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REAL ACTIVITY AND UNCERTAINTY SHOCKS: THE LONG AND THE SHORT OF IT

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Real Activity and Uncertainty Shocks: The Long and the Short of It *

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Abstract

We extend a state-of-the-art DSGE model to include short- and long-term uncertainty shocks that differ in terms of persistence. Considering the two shocks is essential for capturing the imperfect empirical relationship between short- and long-term financial uncertainty as proxied by the VIX. Leveraging the model's implications about the VIX term structure, we suggest a theory-informed, nonrecursive identification strategy to separately identify the macroeconomic effects of the two shocks in a structural VAR. In line with the DSGE model, long-term uncertainty shocks have stronger and more persistent real effects than short-term shocks. Moreover, they explain a substantial fraction of the forecast error variance in unemployment and the policy rate at horizons greater than two years. In a supplementary analysis of uncertainty news shocks, we show that news about higher uncertainty in the future is recessionary.

Keywords: uncertainty shocks, medium-scale DSGE model, structural VAR, nonrecursive identification, VIX term structure.

JEL Classification: C32, E10, E32.

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1. Introduction

Are the effects of uncertainty shocks all alike, or can they differ fundamentally according to the resolution horizon of uncertainty? In principle, uncertainty can relate to both short-term aspects of the economy but also to longer-term dynamics. The conventional approach in the empirical literature on the macroeconomic effects of uncertainty shocks is to use a single measure of uncertainty from which a generic uncertainty shock is identified (e.g., Bloom, 2009; Fernández-Villaverde et al., 2015; Leduc and Liu, 2016; Baker et al., 2016; Basu and Bundick, 2017). We theoretically study the effects of short-term and long-term uncertainty shocks in a state-of-the-art DSGE model and show that jointly considering short-term and long-term financial uncertainty, proxied using the term structure of VIX, allows the separate identification of the macroeconomic effects of short-term vs. long-term uncertainty shocks in a structural VAR model.[1]

Financial uncertainty, as proxied by the VIX, is imperfectly correlated across horizons (Luo and Zhang, 2012; Barrero et al., 2017). To illustrate this insight, Figure 1 shows the evolution of the expected volatility on the S&P500 index over the following one month (VIX 1M) and two years (VIX 2Y) around three historical events. The left panel considers the period from the initial phase of the COVID-19 pandemic until the summer of 2020. Initially, the short-term VIX increased while the long-term VIX was relatively constant, consistent with the view that uncertainty in this period related to the short-term spread of the virus. Subsequently, from the beginning to the end of March, with the declaration of the pandemic by the WHO and the fear of a severe drag on the economy, the two uncertainty measures both increased substantially relative to pre-pandemic levels. After the peak of the first wave, the short-term VIX declined considerably as governments gradually lifted their restrictions on economic activity and as the short-term prospects for

[1]Distinguishing between short-term and long-term uncertainty shocks is crucial for policymakers. An example illustrating policymakers' concern for the resolution horizon of uncertainty is found in the Monetary Policy Committee Report of the Bank of England on November 7th, 2019: *"The progress of the Withdrawal Agreement and the extension of the UK's EU membership are likely to remove some uncertainty and support confidence in the near term, partly driven by a reduction in the risk of a no-deal Brexit. Some uncertainty is likely to* ***persist****, however, as the details of the UK and EU's eventual relationship are assumed to emerge only gradually over time and the smoothness of the transition to it remains to be determined."*

the economy became more positive and tranquil. The long-term VIX, however, stabilized at a higher point than its pre-pandemic level, indicating that long-term uncertainty remained high, potentially due to the fear of a second wave.[2]

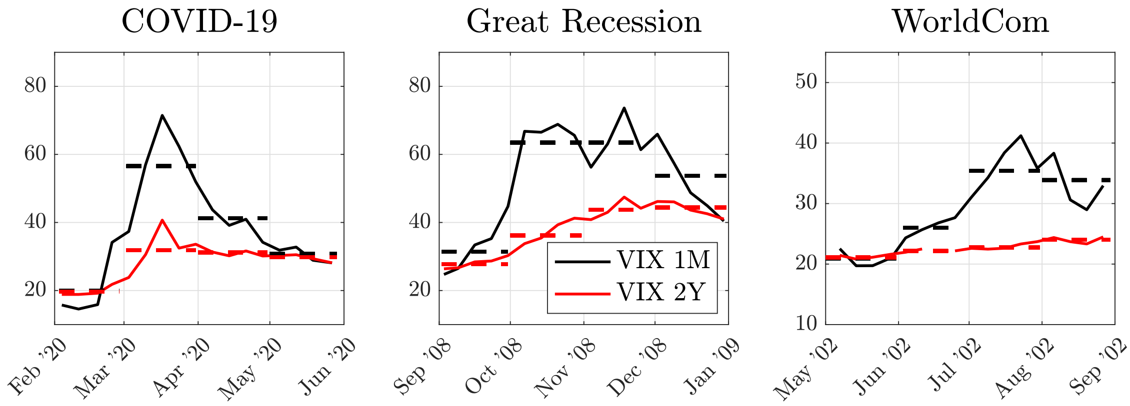

Figure 1: VIX-1M and VIX-2Y. Dynamics of the one-month (black) and the two-year VIX (red) during the initial phase of the COVID-19 pandemic in 2020, the Great Recession in 2008, and the WorldCom bankruptcy in 2002. Solid lines are weekly averages, and dashed lines are monthly averages. Authors' calculations based on OptionMetrics data (Wharton Research Data Services.)

The middle panel of Figure 1 shows the dynamics of the two uncertainty measures around the Great Recession. Following the collapse of Lehman Brothers in September 2008 and amidst the subsequent financial panic, the short-term VIX reached unprecedented levels in October. In November, however, the short-term VIX remained stable relative to October, while the long-term VIX increased substantially. So what happened in November 2008? As the Federal Reserve cut the federal funds rate from 2.00% in August to 0.16% in December, the US economy entered its first zero lower bound phase in roughly seventy years, and it was unclear how the Federal Reserve would help the economy escape the recession with interest rates resting at zero. In our view, the exceptional circumstances for monetary policy in this period likely contributed to creating long-term uncertainty about the severity and length of the recession.[3] In contrast, the right Panel of Figure 1 considers

[2]For example, in an interview on April 1 2020, Yale University Professor Nicholas Christakis (MD, PhD, MPH) states that in Fall 2020 the United States will have a 75% chance of getting a second wave of the pandemic (the podcast by the Journal of the American Medical Association (JAMA) Network is available at https://edhub.ama-assn.org/jn-learning/audio-player/18393767 (around 25')). In particular, by the end of March, the short-term VIX decreased whereas the long-term VIX increased for a while.

[3]For example, in the minutes of the October 28-29, 2008 FOMC meeting it is stated: *"Some participants [the members of the Board of Governors and the presidents of the Federal Reserve Banks] noted that further monetary policy easing could eventually become constrained by the lower bound of zero on nominal interest rates, in which case an elevated degree of uncertainty might be associated with gauging the magnitude and stimulative effects of other policy tools such as quantitative easing."*.

a historical event that arguably reflects a surge in short-term uncertainty. Specifically, we observe a sizeable increase in the short-term VIX around the WorldCom bankruptcy in 2002 that occurred in the presence of a relatively constant long-term VIX.

The remainder of this paper proceeds in four steps. First, we estimate the term structure of VIX using a large dataset of S&P500 options and show that monthly changes in the one-month VIX explain only between one-half and two-thirds of the monthly changes in the two-year VIX. We take this fact to suggest that the standard one-month VIX captures only part of the market's expectations about future financial uncertainty. Hence, considering the long-term VIX in addition to the short-term VIX in a VAR allows us to account for an additional source of information regarding long-term expectations. We also show within a VAR that the marginal information contained in the long-term VIX has additional predicting power for macroeconomic dynamics with respect to the information contained in the short-term VIX.

Second, we use the Basu and Bundick (2017) DSGE model, which includes a well-defined financial uncertainty index, to show that the imperfect empirical relationship between the short- and long-term VIX is not reconcilable with the existence of just one generic uncertainty shock as typically featured in the DSGE literature (Fernández-Villaverde et al., 2011; Mumtaz and Zanetti, 2013; Fernández-Villaverde et al., 2015; Leduc and Liu, 2016; Basu and Bundick, 2017; Fernández-Villaverde and Guerrón-Quintana, 2020; Cacciatore and Ravenna, 2021). Instead, we rationalize the imperfect relation between the VIXs by extending the Basu and Bundick (2017) model to consider both short-term and long-term uncertainty shocks. Within this framework, both uncertainty shocks impact the entire VIX term structure such that Cholesky-identification is invalid. However, the key distinguishing feature between the two uncertainty shocks is the *persistence* of their effects on the VIXs, and we exploit this insight in the third step of our analysis.

The third step is to apply a theory-informed, nonrecursive identification scheme to separately identify the macroeconomic effects of long-term and short-term uncertainty shocks within a structural VAR. Our analysis is closely related to those of Leduc and Liu (2016, 2020), who use a small-scale VAR to identify uncertainty shocks recursively based on the standard one-month VIX.[4] In contrast, we augment a similar model with the two-year VIX to capture market expectations about financial uncertainty at long horizons and identify uncertainty shocks with a nonrecursive approach. Specifically, we rely on standard sign restrictions derived from theory and narrative sign restrictions building on Ludvigson et al. (2021). As in Ludvigson et al. (2021), we impose no zero restrictions on the parameters in the model, and our approach thus allows for uncertainty to be partly endogenous to the business cycle. Similar identification schemes have recently been employed in the empirical literature on uncertainty shocks (see Castelnuovo (2022) for a recent survey). However, to the best of our knowledge, we are the first to obtain separate identification of short-term and long-term shocks.

We find that long-term uncertainty shocks contribute sizeably to business cycle fluctuations and have more persistent effects on the macroeconomy than short-term shocks. Specifically, the peak effect of a long-term shock on the unemployment rate more than doubles that of a short-term shock and arrives one year later (twenty-four vs. twelve months). We also find that the two uncertainty shocks explain around two-thirds of the variation in both VIXs, while first-moment shocks drive the remaining one-third. Moreover, a historical decomposition exercise suggests that long-term uncertainty shocks contributed significantly to the severity and duration of the Great Recession – explaining roughly one-fourth of the observed increase in unemployment – and to hitting the zero lower bound.

The fourth and final step of the analysis offers an alternative way to conceptualize long-term uncertainty shocks. Specifically, we identify an uncertainty news shock by imposing sign and zero restrictions taken from a slightly altered DSGE model where the news shock does not affect the short-term VIX on impact. In the data, uncertainty news shocks have contractionary effects on the real economy that align with theory. Moreover,

[4] Many empirical studies have used the (short-term) "standard" VIX – or the VXO, i.e., the equivalent 1-month ahead volatility index referring to the S&P100 rather than the S&P500–, to identify uncertainty shocks. See, for example: Bloom (2009); Caggiano et al. (2014); Carriero et al. (2015); Leduc and Liu (2016); Basu and Bundick (2017); Barrero et al. (2017); Caggiano et al. (2017); Piffer and Podstawski (2018); Berger et al. (2020); Pellegrino et al. (2022). The VIX and VXO are almost identical, having a monthly correlation coefficient of 0.99, a reason for which several studies refer to either the VIX or VXO interchangeably (see, e.g., Leduc and Liu (2016)), with another possible reason being the fact that the VIX was originally based on the S&P100. The advantage of the standard VIX (VXO) index over the long-term VIX is that it is available since 1990 (1986), whereas the VIX-2Y is available since 1996.

they are inflationary, contrasting conventionally identified uncertainty shocks (including those considered in step three).[5] This finding offers a puzzle for future models to explain.

The main takeaway from our paper is that policymakers and analysts should monitor uncertainty at multiple horizons to avoid the risk of myopic decision-making. Using a single-horizon uncertainty index in a macroeconomic VAR confounds the effects of short- and long-term uncertainty shocks. Relatedly, it understates the importance of uncertainty if a short-term uncertainty index is adopted. In what follows, we relate our findings to other papers on the importance of the horizon of uncertainty for macro dynamics.

Related literature

The closest contributions to ours are those of Barrero et al. (2017), Bandi et al. (2021), Faccini and Palombo (2021), Meyer et al. (2022), and Tornese (2023).

Barrero et al. (2017) empirically study the firm-level effects of short- and long-term uncertainty, as proxied by the short and long ends of the VIX term structure, respectively. They find that an increase in long-term uncertainty has a more pronounced negative effect on research and development than investment at the firm level. Investment, however, is more negatively impacted than hiring. Our paper complements Barrero et al. (2017) with a structural empirical analysis at the aggregate level. Similarly to Barrero et al. (2017), we also study short-term and long-term uncertainty shocks theoretically and differentiate them based on their persistence. However, we employ a general equilibrium New Keynesian model instead of a firm-level partial equilibrium model. Our findings suggest that the macroeconomy is more sensitive to long-term uncertainty shocks.

Bandi et al. (2021) argue that persistent volatility shocks to TFP growth play a crucial role in explaining time variation in the equity premium both empirically, in a recursively identified VAR, and theoretically, in a model with endogenous growth, Epstein-Zin preferences, and nominal rigidities. In line with our findings, Bandi et al. (2021) show that persistent uncertainty shocks are highly contractionary. In contrast, however,

[5] See, for example, Oh (2020), who finds from several recursively-identified SVARs that shocks to various types of uncertainty measures such as macroeconomic uncertainty, financial uncertainty, survey-based uncertainty, and policy uncertainty are all deflationary.

our paper illustrates that pure long-term shocks are difficult to identify in a setting with uncertainty shocks of different persistence and proposes an empirical identification strategy to disentangle the effects of short- and long-term shocks.

Faccini and Palombo (2021) use a partial equilibrium model with heterogeneous firms to show that uncertainty news shocks, i.e., shocks that only increase uncertainty in the future, are crucial in explaining the trajectory of U.K. macroeconomic aggregates following the 2016 Brexit referendum. To our knowledge, we are the first to identify uncertainty news shocks empirically within a structural VAR framework. We do so by leveraging the implications of a general equilibrium model.

Meyer et al. (2022) study the role of uncertainty since the outbreak of the COVID-19 pandemic using purely descriptive methods. Similarly to us, they show that the increase in the one-month VIX during the pandemic outbreak was more volatile and less persistent than the simultaneous increase in the long-term VIX. With respect to them, we conduct a SVAR analysis to quantify the effects of short- and long-term uncertainty shocks. I.e., we add a structural layer to the analysis of VIX movements.

In contemporary work, Tornese (2023) estimates a mixed-frequency VAR with functional shocks á la Inoue and Rossi (2021) and identifies via heteroskedasticity three uncertainty shocks to the option-implied volatility (IV) surface: a traditional shock, a long-term shock (exploiting the maturity of options), and a bad shock (exploiting the moneyness of options). Similarly to us, he finds that long-term shocks are highly recessionary. However, our study differs in three key ways. First, we measure uncertainty using the VIX, a model-free measure widely adopted in empirical research, as opposed to the IV, which relates to the Black and Scholes (1973) option pricing framework. Second, we jointly identify short- and long-term uncertainty shocks through both theory-informed and narrative sign restrictions. Third, we study the theoretical and empirical effects of uncertainty news shocks.[6]

Our paper also relates to Berger et al. (2020), who find that shocks to realized stock

[6] In a less closely related paper, Carriero et al. (2023) study the effects of recursively identified uncertainty shocks at very long horizons, exploiting VARs with rich lag structures. They find that uncertainty shocks produce two contractionary waves: one at short horizons and one that troughs after eight years from the shock. Unlike their approach, which considers a generic uncertainty shock and analyzes its effects over the short and very long run, our study jointly identifies short- and long-term uncertainty shocks (differing in terms of their effects on the VIX term structure) and examines their distinct impact on the economy.

market volatility have sizeable contractionary effects, while shocks to forward-looking uncertainty (as proxied by the VIX) have no significant impact on the economy. Our study suggests that forward-looking uncertainty shocks have significant contractionary effects when they affect the long end of the VIX term structure, i.e., when uncertainty is highly persistent. Additionally, we find that uncertainty news shocks, which are orthogonal to short-term VIX changes, have strong contractionary effects.

Finally, our paper also relates to earlier work on uncertainty measurement at multiple horizons (Jurado et al., 2015; Binder et al., 2021). Jurado et al. (2015) use large-scale factor models for macroeconomic and financial variables to estimate a common component in the conditional variances of forecast errors at horizons from one to twelve months. Binder et al. (2021) construct survey-based measures of subjective uncertainty at horizons from one to five years. In contrast, our paper considers the VIX term structure, which is a model-free measure of multiple-horizon financial uncertainty based on option prices.[7]

2. The VIX term structure and macro dynamics

This section aims to show that jointly considering short-term and long-term VIX in a macroeconomic VAR opens the door for distinguishing between short-term and long-term uncertainty shocks. First, we briefly describe our data. Then, we show that the relationship between the short- and long-term VIX is imperfect, meaning that the short-term VIX explains only part of the variation in the long-term VIX. We take this fact to suggest that the standard one-month VIX captures only part of the market's expectations about future financial volatility. Finally, we show that the marginal information about future uncertainty carried by the long-term VIX helps predict macro dynamics.

[7]Like the VIX, the financial uncertainty index of Ludvigson et al. (2021), who borrow the methodology of Jurado et al. (2015) (henceforth JLN), is commonly used to proxy for uncertainty in structural VARs. As such, it would be natural to use the multiple-horizon JLN indices instead of multiple-horizon VIXs in our analysis. However, the correlation between the one-month and two-year VIXs is 77.26% in the 2000:01-2020:02 sample, and the correlation between one-month and one-year JLN financial uncertainty indices is 98.95%, suggesting that the VIXs term structure is more informative about long-term uncertainty, likely as it directly reflects financial markets participants' uncertainty expectations at different horizons.

2.1. VIX at different horizons

To estimate financial uncertainty at multiple horizons, we obtain daily price information on all put and call options with European exercise style written on the S&P500 index and listed on US exchanges. Collecting this data from OptionMetrics (IvyDB), accessed through the Wharton Research Data Services (WRDS), we obtain an unbalanced panel with an average of 5012 option contracts per trading day between January 1996 and December 2022. If n_t denotes the time-to-maturities available in period t, we can only construct VIX indices at these n_t horizons. Following Luo and Zhang (2012) and Barrero et al. (2017), we estimate the term structure of VIX by first calculating VIXs for each of the n_t horizons on all days in the sample. We then construct a balanced panel of VIXs at the fixed set of maturities $\{10, 30, 60, 91, 122, 152, 182, 273, 365, 547, 730\}$, using simple linear interpolation between the observable maturities. Finally, we aggregate the daily VIXs to monthly frequency by averaging over each trading day. This approach agrees with Barrero et al. (2017) and the standard practice of aggregating with averages.

For each day t and horizon h, we calculate the VIX with the original formula of the VIX white paper (CBOE, 2019), following Barrero et al. (2017).[8] Due to missing observations and other issues with the long-term VIX estimates in the first few years of the dataset, we consider a shortened sample starting in January 2000 to ensure the quality of our empirical analysis.[9] The upper graph of Figure 2 plots monthly estimates of the VIX at horizons of one month, six months, one year, and two years. The longer-term VIXs are notably less volatile than the (standard) one-month VIX. Moreover, the term structure of VIX exhibits a persistent level component causing the VIXs to be highly correlated.

Consistent with the view that the VIXs are driven by more than just a single factor, the lower graph of Figure 2 illustrates the slope of the term structure, i.e., the difference

[8] More details on how we construct the term structure of VIX are provided in the Appendix.

[9] Liquidity issues in the early phase of the sample are a potential explanation behind some unusual dynamics that only occur in this period (as shown in the Appendix). E.g., we observe *i*) a flip in the term structure caused by a decrease in the two-year VIX rather than a spike in the one-month VIX and *ii*) a non-monotonic relationship between VIX1M, VIX1Y, and VIX2Y over an extended period. Relatedly, Martin (2017) notes that long-term index options are somewhat illiquid and that open interest and trading volume for index options in the OptionMetrics database increased substantially after the change of the millennium. Initializing our sample in January 2000 mitigates the effects of the data issues but still includes three recessions. However, we verify that our results are robust to starting in 1996.

between the two-year VIX and the one-month VIX. Intriguingly, the slope is highly variable over time and occasionally switches signs – indicating a flip in the term structure –, for example around NBER-dated recessions, as illustrated by grey bars.

While slope and level components are significant determinants of the term structure of the VIX, it is natural to wonder whether more factors are also worth considering. In this spirit, Luo and Zhang (2012) use a principal component analysis to show that two components are sufficient to explain the bulk of the variation in the VIXs. Similarly, Barrero et al. (2017) argue that the term structure of VIX is approximately linear and thus driven by two factors. For this reason, we restrict our attention to only the one-month VIX and the two-year VIX in the VAR analysis to follow. Intuitively, a model including these two variables jointly incorporates information about the level and slope of the term structure.

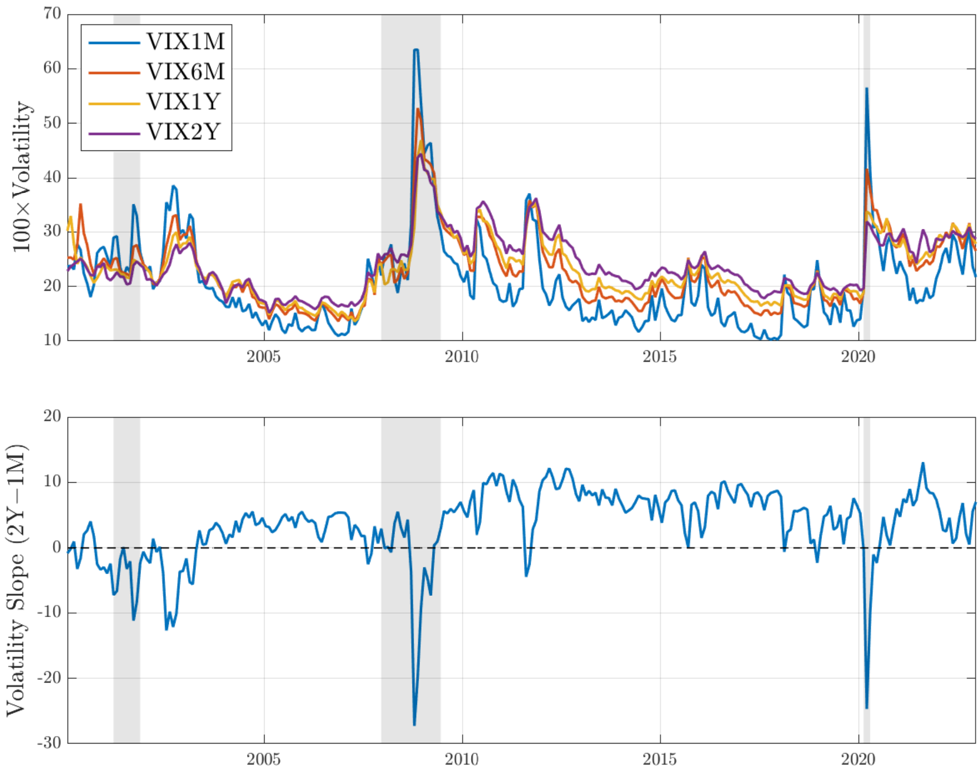

Figure 2: The term structure of VIX. The upper graph shows the one-month, six-month, one-year, and two-year VIXs. The lower graph shows the 2Y-1M slope. Both graphs consider the 2000:01-2022:12 sample.

2.2. Imperfect relationship between the short- and long-term VIX

With some abuse of notation, the h-horizon VIX estimates integrated volatility such that

$$VIX_t^h \approx 100 \times \sqrt{\frac{1}{h}\int_0^h \sigma_{t+s}^2 ds}, \tag{1}$$

where σ_t^2 denotes the continuous time instantaneous volatility of the S&P500 index at time t. Crucially, VIX_t^h is scaled by $h^{-1/2}$, implying that we measure the VIXs on the same scale. We can think of the relation between the one-month and two-year VIX as

$$\left(VIX_t^{2Y}/100\right)^2 \approx \frac{1}{24}\left(\underbrace{\int_0^1 \sigma_{t+s}^2 ds}_{=\left(VIX_t^{1M}/100\right)^2} + \int_1^{24} \sigma_{t+s}^2 ds \right), \tag{2}$$

from which it is clear that the two-year VIX is informative about both the one-month VIX and volatility in the more distant future. As such, the two-year VIX should capture more detailed information about uncertainty that will only *resolve at long horizons*. Thus we would expect an imperfect correlation between the changes in the two variables. Accordingly, Figure 3 illustrates a scatter plot of monthly changes in the one-month VIX (Δvix_t^{1M}) and the two-year VIX (Δvix_t^{2Y}) and shows a simple regression line of Δvix_t^{2Y} on Δvix_t^{1M}. The R^2 of this regression amounts to 57%, indicating that changes in the short-term VIX are not perfectly correlated with changes in the long-term VIX.[10] In other words, one of the indices sometimes moves significantly while the other does not. For example, this occurs in 2008:11 and 2002:7, i.e., the two dates described in the Introduction and also highlighted in Figure 3.

2.3. The VIX term structure and business cycle fluctuations

We now investigate if the marginal information about long-term uncertainty in the two-year VIX informs about business cycles. Specifically, we proceed in two steps. First, we show in a Cholesky-identified VAR that it matters for macro dynamics whether the two-year

[10] If we exclude COVID-19 data and cut the sample at February 2020, then $R^2 = 0.52$. When using daily data (quarterly averages) from 2000:01 to 2022:12, we obtain $R^2 = 0.19$ ($R^2 = 0.64$).

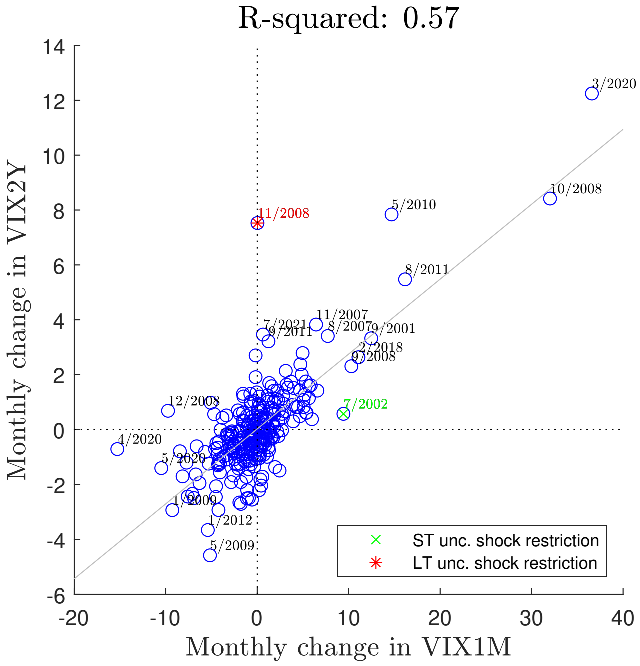

Figure 3: The imperfect empirical relationship between VIX-1M and VIX-2Y changes. Scatter plot of monthly differences in the one-month (Δvix_t^{1M}) and two-year VIX (Δvix_t^{2Y}) in the 2000:01-2022:12 sample. Fitted line: $\Delta vix_t^{2Y} = \alpha + \beta \Delta vix_t^{1M} + e_t$.

VIX increases or remains at parity when the economy experiences a sudden increase in the one-month VIX. Second, we show that adding the two-year VIX to the VAR allows us to gain additional explanatory power for macro variables at long horizons.

We augment a monthly VAR à la Leduc and Liu (2016, 2020) with the two-year VIX such that the vector of endogenous variables contains (1) the two-year VIX, (2) the one-month VIX, (3) the unemployment rate as a proxy for real activity, (4) the year-over-year CPI inflation rate, and (5) the policy rate.[11] In this framework, the first-order Cholesky innovation explains all variation in the two-year VIX at the one-month forecast horizon and accounts for any contemporaneous comovement between the two VIXs. As such, it represents an innovation to the overall level of the VIX term structure as occurred, e.g., in October 2008 and March 2020 (see Figure 3). In contrast, the second-order Cholesky innovation accounts for the residual variation in the one-month VIX. In other words, it increases only the short end of the term structure, which roughly is what happened in July 2002. To compare the business cycle dynamic responses to these two innovations, we

[11] Section 4 provides a detailed presentation of our VAR methodology and the data. This Subsection aims to provide suggestive evidence on the marginal information in the long-term VIX about business cycle fluctuations. As we illustrate theoretically in Section 3, a Cholesky identification strategy is ill-suited to identify short- and long-term shocks.

normalize their IRFs to imply a 10% increase in the one-month VIX.[12]

Figure 4 shows the response of each endogenous variable to the first-order innovation (dashed red line) and the second-order innovation (dashed-dotted green line). We observe that the disturbance affecting both VIXs on impact has a highly contractionary and persistent effect. In contrast, the disturbance that only affects the one-month VIX on impact is also contractionary, but its effects on the economy are more limited. While the unemployment response to the first-order innovation peaks at around +0.2% after two years, that of the second-order innovation peaks at roughly +0.05% after only one year. Similar considerations hold for the policy rate, with a maximum effect of around −25 basis after two years for the first-order innovation and −10 basis points after one year for the second-order innovation. Hence, it matters substantially for macro dynamics whether or not an uncertainty innovation affects the long end of the term structure and thus reflects long-term uncertainty.

The black lines in Figure 4 illustrate impulse responses to a first-order Cholesky innovation in a four-variable VAR that omits the two-year VIX. Intriguingly, these responses can be compared to those from the five-variable model. At parity of a 10% increase in the one-month VIX, we note that a Cholesky innovation to the two-year VIX in the five-variable system implies a stronger and more persistent effect on the economy than a Cholesky innovation to the 1-month VIX in the four-variable system. For instance, in the latter case, the unemployment response peaks at around +0.1% after one year (compared to +0.2% after two years). This suggests that the two-year VIX provides valuable predictive information about macroeconomic dynamics not featured in the one-month VIX.

3. Theory

This section briefly describes a DSGE framework and uses it to show that the joint modeling of short-term and long-term uncertainty shocks is crucial for explaining the imperfect empirical relationship between the long and short ends of the VIX terms structure.

[12] A unit standard deviation Cholesky innovation to the one-month (two-year) VIX implies an impact increase in the one-month VIX of 10.19% (12.94%).

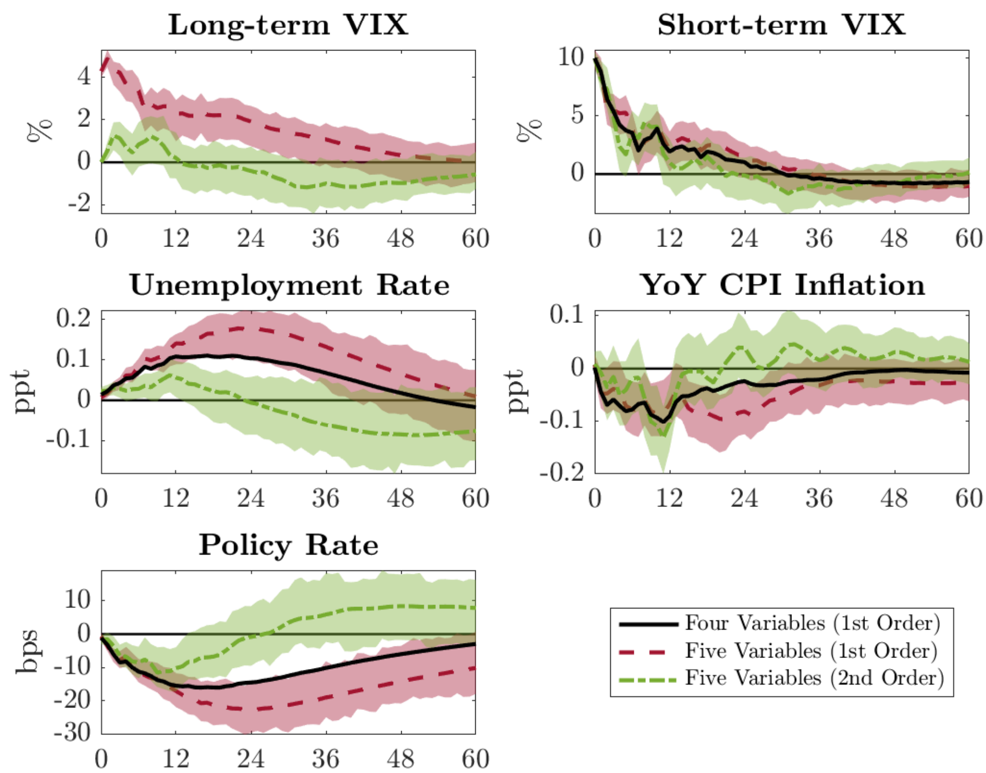

Figure 4: The importance of long-term VIX for business cycle fluctuations: IRFs from recursive ordering. Solid black lines indicate responses to the first-order Cholesky innovation in a VAR with variables $\mathbf{X}_t = [vix_t^{1M}, u_t, \pi_t, i_t]$, where vix_t^{1M} is the one-month VIX, u_t is the unemployment rate, π_t is the inflation rate, and i_t is the Wu and Xia (2016) shadow rate. Dashed red lines (dashed-dotted green lines) are responses to the first (second) order Cholesky innovation in a VAR with variables $\mathbf{Y}_t = [vix_t^{2Y}, \mathbf{X}_t]$, where vix_t^{2Y} is the two-year VIX. Both VIXs are in logs, and all innovations are scaled to imply a ten percent increase in the one-month VIX. The VARs include a constant and twelve lags and are estimated with a Jeffreys prior using the 2000:m1-2020:m2 sample. The shaded areas indicate 68% highest posterior density intervals.

3.1. DSGE model: description

The DSGE framework of Basu and Bundick (2017) extends a medium-scale New Keynesian model to entertain a second-moment (uncertainty) shock in the preference shock process. We work with this model as our baseline as it includes a model-implied measure of financial volatility akin to the VIX that can be affected by uncertainty shocks. This is the reason why we prefer to work with this model with respect to other DSGE models in the literature that have successfully captured the business cycle effects of alternative uncertainty shocks, e.g., shocks to the volatility of the world interest rate (Fernández-Villaverde et al., 2011), fiscal policy (Born and Pfeifer, 2014; Fernández-Villaverde et al., 2015), technology (Bloom et al., 2018), and monetary policy (Mumtaz and Zanetti, 2013). We briefly describe our model here and emphasize the elements crucial to our study. The Appendix provides further details.

Households work, consume, and invest in equity shares and one-period risk-free bonds. They are all similar, and feature Epstein-Zin preferences over streams of consumption and leisure, formalized using a value function given by

$$V_t = \left[\left(1-\beta)(a_t C_t^{\eta}(1-N_t)^{(1-\eta)}\right)^{(1-\sigma)/\theta_V} + \beta((\mathbb{E}_t V_{t+1})^{1-\sigma})^{1/\theta_V} \right]^{\theta_V/(1-\sigma)}, \tag{3}$$

where C_t is consumption, N_t is hours worked, β is the discount factor, σ is a parameter directly influencing the degree of risk aversion, ψ is the intertemporal elasticity of substitution, $\theta_V \equiv (1-\sigma)/(1-\psi^{-1})^{-1}$ captures the households' preferences for the resolution of uncertainty, η weights consumption and labor in the households' utility function, and a_t is a stochastic shifter influencing the relevance of today's realizations of consumption and labor relative to expected next-period realizations.[13]

Relative to Basu and Bundick (2017), we extend the preference shock process to include two stochastic volatility shocks with different degrees of persistence. We have

$$\begin{aligned}
a_t &= (1-\rho_a)a + \rho_a a_{t-1} + e^{\sigma^a_{t-1}}\varepsilon^a_t && (4)\\
\sigma^a_t &= (1-\rho_{\sigma^a})\sigma^a + \rho_{\sigma^a}\sigma^a_{t-1} + \sigma^a_{ST,t} + \sigma^a_{LT,t} && (5)\\
\sigma^a_{ST,t} &= \sigma^{\sigma^a}_{ST}\varepsilon^{\sigma^a}_{ST,t} && (6)\\
\sigma^a_{LT,t} &= \rho_{LT,\sigma^a}\sigma^a_{LT,t-1} + \sigma^{\sigma^a}_{LT}\varepsilon^{\sigma^a}_{LT,t}, && (7)
\end{aligned}$$

where ε^a_t is the first-moment preference shock, σ^a_t reflects the time-varying conditional variance of a_{t+1}, and $\varepsilon^{\sigma^a}_{ST,t}$ and $\varepsilon^{\sigma^a}_{LT,t}$ are second-moment shocks, denoted as short-term and long-term uncertainty shocks. Both uncertainty shocks increase the conditional variance of the preference shock process, but long-term shocks increase it more persistently. Our model nests Basu and Bundick's (2017) specification when only one uncertainty shock

[13] de Groot et al. (2018) show that the households' preferences in the model of Basu and Bundick (2017) imply an asymptote in the responses to an uncertainty shock when the intertemporal elasticity of substitution equals one. Our paper employs the preferences suggested by Gourio (2012), as also analyzed by de Groot et al. (2018) and Basu and Bundick (2018), which do not feature an asymptote.

enters the second-moment equation. I.e., when $\sigma_{LT}^{\sigma^a} = 0$ or $\sigma_{ST}^{\sigma^a} = \rho_{LT,\sigma^a} = 0$.[14]

Intermediate goods-producing firms operate in a monopolistically competitive environment, rent labor from households, and pay wages. They own capital and choose its utilization rate, issue equity shares and one-period riskless bonds, set the price of their product, and invest in physical capital to maximize the discounted stream of their profits. In doing so, they face quadratic costs of adjusting nominal prices á la Rotemberg (1982), capital adjustment costs á la Jermann (1998), and capital utilization costs influencing the capital depreciation rate. All intermediate firms have the same Cobb-Douglas production function and are subject to a fixed cost of production and stationary technology shocks. Intermediate goods are packed by a representative final goods producer operating in a perfectly competitive market. The model is closed by assuming that the central bank follows a standard Taylor rule, according to which monetary policymakers systematically respond to changes in inflation and the growth rate of output.

As previously noted, the model exhibits a well-defined implied financial volatility index similar to the VIX. Specifically, we can exploit that intermediate firms issue equity shares whose prices feature time-varying volatility.[15] Each equity share has a price of P_t^E, implying an h-period capital gain $R_{t+h}^E = P_{t+h}^E / P_t^E$. The model-implied financial uncertainty index at horizon h, VIX_t^h, is computed as the annualized expected volatility of capital gains, i.e., $VIX_t^h = 100\sqrt{\frac{4}{h}\mathbb{V}AR_t\left(R_{t+h}^E\right)}$, where $\mathbb{V}AR_t\left(R_{t+h}^E\right)$ is the conditional variance of the capital gain.[16] Capital gains and the VIX term structure are endogenous in the model. However, in this model, VIX_t^h is almost entirely driven by second-moment preference shocks, as in the original version of Basu and Bundick's (2017) model. In our case, the

[14]With respect to Basu and Bundick (2017), we use $e^{\sigma_t^a}$ rather than σ_t^a to denote the standard deviation of the preference shock so that to avoid negative values for volatility, following Fernández-Villaverde and Guerrón-Quintana (2020).

[15]Basu and Bundick (2017) assume that firms finance a share ν of their capital stock each period with one-period riskless bonds. Given the Modigliani-Miller theorem holds, leverage does neither influence firms' value nor firms' optimal decisions. Firms' leverage influences the first two unconditional moments of financial-related quantities (e.g., the level and unconditional volatility of the model-implied VIX and the equity premium) but does not influence impulse responses to an uncertainty shock.

[16]This convention contrasts Basu and Bundick's (2017) definition of the VIX as the conditional volatility of one-period equity returns (i.e., the sum of capital gains and the dividend yield, $P_{t+1}^E/P_t^E + D_{t+1}^E/P_t^E$). Our definition aligns with the observation that VIX_t^h estimates h-horizon integrated volatility of the S&P500 index *excluding dividends*. We obtain similar results when defining VIX as the annualized conditional volatility of $\tilde{R}_{t+h}^E \equiv \left(P_{t+h}^E + D_{t+h}^E\right)/P_t^E$.

term structure of VIX is driven primarily by short-term and long-term uncertainty shocks.

After an uncertainty shock hits the economy, households reduce consumption due to precautionary savings. Moreover, they supply more labor, driving real wages and marginal costs down and increasing markups in the presence of sticky prices. In equilibrium, output, which is demand-driven in New-Keynesian models, falls due to lower consumption and higher markups, and hours worked fall due to contracting labor demand. Given the lower return on capital, investment falls too. Further, firms' cash flows, which influence the households' capital gains, are expected to be more volatile after an uncertainty shock, implying that the VIX indices increase.

We work with a third-order approximation of the nonlinear DSGE model, which we solve via perturbation (Schmitt-Grohe and Uribe, 2004). The third-order approximation of the agents' decision rules features an independent role for uncertainty, whose effect on the equilibrium values of the endogenous variables can therefore be studied, following Andreasen (2012). Importantly, perturbation represents an accurate and fast way to solve nonlinear DSGE models featuring recursive preferences (Caldara et al., 2012).

3.2. Theoretical results

We calibrate all parameters except those in the volatility process following Basu and Bundick (2018).[17] To illustrate the different propagation of equal-sized short- and long-term uncertainty shocks, we calibrate their processes to only differ in terms of persistence (similarly to Barrero et al. (2017)). Hence, following Fernández-Villaverde and Guerrón-Quintana (2020) we calibrate $\sigma_{ST}^{\sigma^a} = \sigma_{LT}^{\sigma^a}$ to imply that a unit standard deviation shock doubles the level of volatility around the steady state. We calibrate the persistence parameters as $\rho_{\sigma^a} = 0.15$ and $\rho_{LT,\sigma^a} = 0.75$ to ensure that short- and long-term shocks are sufficiently different.[18]

Can the DSGE model help explain why the variation in the short-term VIX only accounts partly for the variation in the long-term VIX? To answer this question, Figure 5

[17]The Appendix provides further details on the calibration.

[18]The key assumption implying more persistent effects of long-term shocks on the VIXs than short-term shocks is $\rho_{LT,\sigma^a} >> 0$. Having uncertainty shocks with substantially different levels of persistence ($\rho_{LT,\sigma^a} >> \rho_{\sigma^a}$), however, allows us to generate a scatter plot on simulated data comparable to Figure 3.

illustrates the equivalent of the empirical scatter plot in Figure 3 for simulated data from three alternative calibrations. The left panel represents our baseline calibration, and the middle and right panels consider calibrations with only one shock (short-term or long-term, respectively).[19] The results indicate that combining uncertainty shocks with sufficiently different levels of persistence is essential to match the imperfect empirical relationship between the short and long ends of the VIX term structure. In particular, Figure 5 shows that the changes in VIX^{1Q} explain 67% of the changes in VIX^{2Y}, which is close to the 64% obtained in the quarterly aggregated counterpart of Figure 3 (as documented in footnote 10). These findings motivate our empirical SVAR analysis aimed at disentangling the effects of short-term and long-term uncertainty shocks.

Figure 6 shows the macroeconomic effects of the two shocks implied by the DSGE model. Intuitively, the long-term uncertainty shock has more potent and persistent effects on real variables, inflation, and the policy rate. The peak reactions in output, investments, and hours worked to the long-term shock arrive later than the short-term shock.[20] Moreover, the response to the long-term shock builds gradually over time for investment. Regarding the VIX indices, the one-quarter VIX increases by the same amount for both shocks on impact.[21] Still, it reacts less persistently to short-term shocks. Similarly, the eight-quarter VIX responds more persistently to long-term shocks, but its on-impact response is weaker for short-term shocks. These findings suggest that the joint reaction of the two VIX indices to an uncertainty shock is crucial to identify whether the shock is short- or long-term. Indeed, in the case of long-term shocks: i) both VIXs react more persistently, and ii) the long-term VIX increases more.[22] Another clear implication of our findings is that a

[19]Since the model is quarterly, the shortest horizon VIX we can construct is the one-quarter VIX, VIX_t^{1Q}. We shift the $\mathbb{V}AR_t\left(R_{t+h}^E\right)$ used for the computation of the VIX indices for different maturities by an identical amount to ensure it is never negative. Given our focus on more than one VIX index, we prefer this approach to the one in the Basu and Bundick's codes of truncating $\mathbb{V}AR_t\left(R_{t+h}^E\right)$ at 0 so that to not artificially lose information on the relationship between the different VIX indices. However, our key results are robust to the latter approach. Note also that TFP shocks are active and calibrated following Basu and Bundick (2018) when simulating the model. We verify that our results are practically unchanged if we add markup shocks specified following Ireland (2011).

[20]Consumption reacts stronger and more persistently to long-term uncertainty shocks, but it does not display a protracted peak reaction because the model does not feature habits in consumption.

[21]The equal increase in the one-quarter VIX across shocks hinges on the calibration $\sigma_{LR,t}^{\sigma^a} = \sigma_{SR,t}^{\sigma^a}$ and hence is not a general theoretical result. However, the empirical analysis that we perform later gives a finding close to this one (without imposing it).

[22]In the next Section we use i) as an identifying restriction and ii) as an implication to validate our

Cholesky identification cannot separately identify short- and long-term shocks.

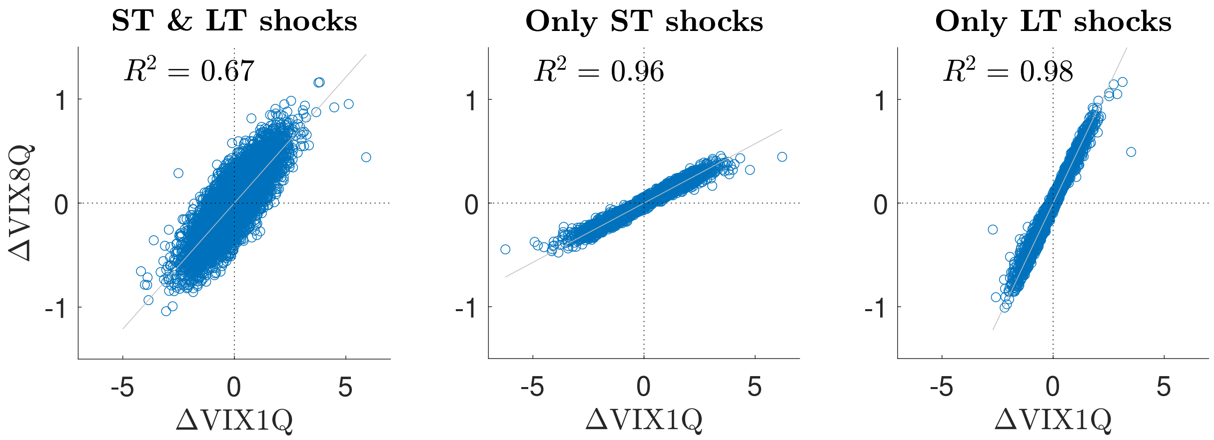

Figure 5: The theoretical relationship between VIX-1Q and VIX-8Q changes. Scatter plot of one-period differences in the one- and eight-quarter VIX for 10,000 simulated observations (burn-in of 500 periods). Fitted line: $\Delta vix_t^{8Q} = \alpha + \beta \Delta vix_t^{1Q} + e_t$.

4. SVAR analysis

This section applies a theory-informed nonrecursive identification strategy to separately identify short-term and long-term uncertainty shocks in a structural VAR framework.

4.1. Empirical identification strategy

Our baseline model extends the small-scale monthly VAR of Leduc and Liu (2016, 2020) by introducing the two-year VIX on top of the conventional VIX. We conduct a monthly VAR analysis instead of a quarterly analysis (e.g., Basu and Bundick, 2017) to better capture the high-frequency relationship between the short and long ends of the VIX term structure. We consider a vector of five endogenous variables given by $\mathbf{Y}_t = [vix_t^{1M}, vix_t^{2Y}, u_t, \pi_t, i_t]'$, where vix_t^{1M} (vix_t^{2Y}) is the natural logarithm of option implied volatility at the one-month (two-year) horizon, u_t is the seasonally adjusted US unemployment rate (FRED mnemonic: UNRATE),[23] π_t is the year-over-year CPI inflation rate (FRED mnemonic: CPIAUCSL), and i_t is the Wu and Xia (2016) shadow rate in annualized percentage points. The shadow

empirical results.

[23]We use the unemployment rate as a monthly proxy for real activity to remain close to Leduc and Liu (2016), but our main findings are robust to using either year-over-year industrial production growth or log levels of industrial production.

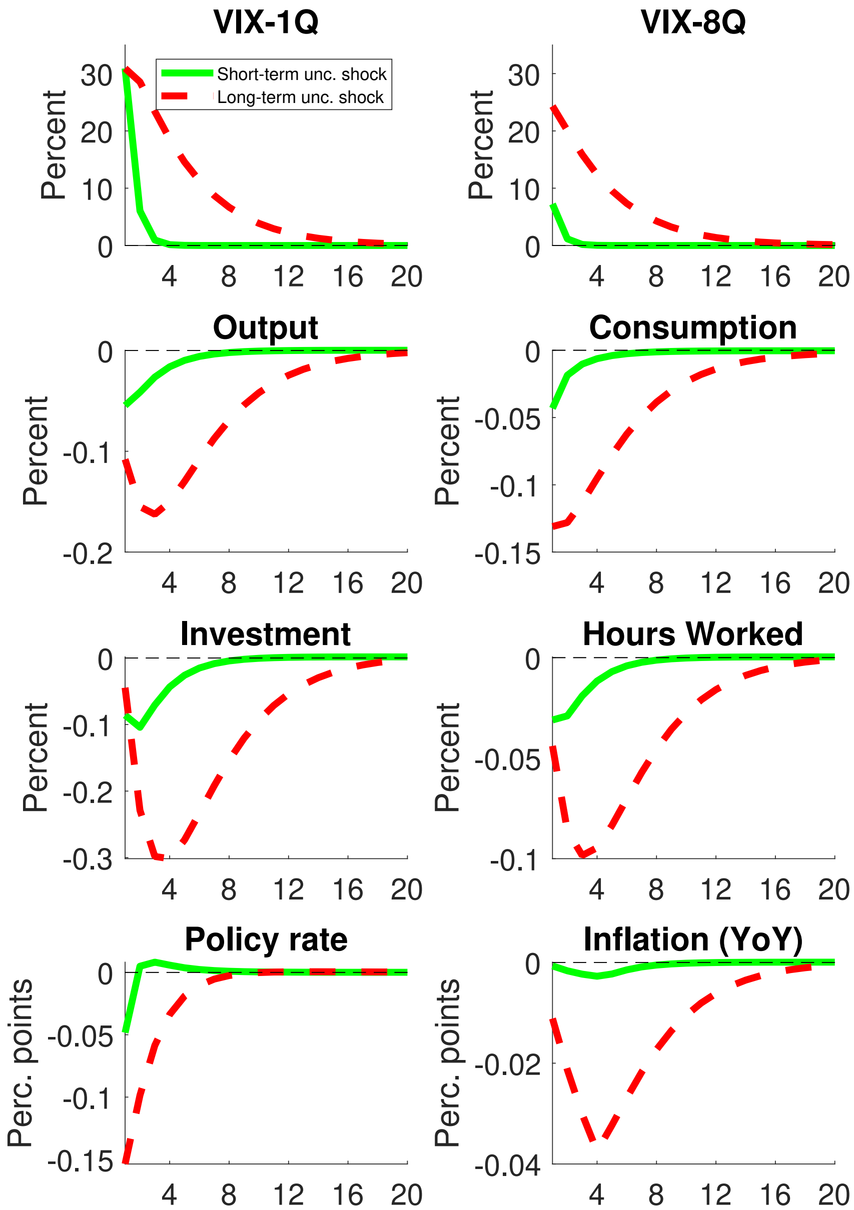

Figure 6: Theoretical impulse response functions. Solid green (dashed red) line: IRFs to short-term (long-term) uncertainty shocks in the DSGE model.

rate approximates the federal funds rate (FFR) when short-term interest rates are positive, and it allows us to account for unconventional monetary policy in periods where the FFR is close to zero. Importantly, the ordering of these variables does not matter.

The vector $\mathbf{Y}_t$ follows a linear VAR of the form

$$\mathbf{Y}_t = \alpha + \sum_{j=1}^{L} \mathbf{A}_j \mathbf{Y}_{t-j} + \eta_t, \tag{8}$$

where α is a 5×1 vector of constants, $L = 12$, $\{\mathbf{A}_j\}_{j=1}^{L}$ are 5×5 matrices of slope coefficients, and η_t is a 5×1 vector of reduced form residuals with $\eta_t \sim \mathcal{NIID}(\mathbf{0}, \mathbf{\Omega})$. Our main empirical results estimate the reduced-form VAR using a Jeffreys (uninformative) prior in the pre-pandemic sample spanning from January 2000 to February 2020.[24]

The main objective of this paper is to identify short-term and long-term uncertainty shocks separately. A widely adopted procedure for identifying (generic) uncertainty shocks is to impose a recursive ordering on all shocks in the system, effectively assuming a contemporaneous causal chain between uncertainty and all other variables (e.g., Bloom, 2009; Jurado et al., 2015; Leduc and Liu, 2016; Basu and Bundick, 2017). However, this approach has two disadvantages in our setting. First, it is clear from Figure 6 that both short-term and long-term uncertainty shocks affect the entire VIX term structure on impact in our DSGE model, implying that we cannot identify the two shocks by recursive ordering. Second, recent literature emphasizes that uncertainty can be partly endogenous to first-order shocks such that recursive identification is invalid even when identifying a single uncertainty shock (e.g., Ludvigson et al., 2021; Kilian et al., 2022).

To identify our shocks, we thus impose theory-informed traditional sign restrictions (SR) on impulse responses and, following Ludvigson et al. (2021), we also add narrative sign restrictions (NSR) on the sign and magnitude of uncertainty shocks on specific dates. To implement our mix of SRs and NSRs, we adopt the algorithm proposed by Antolín-Díaz and Rubio-Ramírez (2018) as modified by Giacomini et al. (2023).[25] To present this approach, let ε_t be the 5×1 vector of structural shocks with covariance matrix I_5 (where I_n is the n-dimensional identity matrix). The mapping between reduced-form residuals η_t and structural shocks ε_t is $\eta_t = \mathbf{B}\varepsilon_t$, where $\mathbf{B} = \mathbf{PQ}$ is a 5×5 matrix, with $\mathbf{P}$ being the lower-triangular Cholesky factor of $\mathbf{\Omega}$ and $\mathbf{Q}$ being any orthogonal matrix such that $\mathbf{QQ}' = I_5$. Imposing a uniform prior on the set of all orthogonal matrices, denoted by

[24] As explained in Section 2, the starting date reflects our intention of using a sample with reliable estimates of the long-term VIX. The end date avoids outlier observations in the initial phase of the COVID-19 pandemic. As shown in the Appendix, our main results are robust to starting the sample in 1996 and to various specifications that include the pandemic observations.

[25] Giacomini et al. (2023) argue that the Markov Chain importance-sampling step of the algorithm proposed by Antolín-Díaz and Rubio-Ramírez (2018) is likely to distort inference by updating the prior distribution in a direction that makes the NSRs unlikely to hold ex-ante. In the Appendix, we also implement the robust bayesian algorithm of Giacomini et al. (2023), illustrating that our main empirical results are robust to the critique of Baumeister and Hamilton (2015, 2019) and exhibit frequentist validity.

$\mathbf{\Omega}$, we sample from the posterior conditional on reduced form parameters by drawing randomly from $\mathbf{\Omega}$ until we obtain a $\mathbf{Q}$ that satisfies all sign restrictions.[26]

Our identifying restrictions are summarized in Table 1. The first set of restrictions on the structural representation of the VAR relates to the responses of the VIXs to uncertainty shocks. Specifically, we impose that both uncertainty shocks have nonnegative effects on both volatility measures. In line with the DSGE model, we impose this restriction on impact and going twelve months forward. While this assumption helps us identify uncertainty shocks, it is not helpful in *separating* the effects of short-term and long-term shocks. We thus impose two additional restrictions that require the *half-life* of the response of any uncertainty measure to long-term shocks to be greater than the half-life of the response to short-term shocks. Specifically, we define the half-life of an impulse response function to be the horizon at which the impulse response function reaches one-half of its initial response.[27] As such, the reaction of any volatility measure to short-term shocks must be less persistent than the response of the same volatility measure to long-term shocks. Clearly, these restrictions align with the DSGE model.

Our second set of restrictions relates to a narrative understanding of *when* uncertainty shocks occurred in the historical sample. Specifically, we impose two types of restrictions: *specific events* and *common events*. Specific events help us disentangle the effects of short-term and long-term shocks by assuming that a specific type of shock was a significant driver of the VIXs on a given date. As briefly motivated in the introduction, we impose that a short-term shock occurred in July 2002 (due to the WorldCom bankruptcy) and a long-term shock occurred in November 2008 (due to the financial crisis and uncertainty about monetary policy). Further, to ensure that these shocks were significant drivers of the VIX term structure, we also impose that the short-term (long-term) shock was the largest contributor to unexpected changes in the one-month (two-year) VIX in July 2002

[26]We sample from a uniform prior on $\mathbf{Q}$ using the algorithm of Rubio-Ramírez et al. (2010). Specifically, we construct a 5×5 matrix $\mathbf{M}$ by drawing each of the 5^2 entries independently from a standard normal distribution. We then define the draw for $\mathbf{Q}$ as the Q-component in the QR decomposition of $\mathbf{M}$.

[27]Let $IRF_j^X(h)$ be the impulse response of variable X to shock j at horizon h, and let $\mathbb{1}(\cdot)$ be an indicator function that takes the value one if its argument is true and zero otherwise. Given $IRF_j^X(0) > 0$, and given the maximum horizon of interest is H, we define the half-life of IRF_j^X as $HL\left(IRF_j^X\right) = \arg\max_{h \in \{1,2,\ldots,H\}} \left\{h^{-1} \times \mathbb{1}\left(IRF_j^X(h) \leq \frac{1}{2} IRF_j^X(0)\right)\right\}$, which is easy to solve numerically.

(November 2008).[28]

The collapse of WorldCom in July 2002 was, at that time, the largest bankruptcy in US history. It was the result of a significant accounting scandal that naturally led investors to reassess the risks associated with equity investments, causing a sharp decline in stock prices and a corresponding increase in financial uncertainty. As shown in Figure 1, the one-month VIX experienced a notable increase in July 2002 and returned to substantially lower levels within a few months. In contrast, the two-year VIX remained largely unaffected, suggesting that market participants perceived the bankruptcy as a short-term uncertainty shock with limited and manageable effects. Arguably, this pattern is attributable to the functioning of the price mechanism: when stock prices drop due to increased uncertainty and concerns over the validity of financial reporting, investors have incentives to identify undervalued stocks by conducting more rigorous analyses of corporate fundamentals. Such diligence naturally mitigates uncertainty as individual investors convey their newfound information to the market when buying undervalued securities.

In contrast to the WorldCom bankruptcy, the Great Recession was characterized by highly persistent uncertainties due to systemic risks in financial markets and the Federal Reserve's limited capacity to stimulate the economy with interest rates stuck at the zero lower bound. As such, it is natural to attribute a large part of the variation in the VIX term structure in this period to long-term uncertainty shocks. As Figure 1 demonstrates, the two-year VIX experienced a substantial increase in November 2008 and almost no change in the one-month VIX. Given the inevitability of the transition into a new monetary regime at this point in the recession, it seems likely that a long-term uncertainty shock took hold in November 2008.[29]

Unlike specific events, common events do not disentangle the two uncertainty shocks.

[28]We define the contribution of shock j to the unexpected change in variable i in period t as $H_j^i(t) = b_{ij}\varepsilon_{j,t}$, where b_{ij} is entry (i, j) in the matrix B for which $\eta_t = B\varepsilon_t$. As such, the restriction that shock j is the single largest contributor to variable i in period t reads $|H_j^i(t)| \geq \max_{j' \neq j} |H_{j'}^i(t)|$. This is the weak NSR considered in Antolín-Díaz and Rubio-Ramírez (2018), whereas the strong one would have required that the shock j is the overwhealming contributor of variable i.

[29]In support of the significance of our specific events restrictions, Figure 3 shows that November 2008 (July 2002) exhibited large changes in the long-term (short-term) VIX in correspondence with no significant changes in the short-term (long-term) VIX. As shown in the Appendix, associating the points close to the horizontal and vertical axes to short-term and long-term uncertainty shocks, respectively, is consistent with the DSGE model in Section 3.

Instead, they strengthen our claim that we identify uncertainty shocks more generally. Following Ludvigson et al. (2021), we require that *at least one* uncertainty shock materialized in September 2008 when Lehman Brothers filed for bankruptcy and global financial markets spiraled into a liquidity crisis of unprecedented dimension in the post-World War II period. Moreover, we require that the *joint* contribution of the two uncertainty shocks to both VIXs was greater than the sum of the absolute contributions of any other shock.[30] Also following Ludvigson et al. (2021), we impose that at least one uncertainty shock was positive in both July and August 2011 during the US debt ceiling crisis, which put substantial stress on financial markets. On these dates, however, we do not take a stance on the magnitudes of the shocks (again following Ludvigson et al., 2021).

Figure 7 illustrates the informativeness of the NSRs by plotting histograms of 5.000 posterior draws of the model-implied shocks when all restrictions are active (colored bars) and when the NSRs are omitted (grey bars). Intriguingly, we find that the specific event restriction on November 2008 is highly informative about the shocks and that short-term shocks were the primary drivers of uncertainty in September 2008 and July 2011.

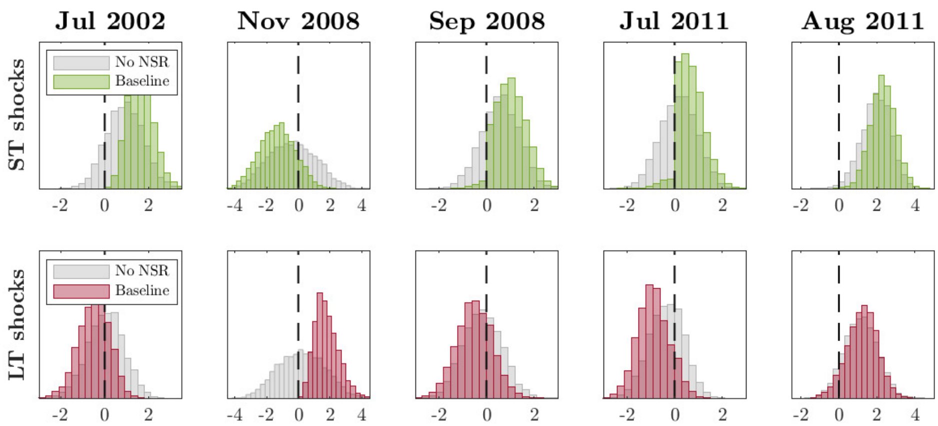

Figure 7: Posterior distributions of shocks. Histograms of short-term (ST) and long-term (LT) uncertainty shocks on sign-restricted dates based on 5.000 draws from the posterior distribution of SVAR parameters. Colored histograms illustrate the shocks obtained using the baseline identification strategy, and grey histograms show the shocks obtained without imposing narrative sign restrictions.

[30] Following the definition of $H_j^i(t)$ in footnote 28, this restriction may be expressed as $|H_1^i(t) + H_2^i(t)| \geq \sum_{j=3}^{5} |H_j^i(t)|$ for $i = 1, 2$ and $t =$2008:9. In the words of Antolín-Díaz and Rubio-Ramírez (2018), the uncertainty shocks are "overwhelming"-contributors to the changes in both VIXs on this date.

	Conditions
IRF Restrictions	
Short-term shocks	$IRF^X_{ST}(h) \geq 0$ for $h = 0, 1, ..., 12$ and $X \in \{vix^{1M}, vix^{2Y}\}$
Long-term shocks	$IRF^X_{LT}(h) \geq 0$ for $h = 0, 1, ..., 12$ and $X \in \{vix^{1M}, vix^{2Y}\}$
Half-life Restrictions	
1M VIX	$HL\left(IRF^X_{LT}\right) > HL\left(IRF^X_{ST}\right)$ for $X = vix^{1M}$
2Y VIX	$HL\left(IRF^X_{LT}\right) > HL\left(IRF^X_{ST}\right)$ for $X = vix^{2Y}$
Specific Events	
$t =$ 2002:7	$\varepsilon_{ST,t} \geq 0$ and $\lvert H^X_{ST}(t)\rvert \geq \max_{j \neq ST} \lvert H^X_j(t)\rvert$ for $X = vix^{1M}$
$t =$ 2008:11	$\varepsilon_{LT,t} \geq 0$ and $\lvert H^X_{LT}(t)\rvert \geq \max_{j \neq LT} \lvert H^X_j(t)\rvert$ for $X = vix^{2Y}$
Common Events	
$t =$ 2011:7	$\varepsilon_{j,t} \geq 0$ for at least one $j \in \{ST, LT\}$.
$t =$ 2011:8	$\varepsilon_{j,t} \geq 0$ for at least one $j \in \{ST, LT\}$.
$t =$ 2008:9	$\varepsilon_{j,t} \geq 0$ for at least one $j \in \{ST, LT\}$.
$t =$ 2008:9	$\lvert H^X_{ST}(t) + H^X_{LT}(t)\rvert \geq \sum_{j \notin \{ST,LT\}} \lvert H^X_j(t)\rvert$ for $X \in \{vix^{1M}, vix^{2Y}\}$

Table 1: Identifying restrictions for short-term (ST) and long-term (LT) uncertainty shocks in the structural VAR. $IRF^X_j(h)$ is the reponse of variable X to shock j at horizon h. $HL\left(IRF^X_j\right)$ is the half-life of the response of variable X to shock j. $H^X_j(t)$ is the contribution of shock j to the unexpected change in variable X in period t.

4.2. Empirical results

The effects and relevance of short-term and long-term uncertainty shocks

Figure 8 illustrates the impulse response functions for short-term uncertainty shocks (left panel) and long-term uncertainty shocks (right panel). Several considerations are in order. First, the two shocks cause a similar on-impact increase in the one-month VIX, reinforcing our argument that only looking at a single uncertainty measure confounds the effects of the shocks. Second, both VIXs react more persistently to long-term uncertainty shocks, as we require by assumption. Third, on impact, the two-year VIX responds more strongly to long-term shocks. Although entirely in line with our DSGE model, this result is not imposed ex-ante, and it thus validates our identification strategy (see Figure 6). Fourth, short-term shocks mildly impact unemployment, peaking at less than 0.09 percentage points after 12 to 21 months, whereas long-term shocks have a stronger and more persistent effect, peaking at around 0.24 percentage points after 25 months. Fifth, turning to the nominal side of the economy, we observe that the policy rate decreases in response to both shocks but again with a longer-lasting effect from the long-term shock (approximately 25 basis points after two years). Sixth, both shocks are deflationary, but the responses of inflation are mild and turn insignificant within one year from the initial impact.

Figure 9 illustrates the forecast error variance contributions of the two shocks to each variable in the system. The upper left panels suggest that the short-term shock is a significant driver of the one-month VIX and a less important driver of the two-year VIX. In contrast, the upper right panels indicate that the long-term shock explains more than half of the variation in the two-year VIX and also contributes substantially to the one-month VIX. Moreover, in line with the findings by Ludvigson et al. (2021), our analysis suggests that uncertainty is partly endogenous. According to the posterior mean estimates, 35% and 32% of the fluctuations in the short- and long-term VIXs are due to unidentified shocks at the two-year horizon. Turning to the unemployment rate, we notice that short-term shocks play only a minor and insignificant role (contributing around 11% at the two-year horizon). In contrast, long-term shocks are critical (contributing with 40-50% at the 6- to 24-month horizon). Similar conclusions are valid for the policy rate, for which the long-term shock is quite important after two years, reaching a contribution of 42% at the five-year horizon. Regarding inflation, short-term and long-term shocks are equally important.

The Appendix documents further results and sensitivity checks. We show that the NSRs are not essential to obtain our baseline results. We also show that our main results are robust to various specifications that include the pandemic observations and to other perturbations. Moreover, we implement the robust bayesian algorithm of Giacomini et al. (2023), which shows that our main empirical results are robust to the critique of Baumeister and Hamilton (2015, 2019) and exhibit frequentist validity.

Ex-post validity of shocks

Narrative sign restrictions allow researchers to impose some degree of ex-ante validity on the posterior distributions of shocks. In our setting, we know by default that the shocks recovered using our identification strategy exhibit reasonable properties in July 2002, September and November 2008, and July and August 2011. A natural concern, however, is whether the recovered shocks are also reasonable on dates that are not restricted. To

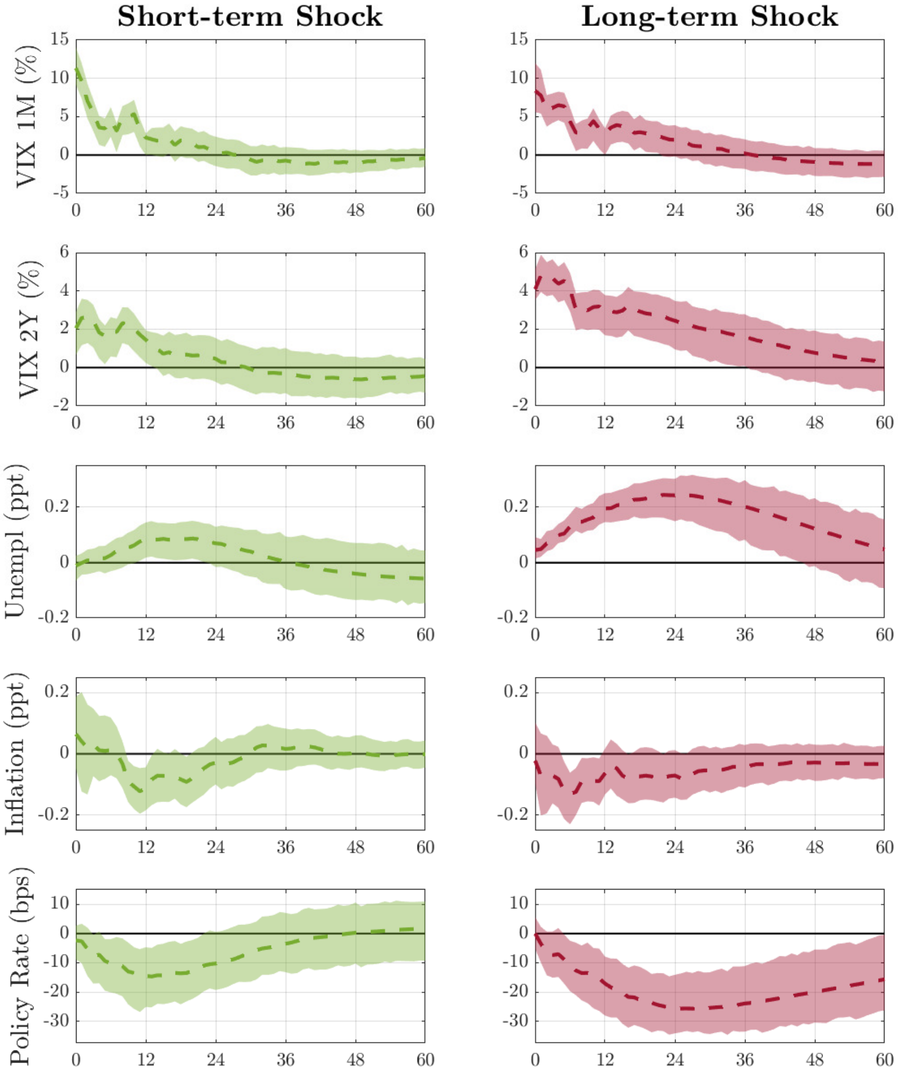

Figure 8: SVAR impulse response functions. Impulse responses of the endogenous variables in the SVAR to short-term (left) and long-term (right) uncertainty shocks. Dashed lines are posterior means, and shaded areas are 68% highest posterior density intervals based on 5.000 draws from the posterior.

alleviate this concern, Figure 10 presents histograms associated with 5.000 posterior draws of short-term shocks (green bars) and long-term shocks (red bars). Specifically, the upper (lower) three graphs in the Figure illustrate posterior distributions of shocks for the three dates on which we observe the largest short-term (long-term) shocks in terms of posterior means. All of these dates align well with our narrative understanding of the shocks.

The single largest short-term shock in our sample occurred in February 2018 when financial markets saw a substantial crash in short-term volatility products that since has been dubbed "*Volmageddon*" (a portmanteau of "*volatility*" and "*armageddon*"). The panic

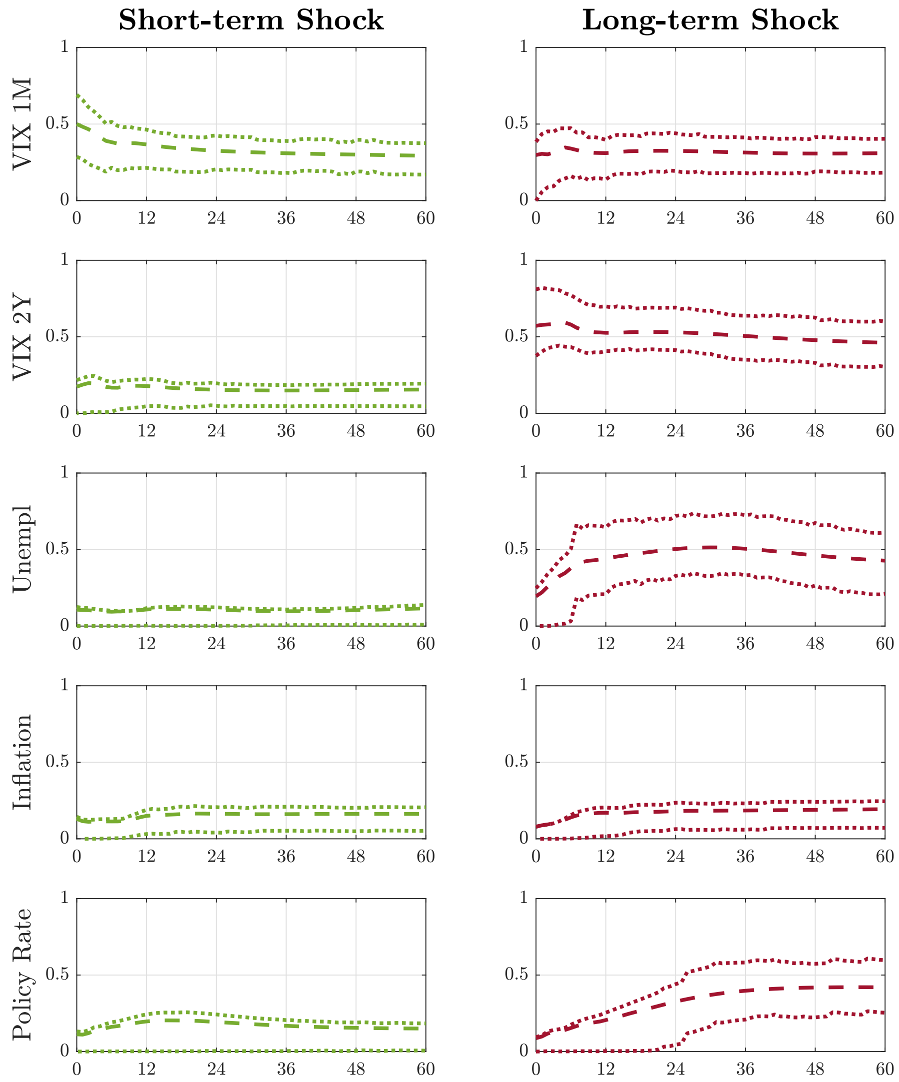

Figure 9: Forecast error variance decomposition. Contributions of short-term (left) and long-term (right) uncertainty shocks to the forecast error variance of the endogenous variables in the SVAR. Dashed lines are posterior means, and shaded areas are 68% highest posterior density intervals.

in this period was short-lived and seemingly disconnected from fundamentals (Augustin et al., 2021), and we thus find it appropriate to label this event as a short-term uncertainty shock. While the second largest short-term shock occurred on a restricted common date (August 2011, the debt ceiling crisis), the third largest shock occurred in January 2016, a month in which oil prices plummeted and the Dow Jones Industrial Average declined substantially. Newspaper articles from this period also indicate a decline in market sentiment about the macroeconomic outlook that seems difficult to justify in hindsight, making it reasonable to associate this month with a short-term shock.[31]

[31]We base this assessment on an informal search on the website of the Wall Street Journal for articles

Considering the lower three graphs in Figure 10, focusing on unrestricted dates, it is interesting to note that both the largest (October 2008) and third largest (May 2010) long-term shocks coincide with large short-term shocks. While this result could raise concerns about identification, it can be argued that both shocks were important drivers of volatility in these periods. As previously discussed, September and October 2008 exhibited a financial panic that is likely to be driven, at least in part, by short-term shocks. However, a narrative account of the Great Recession is incomplete without acknowledging the persistent nature of uncertainty in this period. Turning to May 2010, intriguingly, this month contains not only the initial bailout package to aid Greece in its sovereign debt crisis (reflecting both short-term uncertainty about sovereign debt instruments and longer-term uncertainty about the global macroeconomic outlook) but also a flash crash in US markets on May 6th (reflecting short-term uncertainty).

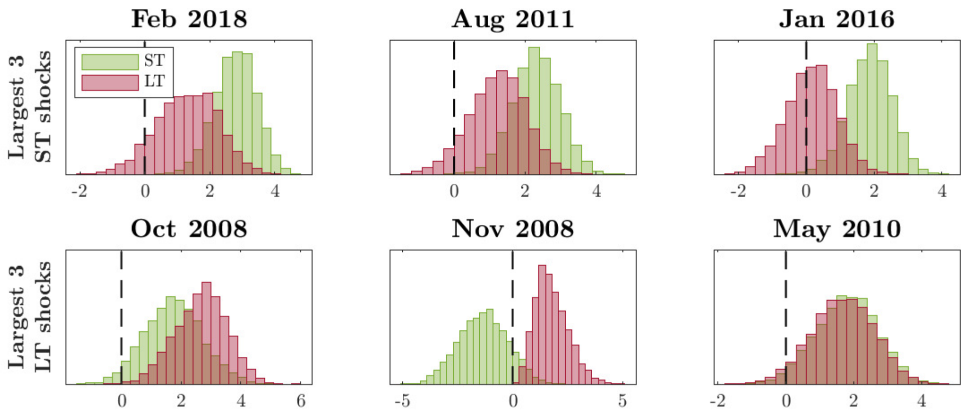

Figure 10: Ex-post shock validation. Histograms of short- (green) and long-term (red) shocks on six dates based on 5,000 draws from the posterior distribution of SVAR parameters. The upper (lower) graphs illustrate the dates on which the posterior mean of the short-term (long-term) shock was the largest (left), second largest (middle), and third largest (right) in the 2000:01-2020:02 sample.

How did uncertainty shocks contribute to the Great Recession?

The Great Recession is one of the most prominent examples of spectacularly high levels of financial uncertainty in modern economic history. Several policymakers have argued that heightened uncertainty significantly contributed to the length and severity of the Great Recession, which is a narrative supported by recent research on the role of uncertainty

published in January 2016 using the search words "*panic*," "*stock market*," and "*oil prices*."

shocks, e.g., Alessandri and Mumtaz (2019) and Pellegrino et al. (2022).[32]

We now revisit the role of uncertainty shocks at the time of the Great Recession in a context where (*i*) we can separate between short- and long-term uncertainty shocks, and (*ii*) we can account for the fact that an increase in uncertainty may have been an endogenous reaction to the business cycle rather than an exogenous shock. Notably, given that our VAR is linear, our analysis is likely conservative as regards the importance of uncertainty shocks in the Great Recession (Born et al., 2017; Caggiano et al., 2021).

To illustrate the contributions of uncertainty shocks to the Great Recession, Figure 11 compares the realized historical (or factual) path of the unemployment rate, the policy rate, and the two VIXs with two counterfactual scenarios: a world where no uncertainty shocks materialized between September 2008 and March 2010, and a world where only short-term shocks occurred. The black line, representing the factual path, shows that in September and October 2008, i.e., amid the financial panic of the crisis, the VIXs increased massively. From December 2008, they started to decay and returned to their initial value around March 2010. In the same period, the unemployment rate rose from 6% to 10%, and the policy rate fell from around two percent in August 2008 to the zero lower bound (ZLB) in December 2008. Later, after having reached the ZLB, unconventional monetary policy was adopted as conveniently captured by the shadow rate of Wu and Xia (2016).

The dashed red line indicates what would have happened had long-term shocks not materialized. In particular, the short-term VIX would have increased less from October 2008 onward, whereas the long-term VIX would have increased substantially less. The unemployment rate would have increased by one percentage point less at its peak in October 2009 (a statistically significant difference), and the policy rate would have exhibited a less dramatic decline. Hence, our analysis suggests that one-fourth of the increase in the unemployment rate during the Great Recession was due to long-term uncertainty shocks

[32] In Olivier Blanchard's words in The Economist on January 29, 2009, while serving as IMF's chief economist: "*If you think that another Depression might be around the corner, better to be careful and save more. Better to wait and see how things turn out. Buying a new house, a new car or a new laptop can surely be delayed a few months. The same goes for firms: given the uncertainty, why build a new plant or introduce a new product now? Better to pause until the smoke clears. This is perfectly understandable behavior on the part of consumers and firms – but behaviour which has led to a collapse of demand, a collapse of output and the deep recession we are now in.*"

and that these shocks contributed to the policy rate hitting the ZLB.

What about short-term shocks? The dashed-dotted green lines in Figure 11 show counterfactual paths when neither short-term nor long-term shocks materialized. The greater the difference between the dashed-dotted green lines and the dashed red lines, the more short-term shocks contributed to the dynamics of the variables of interest. Intriguingly, the results suggest that the role of short-term uncertainty shocks during the Great Recession was negligible except for the dynamics of the one-month VIX.

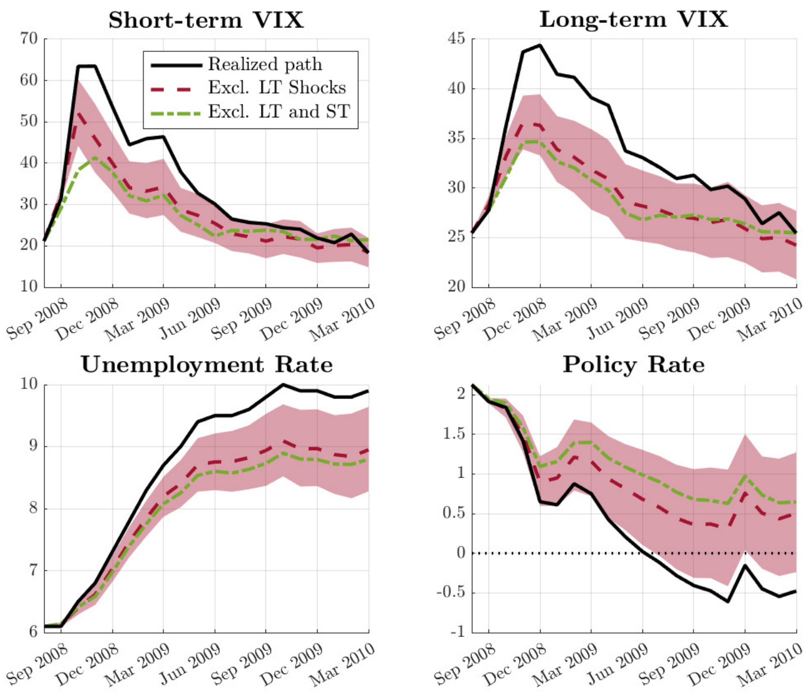

Figure 11: Counterfactual on the Great Recession. Black lines indicate the realized paths of the one-month VIX, the two-year VIX, the unemployment rate, and the policy rate between 2008:08 and 2010:03. Dashed red lines (dashed-dotted green lines) illustrate posterior means of the counterfactual paths that would have occurred if no long-term shocks (no uncertainty shocks) had materialized from 2008:09 and onwards. Shaded areas indicate 68% highest posterior density intervals.

5. Uncertainty news shocks: any evidence?

To what extent do uncertainty news shocks drive business cycle fluctuations? To answer this question, let us reconsider Equation (2), which (with abuse of notation) implies

$$\left(VIX_t^{2Y}/100\right)^2 \approx \frac{1}{24}\Bigg(\underbrace{\int_0^1 \sigma_{t+s}^2 ds}_{=\left(VIX_t^{1M}/100\right)^2} + \underbrace{\int_1^2 \sigma_{t+s}^2 ds}_{=\left(VIX_{t+1}^{1M}/100\right)^2} + \underbrace{\int_2^3 \sigma_{t+s}^2 ds}_{=\left(VIX_{t+2}^{1M}/100\right)^2} + \int_3^{24} \sigma_{t+s}^2 ds \Bigg). \quad (9)$$

Intuitively, the two-year VIX depends on the one-month VIX, reflecting current expectations about short-term financial volatility. Further, it depends on expectations about future realizations of the VIX, e.g., future one-month VIXs. Hence, agents' *anticipation* of future uncertainty is another possible explanation for the imperfect empirical relationship between the long and short ends of the VIX term structure. A potential example of an uncertainty news shock could be April 2020, when the peak of the first wave of the pandemic was over, but experts anticipated a second wave in the next Fall.[33] Another potential example is the immediate aftermath of the Brexit referendum of June 2016 in the UK, when short-run uncertainty about the referendum outcome was resolved but long-run uncertainty emerged, part of which referred to the post-Brexit UK.[34] From Equation (9), it is clear that news about future uncertainty that is orthogonal to current-period uncertainty will increase the two-year VIX while the one-month VIX will remain constant.[35]

To study the effects of uncertainty shocks in the previously outlined DSGE model, we consider a simple modification of the stochastic process for long-term uncertainty in Equation (7) so that to consider second-moment news shocks. Specifically, we have

$$\sigma^a_{LT,t} = \rho_{LT,\sigma^a}\sigma^a_{LT,t-1} + \sigma^{\sigma^a}_{LT}\varepsilon^{\sigma^a}_{LT,t-h}, \tag{10}$$

where we lag the long-term uncertainty shock, consistent with DSGE models featuring first-moment news shocks (e.g., Schmitt-Grohe and Uribe, 2012; Beaudry and Portier, 2014; Christiano et al., 2014; Del Negro et al., 2023). In particular, we lag the shock by h

[33] For example, quoting the words of Yale University Professor Nicholas Christakis (MD, PhD, MPH) in an interview on April 1 2020 by the Journal of the American Medical Association (JAMA) Network available at https://edhub.ama-assn.org/jn-learning/audio-player/18393767 (around 25')): *"[...] in the Fall, I think, there is at least 75% chance we'll have a second wave like we had in 1919, like we had in 1957, like we had in 2009 with the H1 second and third waves and then eventually dumps down and dies out."*

[34] In the words of Faccini and Palombo (2021): *"An uncertainty shock is defined as a second-moment shock to aggregate and idiosyncratic fundamentals over the short run. But in the case of Brexit, uncertainty is primarily about fundamentals in the long run. Moreover, Brexit will affect fundamentals directly only after it takes place; the outcome of the referendum itself does not affect fundamentals directly but only indirectly, through expectations. We therefore model the referendum as a news shock [...]."*

[35] This consideration refers to the *marginal* effects of an uncertainty news shock. Instead, if in the data one observes an increase in the two-year VIX at parity of the one-month VIX, this is also consistent with a long-term uncertainty shock hitting simultaneously with either mean reversion in the one-month VIX (after past shocks) or a negative short-term shock. But, as we show later, a theoretical impulse response function analysis of uncertainty news shocks confirms our reasoning in the text by only capturing the marginal effects of shocks.

periods such that agents anticipate it h quarters in advance. Figure 12 shows the effects of the news shock on the VIXs for $h = 1, 2, 3$.[36] When the news shock hits, the eight-quarter VIX increases immediately, whereas the one-quarter VIX only increases in the future. The increase in the eight-quarter VIX is persistent initially, with a slight rise until the shock realizes and with a gradual mean reversion afterward. We now use this theoretical result to inform an empirical identification strategy for (long-term) uncertainty news shocks.[37]

We modify the previous identification strategy summarized in Table 1 to separately identify short-term uncertainty shocks and uncertainty news shocks. In particular, we impose that the short-term VIX does not react to news shocks on impact and that its response is nonnegative in the following twelve months, consistent with Figure 12.[38] As earlier, we also require that the response of the short-term VIX to short-term uncertainty shocks is nonnegative for the first twelve months and that the response of the long-term VIX to uncertainty news shocks is more persistent (in terms of half-life) than its response to short-term shocks. Since the zero restriction on the news shock is highly informative, we do not impose NSRs. See Table 2 for a summary of these restrictions.

The left panel of Figure 13 presents the impulse response functions for uncertainty news shocks. When a news shock hits, the one-month VIX does not move but increases significantly after three months and remains high until roughly one year has passed. The two-year VIX rises initially and peaks around the same time as the one-month VIX, i.e., after five to six months. Hence, according to our results, uncertainty news shocks are mostly anticipated with a horizon of 5-6 months.[39] Regarding the unemployment rate, the effects of the shock gradually build over time and are persistent, lasting for more than four years.[40] Intriguingly, we also find that uncertainty news shocks are inflationary, differently from long-run (unanticipated) uncertainty shocks. In terms of theoretical

[36]We compute the impulse responses to uncertainty news shocks using the same calibration we adopted earlier. The Appendix shows the complete set of theoretical impulse responses to uncertainty news shocks and compares them with the responses to short-term and long-term uncertainty shocks.

[37]In this paper, with "uncertainty news shocks" we mean long-term anticipated uncertainty shocks. In the previous analysis, we instead focused on long-term unanticipated uncertainty shocks.

[38]We jointly impose zero and sign restrictions using the algorithm proposed by Arias et al. (2018).

[39]Our results are likely averaging the effects of news shocks with various anticipation horizons.

[40]The uncertainty news shock implies more persistent effects than the long-term uncertainty shock identified earlier. The Appendix shows that this is consistent with the DGSE model.

transmission channels, the inflationary effect may occur because of the upward nominal pricing bias channel (Fernández-Villaverde et al., 2015; Born and Pfeifer, 2021; Andreasen et al., 2023), according to which firms precautionarily bias their pricing decision upward after an uncertainty shock, which can be more potent for anticipated uncertainty shocks regarding the future.[41] The policy rate does not decrease initially after a news shock, which is consistent with the inflation response, and it is cut only after three years from the shock. At this point, unemployment is still high, but inflation has reverted.

The right panel of Figure 13 illustrates the forecast error variance contributions of the uncertainty news shock. Uncertainty news shocks are important drivers of the long-term VIX, the unemployment rate, and inflation, contributing 20.7%, 32.3%, and 23.5% to their fluctuations at the two-year horizon, respectively.

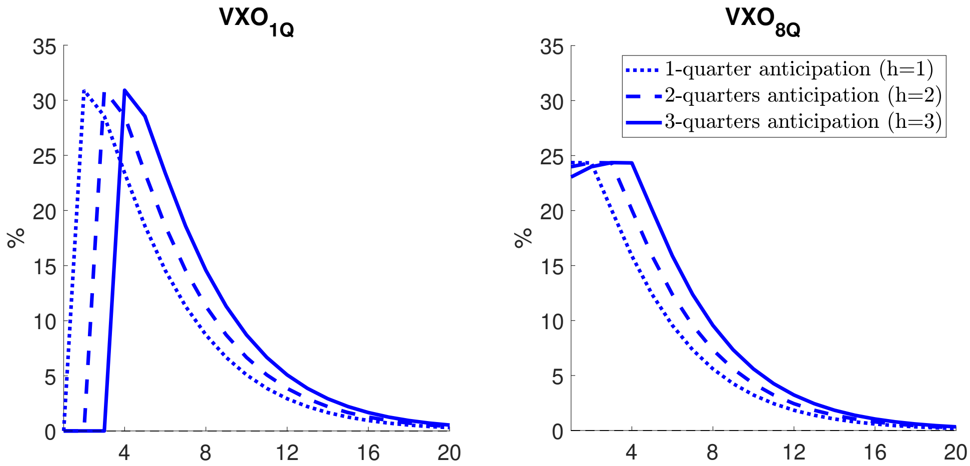

Figure 12: Theoretical IRFs to uncertainty news shocks. DSGE-implied impulse responses of the one- and eight-quarter VIX to unit standard deviation uncertainty news shocks with anticipation horizons of $h = 1, 2, 3$.

[41]The Appendix shows that the DSGE model of Basu and Bundick (2017) with Rotemberg-type pricing does not imply an increase in inflation in response to uncertainty news shocks. In general, the upward nominal pricing bias channel is more potent in a Calvo-type pricing setting (Oh, 2020), where trend inflation amplifies the channel (Castelnuovo et al., 2023).

	Conditions
IRF Restrictions	
Short-term shocks	$IRF_{ST}^{X}(h) \geq 0 \quad \text{for} \quad h=0,1,...,12 \quad \text{and} \quad X \in \{vix^{1M}, vix^{2Y}\}$
Uncertainty news shocks	$IRF_{LTN}^{X}(h) = 0 \quad \text{for} \quad h=0 \quad \text{and} \quad X \in \{vix^{1M}, vix^{2Y}\}$
Uncertainty news shocks	$IRF_{LTN}^{X}(h) \geq 0 \quad \text{for} \quad h=1,...,12 \quad \text{and} \quad X \in \{vix^{1M}, vix^{2Y}\}$
Half-life Restrictions	
2Y VIX	$HL\left(IRF_{LTN}^{X}\right) > HL\left(IRF_{ST}^{X}\right) \quad \text{for} \quad X = vix^{2Y}$

Table 2: Identifying restrictions for short-term shocks (ST) and uncertainty news shocks (LTN) in the Structural VAR. $IRF_j^X(h)$ is the response of variable X to shock j at horizon h. $HL\left(IRF_j^X\right)$ is the half-life of the response of variable X to shock j.

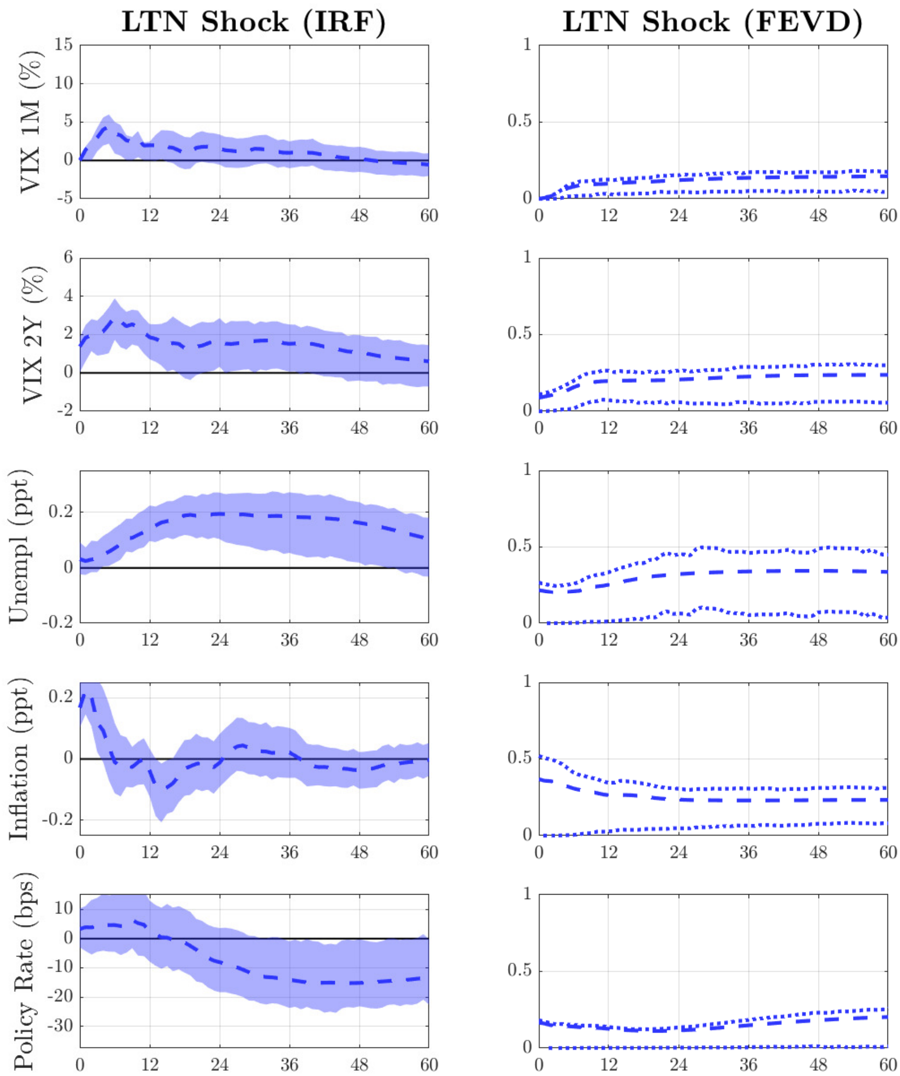

Figure 13: IRFs and FEVDs to uncertainty news shocks (denoted by LTN). Left panels: Impulse responses functions of the endogenous variables in the SVAR to LTN shocks. Right panels: contributions of uncertainty news shocks to the forecast error variance of the variables. Dashed lines are posterior means, and shaded areas are 68% highest posterior density intervals.

6. Conclusion

We extend a state-of-the-art DSGE framework to study short-term and long-term uncertainty shocks. These second-moment shocks differ in terms of persistence and represent uncertainty shocks with different resolution horizons. Leveraging the model's predictions about the term structure of VIX, we propose a nonrecursive identification method for short- and long-term shocks in a Structural VAR. We find that long-term uncertainty shocks are important drivers of business cycle fluctuations, while short-term shocks are not.

In a supplementary analysis, we incorporate uncertainty news shocks into the DSGE model and revise our theory-driven identification restrictions. Similarly to our initial results, we find that uncertainty news shocks contribute significantly to macro dynamics. Notably, uncertainty news shocks differ from the short- and long-term shocks as regards their effects on inflation. While the short- and long-term shocks are deflationary, uncertainty news shocks are inflationary. Our DSGE model cannot replicate the inflationary effects of uncertainty news shocks, and explaining this result thus serves as an interesting direction for future research.

Regarding policy implications, our study highlights the potential pitfalls of monitoring only a single-horizon uncertainty index. Doing so could lead to shortsighted decision-making, and it is thus recommendable to monitor uncertainty at multiple horizons. Similarly, for applied work, our results imply that using only a single-horizon uncertainty index in a macroeconomic VAR confounds the effects of short- and long-term uncertainty shocks and may understate the importance of uncertainty.

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Online Appendix for

Real Activity and Uncertainty Shocks: The Long and the Short of It

A. Construction of VIX at different horizons

To estimate financial volatility at alternative horizons, we obtain daily price information on all put and call options with European exercise style that are written on the S&P500 index and listed on US exchanges. Collecting this data from OptionMetrics (IvyDB), accessed through the Wharton Research Data Services (WRDS), we obtain an unbalanced panel with an average of 3734 option contracts per trading day between 1996:01 and 2020:12.

In stylized terms, an option contract is characterized by three variables at any point in time: time-to-maturity, strike price, and whether the contract constitutes a call or a put option. With the objective of estimating uncertainty at various horizons, it is key to differentiate the options in terms of time-to-maturity. However, as new options are issued in discrete intervals of time, only a limited set of maturities is available on each trading day. To illustrate this fact, Figure A.1 indicates the total number of maturities (blue line, left axis), the longest time-to-maturity (orange line, right axis), and the shortest time-to-maturity (black line, right axis) for each day in the sample. We observe two things. First, we notice that the number of maturities increases substantially over time, ranging from seven at its lowest in the pre-2006 sample to forty-one at its highest in March 2020. In the late sample, i.e., post-2006, the options with the longest (shortest) time-to-maturity at issuance changed from two to three years (thirty to ten days). Second, we notice a zigzag behavior in the longest maturities available. This occurs because the longest-term options were issued only semi-annually in the pre-2006 sample and annually in the post-2006 sample.

Suppose n_t denotes the number of maturities available in period t such that we can only construct VIX indices at these n_t horizons. Following Luo and Zhang (2012) and Barrero

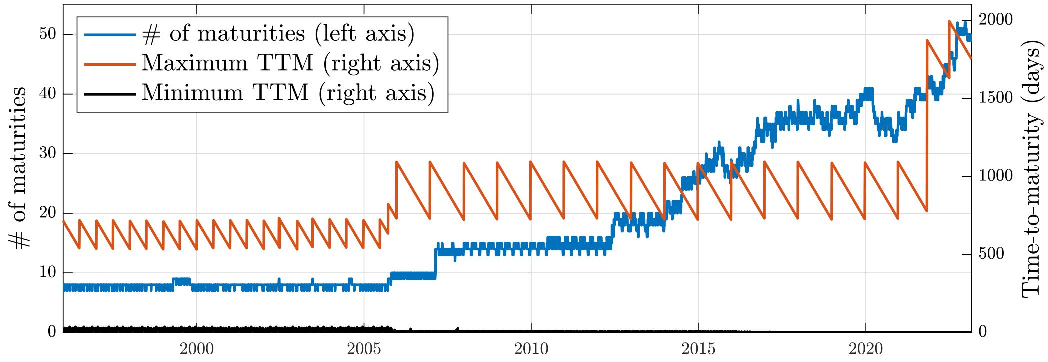

Figure A.1: Option data characteristics. Plot of the total number of time-to-maturities (TTM) available (blue line, left axis), the maximum TTM (orange line, right axis), and the minimum TTM (black line, left axis).

et al. (2017), we therefore construct the term structure of VIX by first calculating VIXs for each of the n_t horizons on all days in the sample. We then construct a balanced panel of VIX indices at the fixed set of maturities $\{10, 30, 60, 91, 122, 152, 182, 273, 365, 547, 730\}$ by using simple linear interpolation between the observable maturities (if a maturity falls outside of the observable domain, e.g., 10 or 730 in the pre-2006 sample, we extrapolate by assigning corner observations). Finally, we aggregate daily VIX indices to the monthly frequency by averaging over each trading day in the month. This agrees with Barrero et al. (2017) and the standard practice of averaging the one-month VIX in related literature.

For each day t and days-to-maturity m, the VIX is calculated with the formula

$$VIX_t^m = 100 \times \sqrt{\frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2}, \tag{A.1}$$

which is taken from the VIX white paper (CBOE, 2019). In this formula, R is the (cubic spline interpolated) risk-free yield at maturity m based on yield curve data from OptionMetrics, and $T = m/365$ is the time-to-maturity in years. K_i is the ith strike price in the cross-section in ascending order, $Q(K_i)$ is the midpoint of the bid-ask spread for each option with strike K_i, F is the forward price of the S&P500 index, and K_0 is the first strike below F. Following Barrero et al. (2017), we assume $F = e^{RT}P$, where P is the spot price of the S&P500 index, and we apply Equation (A.1) to put and call options separately and thereafter calculate the VIX as the simple mean of these two figures.[42]

[42]Note that the VIX formula is based on out-of-the-money options only. I.e., $K_i > F$ holds for all call

Figure A.2 illustrates the term structure of VIX over the full sample starting in 1996.

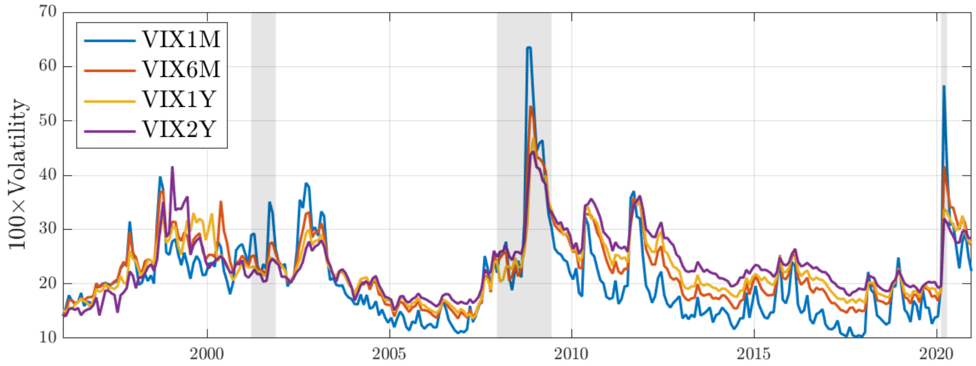

Figure A.2: The term structure of VIX. One-month, six-month, one-year, and two-year VIXs from 1996:01 to 2022:12.

B. The DSGE model

The DSGE model we adopt is based on Basu and Bundick (2017) and its modification in Basu and Bundick (2018). The model is summarized below.

B.1. Households

A representative household maximizes lifetime utility given by recursive preferences over consumption C_t and leisure $1 - N_t$. The utility of consumption and leisure are subject to preference shocks, denoted a_t. The household receives real labor income W_t for each unit of labor N_t supplied to the intermediate goods producing firms. The household owns these firms and hold equity shares S_t in these firms. Each equity shares have a real price of P_t^E and pay real dividends D_t^E per share S_t. The household also holds one-period real bonds issued by the government, giving a gross return of R_t^R. The parameter $\vartheta_V \equiv (1-\sigma)/(1-\psi^{-1})^{-1}$ controls the household's preference for the resolution of uncertainty.

The household maximizes lifetime utility by choosing C_{t+s}, N_{t+s}, B_{t+s+1}, and S_{t+s+1} for all $s = 0, 1, 2, \ldots$ by solving the problem

$$V_t = \max \left[(1-\beta) \left(a_t C_t^{\eta} (1-N_t)^{1-\eta} \right)^{(1-\sigma)/\vartheta_V} + \beta \left(\left(\mathbb{E}_t V_{t+1}^{1-\sigma} \right)^{1/\vartheta_V} \right) \right]^{\vartheta_V/(1-\sigma)},$$

options and $K_i < F$ holds for all put options.

subject to its real intertemporal budget constraint each period

$$C_t + P_t^E S_{t+1} + \frac{1}{R_t^R} B_{t+1} \leq W_t N_t + \left(D_t^E + P_t^E\right) S_t + B_t.$$

Standard derivations imply

$$\begin{aligned}
\frac{\partial V_t}{\partial C_t} &= (1-\beta)\, V_t^{\psi^{-1}} \eta a_t^{1-\psi^{-1}} \frac{(C_t^\eta (1-N_t)^{1-\eta})^{1-\psi^{-1}}}{C_t} \\
\frac{\partial V_{t+1}}{\partial C_{t+1}} &= (1-\beta)\, V_{t+1}^{\psi^{-1}} \eta a_{t+1}^{1-\psi^{-1}} \frac{(C_{t+1}^\eta (1-N_{t+1})^{1-\eta})^{1-\psi^{-1}}}{C_{t+1}} \\
\frac{\partial V_t}{\partial C_{t+1}} &= \beta V_t^{\psi^{-1}} \left(\mathbb{E}_t V_{t+1}^{1-\sigma}\right)^{1/\vartheta_V - 1} \mathbb{E}_t \left\{ V_{t+1}^{-\sigma} \left(\frac{\partial V_{t+1}}{\partial C_{t+1}} \right) \right\}
\end{aligned}$$

where λ_t denotes the Lagrange multiplier on the household budget constraint. Thus, the household's stochastic discount factor M_{t+1} between periods t and $t+1$ is

$$\begin{aligned}
M_{t+1} &= \frac{\partial V_t / \partial C_{t+1}}{\partial V_t / \partial C_t} \\
&= \beta \left(\frac{a_{t+1}}{a_t}\right)^{1-\psi^{-1}} \frac{C_t}{C_{t+1}} \left(\frac{C_{t+1}^\eta (1-N_{t+1})^{1-\eta}}{C_t^\eta (1-N_t)^{1-\eta}} \right)^{1-\psi^{-1}} \left(\frac{V_{t+1}^{1-\sigma}}{\mathbb{E}_t [V_{t+1}^{1-\sigma}]} \right)^{1-\frac{1}{\vartheta_V}}
\end{aligned}$$

The first-order conditions for the household are then easily shown to be

$$\begin{aligned}
\frac{(1-\eta)}{\eta} \frac{C_t}{1-N_t} &= W_t, \\
P_t^E &= \mathbb{E}_t \left[M_{t+1} \left(D_{t+1}^E + P_{t+1}^E \right) \right], \\
1 &= R_t^R \mathbb{E}_t \left[M_{t+1} \right],
\end{aligned}$$

which represent the household intratemporal optimality condition with respect to consumption and leisure, the Euler equations for equity shares, and one-period risk-less firm bonds, respectively.

B.2. Intermediate Goods Producing Firms

The ith intermediate goods producing firm rents labor $N_t(i)$ from the household to produce the intermediate good $Y_t(i)$, where $i \in [0,1]$. Each intermediate good is produced in a monopolistically competitive market, where the producer faces quadratic costs à la Rotemberg (1982) (determined by ϕ_P) of changing the nominal price $P_t(i)$ each period. The intermediate firm owns its capital stock $K_t(i)$ and faces convex adjustment costs (controlled by ϕ_K) when changing the quantity of installed capital. The firm also chooses its investment $I_t(i)$ and the rate of utilization $U_t(i)$ of its capital stock. Each firm issues equity shares $S_t(i)$ and one-period risk-less bonds $B_t(i)$. Firm i chooses $N_t(i)$, $I_t(i)$, $U_t(i)$, and $P_t(i)$ to maximize firm real cash flows $D_t(i)$ given aggregate demand Y_t, the elasticity of substitution among intermediate goods $\theta_{\mu,t}$, and the price P_t of the finished good. Note that we deviate from Basu and Bundick (2017) by allowing the elasticity of substitution among intermediate goods to be time-varying to capture the presence of cost-push (or markup) shocks. All intermediate firms have the same constant-returns-to-scale Cobb–Douglas production function, subject to a fixed cost of production Φ and the level of productivity Z_t.

Each intermediate firm maximizes the discounted cash flow using the household's real stochastic discount factor $M_{t,t+s}$, i.e.

$$\max\ \mathbb{E}_t \sum_{s=0}^{\infty} M_{t,t+s} D_{t+s}(i),$$

subject to the production function

$$\left[\frac{P_t(i)}{P_t}\right]^{-\theta_{\mu,t}} Y_t = \left[K_{t-1}(i)U_t(i)\right]^{\alpha} \left[Z_t N_t(i)\right]^{1-\alpha} - \Phi,$$

and the capital accumulation equation

$$K_t(i) = \left(1 - \delta(U_t(i)) - \frac{\phi_K}{2}\left(\frac{I_t(i)}{K_{t-1}(i)} - \delta_0\right)^2\right) K_{t-1}(i) + I_t(i).$$

The expression for dividends is given by

$$D_t(i) = \left[\frac{P_t(i)}{P_t}\right]^{1-\theta_{\mu,t}} Y_t - W_t N_t(i) - I_t(i) - \frac{\phi_P}{2}\left(\frac{P_t(i)}{\Pi_{ss} P_{t-1}(i)} - 1\right)^2 Y_t,$$

where Π_{ss} denotes gross inflation in the steady state. Depreciation depend on utilization in the following way

$$\delta(U_t(i)) = \delta_0 + \delta_1(U_t(i) - U) + \frac{\delta_2}{2}(U_t(i) - U)^2,$$

where U is the utilization rate in the steady state.

Each intermediate firm finances a percentage ν of its capital stock each period with one-period risk-less bonds. Thus, the quantity of issued bonds equals $B_t(i) = \nu K_{t-1}(i)$. The total real cash flow of the firm is divided between payments to bond holders and equity holders as follows

$$D_t^E(i) = D_t(i) - \nu(K_{t-1}(i) - \frac{1}{R_t^R}K_t(i)).$$

The optimization problem for the firm reads

$$\begin{aligned}
&Max_{N_t(i),U_t(i),K_t(i),P_t(i),I_t(i)\ \forall t>0} \\
&= \mathbb{E}_t \sum_{s=0}^{\infty} M_{t+s} \left[\left[\tfrac{P_{t+s}(i)}{P_{t+s}}\right]^{1-\theta_{\mu,t+s}} Y_{t+s} - W_{t+s}N_{t+s}(i) - I_{t+s}(i) - \tfrac{\phi_P}{2}\left(\tfrac{P_{t+s}(i)}{\Pi_{ss}P_{t-1+s}(i)} - 1\right)^2 Y_{t+s}\right] \\
&\quad + \mathbb{E}_t \sum_{s=0}^{\infty} M_{t+s}\Xi_{t+s}\left(\left[K_{t-1+s}(i)U_{t+s}(i)\right]^{\alpha}\left[Z_{t+s}N_{t+s}(i)\right]^{1-\alpha} - \Phi - \left[\tfrac{P_{t+s}(i)}{P_{t+s}}\right]^{-\theta_{\mu,t+s}} Y_{t+s}\right) \\
&\quad + \mathbb{E}_t \sum_{s=0}^{\infty} M_{t+s}q_{t+s}\left[\left(1 - \delta(U_{t+s}(i)) - \tfrac{\phi_K}{2}\left(\tfrac{I_{t+s}(i)}{K_{t-1+s}(i)} - \delta\right)^2\right)K_{t-1+s}(i) + I_{t+s}(i) - K_{t+s}(i)\right]
\end{aligned}$$

where the Lagrange multipliers Ξ_t and q_t denote, respectively, the marginal cost of producing one additional unit of intermediate good i and the price of a marginal unit of installed capital.

We get the following first order conditions

1) For $N_t(i)$

$$\frac{\partial}{\partial N_t(i)} = -W_t + \Xi_t\left(1-\alpha\right)\left[K_{t-1}(i)U_t(i)\right]^{\alpha}\left[Z_tN_t(i)\right]^{-\alpha}Z_t = 0$$

$\Updownarrow$

$$W_t = \Xi_t\left(1-\alpha\right)\left[K_{t-1}(i)U_t(i)\right]^{\alpha}\frac{\left[Z_tN_t(i)\right]^{1-\alpha}}{N_t(i)}$$

$\Updownarrow$

$$W_tN_t(i) = \Xi_t\left(1-\alpha\right)\left[K_{t-1}(i)U_t(i)\right]^{\alpha}\left[Z_tN_t(i)\right]^{1-\alpha}$$

2) For $U_t(i)$:

$$\frac{\partial}{\partial U_t(i)} = \Xi_t \alpha \left[K_{t-1}(i)U_t(i)\right]^{\alpha-1} K_{t-1}(i)[Z_t N_t(i)]^{1-\alpha} - q_t \delta'(U_t(i))K_{t-1}(i) = 0$$

$\Updownarrow$

$$q_t \delta'(U_t(i))K_{t-1}(i)U_t(i) = \Xi_t \alpha \left[K_{t-1}(i)U_t(i)\right]^{\alpha} \left[Z_t N_t(i)\right]^{1-\alpha}$$

3) For $P_t(i)$:

$$\begin{aligned}\frac{\partial}{\partial P_t(i)} &= (1-\theta_{\mu,t})\left[\frac{P_t(i)}{P_t}\right]^{-\theta_{\mu,t}} \frac{Y_t}{P_t} - \phi_P\left(\frac{P_t(i)}{\Pi_{ss}P_{t-1}(i)} - 1\right)\frac{1}{\Pi_{ss}P_{t-1}(i)}Y_t + \Xi_t\theta_{\mu,t}\left[\frac{P_t(i)}{P_t}\right]^{-\theta_{\mu,t}-1}\frac{1}{P_t}Y_t \\ &\quad -\phi_P \mathbb{E}_t\left\{M_{t+1}\left(\frac{P_{t+1}(i)}{\Pi_{ss}P_t(i)} - 1\right)\frac{-\Pi_{ss}P_{t+1}(i)}{\left(\Pi_{ss}P_t(i)\right)^2}Y_{t+1}\right\} \\ &= 0\end{aligned}$$

$\Updownarrow$

$$\begin{aligned}\phi_P\left(\frac{P_t(i)}{\Pi_{ss}P_{t-1}(i)} - 1\right)\frac{1}{\Pi_{ss}P_{t-1}(i)}Y_t &= (1-\theta_{\mu,t})\left[\frac{P_t(i)}{P_t}\right]^{-\theta_{\mu,t}}\frac{Y_t}{P_t} + \Xi_t\theta_{\mu,t}\left[\frac{P_t(i)}{P_t}\right]^{-\theta_{\mu,t}-1}\frac{1}{P_t}Y_t \\ &\quad +\phi_P\mathbb{E}_t\left[M_{t+1}\left(\frac{P_{t+1}(i)}{\Pi_{ss}P_t(i)} - 1\right)\frac{P_{t+1}(i)}{\Pi_{ss}\left(P_t(i)\right)^2}Y_{t+1}\right]\end{aligned}$$

$\Updownarrow$

$$\begin{aligned}\phi_P\left(\frac{P_t(i)}{\Pi_{ss}P_{t-1}(i)} - 1\right)\frac{P_t}{\Pi_{ss}P_{t-1}(i)} &= (1-\theta_{\mu,t})\left[\frac{P_t(i)}{P_t}\right]^{-\theta_{\mu,t}} + \theta_{\mu,t}\Xi_t\left[\frac{P_t(i)}{P_t}\right]^{-\theta_{\mu,t}-1} \\ &\quad +\phi_P\mathbb{E}_t\left[M_{t+1}\frac{Y_{t+1}}{Y_t}\left(\frac{P_{t+1}(i)}{\Pi_{ss}P_t(i)} - 1\right)\frac{P_{t+1}(i)}{\Pi_{ss}P_t(i)}\frac{P_t}{P_t(i)}\right]\end{aligned}$$

4) For $K_t(i)$:

Before we derive this expression, it is convenient to define R_t^K as the marginal product per unit of capital services $K_{t-1}(i)U_t(i)$, which is paid to the owners of the capital stock, i.e.:

$$R_t^K \equiv \Xi_t \frac{\partial F(K_{t-1}(i)U_t(i), Z_t N_t(i))}{\partial\left(K_{t-1}(i)U_t(i)\right)} = \Xi_t\alpha\left[K_{t-1}(i)U_t(i)\right]^{\alpha-1}\left[Z_t N_t(i)\right]^{1-\alpha}$$

$\Updownarrow$

$$R_t^K K_{t-1}(i)U_t(i) = \Xi_t \alpha \left[K_{t-1}(i)U_t(i)\right]^{\alpha} \left[Z_t N_t(i)\right]^{1-\alpha}$$

This will allow us to simplify the expression below. Now let us consider the first-order condition for capital:

$$\begin{aligned}
\tfrac{\partial}{\partial K_t(i)} &= -q_t + \mathbb{E}_t \left[M_{t+1}\Xi_{t+1}\alpha \left[K_t(i)U_{t+1}(i)\right]^{\alpha-1} U_{t+1}(i)[Z_{t+1}N_{t+1}(i)]^{1-\alpha}\right] \\
&\quad + \mathbb{E}_t \left[M_{t+1}q_{t+1}\left[\left(1-\delta(U_{t+1}(i)) - \tfrac{\phi_K}{2}\left(\tfrac{I_{t+1}(i)}{K_t(i)} - \delta_0\right)^2\right) - \phi_K \left(\tfrac{I_{t+1}(i)}{K_t(i)} - \delta_0\right)\tfrac{-I_{t+1}(i)}{[K_t(i)]^2}K_t(i)\right]\right] \\
&\quad = 0
\end{aligned}$$

$\Updownarrow$

$$\begin{aligned}
q_t = \mathbb{E}_t &\left[M_{t+1}\underbrace{\Xi_{t+1}\alpha \left[K_t(i)U_{t+1}(i)\right]^{\alpha-1}\left[Z_{t+1}N_{t+1}(i)\right]^{1-\alpha}}_{R_{t+1}^K}U_{t+1}(i)\right] \\
&+ \mathbb{E}_t \left[M_{t+1}q_{t+1}\left[\left(1-\delta(U_{t+1}(i)) - \tfrac{\phi_K}{2}\left(\tfrac{I_{t+1}(i)}{K_t(i)} - \delta_0\right)^2\right) - \phi_K \left(\tfrac{I_{t+1}(i)}{K_t(i)} - \delta\right)\tfrac{-I_{t+1}(i)}{[K_t(i)]^2}K_t(i)\right]\right]
\end{aligned}$$

$\Updownarrow$

$$q_t = \mathbb{E}_t \left\{ M_{t+1} \left[R_t^K U_{t+1}(i) + q_{t+1} \left[\begin{array}{c} \left(1-\delta(U_{t+1}(i)) - \tfrac{\phi_K}{2}\left(\tfrac{I_{t+1}(i)}{K_t(i)} - \delta_0\right)^2\right) \\ +\phi_K \left(\tfrac{I_{t+1}(i)}{K_t(i)} - \delta\right)\tfrac{I_{t+1}(i)}{K_t(i)} \end{array} \right] \right] \right\}$$

5) For $I_t(i)$

$$\frac{\partial}{\partial I_t(i)} = -1 + q_t(1 - \phi_K \left(\frac{I_t(i)}{K_{t-1}(i)} - \delta_0\right)\frac{1}{K_{t-1}(i)}K_{t-1}(i)) = 0$$

$\Downarrow$

$$1 = q_t\left(1 - \phi_K \left(\frac{I_t(i)}{K_{t-1}(i)} - \delta_0\right)\right)$$

B.3. The Final Good Producing Firm

A representative final good producer combines the intermediate goods to construct the final output good Y_t. The profit maximizing problem for the final good producing firm results in the following first-order condition, which is the demand schedule for intermediate firms (which has been already used above):

$$Y_t(i) = \left[\frac{P_t(i)}{P_t}\right]^{-\theta_{\mu,t}} Y_t.$$

The market for the final good is perfectly competitive, and thus, the final good producing firm earns zero profits in equilibrium.

B.4. Equilibrium

In the symmetric equilibrium, all intermediate goods firms choose the same price $P_t(i) = P_t$, employ the same amount of labor $N_t(i) = N_t$, and choose the same level of capital and utilization rate $K_t(i) = K_t$ and $U_t(i) = U_t$. Thus, all firms have the same cash flows and are financed with the mix of bonds and equity. The markup of price over marginal cost is $\mu_t = 1/\Xi_t$, and gross inflation is $\Pi_t = P_t/P_{t-1}$.

Note that the households budget constraint implies to (as stocks are $S_t = S_{t+1} = 1$)

$$C_t + P_t^E S_{t+1} + \frac{1}{R_t^R} B_{t+1} = W_t N_t + (D_t^E + P_t^E) S_t + B_t$$

$\Downarrow$

$$C_t + \frac{1}{R_t^R} B_{t+1} = W_t N_t + D_t^E + B_t$$

$\Updownarrow$

$$C_t + \frac{1}{R_t^R} \nu K_t = W_t N_t + D_t^E + \nu K_{t-1}.$$

B.5. Monetary Policy

The central bank adjusts the nominal gross one-period interest rate R_t in accordance with the following rule:

$$\log(R_t/R) = \rho_r \log(R_{t-1}/R) + (1-\rho_r)\left(\rho_\pi \log\left(\Pi_t/\Pi\right) + \rho_y \log(Y_t/Y_{t-1})\right).$$

Changes in the nominal interest rate affect expected inflation and the real interest rate through the Fisher relation. Thus, the following Euler equation for a zero net supply nominal bond is included in the equilibrium conditions:

$$1 = R_t \mathbb{E}_t \left[M_{t+1} \frac{1}{\Pi_{t+1}} \right].$$

B.6. Shock processes

We assume the following processes for the exogenous shocks:

$$\begin{aligned}
a_t &= (1-\rho_a)a + \rho_a a_{t-1} + e^{\sigma^a_{t-1}} \epsilon_{a,t} \\
\sigma^a_t &= (1-\rho_{\sigma^a})\sigma^a + \rho_{\sigma^a}\sigma_{a,t-1} + \sigma^a_{ST,t} + \sigma^a_{LT,t} \\
\sigma^a_{ST,t} &= \sigma^{\sigma^a}_{ST} \epsilon_{ST,t} \\
\sigma^a_{LT,t} &= \rho_{LT,\sigma^a} \sigma^a_{LT,t-1} + \sigma^{\sigma^a}_{LT} \epsilon_{LT,t} \\
Z_t &= (1-\rho_Z)Z + \rho_Z Z_{t-1} + \sigma_Z \epsilon_{Z,t+1} \\
\ln(\theta_{\mu,t+1}/\theta_\mu) &= \rho_{\theta_\mu} \log(\theta_{\mu,t}/\theta_\mu) + \sigma_{\theta_\mu} \epsilon_{\theta,t+1},
\end{aligned}$$

where $\epsilon_{a,t+1}$, $\epsilon_{\sigma,t+1}$, $\epsilon_{Z,t+1}$, and $\epsilon_{\theta,t+1}$ are standard Gaussian, independent across time, and mutually independent.

B.7. The VIX term structure

The VIX index in the US is a market estimate of the expected volatility in the Standard and Poor's 500 index obtained from option prices. A model-implied annualized VIX index for maturity h can be computed as the expected conditional volatility of the return on firm equity (excluding dividends), i.e. as

$$\begin{aligned}
R^E_{t+h} &= \frac{P^E_{t+h}}{P^E_t} \\
VIX^h_t &= 100\sqrt{\frac{4}{h} \times \mathbb{V}_t \left[R^E_{t+h} \right]},
\end{aligned}$$

where $\mathbb{V}_t \left[R^E_{t+1} \right]$ is the quarterly conditional variance of the return on equity R^E_{t+1}. We annualize the quarterly conditional variance and then transform this variance into a standard deviation in percentage points.

B.8. Model calibration

We calibrate most of the parameters of the model as in Basu and Bundick (2018), the reason being that we use a slightly modified version of their model (to which we add an additional stochastic volatility shock and the VIX_t^{8Q}) for our analysis. Table A.1 collects all the calibrated parameters. The consumption weight in the period utility function η is calibrated in order to imply a Frisch elasticity equal to 2, as in Basu and Bundick (2018). Our baseline specification does not include the cost-push shocks, i.e., $\sigma_{\theta_\mu} = 0$.[43]

Par.	Description	Value	Source
σ_{ST,σ^a}	volatility of the short-term uncertainty shock	0.69	This paper
σ_{LT,σ^a}	volatility of the long-term uncertainty shock	0.69	This paper
ρ_{σ^a}	Unc. shocks, common persistence	0.15	This paper
ρ_{LT,σ^a}	Long-term unc. shock, persistence	0.75	This paper
σ^a	steady state volatility of the preference shock	0.005	BB(2018)
ρ^a	persistence of the preference shock	0.98	BB(2018)
ϕ_K	Investment adjustment costs	3.92	BB(2018)
ϕ_P	Price adjustment costs	240	BB(2018)
ρ_π	Taylor rule parameter, inflation	1.5	BB(2018)
ρ_y	Taylor rule parameter, outputgrowth	0.2	BB(2018)
ρ_y	Taylor rule parameter, smoothing	0	BB(2018)
σ	Riskaversion (fixedlaborsupply)	100	BB(2018)
ρ^Z	persistence of the technology shock	0.35	BB(2018)
σ^Z	volatility of the technology shock	0.019	BB(2018)
α	capital's share in production	0.333	BB(2018)
β	household discount factor	0.994	BB(2018)
δ	steady state depreciation rate	0.025	BB(2018)
δ_1	first-order utilization parameter	$1/\beta - 1 + \delta$	BB(2018)
Π	steady state inflation rate	1.005	BB(2018)
ν	firm leverage parameter	0.9	BB(2018)
δ_2	second-order utilization parameter	0.0003	BB(2018)
θ_μ	elasticity of subst. between intermediate goods	6.0	BB(2018)
ψ	intertemporal elasticity of substitution	0.5	BB(2018)
a	steady state of the preference shocks process	1	BB(2018)
Z	steady state technological level	1	BB(2018)

Table A.1: DSGE model: Calibrated parameters. BB(2018) indicates that the calibration is borrowed from Basu and Bundick (2018).

[43] We add the cost-push shock to document robustness of our main results. In this case: $\sigma_{\theta_\mu} = 0.05$ and $\rho_{\theta_\mu} = 0.5$.

C. Extra results for the DSGE model

C.1. Theoretical support for *specific events* restrictions in the data

Here, conditional on our baseline DSGE model featuring both short-term and long-term uncertainty shocks, we provide some theoretical support to our two *specific events* restrictions that we use for disentangling short-term from long-term uncertainty shocks in the data. Our two specific narrative events – i.e., 2002:7 and 2008:11 – relate to dates in correspondence of big variations in the short-term VIX in the absence of significant variations in the long-term VIX (for short-term uncertainty shocks), and vice versa (for long-term uncertainty shocks). In terms of a scatter plot of one-month VIX changes on 2-year VIX changes, our two specific events are in correspondence of points close to the horizontal and vertical axes associated with large changes in a VIX index (see Figure 3).

To provide some theoretical validation to our sign restrictions separating short-term and long-term uncertainty shocks, we simulate 10,000 observations (with a burn-in of 500) from our extended version of the Basu and Bundick (2017, 2018) model, as we do for Figure 5 in the paper. Then, to identify the events in correspondence with big variations in the long-run (short-run) VIX close to the vertical (horizontal) axis, we select the events in correspondence of the intersection between: (i) the top percentile of the long-run (short-run) VIX changes, and (ii) the lowest decile of the short-run (long-run) VIX absolute changes. Figure A.3 shows the scatter plot of one-quarter VIX changes on 2-year VIX changes together with the two types of identified dates, which are 10 for each type. We have verified that all dates associated to big variations in the long-term VIX close to the vertical axis represented with red asterisks correspond to dates where long-term uncertainty shocks hit. Similarly, all dates associated to big variations in the short-term VIX close to the horizontal axis represented with green crosses correspond to dates where short-term uncertainty shocks hit. Hence, our baseline DSGE model suggests that associating the points with large changes in either the short-run VIX or the long-run VIX which are close to the horizontal and vertical axes to short-term and long-term uncertainty shocks, respectively, is theoretically supported.

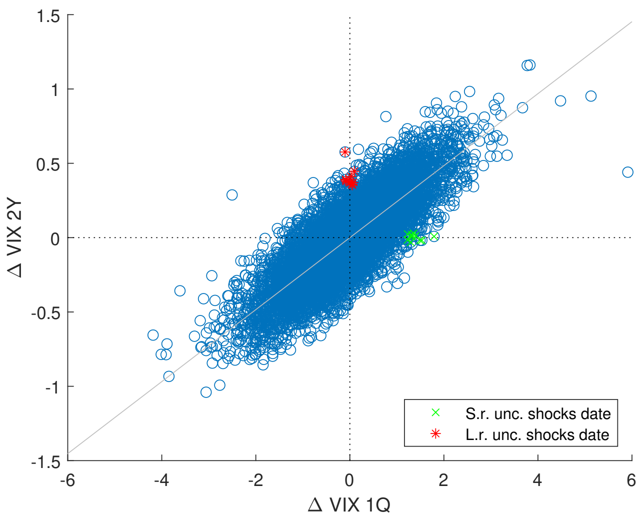

Figure A.3: Theoretical validation of narrative specific events restrictions. Scatter plot of one-period differences in the one- and eight-quarter VIX for 10,000 simulated observations (burn-in of 500 periods). Fitted line: $\Delta vix_t^{8Q} = \alpha + \beta \Delta vix_t^{1Q} + e_t$.

C.2. Impulse responses for the different types of uncertainty shocks

Figure A.4 shows the DSGE model impulse responses of the VIXs, real activity variables, inflation, and the policy rate to short-term, long-term and anticipated uncertainty shocks. The impulse responses have been obtained for the calibration summarized in Table A.1. The anticipated uncertainty (news) shock follows the same process and calibration of the long-term uncertainty shock with the modification that the shock is anticipated by one quarter (as detailed in the paper). We compute the DSGE model-related responses by solving the model with third-order perturbations (see Schmitt-Grohe and Uribe (2004) and Andreasen (2012)) and iterating forward the approximated solution of the DSGE model starting from the stochastic steady state.[44]

Focusing on the responses of real and nominal variables to the anticipated uncertainty shocks (as the other responses are described in the main paper), the findings in Figure A.4 show that these variables react more and more persistently to anticipated long-term

[44]Following Basu and Bundick (2017), we set the value of the exogenous processes to zero and iterate forward until the model converges to its stochastic steady state. Then, we hit the model with an uncertainty shock of one standard deviation and compute impulse responses as the deviation between the stochastic path followed by the endogenous variables and their stochastic steady state. Given that no future shocks are considered, this way of computing GIRFs does not line up with Koop, Pesaran, and Potter's (1996) algorithm. Basu and Bundick (2017) show that the differences between these two ways of computing GIRFs are negligible with a framework like theirs. Basu and Bundick (2017) simulation findings are in line with the general findings in Cacciatore and Ravenna (2021) and Andreasen et al. (2023) showing that third-order perturbations cannot give nonlinear responses to uncertainty shocks. Analytical expressions for GIRFs produced with nonlinear models are available in Andreasen et al. (2018).

uncertainty shocks than to (unanticipated) long-term uncertainty shocks, with a peak reaction that arrives later in time.[45] These theoretical findings validate the empirical findings in the paper, in particular as regards the timing of peak reaction which is more distant in the future.

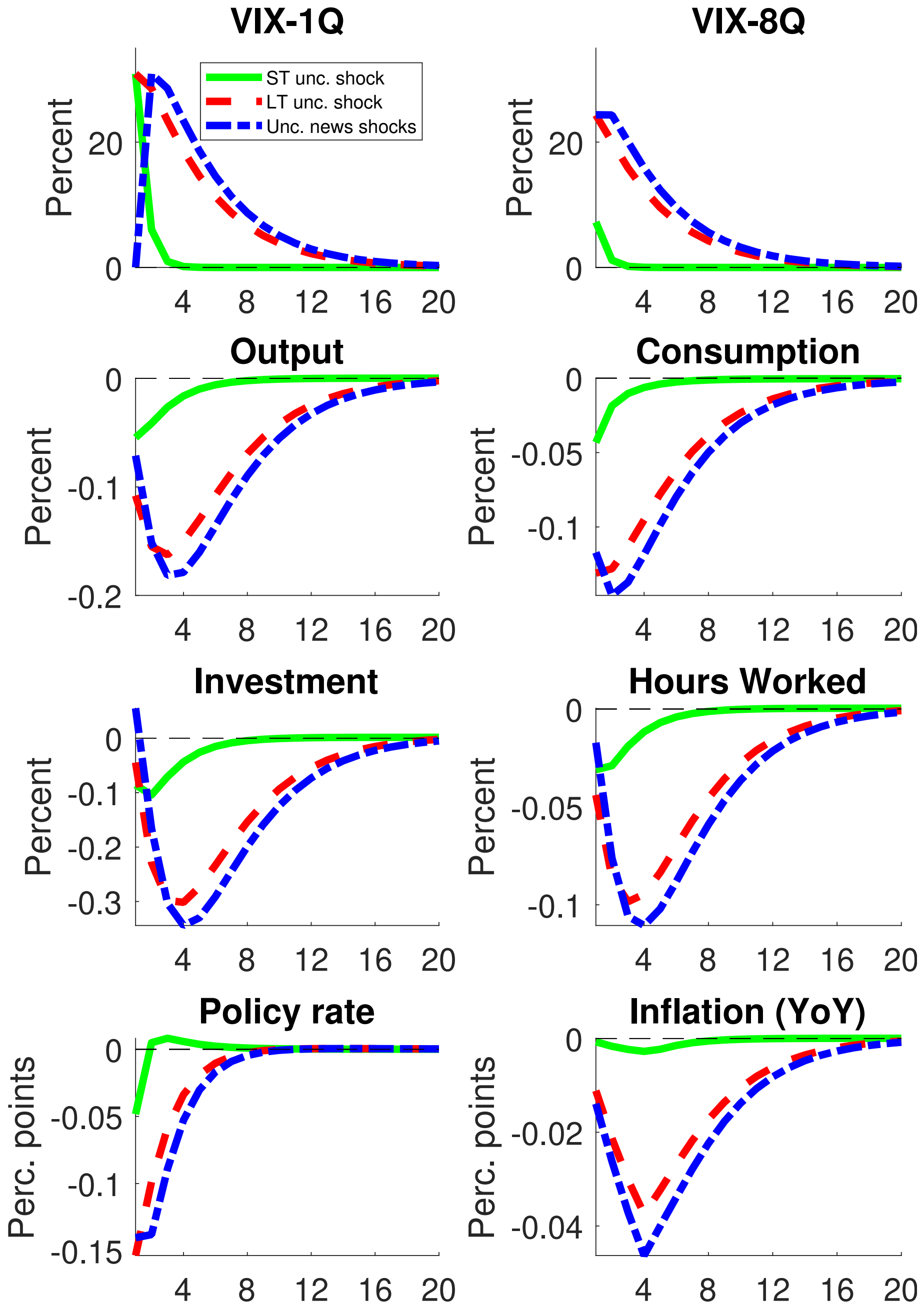

Figure A.4: Theoretical IRFs for all uncertainty shocks types. Impulse responses to unanticipated short-term uncertainty shocks (solid green line), unanticipated long-term uncertainty shocks (dashed red line), and anticipated long-term uncertainty shocks (dashed-dotted blue line).

[45]Consumption displays a hump-shaped reaction also in the absence of habits.

D. Robustness checks for the VAR model

Is the uniform prior on Q informative?

A series of recent articles criticize the conventional practice of specifying a uniform prior for the orthogonal rotation matrix **Q** when identifying structural VARs with sign restrictions (e.g., Baumeister and Hamilton, 2015, 2019; Watson, 2020). The issue is that even though the prior is uninformative about **Q**, it might be unintentionally informative about impulse responses. Giacomini and Kitagawa (2021) propose a novel estimation methodology for structural VARs with traditional SRs, which is robust to this critique, and Giacomini et al. (2023) extend this approach to also allow for NSRs. The key idea is to report Bayesian credible regions for the upper and lower bounds of the *identified set* of impulse responses, effectively allowing researchers to remain agnostic about the prior for **Q**.[46] As such, it is natural to investigate whether our results are robust to using this framework.

Figure A.5 in the Appendix illustrates impulse responses for the baseline model with solid black lines indicating 68% robust credible regions á la Giacomini et al. (2023). As expected, the robust bands are substantially wider than those obtained using the conventional approach. However, our main findings associated with unemployment and the policy rate remain unchanged, speaking to the robustness of our results for two reasons. First, it indicates that we should not worry about unintentional information in the prior on **Q** as any alternative prior would yield similar results. Second, as Giacomini et al. (2023) show that the robust bands obtain frequentist coverage under a few regularity conditions, we may also interpret our results as significant from a frequentist perspective.

Kilian (2022) argues that the robust bands of Giacomini et al. (2023) are only necessary if we cannot document that the prior on **Q** is indeed uninformative about the impulse responses of interest.[47] A way to check if the prior is uninformative or not is to compare impulse responses sampled from the prior to those sampled from the posterior. As we cannot sample from the improper Jeffrey's prior, we adopt a standard Minnesota prior and

[46] The identified set is the set of impulse responses consistent with a given draw from the posterior distribution of reduced-form parameters and all sign restrictions imposed on the system. Reporting bands around the identified set's upper and lower bounds is equivalent to reporting the widest bands among all possible priors on **Q**. Giacomini et al. (2023) denote this a "multiple-prior approach."

[47] See also Inoue and Kilian (2023).

report prior and posterior impulse responses in Figure A.6. As the prior responses of the macroeconomic variables are all around zero, we conclude that the prior is not driving our main results. Moreover, we note that our results are robust to using a Minnesota prior.

Importance of narratives

A natural question is whether the NSRs are essential to obtain our results. To address this question, Figure A.7 in the Appendix plots impulse responses with conventional and robust bands when estimating the model without imposing narratives. We obtain results that are similar to our baseline. However, it is clear from Figure A.7 that the NSRs are informative and help sharpen the robust inference of Giacomini et al. (2023).

COVID-19 data

To avoid issues with extreme observations in the initial phase of the pandemic, we cut the baseline sample in February 2020. Given the modest sample size (2000:1-2020:2), a reasonable question is whether including pandemic observations would change our results substantially. Figure A.8 in the Appendix illustrates the effects of extending the sample until December 2022 by including time dummies for each month between 2020:3 and 2020:8 (Schorfheide and Song, 2023; Cascaldi-Garcia, 2023). Dashed lines are impulse responses based on a Jeffreys prior, and dotted lines are impulse responses based on the modified Minnesota prior with dummies proposed by Cascaldi-Garcia (2023). For comparison, we also report impulse responses based on Minnesota and Jeffreys priors when cutting the sample in February 2020 (dashed-dotted and solid lines, respectively). It is evident from the figure that our results are robust to changing the end date of the sample.

Additional robustness checks

Our empirical findings are robust to other various changes in our baseline framework (exercises unreported for the sake of brevity but available upon request). In particular, our main results are materially unchanged when (1) extending the sample with four years of observations starting in 1996:1, (2) replacing the VIXs with implied volatilities based on the Black and Scholes (1973) option pricing formula, (3) replacing the unemployment rate with year-over-year industrial production growth, and (4) replacing the unemployment rate and inflation with log levels of industrial production and the consumer price index.

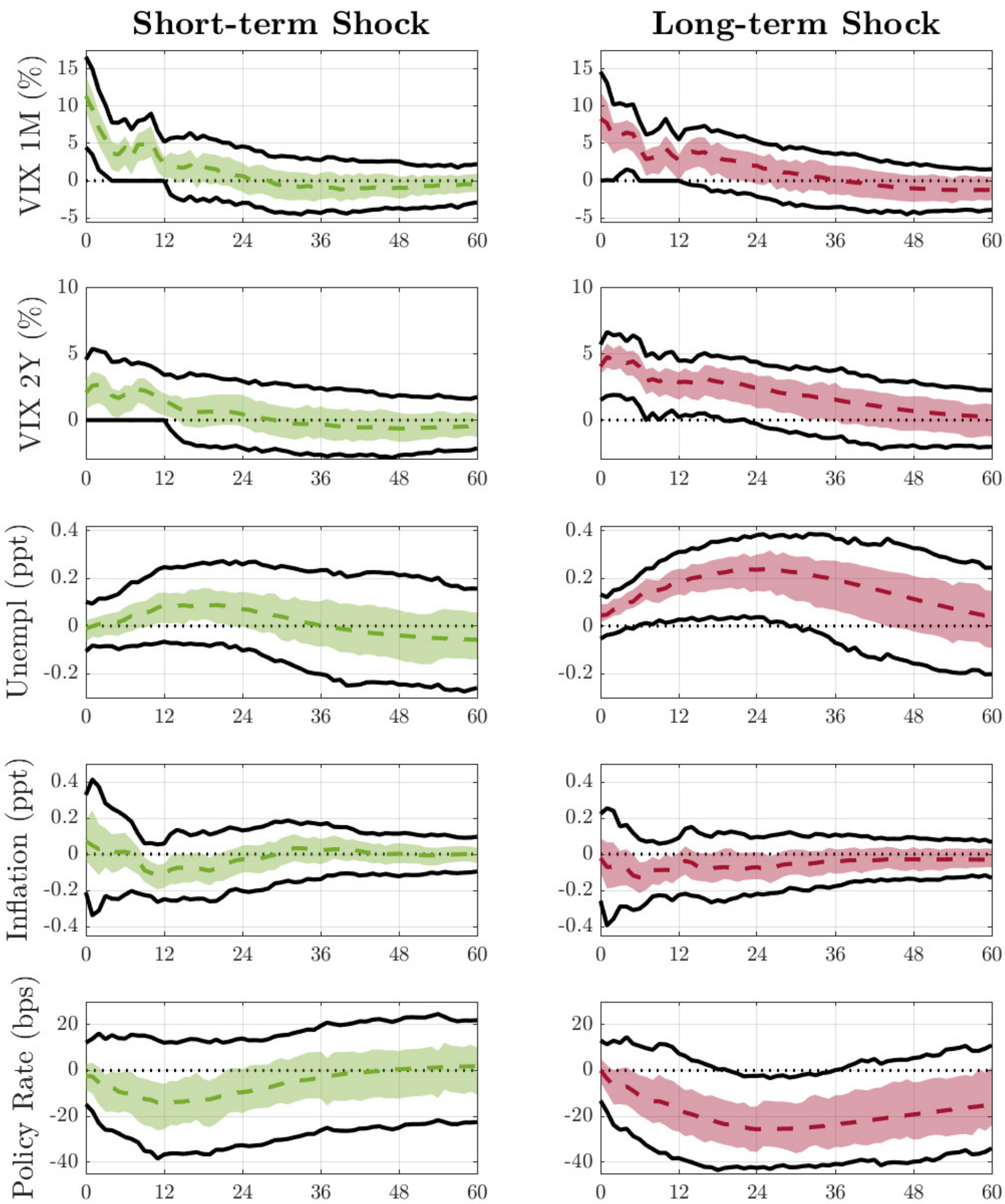

Figure A.5: IRFs with robust bands. Impulse responses of the endogenous variables in the SVAR to short-term (left) and long-term (right) uncertainty shocks. Dashed lines are posterior means, and shaded areas are 68% highest posterior density intervals based on 1.000 draws from the posterior. Solid black lines are 68% robust credible regions based on Algorithm 1 in Giacomini, Kitagawa, and Read (2023) with 1.000 draws of Q for each of the 1.000 draws of reduced-form parameters.

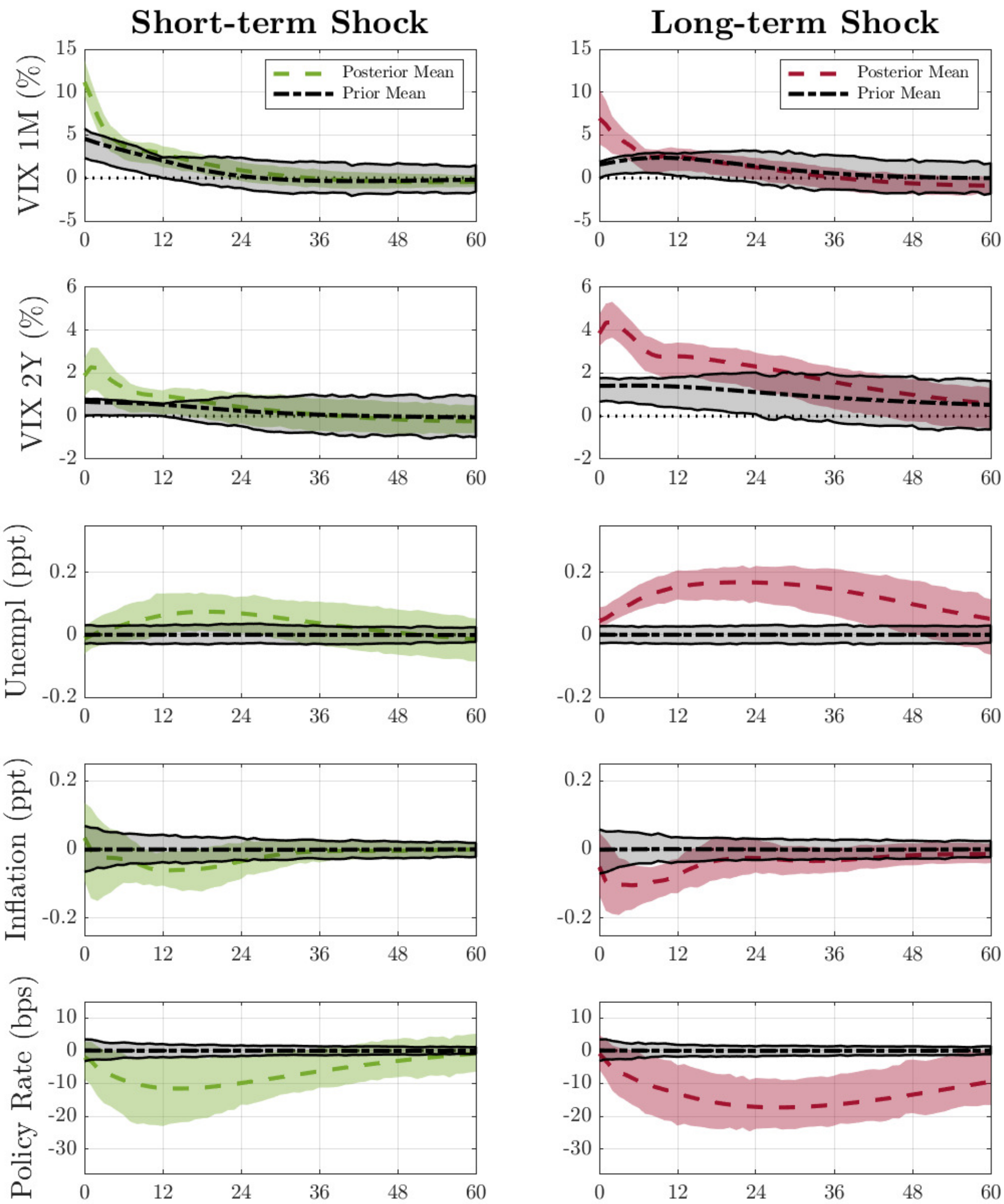

Figure A.6: IRFs for the Minnesota prior. Impulse responses of the endogenous variables in the SVAR to short-term (left) and long-term (right) uncertainty shocks using a Minnesota Prior. Colored dashed lines are posterior means, and shaded areas are 68% highest posterior density intervals based on 5.000 draws from the posterior. Black dashed-dotted lines and grey shaded areas indicate corresponding statistics based on a sample of 5.000 draws from the prior as opposed to the posterior.

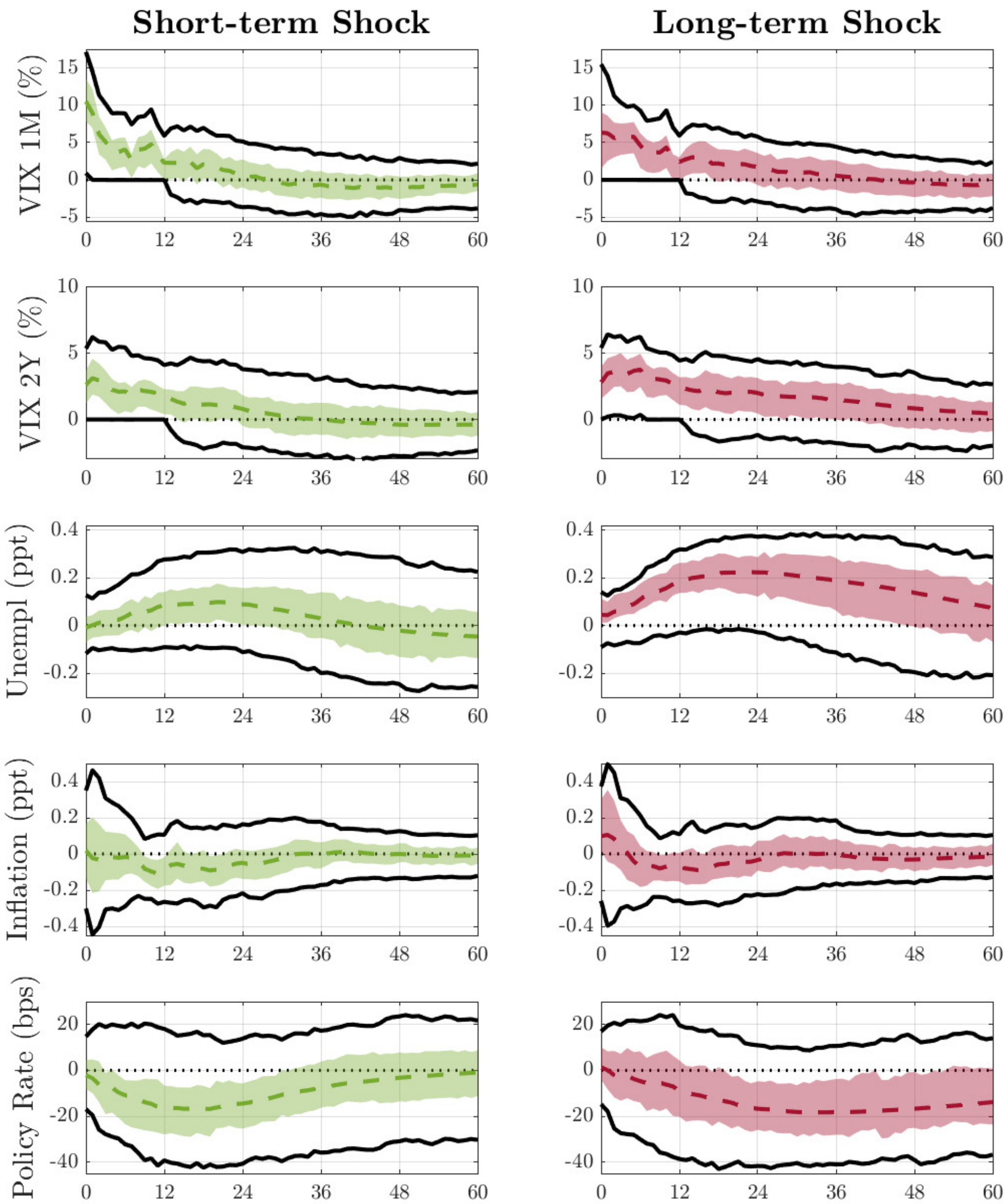

Figure A.7: IRFs with robust bands and no narrative sign restrictions. Impulse responses of the endogenous variables in the SVAR to short-term (left) and long-term (right) uncertainty shocks when the narrative sign restrictions are not imposed. Dashed lines are posterior means, and shaded areas are 68% highest posterior density intervals based on 1.000 draws from the posterior. Solid black lines are 68% robust credible regions based on Algorithm 1 in Giacomini, Kitagawa, and Read (2023) with 1.000 draws of Q for each of the 1.000 draws of reduced-form parameters.

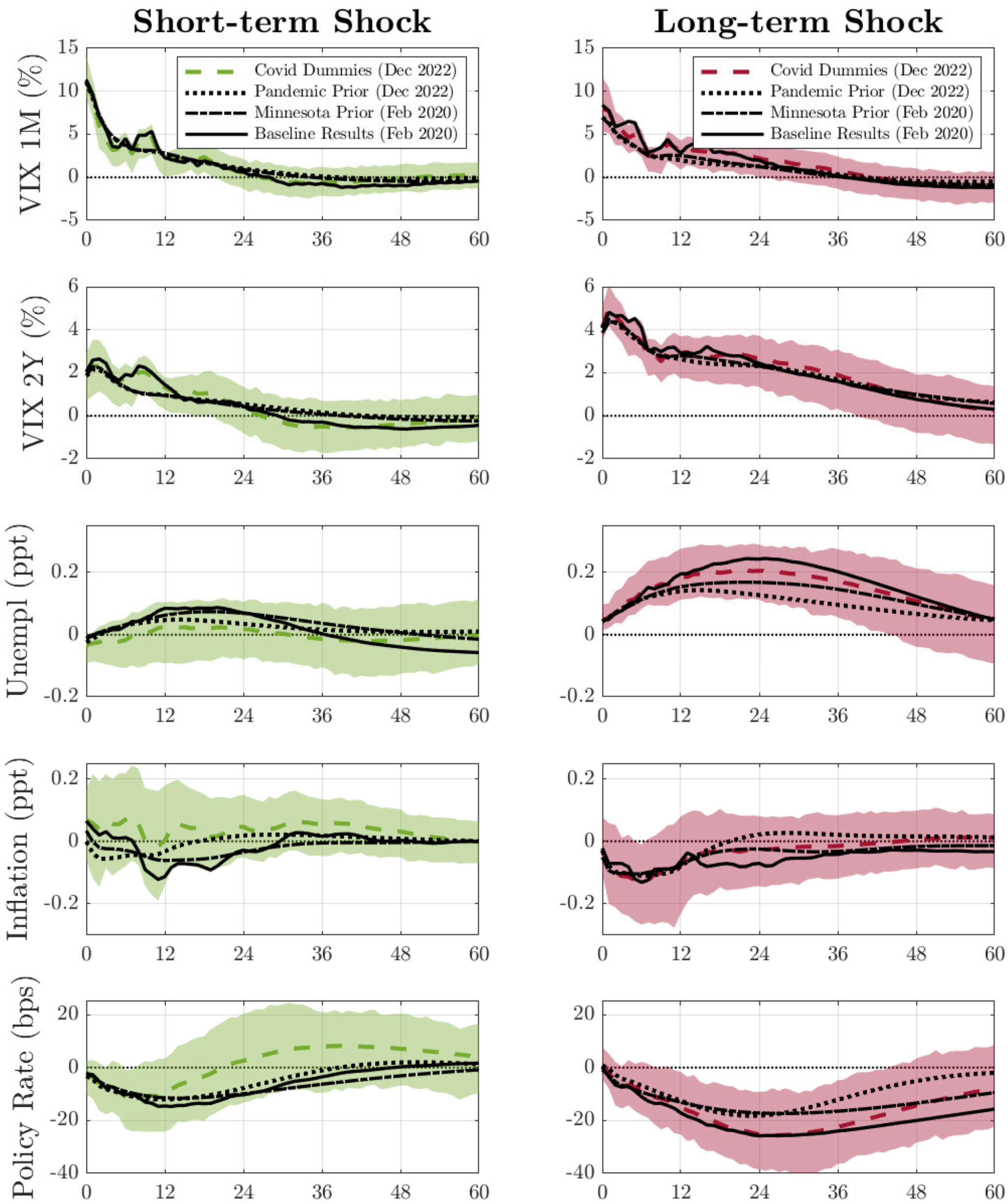

Figure A.8: IRFs for alternative ways of handling Covid Data. Impulse responses of the endogenous variables in the SVAR to short-term (left) and long-term (right) uncertainty shocks. Colored dashed lines are posterior means, and shaded areas are 68% highest posterior density intervals based on 5.000 draws from the posterior (Using a Jeffreys prior and including the 2020:3 to 2022:12 sample by dummying out 2020:3 through 2020:8). Dashed black lines indicate IRFs based on the Pandemic Prior of Cascaldi-Garcia (2023), dashed-dotted black lines indicate IRFs based on the Minnesota prior when ending the sample in 2020:2, and solid black lines indicate baseline IRFs.