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Macroeconomic effects of uncertainty: a Google trends-based analysis for India

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Abstract
This study proposes a new high-frequency indicator to measure economic policy uncertainty in the context of India, a large emerging market economy. Based on internet search intensity data, the proposed index tends to peak around domestic and global events associated with uncertainty that may prompt economic agents to alter their decisions to spend, save, invest and hire. Using an external instrument with structural vector autoregression (SVAR-IV) framework, we provide fresh evidence on the causal impact of uncertainty on the Indian macroeconomy. We show that surprise increases in uncertainty lead to a fall in output growth and an increase in inflation. This effect is found to be mainly driven by a fall in private investments vis-à-vis consumption indicating a dominant supply-side impact of uncertainty. Lastly, taking the case of output growth, we show that adding our uncertainty index to standard forecasting models leads to better forecasting accuracy compared to other alternate indicators of macroeconomic uncertainty.

Keywords Macroeconomy · Google trends · Economic policy uncertainty · Uncertainty shocks · Forecasting

JEL Classification C31 · C55 · E22 · E32 · G18

1 Introduction

Uncertainty about the current state of the economy as well as its future outlook plays an important role in determining the evolution of macroeconomic outcomes. Economic agents find it difficult to take decisions when they are unsure about the likely trajectory

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of the economy. This prompts people to change their decisions—it may force consumers to delay consumption of goods and services (see Kimball 1990; Eberly 1994) or it may influence firms' decision to invest in capital or hire labour (for example, see Bernanke 1983; Pindyck 1993; Bertola and Caballero 1994; Christiano et al. 2014; Arellano et al., 2010). In addition to negative macroeconomic and financial outcomes, uncertainty can also arise due to political economy factors which eventually percolate into economic policies. Statements, actions and decisions taken by policymakers with respect to fiscal, monetary, structural and regulatory policies can also affect the wider economy and its future outcomes.

A general issue related to analysing the economic effects of uncertainty is its measurement. In general, a period of low uncertainty is characterized by stable economic conditions that provides a conducive environment for the economy to grow at its potential. On the other hand, heightened uncertainty, such as that prevailing after a recession, tends to hurt economic activity making the economy perform below its potential. However, since uncertainty is not directly observable, alternate ways of measuring uncertainty become an important task.

For India, a large emerging market economy, an uncertainty index based on newspaper coverage of uncertainty-related keywords has been made available by Baker et al. (2016), henceforth referred to as BBD-EPU index.[1] As a consequence, much of the evolving literature on assessing the economic impact of uncertainty in India has utilized the BBD-EPU index (Anand and Tulin 2014; Ghosh et al. 2017; Kumar et al. 2021). However, given the ubiquity of high-speed internet in today's world, it can be argued that people turn towards the internet to 'search' for more information in the face of heightened uncertainty, such as equity market crashes, firm failures and economic recessions. In such a scenario, data on internet searches can potentially reflect the overall level of uncertainty in the economy even before it starts to appear in news text and/or economic forecasts. Therefore, this paper proposes a new measure of economic policy uncertainty for the Indian economy. In contrast to the existing measure(s) based on news or economic forecasts databases, our uncertainty index can be easily computed using publicly available internet search intensity data from *Google Trends*. Arguably, internet search data reflects the behaviour of a wide variety of agents—households, firms, managers, analysts, policymakers—who would use internet to access information related to economic events and issues that are likely to affect them. Indeed, the proposed index based on internet searches and computed at a monthly frequency from January 2004 onwards, tends to correlate well with domestic and global events associated with heightened uncertainty. These events include the Global Financial Crisis of 2008, the "Taper Tantrum" episode of 2013, the "demonetization" episode of late 2016 and more recently, multiple waves of the Covid-19 pandemic and the associated lockdowns in 2020 and 2021.

While our paper is primarily concerned with the literature on measurement of macroeconomic uncertainty, we also undertake a rigorous empirical analysis to showcase the feasibility of our index in analysing the economic impact of uncertainty. The first part of this analysis focuses on estimating a dynamic causal relationship between

[1] The newspaper-based economic policy uncertainty (EPU) index for India, developed jointly with Bhagat et al. (2013) is available for download at www.policyuncertainty.com.

uncertainty and the broader economy. Most of the studies in this context have relied on vector autoregression (VAR) models with recursive ordering to identify uncertainty shocks (see Baker et al. 2016). However, this approach could lead to erroneous results (Kilian et al. 2022). To this end, we use recently developed methods in empirical macroeconomics literature to identify exogenous uncertainty shocks and study their impact on growth, inflation, consumption and investment activity (Stock and Watson 2018; Mertens and Ravn 2013; Ramey 2016). In particular, we use an external instruments approach in a structural vector autoregression (SVAR-IV) framework to shed light on the role of uncertainty shocks in the case of an emerging market economy like India. We find that surprise increases in uncertainty lead to a fall in output growth while causing inflation to accelerate in the Indian context. This negative supply-side impact of uncertainty seems mainly driven by private investment activity which falls sharply in response to uncertainty shocks. In the second part of our empirical analysis, we focus on a simple prediction exercise to forecast output growth in India. Using an out-of-sample forecasting framework, we show that adding uncertainty-related information to standard time-series forecasting models generally leads to an improvement in forecasting accuracy. This underlines the forward-looking nature of our proposed uncertainty index which can be used as a leading indicator of economic activity.

Our empirical results remain robust to the use of alternate uncertainty indices, including the BBD-EPU index, an in-house newspaper index similar to BBD-EPU index but with larger set of keywords in the spirit of Ghirelli et al. (2019) as well as a conventional equity market-based implied volatility index. By making available a new measure of economic uncertainty along with empirically examining its causal impact on the economy and testing its feasibility in aiding macroeconomic forecasting, our paper adds to the limited literature on economic uncertainty in the context of emerging economies in general and India in particular. The rest of the paper is organized as follows. Section 2 reviews the literature on the concept of uncertainty and its measurement. Section 3 describes data and methodology for computing uncertainty index for India. Section 4 is devoted to the empirical analysis of our uncertainty index, including the structural and forecasting analysis. We conclude the paper in Sect. 5 with some thoughts on further research in this domain.

2 Related literature

The economic concept of uncertainty was first defined by Knight (1921). While he recognized that risk and uncertainty are related, he deemed risk to follow a known probability distribution over a set of events. On the other hand, Knight defined uncertainty as "peoples' inability to forecast the likelihood of events happening" i.e. it is a situation in which economic agents cannot predict the likely state of the economy in the future. A heightened level of uncertainty about the future inhibits the ability of economic agents to take decisions. The Global Financial Crisis 2008 is one such recent example of a period of heightened uncertainty. In fact, an increase in uncertainty during the crisis is considered as one of the main factors behind the deep recession and the prolonged recovery that followed (Stock and Watson 2012). Since then, and not surprisingly, policymakers and economists have taken a renewed interest in understanding the channels through which uncertainty manifests and impacts the economy.

From a theoretical point of view, the potential channels of transmission of uncertainty to the real economy are manifold. The first of such channels works through the firms by affecting their investment decisions. This is often termed as the "real options" channel which causes firms to postpone investments and hiring of labour (Bernanke 1983; Pindyck, 1993; Bertola and Caballero 1994). Similarly, the "cost of financing" channel also plays a role in reducing investment by raising the risk premium and increasing the cost of borrowing (Christiano et al. 2014; Arellano et al., 2010). The "precautionary savings" channel working at the household-level, causes people to often delay consumption expenditure on durable goods—such as houses and cars—when they encounter high uncertainty (Kimball 1990; Eberly 1994). While the transmission channels mentioned above impede consumption, investment and hiring, uncertainty can also have a "positive" effect on economic activity under certain conditions. The *Oi-Hartman-Abel* effect (Oi 1961; Hartman 1976; Abel 1983) postulates that if agents can flexibly expand to benefit from good outcomes, and, quickly contract during bad outcomes, they may benefit from increased uncertainty. Such an effect, however, is believed to be strong only in the medium to long run.

With an increasing interest in uncertainty as a real macroeconomic phenomenon, the literature has also analysed the economy-wide impact of uncertainty. According to Bloom (2014), the empirical literature on uncertainty seems to have taken three main approaches to identify the causal impact of uncertainty on firms and consumers. The first of these approaches relies on estimating the movement of output, investment and employment following increases in uncertainty (Bloom et al. 2007; Novy and Taylor 2014). This approach works well in the case of unanticipated shocks to uncertainty but not when such shocks are correlated with other unobserved factors or are predicted in advance. The second approach uses structural models to quantify the impact of uncertainty shocks. In a general equilibrium model with heterogeneous firms, labour and capital adjustment costs, and countercyclical uncertainty, Bloom et al (2018) found that average increase in uncertainty during recessions reduces output by 3% followed by a rapid recovery, in the first and second year, respectively. On the other hand, some studies have found only a marginal impact of uncertainty on growth (Bachmann and Bayer 2013; Born and Pfeifer 2014). Such mixed results are regarded to be symptomatic of sensitive modelling assumptions and linear nature of standard business cycle models. Nevertheless, accounting for the nonlinear impact of uncertainty on economic activity has been found to produce much amplified effects (Basu and Bundick 2017). Uncertainty shocks have also been found to have high impact in the presence of frictions in the labour and financial markets (Bonciani and van Roye 2016; Leduc and Liu 2016).

Moving from business cycle effects of uncertainty to its potential impact in the long run, Bianchi et al. (2018), Bonciani and Oh (2019) found that uncertainty shocks negatively affect economic activity in the long run. Lastly, the third approach is premised on exploiting natural experiments to estimate the uncertainty impact. Baker and Bloom (2013) use natural disasters, terrorist attacks and political shocks as instruments to capture the impact of uncertainty. Earlier, Stein and Stone (2012) use a similar approach to analyse US firms and find that firms exposed to greater uncertainty have lower investment, hiring and advertisement.

Closely connected with the empirical assessment of uncertainty is the issue of its measurement. Various methods have been suggested in the literature to measure uncertainty through observable economic and financial outcomes. The conventional approach relies on financial markets-based or forecast-based measures to proxy for uncertainty. The financial markets-based approach assumes that asset prices take into account all types of risks and factors affecting the economy at any given time so that it can be used to proxy uncertainty. Typical studies using this approach leverage realized or implied market volatility, such as CBOE Volatility Index, as a measure of uncertainty (Bloom 2009; Gilchrist et al. 2014). On the other hand, the forecast-based approach models the disagreement between forecasts of professional forecasters and the actual economic outcomes (Bachman et al. 2013; Scotti 2016; Jurado et al. 2015). The underlying assumption of this approach is that professional forecasters consider all possible information available at that time to make their forecast about the expected future path of the economy. If forecasters disagree with each other given the widespread uncertainty around the future outlook of the economy, there will be divergence in their forecasts. This divergence can be used to measure uncertainty.

Departing from this conventional approach, some recent efforts have leveraged data on news articles and internet search intensity to quantify uncertainty. Since uncertainty ultimately affects the decisions of the economic agents—consumers, workers, investors and so on—this novel approach measures uncertainty from the perspective of economic agents. Newspapers carry analyses of financial markets, political outlook, expert opinions on the economy and thus reflect the state of the economy allowing people to form their decisions. Similarly, nowadays people make extensive use of internet to search for information, including that on economic and financial events of importance. The data on internet searches can also be leveraged to measure uncertainty. In their influential work, Baker et al. (2016) use text data from newspapers to create an index of economic policy uncertainty (EPU) using the occurrence frequency of certain keywords in the news articles. Ghirelli et al. (2019) build on this approach by increasing both the number of keywords and newspapers, in the case of Spain. Xie (2020) also improves on the EPU construction methodology by proposing an automated computation of EPU index using the Wasserstein Index Generation (WIG) model. In a similar spirit, recognizing that this approach may be subject to measurement error due to human intervention, Azqueta-Gavaldon (2017), Saltzman and Yung (2018) and Tobback et al. (2018) use Natural Language Processing (NLP) and Machine Learning (ML) methods to create uncertainty indices using the same data source. Similarly, data on internet-based search intensity available through *Google Trends* has also been used to create uncertainty indices in various country-specific studies (Dzielinski 2012; Bontempi et al. 2021; Castelnuovo and Tran 2017).

Table 1 List of keywords used in GUI

Category name	Category keywords
Monetary	"Reserve Bank of India—recruitment", "RBI—recruitment—job", "money supply", "monetary policy", "open market operations","omo", "rbi policy", "policy repo", "repo rate", "reverse repo rate", "central bank", "governor—state","rbi governor", "exchange rate", "rupee dollar", "usd inr rate", "deputy governor", "cash reserve ratio", "CRR", "statutory liquidity ratio", "SLR—camera", "money market rate", "liquidity", "liquidity adjustment facility", "marginal standing facility", "inflation", "rate cut", "federal reserve", "monetary policy committee"
Fiscal	"tax rates", "tax rate—calculator", "taxation", "taxed", "government budget", "union budget", "india budget", "fiscal deficit", "government debt", "government expenditure", "revenue deficit", "india fiscal deficit", "fiscal stimulus", "corporate tax", "excise duty", "service tax", "custom duty", "GST", "goods and services tax", "double taxation", "tax slab", "tax slabs—calculator"
Trade	"custom duty", "custom duties", "government subsidies", "government subsidy", "wto—what is", "trade treaty", "trade agreement", "trade act", "trade policy", "anti dumping", 'gatt'

Source: Authors' calculations

3 Internet-based uncertainty measures for India—data and methodology

In the event of economic or financial shocks that induce widespread uncertainty in the minds of people, they tend to 'search' for more information to get clarity about the shock and the likely impact on their livelihoods and income. This behavior of economic agents, represented by internet users, is captured in internet searches over time for a given geographical area (Castelnuovo and Tran 2017). For most of the countries where *Google* operates its search engines, data on internet search intensity are publicly disseminated through *Google Trends*.[2]

The online portal allows a user to obtain internet search intensity for a given keyword, in the form of a search volume intensity (SVI) measure that ranges between 0 and 100. This SVI is a relative measure reflecting the relative search volume of a given keyword with respect to the total search volume during the specified period. The maximum value 100 corresponds to a particular time point where the search volume of the given keyword was maximum during the entire sample. Increased interest in any particular topic results in increased internet searches on the specific topic leading to a higher index value. This forms the underlying principle for using Google Trends to construct an uncertainty index.

To compute an uncertainty index using the internet search data, we begin by preparing a list of relevant keywords that represent different economic policies and tools. In total, we select a set of 70 keywords that pertain to *fiscal*, *monetary* and *trade*-related policies in India (Table 1). These search terms are related to policy decisions that may affect financial markets and induce uncertainty in the economy. Moreover, the selected keywords often appear in central bank's statements on the economy as well

[2] Google Trends data can be accessed on the official web interface, here—https://trends.google.com/trends/.

as policy discussions in the financial press. Since our study is focused on India, we fix the geographical area as India in order to obtain keyword-wise SVIs.

At this stage, it is important to note some of the issues related to using Google Trends data. First, comparing or aggregating SVI for multiple keywords is not meaningful due to their relative scaling with itself. In fact, due to this relative scaling, a keyword with a higher SVI relative to another keyword at time t may actually have a lower search volume compared with a frequently used word. Second, internet search data provided by Google Trends is based on a representative but small sample of the actual search volume data. This is done to ensure computational tractability but may introduce sampling bias in the data (Combes et al., 2016).[3] Third, reflecting the increasing usage of the internet and google search engine over time, the internet search data exhibits a downward trend which may also introduce bias. Fourth, various search terms also exhibit strong seasonality patterns that must be treated before undertaking any analysis.

To address the first set of limitations with respect to scaling and aggregation, we follow the methodology proposed by Castelnuovo and Tran (2017). Under this approach, we use *Google Trends* to extract the search frequency for each search term from our selected list of keywords. We do this in an iterative manner. Since *Google Trends* permits inputting a maximum of only five words in every instance, we allow the first four words to change in each iteration while the fifth word is taken as a benchmark word and kept same across each iteration. The benchmark word, taken as *economy* in our case, must be a highly searched word. This step ensures that the SVI for each keyword is computed relative to the SVI of the benchmark word solving the comparison and aggregation issue. We then aggregate the SVI for individual search terms at all-India level to obtain an aggregate uncertainty index. Put more formally, let there be n keywords $k_1, k_2, \ldots, k_n$ along with the benchmark word k_b. Let $N_{i,t}$ represent the google search volume in time t for keyword i. Therefore, search volume intensity (SVI) $\mathrm{SVI}_{i,t}$ for each keyword i can be defined as:

$$\mathrm{SVI}_{i,t} = \frac{N_{i,t}}{M(k_i)}$$

where

$$M(k_i) = \mathrm{Max}\{N_{i,t} : \forall t\}$$

Similarly, SVI of benchmark word k_b is $\mathrm{SVI}^*{}_{bt}$:

$$\mathrm{SVI}^*{}_{b,t} = \frac{N_{b,t}}{M(k_b)}$$

The keywords are grouped in sets of five with benchmark word (k_b) as the fifth word in all the sets. SVI of word i in a set of words S_j is denoted as SVI_{ijt}. For a

[3] See Woloszko (2020) for more details on Google Trends data.

simplified representation, t is omitted.

$$\mathrm{SVI}_{ij} = \frac{N_{\mathrm{it}}}{M\left(S_j\right)}$$

where

$$M(S_j) = \mathrm{Max}\{N_{i,t} : i \in S_j\}$$

SVI of benchmark word k_b in set S_j is F_{bj}:

$$\mathrm{SVI}_{bj} = \frac{N_{bt}}{M\left(S_j\right)}$$

Further, dividing SVI_b^* by SVI_{bj}:

$$\frac{\mathrm{SVI}_b^*}{\mathrm{SVI}_{bj}} = \frac{N_{b,t}}{M(k_b)} \cdot \frac{M\left(S_j\right)}{N_{b,t}} = \frac{M\left(S_j\right)}{M(k_b)}$$

Multiplying with SVI_{ij} we get F_i:

$$F_i = \mathrm{SVI}_{ij} \cdot \frac{\mathrm{SVI}_b^*}{\mathrm{SVI}_{bj}} = \frac{M\left(S_j\right)}{M(k_b)} \cdot \frac{N_{\mathrm{it}}}{M\left(S_j\right)} = \frac{N_{\mathrm{it}}}{M(k_b)}$$

Finally, we compute the google uncertainty index i.e. raw google uncertainty index (GUI) by summing over F_i:

$$\mathrm{GUI} = \sum_{i=1}^{n} F_i$$

In order to overcome the issue of sampling bias, we use a repeated sampling of internet search volumes to compute the raw GUI as described above. To be precise, we run our data pull query 12 times during a three-hour window with 15-min interval between each query to get multiple samples of GUI. We then take the median value of the repeated samples to obtain a composite uncertainty index. In the last step, we deseasonalize the raw index using X-13 ARIMA method followed by trend filtering using the Hodrick-Prescott filter (with lambda parameter set using the Ravn-Uhlig frequency rule).[4] This ensures the removal of any deterministic trend and seasonality from the data. The final index is obtained by scaling the filtered component of the index by its trend, such that:

$$\mathrm{GUI}_t = 100 \cdot \left(\frac{\mathrm{GUI}_{\mathrm{cycle,t}}}{\mathrm{GUI}_{\mathrm{trend,t}}}\right)$$

[4] Power is set to 4 for monthly data, see Ravn and Uhlig (2002).

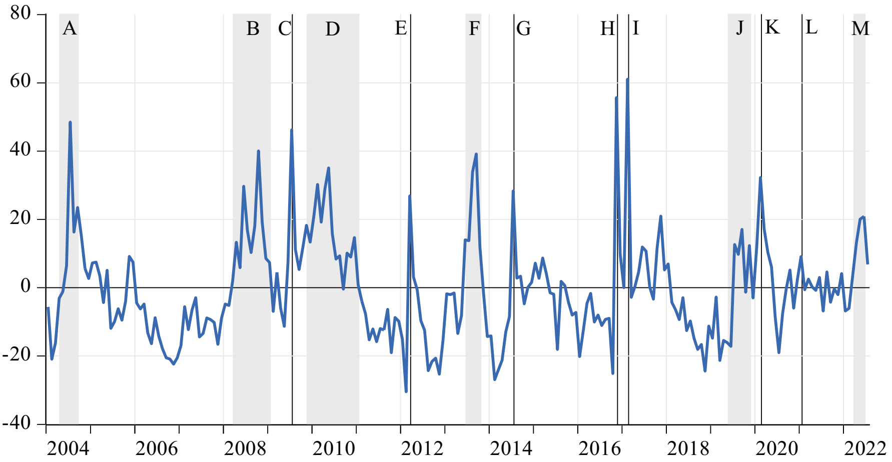

Fig. 1 Google trends-based Uncertainty Index for India (India—GUI). The above plot shows the Google Uncertainty Index for India (solid blue line) from January 2004 to June 2022. Domestic/Global events and policy actions are highlighted in grey shaded area or vertical black lines as follows: A—General Elections 2004; B—Global Financial Crisis 2008; C—General Elections 2009 followed by Union Budget Announcement; D—High fiscal deficits and inflation concerns; E—Sharp increase in policy rate to curtail inflation; F—Taper Tantrum episode; G—General Elections 2014; H—Demonetization; I—Goods and Services Tax Bill introduction; J—large policy response amidst growth slowdown; K—Beginning of Covid-19 Pandemic in India followed by first lockdown; L—second Covid-19 wave; M—Russia-Ukraine war, high inflation. (Color figure online) Source: Authors' estimates

The final google trends-based uncertainty index for India (India-GUI) is shown in Fig. 1. A list of domestic and global events corresponding with heightened macroeconomic uncertainty is provided alongside.

A preliminary statistical analysis shows that the proposed index is well correlated with existing measures of economic and/or financial uncertainty for India, namely BBD-EPU index and India VIX index. The latter index is an implied volatility measure derived from equity futures and option prices. The India-GUI index is also correlated with broad macroeconomic indicators and contains forward-looking information on economic activity as shown from a Granger Causality analysis. The results are provided in the appendix.

Lastly, our approach based on keyword-based search volumes can also aid a researcher in identifying the sources of uncertainty. As an illustration, consider the two consecutive peaks corresponding to event (H) and event (I) in Fig. 1. Reflecting an increase in overall uncertainty following the Indian government's decision to demonetize 86 per cent of its currency in circulation, we observe a sharp increase in underlying search volumes for keywords like "central bank", "RBI", "money supply", "governor" etc. in November 2016.[5] This suggests that policy uncertainty in case of event (H) was driven by domestic monetary policy-related concerns. Soon after the demonetization episode, in February 2017, the federal government decided to (i) introduce the national Goods and Services Tax (GST) reform bill in the Indian parliament and (ii) present its

[5] To read more about India's demonetization exercise, please refer to Lahiri (2020).

annual budget in the month of February instead of March. Consequently, we observe a relative increase in search volumes for tax and budget-related keywords highlighting the role of fiscal policy in driving the increase in economic uncertainty in early 2017.

4 Uncertainty and the Indian macroeconomy—empirical analysis

In this section, we devote our attention to a formal empirical analysis of our proposed index, namely the India-GUI. We do this in two ways which includes a structural analysis to ascertain the dynamic impact of uncertainty on the Indian macroeconomy as well as by analysing the feasibility of using uncertainty index for macroeconomic forecasting.

4.1 A proxy-SVAR based analysis of uncertainty shocks

Uncertainty, notwithstanding its source, impacts financial markets as well as the real economy leading to economy-wide adverse effects, such as heightened risk and volatility along with sharp declines in investment, hiring and output. To understand the dynamic causal impact of uncertainty shocks on the Indian economy, we use a structural vector autoregession (SVAR) framework with instrumental variable framework. Consider the following SVAR framework:

$$A \cdot y_t = \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} + \varepsilon_t \tag{1}$$

where y_t is $n \times 1$ vector of endogenous variables while α_i and A are $n \times n$ parameter matrices. The error term components i.e. ε_t are assumed to be uncorrelated with each other. They are interpreted as structural shocks. By pre-multiplying the above equation by A^{-1}, we can obtain a reduced form VAR that can be easily estimated using actual data:

$$y_t = \delta_1 y_{t-1} + \ldots\ldots\cdots + \delta_p y_{t-p} + \omega_t \tag{2}$$

where $\omega_t = B \cdot \varepsilon_t$, $A^{-1} = B$ and $E\left[u_t u_t^{'}\right] = BB^{'} = \sum$. However, identification of the impulse responses to structural shocks requires further identifying restrictions to estimate the matrix $B = A^{-1}$. Assuming that the structural shock cannot be directly observed but can be approximated through an instrument Z_t, we use the external instruments approach developed in Mertens and Ravn (2013) and Stock and Watson (2018) for structural identification in our paper. Under this approach, the key is to find an instrument that is correlated with the shock of interest and uncorrelated with other structural shocks, such that:

$$E\left[Z_t \cdot \varepsilon_t^{s^{'}}\right] = \varnothing \tag{3}$$

$$E\left[Z_t \cdot \varepsilon_t^{o^{'}}\right] = 0 \tag{4}$$

where ε_t^s is the structural shock of interest, while ε_t^o denotes all other structural shocks. See Mertens and Ravn (2013) for more details. Juxtaposing this to our case, in the first stage, we instrument the uncertainty indicator with a relevant proxy. In the second stage, we regress the endogenous variables on the instrumented uncertainty indicator in the VAR framework. The estimated coefficients from the model are used to compute impulse responses to uncertainty shocks.[6]

To determine the economic effects of uncertainty, we consider the impact of uncertainty shocks on economic activity proxied by real gross domestic product (GDP) and its components, namely private investment activity measured by real gross fixed capital formation (GFCF) and private consumption measured using real private final consumption expenditure (PFCE). We measure inflation using the consumer price index (CPI), while the exchange rate is proxied by the bilateral nominal exchange rate between US Dollar and Indian Rupee (USD-INR rate). In line with previous studies, the weighted-average call money rate (WACR) is taken as an indicator of monetary policy. The data is seasonally adjusted using the X-13 ARIMA procedure and converted into stationary data by applying a year-on-year percentage change transformation. Our data sample consists of quarterly data beginning in 2004 and ending in the first quarter of 2020. Considering that the pandemic induced high volatility in the data besides potentially causing structural breaks in the economic relationships between various variables, we restrict our sample to pre-pandemic data. However, results based on estimation with pandemic data are also reported in the appendix for robustness. The data is obtained from the *Database on the Indian Economy (DBIE)* maintained by the Reserve Bank of India (RBI). More details on our data and variable construction are provided in the appendix.

For measuring economic uncertainty in India, we use our proposed index i.e. the India-GUI index. The India-GUI measure, at a quarterly frequency, is plotted in Fig. 2. Most studies on macroeconomic assessment of uncertainty shocks, including Baker et al. (2016), use a VAR model with recursive ordering placing their EPU index first to identify uncertainty shocks. However, this approach may lead to attenuation bias on account of measurement error in the proxy indicator (Carriero et al. 2015; Caballero and Kamber 2019). The literature suggests the use of SVAR with external instruments as described earlier. An additional benefit of the external instruments approach lies in the fact that it allows for a measurement error in the variable that is used to proxy for a given shock.

Following this approach, we create a dummy indicator that takes a value 1 when the GUI index is greater than 1.65 times the standard deviation of the index over time, and 0 otherwise.[7] This indicator, also shown in Fig. 2, is used as an instrument for the structural shock measured using the India-GUI index in the SVAR framework. The first-stage regression results of the reduced form residuals are provided in the appendix. The table shows the results from the regression of reduced-form residuals from the uncertainty equation of our four-variable VAR on the constructed instrument variable. The estimates are statistically significant and carry the correct sign. Moreover,

[6] We use the *sovereign* R package for our analysis. Please see here—https://CRAN.R-project.org/package=sovereign.

[7] A similar approach was also followed by Lakdawala and Singh (2019) to investigate the effects of foreign shocks on the Indian economy.

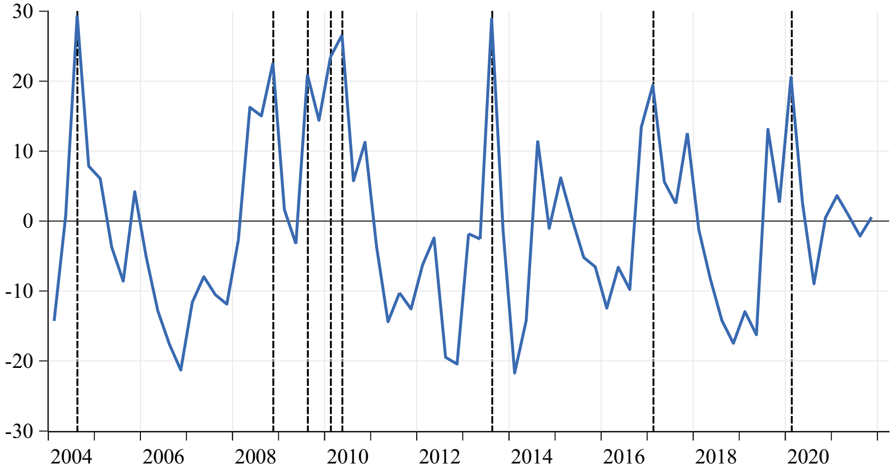

Fig. 2 Uncertainty shocks. The above figure plots the main shock measure from 2004q1 to 2022q2. Source: Authors' estimates

the F-statistic is greater than 10 indicating that the constructed instrument is a strong instrument.

We now turn our attention to the impulse response analysis. Quantifying the impact of uncertainty shock on the Indian economy, Fig. 3 plots the impulse responses of economic activity, inflation, exchange rate and the monetary policy rate to a one standard deviation uncertainty shock. The impulse responses show that overall economic

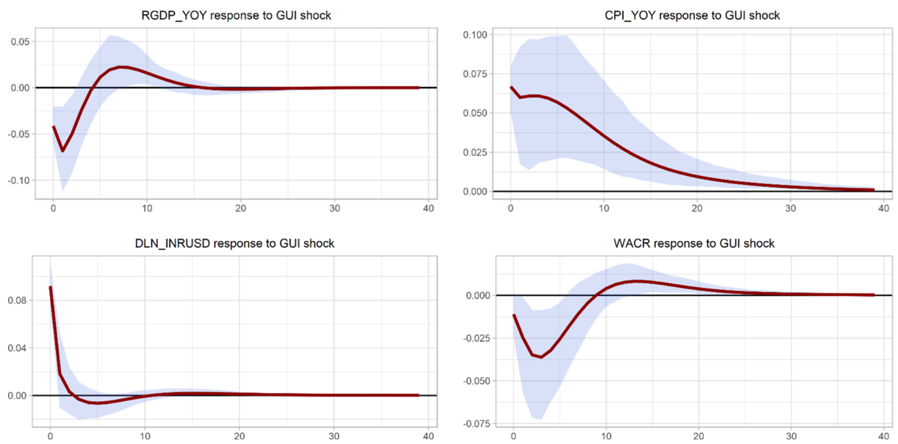

Fig. 3 Response to uncertainty shocks—output growth and inflation. The above plot shows the impulse responses (solid red line) of real GDP growth (RGDP_YOY), inflation (CPI_YOY), exchange rate (DLN_INRUSD) and monetary policy rate (WACR) to a one standard deviation shock to uncertainty measured using the India-GUI index. The 95% confidence interval calculated using wild bootstrap approach is shown by the shaded blue area. The horizontal axis shows the horizon in quarters after the shock. (Color figure online) Source: Authors' estimates

activity (real GDP growth) witnesses a sharp fall while inflation tends to increase as a response to an uncertainty shock. The impact on inflation, in particular, is highly persistent. The opposite response of output growth and inflation to an uncertainty shock suggests that uncertainty shocks act as a negative supply shock to the economy. This is in line with the earlier findings of Kumar et al. (2021). Despite an increase in the inflation rate, monetary policy reacts by decreasing the policy interest rate to curb the fall in output growth. Lastly, as a result of heightened uncertainty in the domestic economy, the domestic currency rate tends to depreciate, although the response is not statistically significant.

Digging deeper into the supply-side impact of uncertainty shocks, we re-estimate the model while replacing output growth with growth in private consumption and private investments one-at-a-time. Rest of the variables and identification procedure is kept the same. The resulting impulse responses of consumption and investment activity to a one standard deviation shock to uncertainty are given in Fig. 4. While both consumption and investments growth falls in response to an uncertainty shock, the fall in investment is larger as compared to the fall in consumption. The statistically significant and highly persistent negative response of investment confirms the dominant supply-side impact of uncertainty in the Indian context.

Our findings satisfy a battery of robustness checks. First, we extend our baseline empirical model to include long-term interest rates and equity prices by adding 10-year benchmark sovereign bond yields and the NIFTY index of the National Stock Exchange, respectively. The impulse responses for output growth, inflation and exchange rate were found to be largely similar to our baseline model. In line with the empirical literature, equity prices fall in response to heightened uncertainty. Moreover, long-term interest rates also tend to decrease in response to an uncertainty shock. Second, we extend the data sample to include pandemic data ending in the last quarter of 2021. While qualitatively similar, we observe that the magnitude of impulse responses changes when compared to the pre-pandemic sample, especially the response of output growth and inflation. This may not be surprising given the volatility in the data. Lastly, we repeat our analysis using the BBD-EPU index instead of the India-GUI index. The impulse response to EPU shock was found to be relatively smaller as compared to the GUI shock. Additional results from the robustness analysis are reported in the appendix.

4.2 GDP forecasting with uncertainty index

An emerging strand in macroeconomic forecasting literature has shown that alternate data, such as news text, social media, internet searches can be leveraged to improve the predictive accuracy of forecasting models. To test whether this holds true in our case, we implement a simple forecasting exercise to predict year-on-year growth in real GDP for India. We estimate various time-series models using a sample of quarterly data from 2004Q1:2015Q4. The forecasting accuracy for each model is tested by generating out-of-sample forecasts for GDP growth over 2016Q1:2019Q4. We then compute the root mean squared error (RMSE) over these out-of-sample forecasts to evaluate the prediction performance of each model.

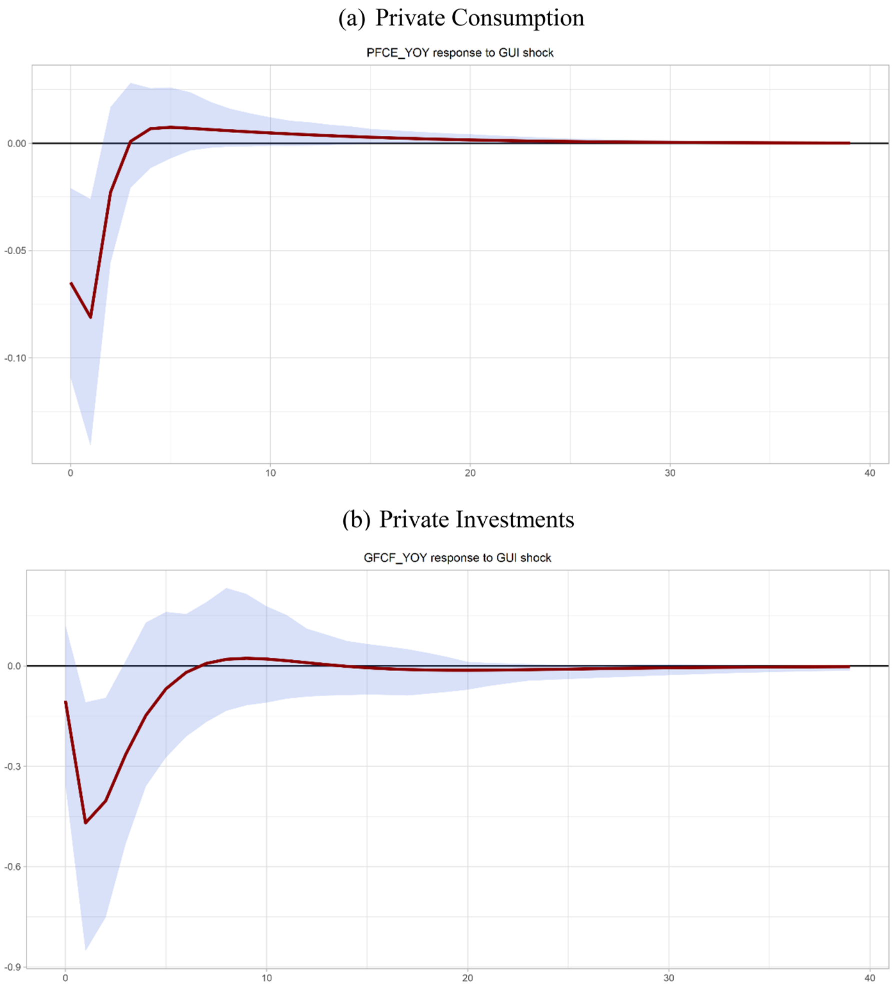

Fig. 4 Response to uncertainty shocks—consumption and investment activity. **a** private consumption, **b** private investments. The above plot shows the impulse responses (solid red line) of private consumption (PFCE_YOY) and private investments (GFCF_YOY) to a one standard deviation shock to uncertainty measured using the India-GUI index. The 95% confidence interval calculated using wild bootstrap approach is shown by the shaded blue area. The horizontal axis shows the horizon in quarters after the shock. (Color figure online) Source: Authors' estimates

For forecasting evaluation, we generate GDP growth forecasts using different models, namely a univariate autoregressive model of order one i.e. an AR(1) model along with a standard, three-variable VAR model consisting of real GDP growth, inflation and monetary policy rate. We augment these models with the BBD-EPU index as well as the India-GUI index to analyse if uncertainty-related information can improve GDP forecasts. As an extension of the autoregressive model estimated over quarterly data, we also estimate the AR(1) model in a mixed data sampling (MIDAS) framework

Table 2 Out-of-sample forecasting accuracy

Models	Target variable: real GDP growth (YoY%)							
	Horizon							
	h = *1*	*h* = *2*	*h* = *3*	*h* = *4*	*h* = *5*	*h* = *6*	*h* = *7*	*h* = *8*
AR(1)	1.26	1.84	2.11	2.27	2.30	2.34	**2.34**	**2.45**
AR(1) + BBD	1.48	2.23	2.66	2.96	3.11	3.21	3.23	3.39
AR(1) + GUI	1.25	1.83	2.11	2.28	2.31	2.37	2.38	2.48
MIDAS + BBD	1.60	2.32	2.71	3.03	3.13	3.17	3.27	3.45
MIDAS + GUI	**1.22**	**1.73**	**1.95**	**2.18**	**2.24**	**2.34**	2.40	2.50
VAR + BBD	1.43	2.14	2.46	2.62	2.69	2.74	2.73	2.87
VAR + GUI	1.41	2.09	2.29	2.36	2.40	2.52	2.60	2.79

The table reports the Root Mean Squared Error (RMSE) for out-of-sample forecasts made over 2016Q1-2019Q4. All models were estimated over a sample of 2004Q1:2015Q4. Source: Authors' estimates

leveraging monthly uncertainty index to predict quarterly GDP (Ghysels et al. 2006; 2007). We also provide RMSE from a simple AR(1) model for benchmark comparison.

The results from our forecasting exercise are reported in Table 2. Our findings indicate that addition of the India-GUI index leads to gains in predictive accuracy, especially in case of MIDAS- based models that see a forecast improvement of 3-8 per cent across forecast horizons. This underlines the forward-looking nature of our uncertainty index. Importantly, models augmented with India-GUI measure perform better than models that include the BBD-EPU index highlighting its superiority over the conventional news-based measure of uncertainty. This analysis shows that adding uncertainty-related information to macroeconomic forecasting models, such as those aimed at predicting or 'nowcasting' GDP, can improve the forecasting accuracy of such models.

5 Conclusion and way forward

The importance of economic uncertainty in determining the evolution of financial markets and macroeconomic fundamentals of an economy has been highlighted in various studies. In this paper, we develop a new measure of economic policy uncertainty for India. The proposed uncertainty index is based on internet search intensity data obtained from Google Trends. The validity of the uncertainty index for India is assessed in terms of its impact on the real economy as well as its performance in a macroeconomic forecasting exercise.

As suggested by economic theory of uncertainty, our structural analysis shows that uncertainty shocks lead to a sharp decline in output growth in India. However, unlike in developed countries, uncertainty has a persistent inflationary impact on the economy. Additionally, we find that investment activity reacts more strongly to uncertainty as opposed to private consumption, indicating a dominant supply-side impact of uncertainty in India. These findings are in line with previous studies and satisfy several robustness checks. From a policy perspective, our results suggest that policymakers can benefit from devising policy frameworks and institutional arrangements that foster sound and predictable policies. The creation of a novel dataset and automated algorithms to compute an internet search-based uncertainty index should pave way for further research on the implications of economic uncertainty and its transmission channels to various sectors of the economy. Lastly, such uncertainty indices can also help in strengthening policy simulation exercises to study the impact of low/high uncertainty scenarios and improve near-term projection of macroeconomic variables, such as real GDP growth, which exhibit high degree of sensitivity to uncertainty.

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Declarations

Conflict of interest The corresponding author states that there is no conflict of interest.

Ethical approval Views expressed in this paper are those of the authors and not of the institution to which they belong. All standard disclaimers apply. An earlier version of this paper titled "Macroeconomic effects of Uncertainty: A big-data analysis for India" was published as a Working Paper on the Reserve Bank of India's website, here: https://www.rbi.org.in/Scripts/PublicationsView.aspx?id=19431.

Appendix

A. Data, additional results and robustness checks

See Tables 3, 4, 5, 6 and Figs. 5, 6, 7, 8, 9, 10.

Table 3 Data and variable construction

No.	Variable	Data	Source
1	Economic uncertainty	India-GUI index	Authors' calculations
2	Economic output	Real gross domestic product (YoY%) with base year 2011–12	Database on the Indian Economy (DBIE), RBI
3	Inflation	Combined consumer prices index (CPI) (YoY%) with base year 2011–12	
4	Policy rate	Weighted average call money rate (WACR, %)	
5	Consumption	Real private final consumption expenditure (YoY%) with base year 2011–12	
6	Investments	Real gross fixed capital formation (YoY%) with base year 2011–12	
7	Long-term interest rate	10-Year benchmark government securities yield (%)	
8	Equity prices	NSE Nifty index (YoY%)	Bloomberg
9	News-based uncertainty	India—economic policy uncertainty (EPU) index	www.policyuncertainty.com

Table 4 Granger-causality tests—India-GUI index and various macroeconomic variables

Null hypothesis	Obs	F-Statistic	*p*-value
CPI_YOY does not Granger Cause GUI	68	0.55961	0.6928
GUI does not Granger Cause CPI_YOY		0.51320	0.7262
DLN_INRUSD does not Granger Cause GUI	67	1.42169	0.2382
GUI does not Granger Cause DLN_INRUSD		0.56822	0.6867
PFCE_YOY does not Granger Cause GUI	63	0.46639	0.7601
GUI does not Granger Cause PFCE_YOY		2.12116	0.0907
GFCF_YOY does not Granger Cause GUI	63	0.57435	0.6824
GUI does not Granger Cause GFCF_YOY		4.62064	0.0028
RGDP_YOY does not Granger Cause GUI	68	0.46162	0.7636
GUI does not Granger Cause RGDP_YOY		2.82244	0.0328

The above table reports the results of the Granger Causality analysis between India-GUI index and various macroeconomic variables related to the Indian economy. The tests are based on quarterly data sample from 2004Q1 to 2020Q1. Upto four lags were used for the causality tests. Source: Authors' estimates

Table 5 First-stage regression results

	M1	M2	M3
Const	− 2.285* (1.21)	− 1.85 (1.26)	− 1,85 (1.29)
Uncertainty IV	20.57*** (3.62)	18.24*** (3.96)	18.20*** (4.05)
Obs	64	60	60
Adj. R-sq	0.345	0.271	0.261
F-Stat	32.21	21.25	20.19

The above table shows the regression of reduced-form residuals from the uncertainty equation of the four variable VAR on the uncertainty instrument constructed in the paper. M1, M2 and M3 correspond to VAR models with real GDP growth, consumption growth and investment growth, respectively. Adjusted standard errors are provided in the parentheses. The *, **, and *** denote 10%, 5% and 1% level of significance, respectively. Source: Authors' estimates

Table 6 Out-of-sample forecasting accuracy—pandemic sample

Models	Target variable: real gdp growth (YoY%)							
	Horizon							
	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 7	h = 8
AR(1) + BBD	9.95	12.37	13.63	18.36	17.43	18.09	12.80	13.49
AR(1) + GUI	10.22	13.16	15.16	21.11	21.18	23.41	12.81	13.52
MIDAS + BBD	10.23	12.77	13.93	18.69	17.77	18.05	12.81	13.52
MIDAS + GUI	10.06	13.29	15.61	22.18	22.95	26.09	12.61	13.34
VAR + BBD	10.24	13.39	15.45	21.55	21.79	24.32	12.46	13.05
VAR + GUI	9.83	12.32	13.54	18.35	17.53	18.44	12.26	12.90

The table reports the Root Mean Squared Error (RMSE) for out-of-sample forecasts made over 2018Q1-2021Q4. All models were estimated over a sample of 2004Q1:2017Q4. Source: Authors' estimates

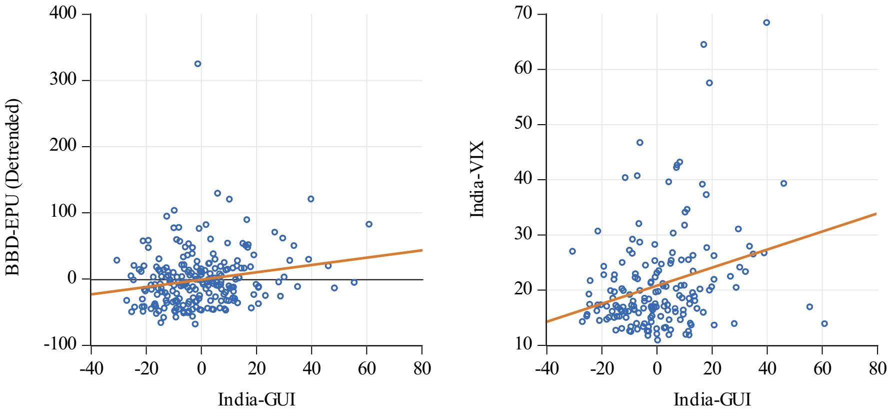

Fig. 5 Correlation Scatter Plot with Existing Measures of Uncertainty**.** The above figure shows the correlation scatter plots for India-GUI index and existing measures of economic/financial uncertainty for India, namely the news-based BBD-EPU index and the India VIX Index. The latter index is an implied volatility measure computed from equity futures. Source: Bloomberg; Authors calculations

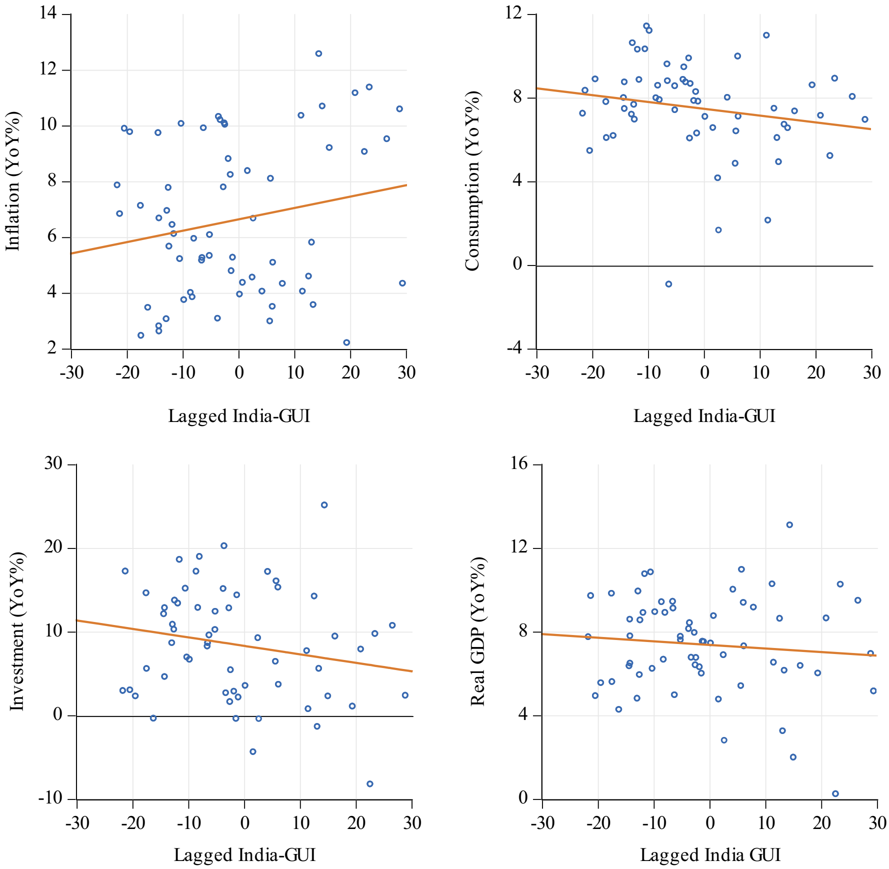

Fig. 6 Correlation Scatter Plot with Macroeconomic Variables. The above figure shows the correlation scatter plots between lagged India-GUI index and various macroeconomic variables for India over a quarterly data sample from 2004Q1 to 2020Q1. Source: Authors calculations

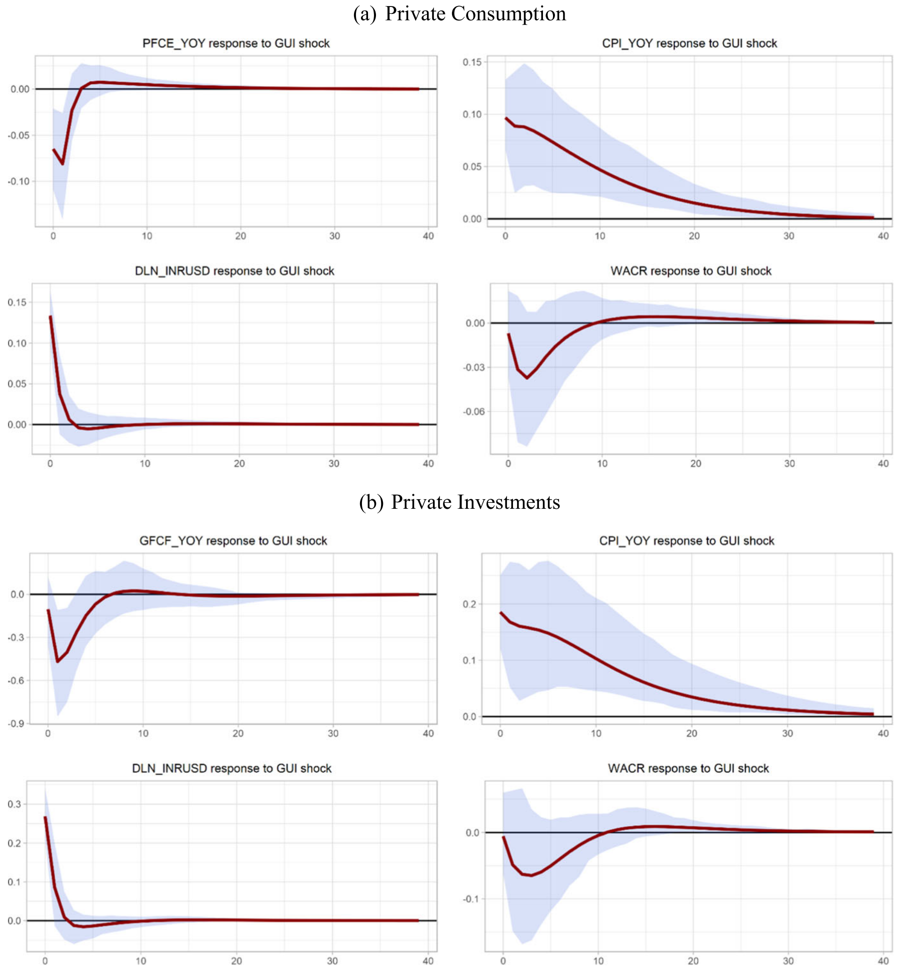

Fig. 7 Response to uncertainty shocks. **a** Private Consumption, **b** Private Investments. The above plots show the impulse responses (solid red line) of real consumption growth (PFCE_YOY), real investment growth (GFCF_YOY), inflation (CPI_YOY), exchange rate (DLN_INRUSD) and monetary policy rate (WACR) to a one standard deviation shock to uncertainty measured using the India-GUI index. The 95% confidence interval calculated using wild bootstrap approach is shown by shaded blue area. The horizontal axis shows the horizon in quarters after the shock. (Color figure online) Source: Authors' estimates

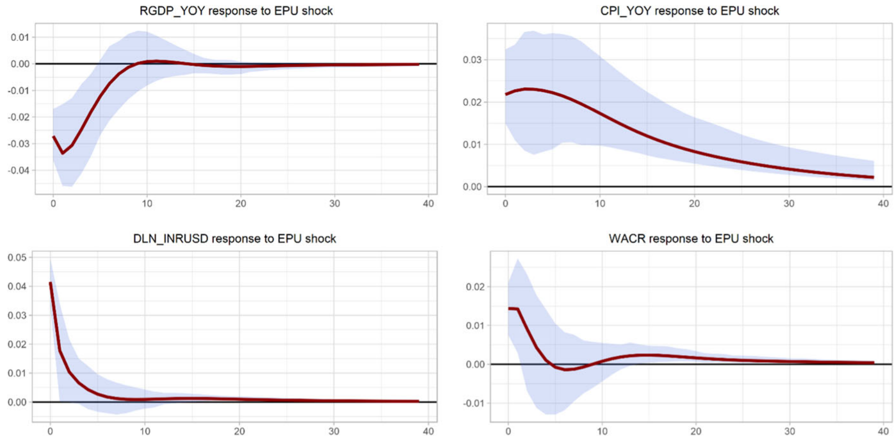

Fig. 8 Response to uncertainty shocks measured using BBD-EPU index. The above plot shows the impulse responses (solid red line) of real GDP growth (RGDP_YOY), inflation (CPI_YOY), exchange rate (DLN_INRUSD) and monetary policy rate (WACR) to a one standard deviation shock to uncertainty measured using the BBD-EPU index. The 95% confidence interval calculated using wild bootstrap approach is shown by the shaded blue area. The horizontal axis shows the horizon in quarters after the shock. (Color figure online) Source: Authors' estimates

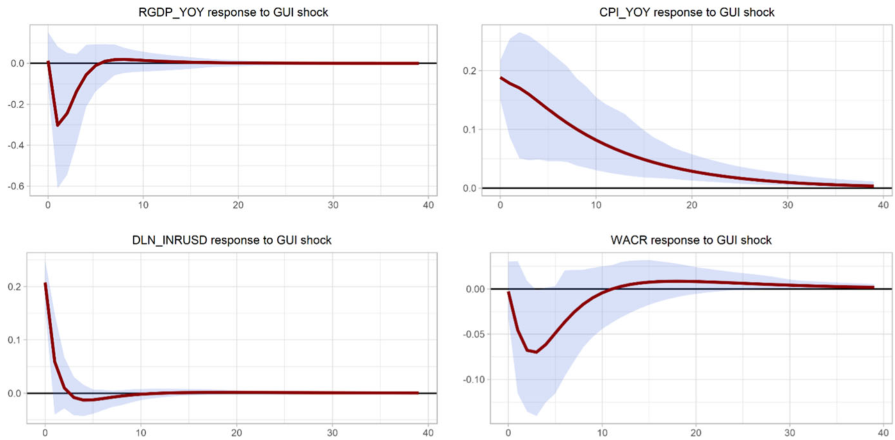

Fig. 9 Response to uncertainty shocks including the pandemic data. The above plot shows the impulse responses (solid red line) of real GDP growth (RGDP_YOY), inflation (CPI_YOY), exchange rate (DLN_INRUSD) and monetary policy rate (WACR) to a one standard deviation shock to uncertainty measured using the India-GUI index. The model was estimated by including the pandemic data from 2020Q2 to 2021Q4. The 95% confidence interval calculated using wild bootstrap approach is shown by the shaded blue area. The horizontal axis shows the horizon in quarters after the shock. (Color figure online) Source: Authors' estimates

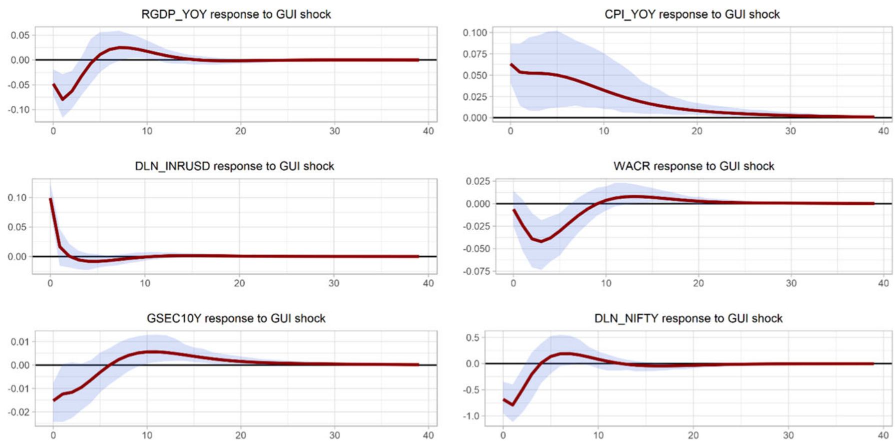

Fig. 10 Response to uncertainty shocks—augmented model. The above plot shows the impulse responses (solid red line) of real GDP growth (RGDP_YOY), inflation (CPI_YOY), exchange rate (DLN_INRUSD), monetary policy rate (WACR), long-term interest rates (GSEC10Y) and equity prices (DLN_NIFTY) to a one standard deviation shock to uncertainty measured using the India-GUI index. The 95% confidence interval calculated using wild bootstrap approach are shown by the shaded blue area. The horizontal axis shows the horizon in quarters after the shock. (Color figure online) Source: Authors' estimates

B. Newspaper-based uncertainty index with extended word list

In order to construct the economic policy uncertainty (EPU) index for India using the Baker et al. (2016) methodology, we target five relevant Indian business news dailies—*Economic Times*, *The Hindu Business Line*, *The Financial Express, The Mint and Business Standard*—available via their online archives. Each digital article in the online newspaper archive was downloaded and converted into machine readable format using automated programs. Our final dataset consists of more than 100,000 news articles. An article is classified as indicating uncertainty if it contains at least one keyword from each of the three sets: **E** containing economy-related keywords; **P** containing policy-related keywords; and, **U** containing words related to uncertainty. An article fulfilling these conditions is classified as an EPU article and is assumed to convey uncertainty. Inspired by Ghirelli et al. (2019), we extend the original set of keywords used by Baker et al. (2016) for India to include more words across the three sets. See Table 7 for the extended keyword list. Once all articles are classified, the daily count of such articles are aggregated and normalized to obtain a monthly series for our extended EPU uncertainty index.

We now define this computation in detail. The process starts with computing the number of articles classified as EPU in each month, which is divided by the total number of articles in the month to give X_{it}, where i denotes a given newspaper and t denotes month. To obtain a normalized series Y_{it}, X_{it} is divided by standard deviation σ_{i} of X_{it} on a fixed i for all$t$. Now, we need to combine the series related to different newspapers into one common series, hence, we take the average of Y_{it} by summing across i and dividing it by the number of newspapers for a given t, to give Z_t. M is average of Z_t over time period T, which is used to rescale the Z_t and compute the

Table 7 Extended keyword list

Economy	Economy, economies, economic, macroeconomic, macroeconomy
Policy	Policy, monetary, interest rate, repo, reverse repo, liquidity, inflation, rate cut, rate hike, open market operations, omos, money supply, exchange rate, currency, rupee, dollar, usd, inr, forex, reserves, cash reserve ratio, statutory reserve ratio, crr, slr, call money rate, wacr, msf, marginal standing facility, gdp, growth, inflation target, bond yield, bond yields, yield curve, transmission, pass-through, term premia, term premium, lending rate, deposit rate, borrowing rate, government securities, asset purchase, forward guidance, business cycle, unconventional, operation twist, ltro, quantitative easing, rbi, reserve bank of india, reserve bank, governor, central bank, monetary policy committee, mpc, fiscal, tax, taxation, tax rate, taxed, taxes, revenue, expenditure, debt, budget, government, union, deficit, debt, stimulus, duty, duties, levy, levies, excise, service, custom, corporate, income, gst, spending, frbm, multiplier, reform, reforms, burden, subsidy, subsidies, parliament, finance, finance minister, gst council, finance commission, trade, foreign, regulation, regulations, import, imports, export, exports, tariff, tariffs, wto, gatt, anti-dumping, treaty, agreement, custom, customs, commerce, fta, free trade, trade war, trade wars, barriers, global value chains, gvcs, global supply chains, quota, quotas
Uncertainty	Uncertainty, uncertainties, uncertain

index, EPU_t, as follows:

$$i = \text{newspaper};\ t = \text{time};\ n = \text{number of newspapers}$$

$$X_{\mathrm{it}} = \frac{\mathrm{epucount}_{\mathrm{it}}}{\mathrm{total}_{\mathrm{it}}};$$

$$Y_{\mathrm{it}} = \frac{X_{\mathrm{it}}}{\sigma_i};$$

$$Z_t = \frac{\sum_i^n Y_{\mathrm{it}}}{n};$$

$$M = \text{Average } Z_t \text{ over} T;$$

$$\mathrm{EPU}_t = \frac{Z_t}{M}$$

The newspaper-based approach to measure uncertainty proposed above rests on the presence of certain words in a news article with the assumption that uncertainty in the economy is reflected in news reports. In an era of widespread communication and globalisation, any favourable or unfavourable information on the economy is rapidly disseminated amongst the public through news media. Sentiments arising from macroeconomic data and industry reports find place in the online news articles in almost real time. Frequent occurrences of a set of words can provide information on an economy, which has the potential to be used for macroeconomic analysis. The extended newspaper-based uncertainty index is plotted in Chart B1.

See Table 7 and Fig. 11.

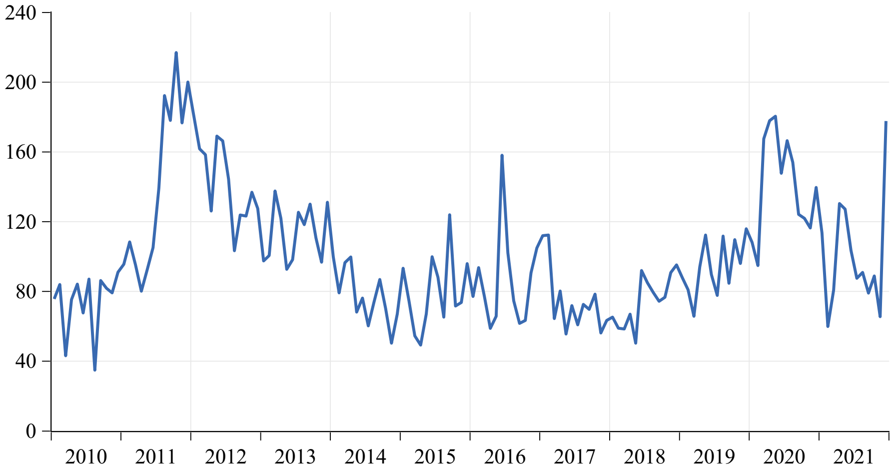

Fig. 11 Broad EPU Index for India. The above plot shows the monthly EPU index for India constructed using the Baker et al. (2016) methodology. The index is constructed using an extended word list provided in Table B1. We construct the index at a daily frequency but present it at a monthly frequency in the paper. The daily news-based extended EPU index is available on our online portal. Source: Authors' estimates

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