Appendix of the paper "Estimating the Real Effects of Uncertainty Shocks at the Zero Lower Bound", by Giovanni Caggiano, Efrem Castelnuovo, and Giovanni Pellegrino

Computation of the Generalized Impulse Response Functions

The algorithm for the computation of the Generalized Impulse Response Functions follows the steps suggested by Koop, Pesaran, and Potter (1996), and it is designed to simulate the effects of an orthogonal structural shock as in Kilian and Vigfusson (2011). The idea is to compute the empirical counterpart of the theoretical GIRF of the vector of endogenous variables $y_t$, $h$ periods ahead, for a given initial condition $\omega_{t-1} = \{y_{t-1}, ..., y_{t-k}\}$, $k$ is the number of VAR lags, and $\delta$ is the structural shock hitting at time $t$. Following Koop, Pesaran, and Potter (1996), such GIRF can be expressed as follows:

$$GIRF_y(h, \delta, \omega_{t-1}) = E[y_{t+h} | \delta, \omega_{t-1}] - E[y_{t+h} | \omega_{t-1}]$$

where $E[\cdot]$ is the expectation operator, and $h = 0, 1, ..., H$ indicates the horizons from 0 to $H$ for which the computation of the GIRF is performed.

Given our model (1)-(2), we compute our GIRFs as follows:

1. we pick an initial condition $\omega_{t-1}$. Notice that, given that uncertainty and the policy rate are modeled in the VAR, such set includes the values of the interaction terms ($unc \times ffr$)$_{i-j}$, $j = 1, ..., k$;

2. conditional on $\omega_{t-1}$ and the structure of the model (1)-(2), we simulate the path $[y_{t+h} | \omega_{t-1}]^r$, $h = [0, 1, ..., 19]$ (which is, realizations up to 20-step ahead) by loading our VAR with a sequence of randomly extracted (with repetition) residuals $\tilde{u}_{t+h} \sim d(0, \tilde{\Omega})$, $h = 0, 1, ..., H$, where $\tilde{\Omega}$ is the estimated VCV matrix, $d(\cdot)$ is the empirical distribution of the residuals, and $r$ indicates the particular sequence of residuals extracted;

3. conditional on $\omega_{t-1}$ and the structure of the model (1)-(2), we simulate the path $[y_{t+h} | \delta, \omega_{t-1}]^r$, $h = [0, 1, ..., 19]$ by loading our VAR with a perturbation of the randomly extracted residuals $\tilde{u}_{t+h}^* \sim d(0, \tilde{\Omega})$ obtained in step 2. In particular, we Cholesky-decompose $\Omega = \hat{C}', \hat{C}$, where $\hat{C}$ is a lower-triangular matrix. Hence,
we recover the orthogonalized elements (shocks) \( \tilde{\epsilon}_t^r = \hat{C}^{-1}\tilde{u}_t^r \). We then add a quantity \( \delta > 0 \) to the \( \tilde{\epsilon}_{\text{unc},t}^r \), where \( \tilde{\epsilon}_{\text{unc},t}^r \) is the scalar stochastic element loading the uncertainty equation in the VAR. This enable us to obtain \( \tilde{\epsilon}_t^r \), which is the vector of perturbed orthogonalized elements embedding \( \tilde{\epsilon}_{\text{unc},t}^r \). We then move from perturbed shocks to perturbed residuals as follows: \( \tilde{u}_t^r = \hat{C}\tilde{\epsilon}_t^r \). These are the perturbed residuals that we use to simulate \( [y_{t+h} | \delta, \omega_{t-1}]^r \);

4. we compute the difference between paths for each simulated variable at each simulated horizon \( [y_{t+h} | \delta, \omega_{t-1}]^r - [y_{t+h} | \omega_{t-1}]^r , h = [0, 1, ..., 19] \);

5. we repeat steps 2-4 a number of times equal to \( R = 500 \). We then store the horizon-wise average realization across repetitions \( r \). In doing so, we obtain a consistent estimate of the GIRF per each given initial quarter of our sample, i.e., \( \hat{GIRF}_y(h, \delta, \omega_{t-1}) = \hat{E}[y_{t+h} | \delta, \omega_{t-1}] - \hat{E}[y_{t+h} | \omega_{t-1}] , h = [0, 1, ..., 19] \). If a given initial condition \( \omega_{t-1} \) leads to an explosive response (namely if this is explosive for most of the \( R \) sequences of residuals \( \tilde{u}_{t+h}^r \), in the sense that the response of the shocked variable diverges instead than reverting to zero), then such initial condition is discarded (i.e., they are not considered for the computation of state-dependent GIRFs in step 6);\(^1\)

6. history-dependent GIRFs are then averaged over a particular subset of initial conditions of interest to produce the point estimates for our state-dependent GIRFs. To do so, we set \( T_{ZLB} = 2008Q4 \). If \( t < T_{ZLB} \), then the history \( \omega_t \) is classified as belonging to the "Normal times" state, otherwise to the "ZLB" one;

7. confidence bands surrounding the point estimates obtained in step 6 are computed via a bootstrap procedure. In particular, we simulate \( S = 1,000 \) samples of size equivalent to the one of actual data. Then, per each dataset, we i) estimate our nonlinear VAR model; ii) implement steps 1-6.\(^2\) In implementing this procedure the initial conditions and VCV matrix used for our computations now depend on the particular dataset \( s \) used, i.e., \( \omega_{t-1}^s \) and \( \Omega_t^s \). Confidence bands are the constructed by considering the 84th and 16th percentiles of the resulting distribution of state-conditional GIRFs. As regards the implementation of step 6, due to

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\(^1\)This never happens for our responses estimated on actual data. We verified that it happens quite rarely as regards our bootstrapped responses.

\(^2\)The bootstrap algorithm we use is similar to the one used by Christiano, Eichenbaum, and Evans (1999) (see their footnote 23). The code discards the explosive artificial draws to be sure that exactly 1,000 draws are used. In our simulations, this happens a negligible fraction of times.
the randomness of the realization of the residuals, we classify as ZLB observations those corresponding to the lowest 13% realizations of the federal funds rate in each given simulated sample, 13% being the share of the ZLB realizations out of the overall number of observations in the actual sample we employ in our empirical analysis.³

**Computation of the Generalized Forecast Error Variance Decomposition**

The algorithm for the computation of the state-dependent Generalized Forecast Error Variance Decomposition (GFEVD) for our nonlinear VAR model is similar to the one proposed in Lanne and Nyberg (2016). The innovations are: i) it is designed to simulate the importance of an orthogonal structural shock, and ii) it considers a one standard deviation shock in each variable. The expression at the basis of our computation of the GFEVD is the same proposed by Lanne and Nyberg (2016, equation 9). In particular, conditional on a specific initial history \( \omega_{t-1} \) and a forecast horizon of interest \( z \), the GFEVD that refers to a variable \( i \) and a shock \( j \) whose size is \( \delta_j \) is given by:

\[
GFEVD_{ij}(z; \omega_{t-1}) = \frac{\sum_{h=1}^{z} GIRF_{yi}(h, \delta_j, \omega_{t-1})^2}{\sum_{j=1}^{n} \sum_{h=1}^{z} GIRF_{yi}(h, \delta_j, \omega_{t-1})^2} \hspace{1cm} i, j = 1, ..., n \tag{A1}
\]

where \( h \) is an indicator keeping track of the forecast errors, and \( n \) denotes the number of variables in the vector \( y \).⁴ Differently from Lanne and Nyberg (2016), in our case the object \( GIRF_{yi}(\cdot) \) in the formula refers to GIRFs à la Koop, Pesaran, and Potter (1996) computed by considering an orthogonal shock as in Kilian and Vigfusson (2011).⁵ In our application we are interested in the contribution of an identified uncertainty shock to the GFEVD of all the variables in the vector \( y \). Further, while formula (A1) defines the GFEVD for a given history, we are interested in computing a state-conditional GFEVD referring to a set of histories.

Given our model (1)-(2), we compute our state-dependent GFEVD for Normal times and ZLB by following the steps indicated below. In particular, we:

³If dealing with a shorter sample, this reference is modified accordingly.
⁴Expression (A1) gives a GFEVD that by construction lies between 0 and 1, and for which the contribution of all the shocks on a given variable sum to 1.
⁵The object \( GIRF_{yi}(\cdot) \) in Lanne and Nyberg’s (2016) expression refers to the GIRFs à la Pesaran and Shin (1998). This definition of the GIRF refers to a non-orthogonalized shock and it can be applied both to linear and to nonlinear VAR models. Details can be found in Pesaran and Shin (1998) and Lanne and Nyberg (2016).
1. consider an orthogonal shock equal to a standard deviation in each variable of the estimated I-VAR model. This is equivalent, for a Cholesky decomposition, to taking a vector of shocks equal to \((\delta_1, \delta_2, \ldots, \delta_n) = (1, 1, \ldots, 1)\) in our algorithm in the previous Section;\(^6\)

2. pick a history \(\omega_{t-1}\) from the set of all histories;

3. compute the GIRF\(_{y}(\cdot, \cdot, \omega_{t-1})\) for each \(\delta_j\) (\(j = 1, \ldots, n\)) and for each \(h \leq z\) according to points 2-5 of the algorithm in the previous Section;

4. plug the GIRFs computed in step 3 into equation (A1) to obtain \(GFED_{ij}(z, \omega_{t-1})\) for the particular forecast horizon \(z\) and history \(\omega_{t-1}\) considered;

5. repeat steps 2–4 for all the histories, distinguishing between the histories belonging to the "Normal times" state and the "ZLB" one (see the definition at point 6 of the GIRFs algorithm);

6. compute the state-dependent GFEVD for the "Normal times" state and the "ZLB" one by computing the average of the \(GFED_{ij}(z, \cdot)\) across all the histories relevant for the two regimes.

**Robustness checks**

We check the solidity of our results to a number of perturbations of the baseline I-VAR model. In particular, we focus on i) different measures of uncertainty and identification schemes; ii) omitted variables. We present our checks below.

**Alternative measures of uncertainty.** Our baseline VAR models the VIX as a measure of uncertainty. This way of modeling uncertainty is common in the literature (see, e.g., Bloom (2009), Caggiano, Castelnuovo, and Groshenny (2014), Leduc and Liu (2016), Basu and Bundick (2017)). A recent contribution by Ludvigson, Ma, and Ng (2016) closely follows the data-rich, factor-approach modelling strategy proposed by Jurado, Ludvigson, and Ng (2015) to construct a financial uncertainty index via the computation of the common component of the volatility of the forecast errors of 147 financial series. Variations in this index are found to: i) significantly affect various real

\(^6\)The size of the shock matters in a nonlinear model. The use of a one standard deviation shock in all variables allows our GFEVD algorithm to return the usual Forecast Error Variance (FEV) and Forecast Error Variance Decomposition (FEVD) quantities referred to an orthogonal shock when the algorithm is applied to a standard linear VAR model.
activity indicators; ii) be largely driven by their own "shocks". Hence, this index is also likely to carry relevant information on exogenous changes in financial uncertainty.

Figure A1 plots Ludvigson et al.’s (2016) measure of financial uncertainty and, to ease the comparison with our baseline measure, the VIX measure used in our baseline regressions. The correlation between these two measures in our sample is 0.74. We then replace the VIX with the LMN financial uncertainty index and re-run our estimates to check the robustness of our impulse responses.

Figure A2 plots the outcome of an exercise in which the uncertainty indicator we use in the paper - the VIX – is replaced with the LMN financial uncertainty index. It also plots the results obtained when either indicator is alternatively modeled as endogenous variable ordered last in the vector. In this way, we maximize the contribution of non-uncertainty shocks to the volatility of the uncertainty proxy and, therefore, challenge the role of uncertainty shocks as a driver of the business cycle. To ease comparison with the results documented in the text, the first row of Figure A2 plots also the baseline results obtained with the VIX ordered first in the vector. Figure A3 reports the differences between the impulse responses in the two regimes conditional on the employment of the LMN financial uncertainty index. To facilitate the comparison with our baseline analysis, the Figure also reports the difference between the GIRFs in the two regimes and the 68% confidence bands estimated with our baseline vector. The responses produced by the two empirical models - the baseline one and the one with the LMN financial uncertainty index - are quantitatively very similar. This is especially true for investment, for which all differences are included in the 68% confidence bands estimated for our baseline specification at all horizons.

**Omitted variables.** Another set of robustness checks regards the omission in our baseline specification of potentially relevant variables. Omitting a variable which is relevant to explain the dynamics of real activity during the ZLB phase could inflate the differences documented with our baseline model. We then consider a variety of possibly relevant omitted variables, including financial indicators, credit and house prices, and government debt. We describe the potential relevance of these checks one-by-one and explain how we modify our baseline framework to take the omitted variable issue into account. We document the outcome of each robustness check in Figure A4.

**Financial conditions.** Stock and Watson (2012) point out that financial strains lead to higher uncertainty, which in turn increases financial risk. Alessandri and Mumtaz (2014), Gilchrist, Sim, and Zakrajšek (2014), Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016), and Alfaro, Bloom, and Lin (2016) find evidence in favor of stronger
real effects of uncertainty shocks in periods of high financial stress. It is important
to control for measures of financial stress in order to distinguish the role played by
uncertainty from that played by financial constraints. Following Alessandri and Mumtaz
(2014), we consider a broad measure of financial stress, i.e., the Chicago Fed Financial
Conditions Index (FCI). The aim of this index is to offer a synthetic measure of financial
stress based on 105 series related to measures of risk, liquidity, and leverage (for a
detailed explanation on the construction of this index, see Brave and Butters (2011)).
We add the FCI as first variable to our VAR and estimate it over the period 1973Q1-
2015Q4.7

S&P500. The baseline specification is based on the implicit hypothesis that our
VAR contains enough information to isolate second moment financial shocks. A way to
control for first moment financial shocks is to add a stock market index to our vector
and order it before uncertainty. Following Bloom (2009), we run an exercise in which
we add the log of S&P500 index to our VAR and order it first.

Credit to the non-financial sector. Schularik and Taylor (2012) use long time series
data and a multi-country analysis to show that credit booms are key to understand the
propagation mechanism of shocks to the real economy. Mian and Sufi (2009, 2014) and
Mian, Rao, and Sufi (2013) highlight the role played by credit to the private sector in
generating and prolonging the effects of the Great Recession in the United States. Mian
and Sufi (2014) show that the drop in employment experienced between 2007 and 2009
is likely to be due to the earlier credit boom. We then estimate a version of our VAR
in which a measure of total credit to private non-financial sector is ordered first in the
vector.8

House prices. Since Iacoviello (2005), there has been a revamped attention toward
the relationship between housing market dynamics and the business cycle. Importantly
for our exercise, Furlanetto, Ravazzolo, and Sarferaz (2017) show that the effects of
uncertainty shocks are dampened if one controls for housing shocks. We then add the
log of real home price index computed by Robert Shiller as first variable to our vector.9

7The choice of the first quarter of this analysis is due to the availability of the FCI, which can be
downloaded from the Federal Reserve Bank of St Louis’ website. Unreported results (available upon
request) show that the baseline findings are robust also to the inclusion of a different indicator of
financial stress, i.e., the spread between the Baa corporate bonds and the 10-year Treasury yield.
8We use the series "Total credit to private non-financial sector" (adjusted for breaks), which is
available on the Federal Reserve Bank of St. Louis’ website. We deflated this series with the GDP
deflator.
9The index is available until 2014Q1 and it can be downloaded from here: http://www.econ.yale.edu/~shiller/data/ Fig2-1.xls .
Differently from house prices, oil prices are typically associated to high inflation in the 1970s and are
considered as one of the drivers of the
Government debt/deficit. It is well known that monetary policy and fiscal policy are tightly connected when it comes to determining the equilibrium value of inflation and real activity (for an extensive presentation, see Leeper and Leigh (2016)). Christiano, Eichenbaum, and Rebelo (2011) show that the effects of expansionary fiscal policy are much larger when the economy is at the zero lower bound. The U.S. Government implemented the stimulus package known as "American Recovery and Reinvestment Act of 2009" in an attempt to lead the economy out of the Great Recession. We control for the role of fiscal policy by conducting an exercise in which the public debt-to-GDP ratio is embedded in our vector.\textsuperscript{10}

Figure A4 depicts the differences between the impulse responses in the ZLB regime vs. normal times estimated with the models described above. To ease comparison with our baseline analysis, it includes also the difference between the GIRFs in the two regimes and the 68% confidence bands estimated with our baseline vector. While some quantitative differences across estimated models arise, the main message of this Figure is that our baseline results are robust to all checks described above.

Figure A5 documents the differences in the GIRFs between ZLB and Normal times obtained with our baseline VAR augmented with a measure of total credit to private non-financial sector (ordered first in the vector), the log of real home price index computed by Robert Shiller (ordered second in the vector), and the public debt-to-GDP ratio (ordered before all measures of real activity and the federal funds rate). These three measures are the same as those used in the empirical exercises documented in the previous Section of this Appendix. The responses in Figure A5 confirm that, even when controlling for these omitted variables contemporaneously, our results turn out to be robust.

Comovements

Our results are related to the literature on comovements. Basu and Bundick (2017) find an unexpected increase in uncertainty to generate comovements in output, consumption, investment, and hours. They show that flexible prices RBC models are unable to generate comovements because of the lack of countercyclicality in firms’ markups.\textsuperscript{10} The debt-to-GDP ratio is taken from the Federal Reserve Bank of St. Louis' website and it is ordered third in our VAR. The analysis is conducted with a sample starting from 1966Q1 due to data availability. Virtually identical results are obtained when we use the deficit-to-GDP ratio as a proxy of the fiscal stance (results available upon request).
Differently, in a new-Keynesian model an increase in uncertainty is followed by a fall in consumption and aggregate demand that leads to a decline in the demand for labor and capital. In equilibrium, output, consumption, investment, and hours fall because of countercyclical markups due to sticky prices.\textsuperscript{11}

Our baseline framework is a parsimonious VAR that does not model hours. While hours are not needed to reject frameworks that do not predict comovements in output, consumption, and investment like RBC frameworks, they are instead needed to fully validate the prediction of the new-Keynesian models proposed in the papers cited above. We then add hours to our baseline vector, estimate the VAR framework, and compute the GIRFs of all four indicators typically used to document comovements (output, consumption, investment, hours).\textsuperscript{12}

Figure A6 documents a clear support in favor of comovements after an uncertainty shock. All four real activity indicators we model respond negatively and significantly to an uncertainty shock. This prediction offers support to the contributions cited above. Moreover, and in line with the predictions put forth by the models by Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015) and Basu and Bundick (2017), the negative response of all indicators is economically (Figure A6, top panel) and statistically (Figure A6, bottom panel) stronger in presence of the ZLB. Hence, this exercise confirms that new-Keynesian models featuring countercyclical markups are able to replicate the empirical evidence on the real effects of uncertainty shocks in Normal times as well as in presence of the ZLB.

**Extra results and material**

Figure A7 shows selected GIRFs which are intended to shed light on the relevance of initial conditions. Our baseline results point to stronger effects of uncertainty shocks in presence of the ZLB. This finding supports recent contributions singling out the channels through which negative shocks affect the real economy when the ZLB prevents monetary authorities to set the policy rate at its desired level (Johannsen (2014), Nakata (2016), Basu and Bundick (2015, 2017)). However, other contributions suggest

\textsuperscript{11}Born and Pfeifer (2015) build a model in which both price and wage markups are present. They show that the key element behind the response of real activity to uncertainty shock is the wage markup (as opposed to the price markup). While not taking a stand on which of the two channels is more relevant, our empirical analysis confirm that uncertainty shocks are able to generate macroeconomic comovements as also predicted by Born and Pfeifer (2015).

\textsuperscript{12}Following the literature, we consider average weekly hours of production and nonsupervisory employees - manufacturing (seasonally adjusted). This measure enters the VAR in log-levels.
that monetary policy is likely to be less effective in recessions, regardless of a binding ZLB (Mumtaz and Surico (2015), Tenreyro and Thwaites (2016)). The period of the ZLB corresponds, in its initial observations, to one of the most dramatic recessions experienced by the U.S. economy in its recent history. It is then key to understand if our results are indeed due to the binding ZLB or instead to the corresponding deep recession experienced by the U.S. economy. We tackle this issue by isolating histories which may be informative to discriminate between effects of uncertainty shocks in recessions vs. the ZLB. In particular, we select five relevant histories. One selected history is 2008Q4, i.e., the first quarter affected by a binding ZLB.\textsuperscript{13} The remaining four histories are selected by focusing on "extreme events", i.e., we select, within each state, the two histories associated to the "highest" realizations of the VIX "shocks".\textsuperscript{14} The idea is to select histories corresponding to uncertainty shocks that are likely to have played a significant role in shaping the dynamics of the U.S. economy. We choose two observations per state (recessions/expansions) to make sure that our results are not driven by any peculiar, outlier-type observation. According to the criterion singled out above, our selected quarters are the following: 1974Q3 and 1982Q4 (recessions), 1987Q4 and 2002Q3 (expansions). Following Bloom’s (2009) classification of these high realizations of the VIX, the spikes in uncertainty are associated to the collapse of the Franklin National bank in quarter 1974Q3, the Black Monday in 1987Q4, aggressive monetary policy moves in 1982Q4, and Worldcom and Enron scandals in 2002Q3. Quite interestingly, these episodes are associated to very different monetary policy histories, as measured by the level of the federal funds rate in the quarter prior to that of the uncertainty shock. The 1974Q2, 1982Q3, and 2008Q4 histories, which are associated to recessions, feature federal funds rate levels equal to 11.2%, 11.0%, and near zero, respectively. Differently, the 1987Q3 and 2002Q2, which are associated to expansions, feature 6.8% (the former) and 1.7% (the latter). This interest rate level heterogeneity is potentially informative to discriminate between ZLB and recessions in understanding the drivers of the different responses to uncertainty shocks in the pre- vs. post 2008Q4 periods. If the different effects are mainly due to recessions, one should find some similarities between GIRFs in recessions despite of the different federal funds rate levels. In other words, we should

\textsuperscript{13}Given that our baseline VAR features three lags, an alternative choice would be 2009Q3, i.e., a quarter associated to a history characterized by initial conditions all belonging to the ZLB state. The qualitative message of this Section remains unaltered if we use 2009Q3 instead of 2008Q4 as a reference for the ZLB.

\textsuperscript{14}For an "extreme" events analysis with nonlinear VARs concerned with deep recessions and strong expansions and the different fiscal multipliers arising in correspondence to such events, see Caggiano, Castelnovo, Colombo, and Nodari (2015).
observe a "recessions" cluster and an "expansions" one. If, instead, it is the level of the federal funds rate that mostly matters, we should observe two clusters, one related to histories associated to relatively high realizations of the federal funds rate (the 1974Q2 and 1982Q3 recessions and the 1987Q3 expansion), and the other one to the 2002Q2 expansion and the 2008Q4 recession, which are histories characterized by very low values of the policy rate. A clear indication arises from Figure A7. The relevant conditioning element is the federal funds rate, and not the state of the business cycle. Indeed, the contractionary effects of uncertainty shocks are more severe when the economy is hit in quarters associated to relatively low interest rates. This finding clearly emerges for all three real activity indicators we consider. Moreover, the drop, rebound and overshoot dynamics is present only for initial conditions associated to high interest rate levels. Hence, the data seems to point towards the stance of monetary policy as the key element in transmitting the effects of uncertainty shocks to the real economy. Importantly, the difference in the depth of the recession induced by an uncertainty shock hitting the system conditional on a low- vs. high-interest rate history is statistically significant after controlling for the randomness of the future shocks needed to compute our GIRFs (68% confidence bands not shown here for the sake of clarity of the Figure, but available upon request).

Figure A8 refers to an exercise we conducted to be sure that our GIRFs related to the ZLB period are not driven by non-uncertainty shocks. This exercise is conducted to make sure that no shock which could have led to the ZLB keeps operating, possibly with bigger strength, and drives the results which we instead attribute to the presence of the ZLB. The Figure documents four scenarios for which we compute GIRFs by switching off one set of shocks at a time among the non-uncertainty ones. The sets refer to shocks to prices, real GDP, investment, and consumption. The results documented in Figure A9 point to the irrelevance of these non-uncertainty shocks in the computation of the GIRFs to an uncertainty shock.

Finally, Table A1 confirms that the stylized fact studied in the paper - i.e., the larger correlation between uncertainty and the growth rate of real GDP, investment, and consumption - holds true when uncertainty indicators alternative to those employed in the paper are considered.

**References**


Figure A1: Proxies for financial uncertainty. VIX: Measure of implied volatility of stock market returns over the next 30 days commonly used in literature. LMN: Measure of financial uncertainty proposed by Ludvigson, Mah, and Ng (2016). The measure we consider refers to forecasts for the next month. Both measures are standardized (zero mean, unitary variance) to enhance comparability.
Figure A2: Uncertainty shocks and the ZLB: Alternative measures/ordering of uncertainty. GIRFs to a one-standard deviation uncertainty shock. Proxies of uncertainty: VIX and LMN (measure proposed by Ludvigson, Ma and Ng (2016)). Row 1: VIX ordered first. Row 2: VIX ordered last. Row 3: LMN ordered first. Row 4: LMN ordered last.
Figure A3: Alternative measures/ordering of uncertainty: Differences in GIRFs between ZLB and Normal times. Differences between the average GIRF to a one-standard deviation uncertainty shock in the ZLB state and in the Normal times state for different empirical models. Uncertainty proxied by the either the VIX or the LMN financial uncertainty proxy. Grey areas: 68% confidence bands relative to the baseline case.
Figure A4: **Uncertainty shocks and the ZLB: Differences: Robustness checks.** Differences between the average GIRF to a one-standard deviation uncertainty shock in the ZLB state and in the Normal times state for different empirical models. Uncertainty proxied by the VIX. Grey areas: 68% confidence bands relative to the baseline case.
Figure A5: Medium-scale VAR with credit, house prices, and debt/GDP ratio. Alternative measures/ordering of uncertainty: Differences in GIRFs between ZLB and Normal times. Differences between the average GIRF to a one-standard deviation uncertainty shock in the ZLB state and in the Normal times state for the baseline model and the medium-scale model with credit, house prices, and debt/GDP ratio. Grey areas: 68% confidence bands relative to the baseline case.
Figure A6: Uncertainty shocks and Comovements: Generalized Impulse Responses to a one-standard deviation uncertainty shock. Uncertainty proxied by the VIX. Upper panels: Dashed-red line: ZLB regime; solid-blue line: Normal times. Solid-red lines and gray areas: 68% confidence bands. Lower panel: Differences between ZLB and Normal times. Solid black line: Difference between the average GIRF to a one-standard deviation uncertainty shock in the ZLB state and in the Normal times state; grey areas: 68% confidence bands.
Figure A7: **Real effects of uncertainty shocks: Role of the monetary policy stance.** Uncertainty proxied by VIX. Impulse responses to a one standard deviation uncertainty shock for selected histories differing because of different levels of the federal funds rate.
Figure A8: **GIRFs during the ZLB: Role of non-uncertainty shocks.** Comparison between GIRFs computed for the ZLB phase as in our baseline exercise and GIRFs computed by muting four non-uncertainty shocks one at a time. Muted shocks: "No Pr. shocks" refers to the case in which shocks to prices are muted; "No GDP shocks" to the case in which shocks to real GDP are muted; "No Inv. shocks" refers to the case in which shocks to real investment are muted; "No Cons. shocks" refers to the case in which shocks to consumption are muted.
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<td>-0.15</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ZLB</td>
<td>-0.50</td>
<td>-0.45</td>
<td>-0.33</td>
</tr>
</tbody>
</table>

Table A1: **Uncertainty-Real activity correlations: Normal times vs. ZLB.**

Real GDP, investment, and consumption considered in quarterly growth rates. Normal times: 1962Q3-2008Q3, ZLB: 2008Q4-2015Q4. Correlation coefficients conditional on the following periods: 1962Q3-2015Q4 - uncertainty proxied by the VIX, the financial uncertainty proxy estimated by Ludvigson, Ma, and Ng (2016) (LMN in the Table), the macroeconomic uncertainty proxy estimated by Jurado, Ludvigson, and Ng (2015) (JLN in the Table), and the economic policy uncertainty index built up by Baker, Bloom, and Davis (2016) (BBD in the Table); 1968Q4-2015Q1 - uncertainty proxied by the Rossi and Sekhposyan (2015) index (RS in the Table); Differences in samples due to differences in the availability of the uncertainty proxies. LMN’s and JLN’s proxies refer to an uncertainty horizon equal to one month. RS’s proxy refers to an uncertainty horizon equal to one year (revised version of the index). Cyclical component of the EPU index - considered for computing the correlations in the Table - extracted by using the Hodrick-Prescott filter, smoothing weight: 14,400).