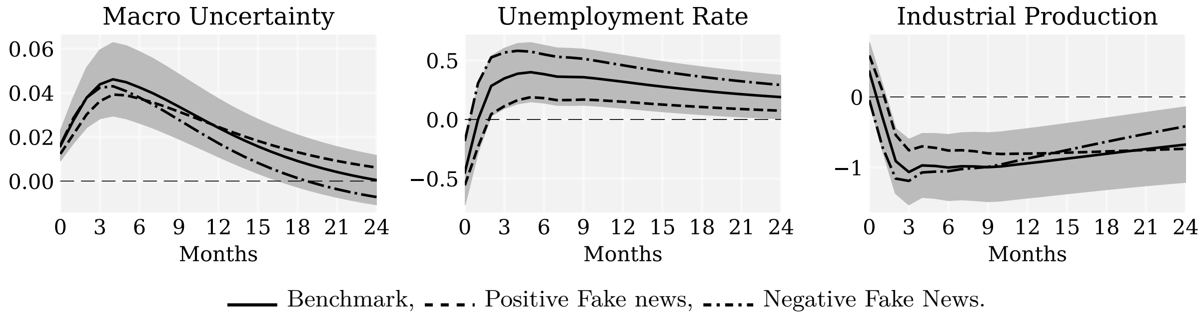
the rather small sample size, the IRFs are precisely estimated, which suggests that there is enough information in the sample to obtain precise estimates and that our instrument clearly identify the fake technology news shock. These findings are reminiscent of Pei (2023) who showed that pessimistic bias and the cross-sectional dispersion of subjective beliefs of households increases during recessions. He shows that these findings can be rationalized based on a theory of ambiguity-driven business cycles. In his model, agents face an ambiguity shock that generates countercyclical pessimism and disagreement. The source of this ambiguity shock remains unclear; our results provide a potential rationale for it.

3.3 Positive or Negative Fake News?

So far, our instrument strategy has rested on exploiting changes in the number of fake news related to technology, regardless of the news's meaning. In other words, among the fake news, we considered some that announced positive technology developments, while some, on the contrary, had a negative flavor. In this section, we ask whether negative fake news is more likely to harm the economy than positive fake news. This immediately raises the question of the classification of fake news. To address the question, we rely on sentiment analysis, which is a branch of natural language processing that focuses on detecting and understanding the emotional tone of a piece of text. Sentiment analysis, therefore, aims to identify whether a statement expresses positive, negative, or neutral sentiment toward a particular topic—technology in this instance. In this paper, we rely on a specific tool, the VADER (Valence Aware Dictionary and sEntiment Reasoner) classifier — a mainstream model for sentiment analysis using a general-language human-curated lexicon (see Hutto and Gilbert, 2014). This tool computes an index ranging between -1 and 1, allowing the classification of a text as negative or positive. One potential limitation of this type of tool is that it relies on a specific lexicon. In order to avoid this issue, we used FinVADER, which extends VADER's general lexicon with two finance-specific lexicons: SentiBignomics developed by Barbaglia et al. (2023), and Henry's 2008 word list. We apply FinVADER to our fake news database and classify technology news as negative or positive according to the sign of the valence. A typical example of positive fake news can be found in the following tweet post from November 20^{th}, 2019, in which Donald Trump stated: "*Today I opened a major Apple Manufacturing plant in Texas that will bring high paying jobs back to America.*". On the other side of the spectrum, the Instagram post of August 2^{nd}, 2022, stating "*AirPods are essentially microwaving your brain.*" is classified as negative news.

Figure 11 compares the response of the economy to a fake technology news shock in our benchmark VAR —that mixes all technological news— and in VARs where only negative (resp. positive) news are considered. The figure suggests that the direction of the fake news only has a small impact on the responses. If anything, the economy is, on average, less responsive to positive news than to negative news. Interestingly, as shown in Table 5, fake technology news shocks identified relying on negative sentiment news account for a greater share of macroeconomic

Figure 11: Positive vs Negative Fake News



Notes. The solid black line shows the IRF of the model variables to a fake technology news shock (the benchmark), the dashed line the IRFs to a positive sentiment fake technology news shock, the dash-dotted line the IRFs to a negative sentiment fake technology news shock. Shaded areas represent ± 1 standard deviation around average response in our benchmark VAR obtained from 1,000 Bootstrap replications.

uncertainty volatility, the unemployment rate, and industrial production than those based on positive news. This finding is reminiscent of Forni et al. (2024) who show that bad news about future economic developments affects the economy more than good news[39], and Zhaochen (2017), who estimates a depressing impact of exposure to pessimistic economic news on employment and hiring. Similarly, Garz (2013) studies the link between (negativity in) economic news coverage and unemployment expectations in Germany, showing that negativity in reporting promotes pessimism in the long-run. Nguyen and Edda (2013) find asymmetry in consumers' reaction to a set of financial and economic news i.e., consumers react to bad news but not to good news.[40] Taken together, these facts suggest that economic uncertainty increases more strongly with the release of negative fake news than positive ones. This is actually due to a weak instrument problem affecting the positive fake news and, therefore, does not warrant the proper identification of the causal effect of these latter shocks.[41]

The split between positive and negative news offers additional information when taken into account in a proxy-VAR featuring confidence (see Figure 12). Fake news shocks identified on negative news trigger a significant persistent consumer confidence loss, while the same shocks identified on positive news induce a very short-lived surge in confidence. Hence not only fake (negative) news do increase uncertainty but they also lead to a wave of pessimism that positive fake news cannot undo.[42] These negative fake news are also found to contribute to a large share of the overall volatility of confidence in the medium-run —about 43% after 1 year, 38% after 2 years (see Table 5).

[39] Forni et al. (2024) consider the effects of news rather than fake news shocks. Accordingly, they find that a positive (negative) news shock permanently increases (decreases) real economic activity variables.

[40] The existence of an asymmetry in the response to positive and negative fake news is also in line with the literature in media communication, psychology, political science (see e.g. Robertson et al., 2023; Cianci and Falsetta, 2008; Soroka, 2006).

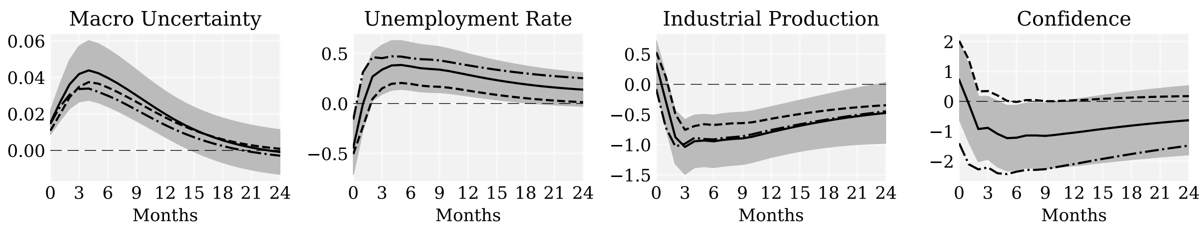
[41] This observation is confirmed when relying on a sentiment classifier based on a Large Language Model (see e.g. Pfeifer and Marohl, 2023, who trained a Large Language Model on Central Bank communication to build a binary sentiment classifier). In that case, the positive sentiment fake technology news shock explains less than 10% of macroeconomic uncertainty, and the weak instrument test cannot be rejected (test=0.16).

[42] This finding aligns with the psychology literature showing a direct relationship between exposure to negative news and negative emotional states (e.g. Balzarotti and Ciceri, 2014; Holman et al., 2014).

Table 5: Variance Contribution: Positive vs Negative Fake News

Variable	Impact	1 Month	1 Quarter	1 Year	2 Years	5 Years
Technology (Benchmark)						
Macro. Uncertainty	83.63	84.15	87.81	87.95	76.42	54.32
Unemployment	56.29	28.55	26.05	31.94	31.19	28.94
Ind. Production	13.33	9.38	37.70	54.59	54.81	27.19
Technology (Positive)						
Macro. Uncertainty	50.45	50.16	56.88	67.85	63.96	42.85
Unemployment	87.16	51.83	24.56	12.73	10.42	8.50
Ind. Production	36.14	15.56	21.09	33.17	40.51	32.28
Technology (Negative)						
Macro. Uncertainty	88.67	90.28	86.59	71.35	59.16	53.54
Unemployment	9.38	18.14	46.96	64.63	64.81	62.99
Ind. Production	0.21	22.54	56.63	61.74	50.53	21.89
Technology (Benchmark)						
Macro. Uncertainty	79.60	80.54	83.43	77.45	55.06	32.22
Unemployment	54.96	27.54	24.44	29.60	28.21	25.38
Ind. Production	11.86	8.43	36.00	54.30	46.87	11.62
Confidence	3.24	1.73	4.36	9.41	8.15	4.65
Technology (Positive)						
Macro. Uncertainty	40.68	44.72	53.82	56.34	40.69	23.10
Unemployment	72.50	43.99	21.45	12.35	9.62	7.46
Ind. Production	29.64	13.15	19.66	28.42	24.43	6.91
Confidence	25.77	20.02	12.64	4.30	2.44	1.36
Technology (Negative)						
Macro. Uncertainty	74.23	68.82	59.65	46.77	32.69	21.39
Unemployment	7.28	17.47	34.84	45.74	49.30	53.15
Ind. Production	0.66	22.91	45.05	53.99	45.53	10.38
Confidence	12.41	21.21	33.20	43.07	37.55	23.20

Figure 12: Positive vs Negative Fake News and Confidence



All Fake News, Positive Fake news, Negative Fake News.

Notes. This VAR includes the Michigan Confidence Index, in addition to the benchmark variables. The solid black line shows the IRF of the model variables to a fake technology news shock, the dashed line the IRFs to a positive sentiment fake technology news shock, the dash-dotted line the IRFs to a negative sentiment fake technology news shock. Shaded areas represent ± 1 standard deviation around average response in the VAR featuring all fake technology news obtained from 1,000 Bootstrap replications.

3.4 Robustness to Identification Method

The set of impulse response functions produced by our benchmark is obtained assuming that the VAR satisfies the invertibility condition, meaning that shocks can be obtained relying only on the current and past history of the data. In Section 2.1, we used Plagborg-Møller and Wolf's (2022) pre-test for invertibility to show that our proxy-VAR does not suffer from non-invertibility problems. The test, however, does not guarantee per se that the VAR is invertible.

Local projection estimator allows one to recover the dynamic causal effect of a shock but dispenses from the invertibility condition. Therefore, we assess the robustness of our findings to using such an approach. We employ a straightforward version of the local projection (LP-IV) estimator, where the impulse responses at horizon h are derived from the estimates of $\{\varphi_h\}_{h=0}^{H}$ obtained from the regression

$$X_{j,t+h} - \overline{X}_{j,t-1} = \alpha_{i,h} + \varphi_{i,h} v_t + \Gamma_{i,h}(L) X_{t-1} + \nu^x_{i,j,t+h},$$

where $X_{j,t}$ represents the j-th variable in vector X_t; $\overline{X}_{j,t-1}$ is a variable that takes the value $X_{j,t-1}$ if the variable is growing (Industrial production in our benchmark VAR) and 0 otherwise; ν^x denotes the residual of the regression. In this regression, v_t denotes the one-month ahead macroeconomic uncertainty which is instrumented by our fake news instrument. This regression relaxes the restrictive invertibility assumption assumed in our benchmark VAR.

Figure 13: Robustness to Methodology (Local Projection IV)

Notes. The solid black line shows the average response (IRFs) of the model variables to a fake technology news shock, using the local projection (LP-IV) approach. Shaded areas represent ± 1 standard deviation around average response obtained from 1,000 Bootstrap replications.

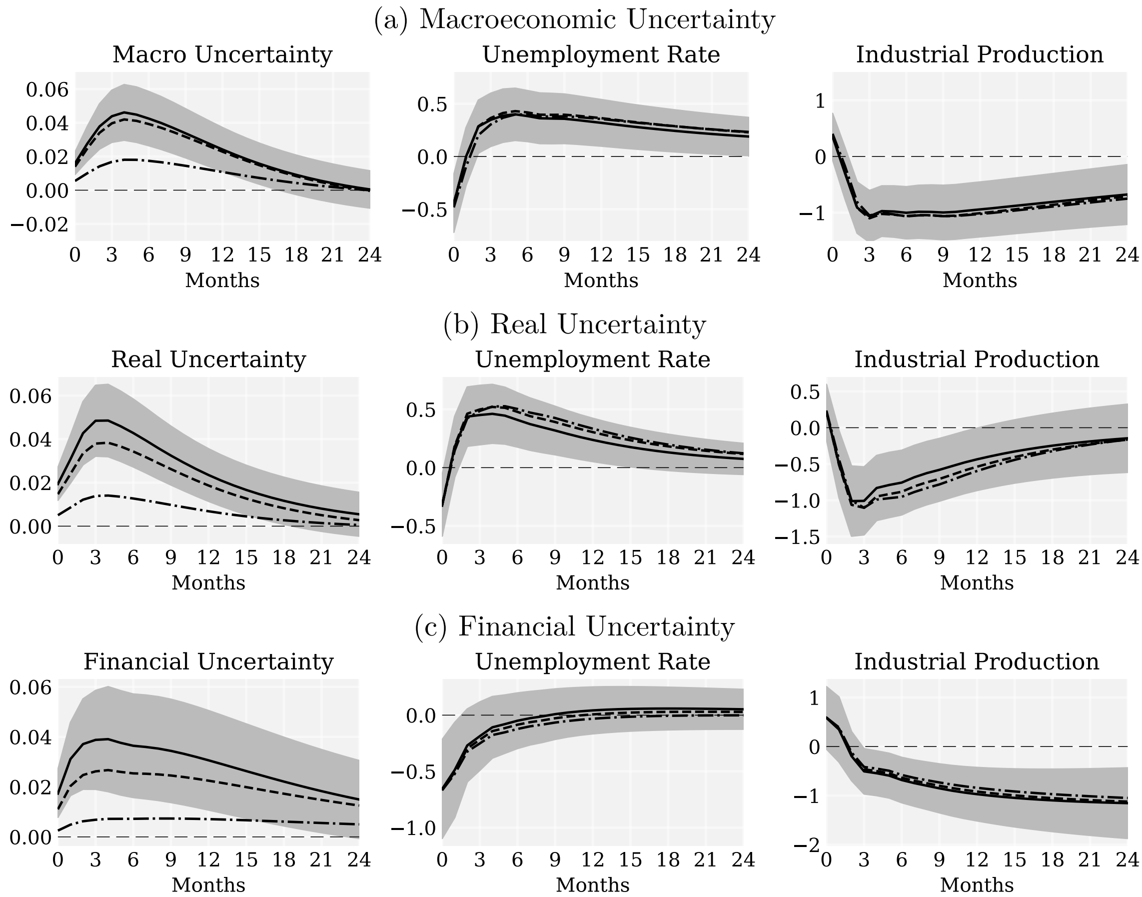
Figure 13 depicts the average response of our economic variables to the fake technology news shock, estimated using the LP-IV approach. Despite its flexibility, the method yields results strikingly similar to our initial findings. Specifically, key economic factors (unemployment and industrial production) exhibit similar dynamics under both methods. The LP-IV estimates are slightly bumpier, but the overall magnitudes of the changes are very comparable. The uncertainty response is somewhat weaker in the new method, but still follows a similar hump-shaped pattern. Overall, these minor differences do not change the main conclusion: The fake technology news shock has a significant negative impact on the economy. This robustness check using a more flexible method strengthens our confidence in the results.

3.5 Robustness to Uncertainty Measure

In this section, we investigate the extent to which our benchmark results are robust to variations in the specification of the information set of the econometrician.

Variations in the exact definition of the macroeconomic uncertainty index (3-month or 1-year ahead macroeconomic uncertainty) does not affect the overall conclusions of our analysis.

Figure 14: Role of Uncertainty



Benchmark (1 Month ahead), 3-Month ahead, 1-Year ahead.

Notes. This Figure shows the IRFs of the model variables to a fake technology news shock—including different proxies to measure uncertainty in the VAR. In Panel a, we include the macroeconomic uncertainty index (the benchmark); in Panel b, a measure of real uncertainty; and in Panel c, a measure of financial uncertainty. The solid black lines show the IRF of the model variables when including a 1-month ahead uncertainty proxy, the dashed line the IRFs when including a 3-month ahead uncertainty proxy, and the dash-dotted line the IRFs when including a 1-year ahead uncertainty proxy. All undertainty measures are borrowed from Jurado et al. (2015). Shaded areas represent ± 1 standard deviation around the average response obtained from 1,000 Bootstrap replications.

The response of the 1-year ahead macroeconomic uncertainty is weaker, reflecting that agents do not perceive the news to have a long-lasting effect on the economy. Likewise, replacing macroeconomic uncertainty with real uncertainty leads to the same conclusions. A fake technology news shock raises macroeconomic uncertainty—to a lesser extent for the longer run index, increases unemployment, and depresses industrial production. In all cases, the fake

Table 6: Variance Contribution: Specification

Variable	Impact	1 Month	1 Quarter	1 Year	2 Years	5 Years
Macroeconomic Uncertainty						
1-Month ahead (Benchmark)						
Uncertainty	83.63	84.15	87.81	87.95	76.42	54.32
Unemployment	56.29	28.55	26.05	31.94	31.19	28.94
Ind. Production	13.33	9.38	37.70	54.59	54.81	27.19
3-Month ahead						
Uncertainty	88.20	88.81	90.52	85.51	72.42	53.00
Unemployment	54.60	29.21	28.60	38.21	38.60	36.98
Ind. Production	13.91	9.75	41.51	62.15	61.88	29.51
1-Year ahead						
Uncertainty	85.54	85.28	84.38	72.50	55.44	34.87
Unemployment	58.81	34.32	27.45	35.38	35.61	33.21
Ind. Production	16.19	8.78	37.88	63.86	66.38	32.36
Real Uncertainty						
1-Month ahead						
Uncertainty	92.99	90.70	93.68	93.23	81.72	50.78
Unemployment	30.67	18.91	31.18	35.40	29.64	19.87
Ind. Production	5.02	11.54	35.39	31.93	21.98	9.60
3-Month ahead						
Uncertainty	97.52	97.87	98.43	90.99	76.28	46.59
Unemployment	30.99	20.80	38.72	48.55	42.62	29.96
Ind. Production	5.53	13.35	42.86	42.60	30.24	13.22
1-Year ahead						
Uncertainty	97.65	98.19	95.06	77.16	57.40	31.28
Unemployment	28.40	18.56	38.25	55.57	51.38	38.91
Ind. Production	5.75	10.93	43.25	49.82	36.26	16.07
Financial Uncertainty						
1-Month ahead						
Uncertainty	33.79	37.65	38.66	40.74	43.21	39.89
Unemployment	79.34	64.60	45.38	17.16	11.79	10.10
Ind. Production	25.77	15.79	14.14	37.00	60.94	68.67
3-Month ahead						
Uncertainty	27.95	31.37	31.97	33.47	36.21	33.53
Unemployment	79.90	65.83	47.75	18.70	12.44	10.40
Ind. Production	25.84	16.14	13.32	33.01	56.85	68.77
1-Year ahead						
Uncertainty	22.07	24.89	24.71	24.55	27.13	25.16
Unemployment	78.93	65.27	49.15	20.56	13.53	11.13
Ind. Production	25.23	15.92	12.19	28.27	51.27	67.11

Notes: The macro-, real-, and financial uncertainty indices are provided by Sydney Ludvigson.

technology news shock explains a substantial share of the volatility of the variables, about the same amount as in our benchmark experiment. Unlike Ludvigson et al. (2021), the results become less robust when, instead of real or macroeconomic uncertainty, one relies on financial uncertainty. As can be seen in Panel (c) of Figure 14, the responses of the uncertainty index and those of the macroeconomic aggregate start to show significant differences from our benchmark, with, in particular, the unemployment rate being reduced for approximately one entire semester. But as alarming as these differences might be, they are actually not. A hint is given by the variance decomposition reported in Table 6 that shows that the fake technology news shock does not account for much of the financial uncertainty. In fact, in this case, our proxy is a weak instrument, with Montiel Olea and Pflueger (2013) statistics ranging between 1 and 2 depending on how far in the future the uncertainty index looks. The imprecision of the IRF of financial uncertainty confirms this. Similar results are obtained when uncertainty is replaced by a volatility measure based on a single indicator: VIX or the Economic Policy Uncertainty Index (see Baker et al., 2016).

All in all, this suggests that fake news indeed has a direct impact on the economy because it increases real and macroeconomic uncertainty and hence directly affects the economic agents, not so much because of its potential effects on specific sectors of the economy (financial markets, economic policy).

4 Concluding Remarks

Does fake news have a significant impact on macroeconomic outcomes? While economic decision makers and policy makers have recently rated fake news as one of the most severe global short-term risks, the empirical macroeconomic literature has remained silent about the potential economic costs they generate. This paper has investigated the impact of fake news on macroeconomic dynamics, making a first attempt to fill this gap. Using a novel fake news dataset and a proxy-VAR methodology, we have shown that fake technology news shocks have a significant and detrimental impact on key macroeconomic indicators and contribute to overall business cycle volatility. Our findings indicate that fake technology news shocks increase macroeconomic uncertainty and unemployment and depress production. For instance, a one standard deviation increase in fake news issuance generates a 0.5 % point increase in unemployment and a 1% loss in production a quarter after one quarter. Fake news also contributes substantially to overall volatility of the business cycle, explaining about a third of unemployment volatility at the one-year horizon and 50% of that of production. Our analysis also indicates that negative fake news has a more detrimental impact on the economy compared to positive ones, with an even greater impact on consumer confidence. Fake news actually harms various parts of the economy, including consumption, labor, and finance. Importantly, all these effects manifest in so far as fake news somehow relates to supply-side factors such as technology, taxes, and gas prices.

Most effects disappear when considering fake news regarding the state of the labor market, government finance, or market regulation—traditionally considered demand-side phenomena in economic literature.

The mechanism at work is simple; by introducing noise in the system, (supply-side) fake news complicates the forecasting task of economic agents, which raises uncertainty and depresses the economy. Relying on data from the Survey of Consumer Expectations, we also show that fake news leads to greater disagreement among agents, hence raising coordination problems that potentially harm the economy. Therefore, our study provides compelling evidence that fake news is not just a social or political issue but also a significant economic concern. While our results suggest that only fake technology (and other supply-side) news exert a significant effect on the economy, they however do not entirely rule out that other types of fake news affect macroeconomic outcomes. Other types of fake news may indeed affect the economy through mechanisms other than rising uncertainty and disagreement.

Existing policy analyses and discussions about the problem of fake news focus on their political and societal impacts, e.g., the damage to the democratic process (see IMCO (2018) & EU code of practice on disinformation)[43]. So far, the direct economic consequences of fake news have remained essentially absent from this debate. However, our findings clearly suggest that fake news creates significant negative spillovers for macroeconomic and financial stability. The implied inefficiencies, such as suboptimal behavior and misallocation problems, provide a rationale for policies targeting fake news.

Addressing this challenge requires a multifaceted approach that involves policy makers, media platforms, and the general public. Several policies are publicly discussed and should be considered to counter the damages created by fake news, including supporting and promoting media training and fact-checking initiatives, developing regulatory frameworks to fight the spread of misinformation, and investing in technological solutions to identify and filter fake news. The analysis of such policies goes beyond the scope of this paper. Finally, our results suggest that policymakers may benefit from monitoring the prevalence of fake economic news, especially fake news that focuses on the supply side of the economy.

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— APPENDIX —

A Data

Most variables are obtained from the Federal Reserve Economic Database (https://fred.stlouisfed.org/). Macroeconomic uncertainty data are kindly provided by Sydney Ludvigson (https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes).

Table A1: Data

Variable	Mnemonic
Unemployment rate	UNRATE
Industrial Production	$100 \times (\log(\texttt{INDPRO}_t) - \log(\texttt{INDPRO}_{t-1}))$
Chained Price non-durables	DNDGRG3M086SBEA
Chained Price services	DSERRG3M086SBEA
Real PCE: non durables	PCENDC96
Real PCE: services	PCESC96
Real PCE: durables	PCEDGC96
Michigan Confidence Index	MCI
Capacity utilization	TCU
Hours Worked (Manufacturing)	AWHMAN
Help Wanted Index⋆	HWI
S&P500 Index⋆	SP500
VIX⋆	VIXCLS
Inflation Rate	CPIAUCSL_PCH
Expected Inflation (1 Year)	EXPINF1YR
Expected Inflation (5 Years)	EXPINF5YR
Federal Fund Rate	FEDFUNDS
AAA Moody's corporate bond rate	AAA
BAA Moody's corporate bond rate	BAA

Note: PCE: Personal Consumption Expenditures. ⋆ variables are obtained from the McCracken and Ng (2021) database.

We now detail the construction of the percent change in consumption of non-durables and services. The BEA reports chained price indices for non-durables, P_t^{ND}, and services, P_t^{S}, as well as the associated real personal consumption expenditures of non-durable goods, C_t^{ND}, and services, C_t^{S}. Following the BEA, we calculate the growth rate of real consumption expenditures of non durables and services according to the ideal chain index (see e.g. Fisher, 1922; Whelan, 2000):

$$\Delta C_t^{\mathrm{ND+S}} = \sqrt{\frac{P_t^{\mathrm{ND}} C_t^{\mathrm{ND}} + P_t^{\mathrm{S}} C_t^{\mathrm{S}}}{P_{t-1}^{\mathrm{ND}} C_t^{\mathrm{ND}} + P_{t-1}^{\mathrm{S}} C_t^{\mathrm{S}}} \times \frac{P_t^{\mathrm{ND}} C_{t-1}^{\mathrm{ND}} + P_t^{\mathrm{S}} C_{t-1}^{\mathrm{S}}}{P_{t-1}^{\mathrm{ND}} C_{t-1}^{\mathrm{ND}} + P_{t-1}^{\mathrm{S}} C_{t-1}^{\mathrm{S}}}} - 1$$

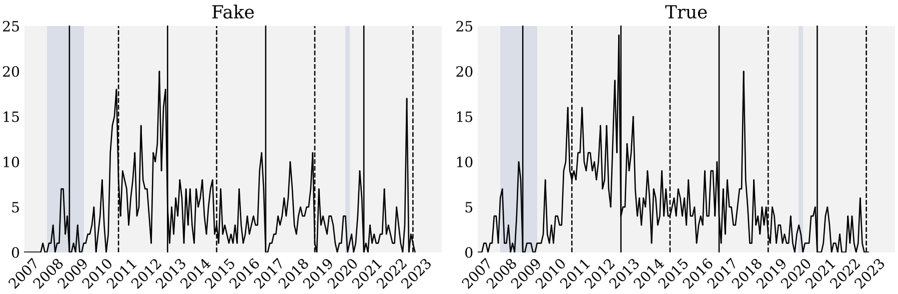
B Other Proxies

Table B1: Granger Causality Test (p-values)

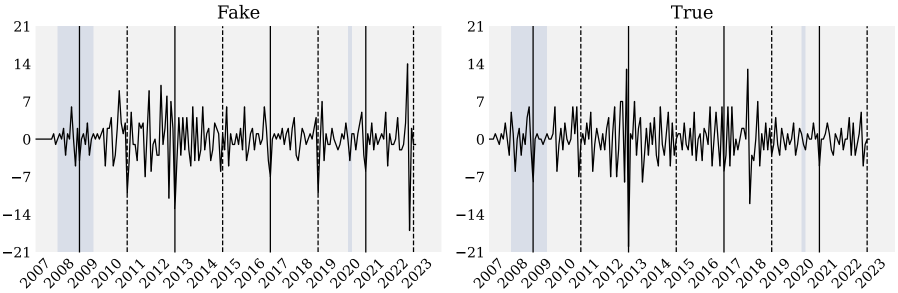
	Technology	Taxes	Gas Prices	Fin. Reg.	Labor	Government
p-value	0.9386	0.7495	0.9093	0.3571	0.9192	0.7718

Figure B1: Tax News

(a) Number of Fact Checked News



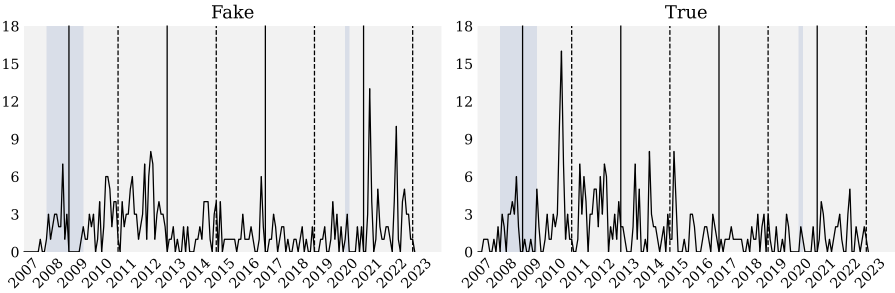
(b) Change in Number of Fact Checked News



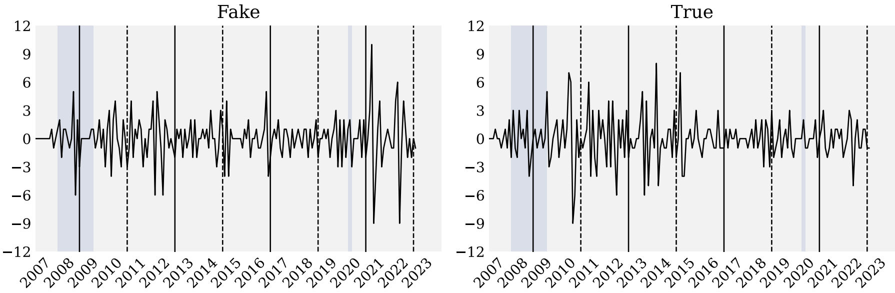
Shaded area: NBER Recessions, Vertical plain line: Presidential election, Vertical dashed line: Midterm election

Figure B2: Gas Price News

(a) Number of Fact Checked News



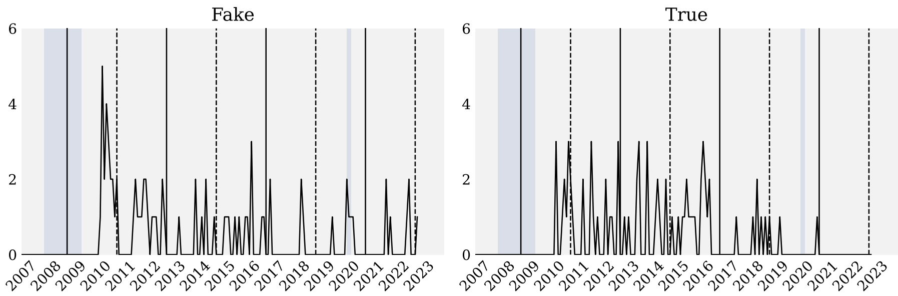
(b) Change in Number of Fact Checked News



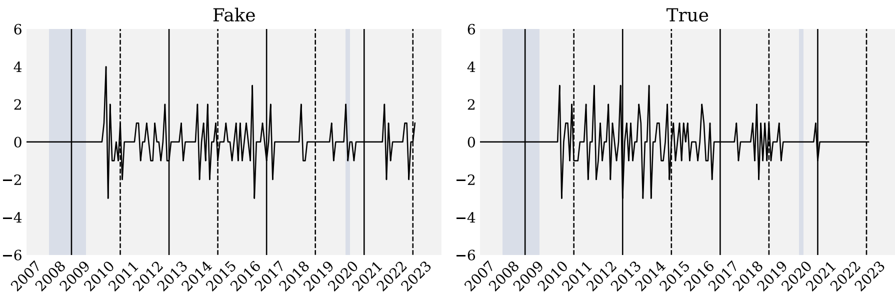
Shaded area: NBER Recessions, Vertical plain line: Presidential election, Vertical dashed line: Midterm election

Figure B3: Financial Regulation News

(a) Number of Fact Checked News



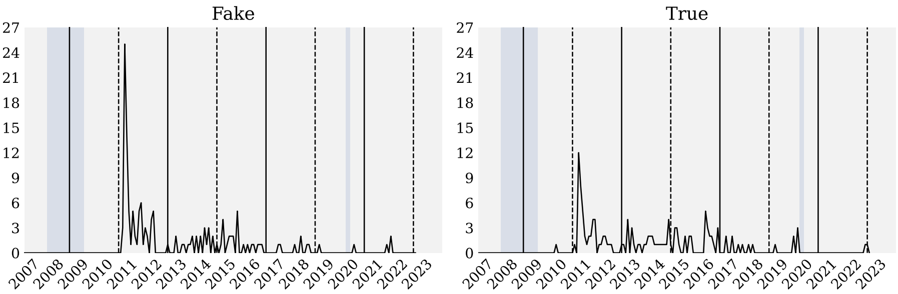
(b) Change in Number of Fact Checked News



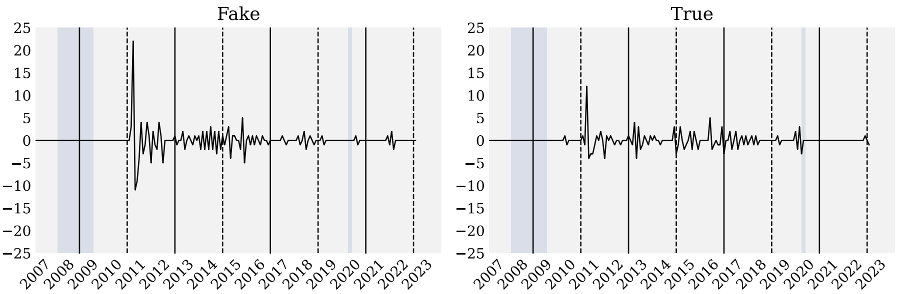
Shaded area: NBER Recessions, Vertical plain line: Presidential election, Vertical dashed line: Midterm election

Figure B4: Labor News

(a) Number of Fact Checked News



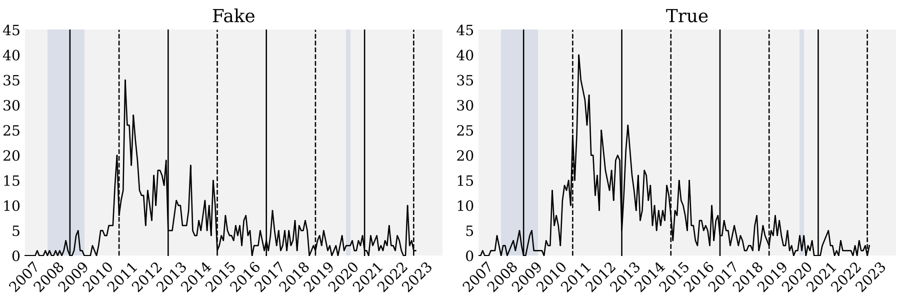
(b) Change in Number of Fact Checked News



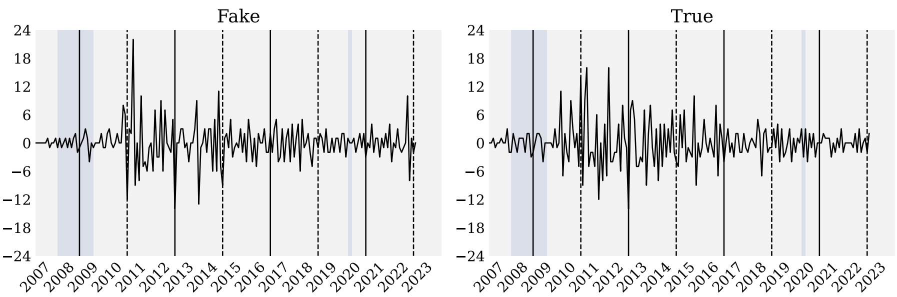
Shaded area: NBER Recessions, Vertical plain line: Presidential election, Vertical dashed line: Midterm election

Figure B5: Government News

(a) Number of Fact Checked News



(b) Change in Number of Fact Checked News



Shaded area: NBER Recessions, Vertical plain line: Presidential election, Vertical dashed line: Midterm election

C Varying the Definition of fake technology news

As stated in Section 1.2, the "Truth-O-Meter" developed by PolitiFact comprises six grades in the rating of fact-checked news: (i) True, (ii) Mostly True, (iii) Half True, (iv) Mostly False, (v) False, (vi) Pants on Fire. Our benchmark classification reduces the notion of fake news to the combination of news classified as mostly false, false, or pants on fire. In this section, we investigate the extent to which this classification matters. More precisely, we start by differentiating between "mostly false", "false", and "pants on fire" news, using each of them as an instrument. We then consider combinations of "mostly false" and "false", and "false" and "pants on fire". The combination of the three types corresponds to our benchmark. In all cases, the instruments are not Granger caused by the state of the Business Cycle. Figure C1 depicts the dynamics of our proxy-VAR variables following any of the various combination; Table C1 reports the associated forecast error variance decompositions. Our results are clearly robust to the exact definition of our instrument, in so far as the instrument includes "false" news. There are two main reasons for this finding: *(i)* these are the most numerous news; *(ii)* they bring relevant information. Ignoring "false" news significantly weakens the instrument and jeopardizes proper identification. It is important to note that considering the "pants on fire" news —ridiculously false news— leads to a weak instrument problem. This is reassuring, as it signals that our results are not related to the effect of a ludicrous proxy and the by-product of an absurd coincidence.

Figure C1: Robustness to Definition of fake technology news

(a) Individual Ranking

Benchmark, Mostly False, False, Pants on Fire.

(b) Combination of Ranking

Benchmark, Mostly False+False, False+Pants on Fire.

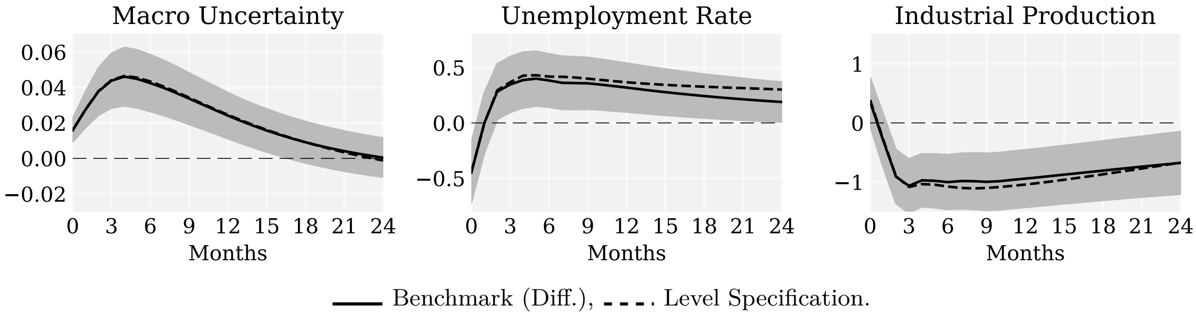
Notes. Shaded areas represent ± 1 standard deviation around average response in the benchmark VAR obtained from 1,000 Bootstrap replications.

Table C1: Variance Contribution: Michigan Survey

Variable	Impact	1 Month	1 Quarter	1 Year	2 Years	5 Years
Mostly False						
Macro. Uncertainty	62.73	64.30	71.16	74.20	64.04	47.22
Unemployment	54.13	27.62	23.90	31.96	32.39	30.82
Ind. Production	17.32	9.76	35.23	54.88	55.50	26.75
False						
Macro. Uncertainty	76.30	79.52	85.37	80.89	67.65	57.78
Unemployment	20.00	14.93	38.23	61.03	62.30	60.63
Ind. Production	8.84	10.61	38.84	48.49	39.92	18.25
Pants on Fire						
Macro. Uncertainty	53.29	49.87	46.69	49.30	49.79	35.23
Unemployment	74.18	43.41	19.83	6.27	4.24	3.46
Ind. Production	7.10	3.45	15.53	26.52	37.98	47.67
Mostly False + False						
Macro. Uncertainty	74.17	76.80	83.44	82.11	69.34	55.45
Unemployment	33.89	18.48	31.37	49.59	50.73	49.09
Ind. Production	12.66	10.36	39.08	53.66	48.15	20.19
False + Pants on Fire						
Macro. Uncertainty	90.35	90.24	91.98	90.59	78.96	55.40
Unemployment	54.70	27.78	25.94	30.49	29.26	26.81
Ind. Production	11.07	8.95	37.20	51.98	51.99	26.17

D Levels vs Difference

Figure D1: Level vs Difference Specification



Notes. Shaded areas represent ± 1 standard deviation around average response in the benchmark VAR obtained from 1,000 Bootstrap replications.

Table D1: Variance Contribution: Specification

Variable	Impact	1 Month	1 Quarter	1 Year	2 Years	5 Years
Level Specification						
Macro. Uncertainty	83.15	83.66	86.80	86.17	74.77	64.88
Unemployment	54.93	29.97	29.93	44.51	49.04	54.10
Ind. Production	14.67	9.82	38.84	61.10	68.26	66.14

E Disagreement LP-IV

Figure E1: Disagreement LP-IV

Notes. Shaded areas represent ± 1 standard deviation around average response obtained from 1,000 Bootstrap replications.

F Disagreement in the Michigan Survey

The Michigan Survey of Consumers asks consumers to formulate a guess about short-run economic outcomes. Table 26 reports the fraction of respondents who expect the business conditions to improve, remain the same, or worsen in a year time. Likewise in Table 28, they have to indicate whether they expect Less, the Same or More unemployment in a year time with respect to the current period. Given the qualitative nature of the question, building a measure of disagreement is not as straightforward as if agents had to report a number.

Carlson and Parkin (1975) offer a simple method in which it is assumed that the survey respondents convert unobserved point forecasts to observed qualitative expectations using a deterministic categorization scheme. In other words, shall the expectation be below (resp. above) a given threshold the respondent reports “Worse” (resp. “Better”). Shall it lie in between, the respondent reports “Same”. Assuming that the thresholds, τ_w, τ_b are constant and distributed around 0 ($\tau_w = -\tau$, ($\tau_b = \tau$), a measure of disagreement is given by

$$\sigma_t = \tau\phi/(F^{-1}(1 - p_{b,t}) - F^{-1}(1 - p_{w,t}))$$

where τ is the threshold (which is irrelevant for our purpose, as we are only interested in co-movements), ϕ is a constant term that we will define next, and $F(\cdot)$ is the assumed distribution of forecasts. $p_{b,t}$ and $p_{w,t}$ denote, respectively, the fraction of agents who expect a better, resp. worse, outcome. Carlson and Parkin (1975) initially assumed that forecasts be normally distributed. Because excess kurtosis is often found in quantitative expectations, this assumption has been criticized (see Maag, 2009; Breitung and Schmeling, 2013, among others). Hence, we follow Dasgupta and Lahiri (1992) and assume that forecasts are distributed according to a Student-t distribution with n degrees of freedom ($n = 2$ in our case). In this case, the constant ϕ is given by $2\sqrt{n/(n-1)}$.

Figure F1 reports the response of the disagreement to a fake technology news shock. The responses are very much in line with those found using the SCE. Compared to the SCE though, the fake technology news shock explains substantially less of the disagreement, which is in fact related to a weak instrument problem that we are facing in this specification.

Figure F1: Disagreement (Michigan Survey)

Notes. The solid black line shows the IRFs to a fake technology news shock in the model featuring disagreement about unemployment. The dashed line shows the corresponding IRFs in the model featuring disagreement about business cycle conditions. Shaded areas represent ± 1 standard deviation around average response in the VAR featuring disagreement about unemployment obtained from 1,000 Bootstrap replications.

Table F1: Variance Contribution: Michigan Survey

Variable	Impact	1 Month	1 Quarter	1 Year	2 Years	5 Years
Unemployment						
Disagreement	44.37	53.52	54.70	53.23	50.23	43.05
Unemployment	41.21	51.45	50.79	37.14	25.37	14.00
Ind. Production	72.88	70.98	65.57	39.49	24.95	16.01
Business Cycle Conditions						
Disagreement	18.44	30.45	38.09	37.72	32.45	25.36
Unemployment	34.25	47.00	51.19	41.78	29.60	17.82
Ind. Production	87.80	83.71	72.81	40.52	24.43	12.25