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ESTIMATING THE REAL EFFECTS OF UNCERTAINTY SHOCKS AT THE ZERO LOWER BOUND

June 2018

Marco Fanno Working Papers - 222

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Abstract

We employ a parsimonious nonlinear Interacted-VAR to examine whether the real effects of uncertainty shocks are greater when the economy is at the Zero Lower Bound. We find the contractionary effects of uncertainty shocks to be statistically larger when the ZLB is binding, with differences that are economically important. Our results are shown not to be driven by the contemporaneous occurrence of the Great Recession and high financial stress, and to be robust to different ways of modeling unconventional monetary policy. These findings lend support to recent theoretical contributions on the interaction between uncertainty shocks and the stance of monetary policy.

Keywords: Uncertainty shocks, Nonlinear structural Vector AutoRegressions, Interacted VAR Generalized Impulse Response Functions, Zero Lower Bound. **JEL:** C32, E32.

1 Introduction

Uncertainty is widely recognized as one of the drivers of the Great Recession and the subsequent slow recovery. Recent empirical studies show that when an unexpected increase in uncertainty realizes, a contraction in real activity typically follows. Theoretically, uncertainty can depress real activity via "real option" effects, which affect investment in presence of nonconvex adjustment costs, and "precautionary savings" effects, which influence consumption if agents are risk averse. Bloom (2014) offers a survey of the recent empirical and theoretical literature.

Unsurprisingly, fluctuations in uncertainty represent a major concern for policymakers.[1] Given its recessionary effects, an increase in uncertainty naturally calls for a cut in the policy rate. In December 2008, however, the U.S. federal funds rate hit the zero lower bound and remained there for seven years. Table 1 documents correlations between different business cycle indicators (real GDP, investment, and consumption, all expressed in quarterly growth rates) and two proxies of financial uncertainty. The first one is the VIX, which is a measure of implied volatility of stock market returns over the next 30 days commonly used in literature. The second one is the financial uncertainty index recently proposed by Ludvigson, Ma, and Ng (2018), which is constructed via a factor approach to forecast errors related to a large number of financial U.S. series.[2] The correlations are computed for two different phases of the U.S. post-WWII economic history, i.e., "Normal times", in which the federal funds rate was unconstrained, and "Zero Lower Bound" (ZLB henceforth), in which the federal funds rate hit its lower bound and stayed at its bottom value.[3] A clear fact arises. The negative correlation between these business cycle indicators and uncertainty doubled - in the case of the VIX, tripled - since the end of 2008. These correlations are in line with the predictions

[1] In an interview to *The Economist* released in the midst of the Great Financial Crisis on January 29, 2009, Olivier Blanchard, Economic Counsellor and Director of the Research Department of the IMF, stated: *"Uncertainty is largely behind the dramatic collapse in demand. Given the uncertainty, why build a new plant, or introduce a new product now? Better to pause until the smoke clears."*

[2] Ludvigson, Ma, and Ng (2018) find financial uncertainty to be an exogenous driver of the U.S. business cycle. This finding justifies our focus on measures of financial uncertainty. However, our Appendix shows that the stylized fact documented in Table 1 is robust to the employment of the measure of uncertainty based on the distribution of the forecast errors of real GDP proposed by Rossi and Sekhposyan (2015), the macroeconomic uncertainty index constructed by Jurado, Ludvigson, and Ng (2015), and the economic policy uncertainty index constructed by Baker, Bloom, and Davis (2016). For a similar evidence, see Plante, Richter, and Throckmorton (2016).

[3] Throughout the paper, we will label as "Normal times" the post-WWII period up to 2008Q3, and "ZLB" the period 2008Q4-2015Q4. This is consistent with the fact that the Federal Reserve set its target federal funds rate to the 0-25 basis points range in December 2008.

coming from the theoretical contributions by Johannsen (2014), Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), Nakata (2017), and Basu and Bundick (2017). These papers employ calibrated New Keynesian general equilibrium models and show that uncertainty shocks generate a much larger and persistent drop in real activity when monetary policy is constrained by the ZLB.

In spite of the obvious relevance of this issue from a policy and theoretical standpoint, no empirical analysis explicitly modeling the nonlinearity related to the real effects of uncertainty shocks due to the ZLB has been proposed so far.[4] This paper addresses this issue by estimating a nonlinear Interacted-VAR (I-VAR) with post-WWII quarterly U.S. data. The I-VAR is particularly appealing to address our research question because it enables us to model the interaction between uncertainty and monetary policy in a parsimonious fashion. A parsimonious approach is desirable here given the limited amount of observations belonging to the ZLB state in the post-WWII U.S. sample. Our baseline I-VAR models measures of real activity (real GDP, consumption, investment), prices (the GDP deflator), the federal funds rate, and the VIX.[5] The model is nonlinear because it augments an otherwise standard linear VAR with an interaction term featuring the VIX, which enables us to identify uncertainty shocks, and the federal funds rate, which identifies the two states we aim at modeling, i.e., normal times and the ZLB. Crucially, the federal funds rate and the VIX are endogenously modeled in our analysis. We account for this endogeneity by computing nonlinear Generalized Impulse Response Functions (GIRFs) as in Koop, Pesaran, and Potter (1996) and Kilian and Vigfusson (2011).

Our main results can be summarized as follows. First, in line with most empirical contributions on the real effects of uncertainty shocks, we find that heightened uncertainty induces a contraction in real activity. In particular, consumption, investment, and output display a temporary negative response to an unexpected increase in uncertainty. This holds true in both states of the economy, a finding suggesting that uncertainty should be a concern for policymakers also in times when conventional

[4] Johannsen (2014), Nodari (2014), Caggiano, Castelnuovo, and Groshenny (2014), Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), Basu and Bundick (2017) engage in VAR investigations dealing with impulse responses estimated over different samples including or excluding the ZLB. As shown in Section 4, our investigation enables us to link the different impulse responses we find in the two scrutinized regimes to the ZLB, and to exclude competing explanations such as the contemporaneous occurrence of the Great Recession or heightened financial stress.

[5] Our analysis does not separately identify macroeconomic effects due to movements in uncertainty *per se* and effects due to movements in risk. Bekaert, Hoerova, and Lo Duca (2013) empirically discriminate between the two and find the business cycle effects triggered by movements in the VIX to be mainly due to variations in uncertainty.

monetary policy is unconstrained. Second, and specifically related to our research question, we find clear-cut evidence in favor of stronger real effects of uncertainty shocks in presence of the ZLB. According to our empirical model, the peak negative response of investment at the ZLB to a jump in uncertainty is about 3% larger relative to the one estimated in normal times, and 37% larger in cumulative terms over a five-year span, while the cumulative relative loss in output and consumption is about 12% and 13% larger, respectively. Third, using alternative interaction terms involving indicators of the business cycle and measures of financial stress, we show that our empirical findings are not driven by the occurrence of the Great Recession or the increase in credit spreads during the ZLB phase. Fourth, exercises dealing with a counterfactual systematic monetary policy during Normal times confirm that the monetary policy stance is likely to be the main driver of the stronger recessionary effects generated by uncertainty shocks during the ZLB. Fifth, we show that the different response of real activity to an uncertainty shock in the two regimes is robust to the employment of various proxies for unconventional monetary policy. Our Appendix shows that our results are also robust to the employment of Ludvigson et al.'s (2016) novel index of financial uncertainty and to the inclusion in our otherwise baseline model of a number of financial and real variables (measures of financial stress, stock prices, house prices, private and public debt).

Our findings lend support to structural frameworks which model mechanisms that imply a larger response of real activity to uncertainty shocks in presence of the ZLB (Johannsen (2014), Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), Nakata (2017), and Basu and Bundick (2017)). All these models' predictions hinge upon the inability of the central bank to offset negative uncertainty shocks because of the ZLB, which prevents the policy rate to lower the real ex-ante interest rate to the level which would otherwise reach in absence of the ZLB. More in general, our results call for models able to generate comovements of output, investment and consumption conditional to uncertainty shocks.[6] Recent contributions in this sense are Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015) and Basu and Bundick (2017), who model countercyclical markups through sticky prices as a crucial element to generate comovements, and Born and Pfeifer (2017), who focus on wage markups.

Our findings are also relevant from a policy standpoint. Bloom (2009) advocates

[6] Our Appendix shows that the evidence on comovements extends to hours, which are modelled in one of our robustness checks.

policies and reforms designed to respond to (or avoid the occurrence of) heightened uncertainty. These may range from the design of norms regulating financial markets to avoid excess volatility to the improvement of the credibility of institutions announcing future policies. Basu and Bundick (2015) propose a state-contingent policy conduct featuring a Taylor rule in "Normal times", and a forward guidance-type of policy able to stabilize the real interest rate when the ZLB binds. Evans, Fisher, Gourio, and Krane (2015) and Seneca (2016) show that uncertainty about future economic outcomes justifies a "wait-and-see" monetary policy strategy and a delayed liftoff of the policy rate. Our empirical results suggest that research on policies optimally designed to tackle the effects of uncertainty shocks, in particular in presence of the ZLB, is clearly desirable.

The paper develops as follows. Section 2 discusses the relation to the literature. Section 3 presents our nonlinear framework and the data employed in the empirical analysis. Section 4 documents our main results, the analysis of alternative channels and policy regimes, and the role of unconventional monetary policy. Section 5 concludes.

2 Relation to the literature

Our empirical analysis relates to theoretical contributions studying the real effects of uncertainty shocks and their effects in normal times and in presence of the ZLB. The paper we explicitly relate to is Basu and Bundick (2017). They estimate the effects of uncertainty shocks with a linear VAR modeling the VIX as a proxy of uncertainty and a number of business cycle indicators. They find an unexpected increase in uncertainty to generate comovements in real activity indicators and a reduction in the policy rate. The empirical evidence is shown to be consistent with a DSGE model with sticky prices and countercyclical markups. Key to our analysis, Basu and Bundick (2017) show that the contractionary effects of uncertainty shocks are magnified by the constraint imposed by the ZLB on a stabilizing conventional monetary policy that follows a standard Taylor rule. Our paper corroborates the predictions by Basu and Bundick (2017) as regards the more recessionary effects of uncertainty shocks on real activity at the ZLB.

Our empirical evidence is also in line with the theoretical models proposed by Johannsen (2014) and Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), who show that the real effects of fiscal policy uncertainty are particularly large in presence of the ZLB, and by Nakata (2017), who finds the effects of uncertainty shocks to households' discount factor to be larger if the policy rate is bounded below at zero. The common observation across these papers is the inability of the central bank to engineer a drop in the real interest rate large enough to fully tackle the recessionary effects of a spike in uncertainty.

A related paper is Bianchi and Melosi (2017). They use a microfounded regime-switching DSGE model - which allows for different monetary-fiscal policy combinations à la Leeper (1991) - to study the missing deflation during the ZLB period. They show that the uncertainty surrounding debt stabilization could be behind such missing deflation because agents could expect a passive monetary/active fiscal policy mix to be in place after the liftoff of the policy rate. Passive monetary policy would allow inflation and real activity to move to stabilize debt, therefore accommodating active fiscal policy. This combination of future policies would therefore sustain current inflation in spite of the drop in real activity recorded during the great recession. While the main goal of Bianchi and Melosi's (2017) paper is to investigate the channel via which the ZLB can induce policy uncertainty, our paper is concerned with the real effects of uncertainty shocks at the ZLB. We see our contribution as complementary to theirs.

Methodologically, I-VARs have recently been employed to study the nonlinear effects of macroeconomic shocks. Towbin and Weber (2013) estimate the response of output and investment to foreign shocks conditional on the level of external debt, import structure, and exchange rate regime. Sá, Towbin, and Wieladek (2014) focus on the effects of capital inflows conditional on the mortgage market structure and securitization. Aastveit, Natvik, and Sola (2017) quantify the real effects of monetary policy shocks in presence of high/low uncertainty. With respect to these studies, our paper: i) focuses on uncertainty shocks, and ii) fully endogenizes the conditioning variable which determines the switch between the states of interest. From a technical standpoint, our paper is close to Pellegrino (2017). He studies the real effects of monetary policy shocks in the United States in presence of time-varying uncertainty by computing fully non-linear GIRFs that admit switches between states after a shock (in his case, a monetary policy shock). A similar paper is Pellegrino (2018), who investigates the same research question with Euro area data. Our paper tackles a different research question, i.e., the effects of uncertainty shocks in normal times vs. when the ZLB is binding.

A strand of the literature examines the effects of uncertainty shocks conditional on the stance of the business or the financial cycle. Caggiano, Castelnuovo, and Groshenny (2014) and Caggiano, Castelnuovo, and Figueres (2017) use a Smooth-Transition VAR to estimate the response of unemployment to uncertainty shocks in recessions. Caggiano, Castelnuovo, and Nodari (2017) employ the same methodology to unveil the power of systematic monetary policy in response to uncertainty shocks in recessions and expansions. Alessandri and Mumtaz (2014) find the effects of uncertainty shocks to depend on the level of financial markets' strain. Our paper is complementary to those cited above because it focuses on a different source of nonlinearity, i.e., the one implied by the policy rate being at the ZLB.

3 Empirical strategy

3.1 Interacted-VAR

Our goal is to investigate whether the real effects of uncertainty shocks are different when the ZLB is in place. To this end, we augment an otherwise standard linear VAR including measures of real activity, prices, monetary policy stance, and a proxy for uncertainty with an interaction term, which involves two endogenously modeled variables. The first one is the VIX, which is our proxy of uncertainty whose exogenous variations we aim at identifying. The second one is the federal funds rate, which is the proxy for the monetary policy stance and it is employed as a conditioning variable to discriminate between normal times and the ZLB.[7]

Our Interacted-VAR reads as follows:

$$\mathbf{y}_t = \boldsymbol{\alpha} + \sum_{j=1}^{k} \mathbf{A}_j \mathbf{y}_{t-j} + \left[\sum_{j=1}^{k} \mathbf{c}_j unc_{t-j} \times ffr_{t-j} \right] + \mathbf{u}_t \quad (1)$$

$$E(\mathbf{u}_t \mathbf{u}_t') = \boldsymbol{\Omega} \quad (2)$$

where $\mathbf{y}_t = [unc_t, lp_t, lgdp_t, linv_t, lcons_t, ffr_t]'$ is the $(n \times 1)$ vector of endogenous variables comprising a measure of uncertainty, the GDP deflator, real GDP, real investment, real consumption, and the federal funds rate, $\boldsymbol{\alpha}$ is the $(n \times 1)$ vector of constant terms, $\mathbf{A}_j$ are $(n \times n)$ matrices of coefficients, and $\mathbf{u}_t$ is the $(n \times 1)$ vector of error terms, whose covariance matrix is $\boldsymbol{\Omega}$. The interaction term in brackets makes an otherwise standard linear VAR a nonlinear I-VAR. The interaction terms involving uncertainty and the policy rate ($unc_{t-j} \times ffr_{t-j}$) are associated to the $(n \times 1)$ vectors of coefficients

[7] As anticipated, our exercise aims at identifying the effects of an uncertainty shock conditional on the stance of monetary policy. Our focus on the exogenous driver of uncertainty excludes the possibility of confounding high levels of uncertainty and low values of the federal funds rate with low levels of uncertainty and high realizations of the federal funds rate. Section 4.4 proposes a counterfactual analysis in which fixed values of the federal funds rate replace the systematic policy response to uncertainty shocks in Normal times. This analysis confirms that it is the federal funds rate (and not the proxy for uncertainty) the conditioning element considered by our model for the computation of our impulse responses.

$\mathbf{c}_j$.[8] We model the data in log-levels (with the exception of the federal funds rate and the measure of uncertainty, which are modeled in levels) to preserve the cointegrating relationships among the modeled variables. However, our results remain basically unchanged when estimating our VAR in growth rates (evidence available upon request).

The choice of our baseline vector of observables is intended to strike a balance between model parsimony and informativeness. On the one hand, estimating a parsimonious model helps maximizing the degrees of freedom of our econometric analysis and, therefore, enables us to obtain more precise estimates. On the other hand, we include in the vector a set of variables rich enough to estimate the real effects of uncertainty shocks taking into account the stance of monetary policy. In spite of its parsimony, our six-variate VAR model contains sufficient information to reject the predictions of RBC frameworks as regards comovements of real activity indicators after an uncertainty shock.[9]

Our I-VAR represents a special case of a Generalized Vector Autoregressive (GAR) model (Mittnik (1990)). In principle, GAR models may feature higher order interaction terms. However, as pointed out by Mittnik (1990), Granger (1998), Aruoba, Bocola, and Schorfheide (2013), and Ruge-Murcia (2017), multivariate GAR models might become unstable when squares or higher powers of the interactions terms are included among the covariates, and it is in general difficult to impose conditions to ensure their stability. Our choice of working only with the $(unc_{t-j} \times ffr_{t-j})$ interaction term enables us to focus on the possibly nonlinear effects of uncertainty shocks due to different levels of the policy rate while preserving stability.[10] Moreover, this choice maximizes the number of degrees of freedom to estimate our I-VAR. Section 4 explores alternative explanations other than the ZLB for the larger impact that uncertainty shocks exert in the December 2008-

[8] The policy rate in our baseline analysis is the federal funds rate. Such rate takes values close to zero in the last part of our sample, but it is never numerically equal to zero. From a theoretical standpoint, it may appear unappealing that, if the federal funds rate took zero values, our nonlinear model would collapse to its linear counterpart right when the ZLB is in place. We stress here that the key role behind our regime-specific impulse responses is played by initial conditions (see Koop, Pesaran, and Potter (1996) for a discussion on the role of initial conditions in nonlinear VARs). Unsurprisingly, an exercise conducted by replacing the federal funds rate with a measure of federal funds rate "gap" (computed as the difference between the federal funds rate and its pre-ZLB sample mean to ensure that ZLB observations are also theoretically nonzero) returns results virtually equivalent to those documented in this paper.

[9] Financial and fiscal indicators are likely to be relevant to fully characterize the Great Recession. Our Appendix documents the robustness of our baseline empirical results to augmenting the VAR with financial variables (financial indices, measures of credit, house prices) and the public debt-to-GDP ratio.

[10] Simulations conducted by working with versions of our model featuring more than one interaction term confirm the presence of the instability issue discussed in the text.

December 2015 period - such as the Great Recession and credit frictions - by modeling alternative interaction terms that involve uncertainty, an indicator of the business cycle, and a credit spread. As shown in Section 4, the flexibility of our framework enables us to investigate also an alternative policy regime such as Volcker's, and to contrast the effects of uncertainty shocks during such regime with those we obtain during the ZLB.

The I-VAR is particularly well suited to address our research questions because it explicitly models an interaction term that clearly connects the uncertainty indicator with the policy rate. In this framework, uncertainty shocks are allowed, but not forced, to have a nonlinear impact on real activity depending on the level of the interest rate. Given that the identification of the normal times and ZLB regimes is dictated by the policy rate level, this feature of the I-VAR model enables us to interpret the macroeconomic effects of uncertainty shocks in light of the theoretical literature modeling these shocks as a function of the stance of monetary policy. Relative to alternative nonlinear specifications (e.g. Smooth-Transition VARs, Threshold VARs, Time-Varying Parameters VARs, nonlinear Local Projections), the I-VAR presents a number of advantages in this context. Smooth-Transition VAR models are designed to study gradual transitions from a regime to another and viceversa. Differently, the U.S. economy experienced an abrupt change of its monetary policy stance. This change is well captured by the dynamics of the effective federal funds rate, which moved from 5.25% in July 2007 to 0.15% in December 2008, and then remained below 0.25% for seven consecutive years. Hence, a Smooth-Transition VAR does not seem to represent an appropriate model here. Abrupt changes can be modeled by Threshold-VARs. However, T-VARs would need to estimate separately one model for normal times and one for the ZLB period. This would likely lead to inefficient estimates because of the small number of observations in the ZLB subsample. The I-VAR, instead, allows to use all available observations for estimation while preserving the possibility of identifying different regimes via the nonlinear interaction term. Time-Varying Parameters VARs are technically able to handle a sample like ours that features a small subset of ZLB observations (see Chan and Strachan (2014) for a recent application). However, it would not be immediate to connect time-varying impulse responses to the source of the nonlinearity we focus on in this study, i.e., the ZLB, whereas our I-VAR enables us to analyze whether the (possibly) nonlinear macroeconomic response to an uncertainty shock in the two regimes of interest is due to the relationship between uncertainty and the stance of monetary policy, or rather to different drivers, e.g., the stance of the business and/or the financial cycle. Finally, nonlinear Local Projections have recently been used in a related context, i.e., to examine the effects of government spending shocks in presence of the ZLB (see Ramey and Zubairy (2016)). Nonlinear Local Projects are powerful when an instrument for the shock one aims at identifying is available. Our analysis deals with financial uncertainty, which is likely to be largely driven by financial volatility shocks but not exclusively so. Hence, a direct application of the single-equation nonlinear Local Projections is not feasible in our case. Differently, our multivariate approach enables us to control for the systematic effect that real activity, inflation, and the policy rate exert on financial uncertainty and, therefore, to isolate the exogenous variations of uncertainty in our sample.[11]

3.2 Generalized Impulse Response Functions

We quantify the regime-specific impact of uncertainty shocks by computing Generalized Impulse Response Functions (GIRFs) à la Koop, Pesaran, and Potter (1996). Formally, the (generalized) impulse response at horizon h of the vector $\mathbf{y}_t$ to a shock of size δ computed conditional on an initial history $\boldsymbol{\omega}_{t-1}$ of observed histories of $\mathbf{y}$ is given by the following difference of conditional means:

$$GIRF_{\mathbf{y}}(h, \delta, \boldsymbol{\omega}_{t-1}) = E[\mathbf{y}_{t+h} \,|\delta, \boldsymbol{\omega}_{t-1}] - E[\mathbf{y}_{t+h} \,|\boldsymbol{\omega}_{t-1}] \tag{3}$$

GIRFs enable us to keep track of the dynamic responses of all the endogenous variables of the system conditional on the endogenous evolution of the value of the interaction terms in our framework. This is important because an unexpected increase in uncertainty has the potential of driving the economy from normal times to ZLB. In computing GIRFs, we follow Kilian and Vigfusson (2011) and work with orthogonalized residuals to identify uncertainty shocks.

As pointed out by Koop, Pesaran, and Potter (1996), GIRFs depend on the sign of the shock, the size of the shock, and initial conditions. In Section 4, we exploit the role of initial conditions to calculate responses to an uncertainty shock conditional to a different stance of monetary policy. Experiments on the role of the sign and the size of the shock (not documented here for the sake of brevity) point to a negligible role in

[11] Notice that the estimation of a linear VAR for two subsamples - before and after the end of 2008 - is not an option here due to the lack of a sufficiently large number of degrees of freedom to obtain reliable estimates. To fix ideas, consider our baseline six-variate VAR. In its linear form, this VAR features 135 independent coefficients (6 constants, 108 coefficients relative to the lag-structure, and 21 coefficients as regards the symmetric, reduced-form covariance matrix). The number of observations with six observables in the 2008Q4-2015Q4 sample is 174, which is clearly insufficient to obtain precise estimates with a multivariate framework like ours.

our empirical application. The description of the algorithm to compute the generalized responses is provided in the Appendix.

3.3 The data

Our VAR includes measures of U.S. real activity, prices, an indicator of the stance of monetary policy and a proxy of uncertainty. The measures of real activity are real GDP, real gross private domestic investment, and real personal consumption expenditures. Prices are measured by the GDP deflator. We use the effective federal funds rate as a measure of the monetary policy stance. Data are taken from the Federal Reserve Bank of St. Louis' database.[12] The sample size is 1962Q3-2015Q4. The choice of the quarterly frequency is justified by our interest in the response of (among other variables) GDP and investment, which are not available at a monthly frequency. Given that the Federal Reserve set its target federal funds rate to the 0-25 basis points range in December 2008, the ZLB regimes in our sample begins in 2008Q4.

Our baseline measure of uncertainty is the VIX, which is a measure of implied stock market volatility.[13] The use of the VIX as a proxy for uncertainty has recently been popularized in the applied macroeconomic context by Bloom (2009). Since then, it has been taken as a reference by a number of studies (for a survey, see Bloom (2014)). The reason of its popularity is that it is a real-time, forward-looking measure of implied volatility. Hence, it matches well with uncertainty as an ex-ante theoretical concept. Importantly for our study, the VIX is the empirical measure of uncertainty which best matches the uncertainty process modeled by Basu and Bundick (2017), who examine the role played by the ZLB in magnifying the real effects of uncertainty shocks. This makes the VIX appealing for our analysis, because it enables us to meaningfully compare the impulse responses produced with our I-VAR analysis with those generated by Basu and Bundick's (2017) theoretical model. Our Appendix shows that the baseline findings documented in the text are robust to the employment of an alternative measure of financial uncertainty recently developed by Ludvigson, Ma, and Ng (2018).

[12] We use Gross Domestic Product: Implicit Price Deflator, Base year 2009, Quarterly, Seasonally Adjusted; Real Gross Domestic Product, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate; Real Gross Private Domestic Investment, 3 decimal, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate; Real Personal Consumption Expenditures, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate; and Effective Federal Funds Rate, Percent, Quarterly, Not Seasonally Adjusted. Source: FredII.

[13] Pre-1986 the VIX index is unavailable. Following Bloom (2009), we extend backwards the series by calculating monthly returns volatilities as the standard deviation of the daily S&P500 normalized to the same mean and variance as the VIX index for the overlapping sample (1986 onwards).

3.4 Specification, identification and empirical evidence in favor of the I-VAR model

We estimate model (1)-(2) via OLS. We impose the same number of lags k for the linear and the nonlinear parts of the I-VAR. According to the Akaike criterion, the optimal number of lags for our baseline VAR (which embeds the VIX as a proxy of uncertainty) is three.[14] To identify the uncertainty shocks from the vector of reduced form residuals, we adopt the conventional short-run restrictions implied by the Cholesky decomposition. The ordering of the endogenous variables adopted for the baseline model is: (i) uncertainty, (ii) prices, (iii) output, (iv) investment, (v) consumption, and (vi) federal funds rate. Ordering the uncertainty proxy before macroeconomic aggregates in the vector allows real and nominal variables to react on impact, and it is a common choice in the literature (see, among others, Bloom (2009), Caggiano, Castelnuovo, and Groshenny (2014), Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), Leduc and Liu (2016)). Moreover, it is justified by the theoretical model developed by Basu and Bundick (2017), who show that first-moment shocks in their framework exert a negligible effect on the expected volatility of stock market returns. Our Appendix documents that our results are robust to ordering uncertainty last.

We provide empirical evidence at the multivariate level in favor of nonlinearity, in particular in favor of the Interacted-VAR model. Given that such a model encompasses a linear VAR, we use a LR-type test for the null hypothesis of linearity versus the alternative of a I-VAR specification. The null hypothesis of linearity is clearly rejected at the 5% significance level. In particular, the likelihood-ratio test suggests a value for the LR statistic $\chi_{18} = 30.33$ with an associated p-value of 0.03.[15]

4 Normal times vs. ZLB: Empirical evidence

4.1 Baseline results

Figure 1 plots the impulse responses to a one-standard deviation uncertainty shock identified with the VIX along with 68% confidence bands. In normal times, an uncertainty shock triggers a temporary recession. Real GDP and consumption fall by about 0.25%

[14] Our results are robust to alternative lag-length selection ranging from one to four (evidence available upon request).

[15] Similar results are obtained when the LMN measure of uncertainty is employed, with $\chi_{24} = 65.08$ with associated p-values taking values lower than 0.01. The different number of degrees of freedom employed in the test is justified by the different number of lags selected by the Akaike criterion when employing the LMN measure (four lags) and the VIX (three lags), respectively.

after two quarters, while investment drops of about 2%. Interestingly, all three variables share a common dynamic pattern. After an uncertainty shock, these real activity indicators display a quick drop followed by a rapid recovery and a (non-statistically significant) overshoot. In response to this downturn in economic activity, the federal funds rate falls of about 40 basis points after three quarters, and remains negative for about two years. Prices fall as well, although their response is not significant from a statistical viewpoint.

Our I-VAR model predicts very different macroeconomic responses to an uncertainty shock in the ZLB regime. First, real activity is predicted to experience a much slower but deeper fall. Real GDP falls by about 0.5%, reaching its trough after approximately three years. Consumption and investment drop substantially, the former by about 0.5% after three years and the latter by about 2% after two years. Second, the recovery is much slower, with no overshoot. After five years, real GDP is still below its trend, although it takes about three years to go back to it from a statistical standpoint. The same dynamics holds for consumption, while investment recovers relatively more rapidly, remaining significantly below its trend for about two years. In all cases, neither a quick drop-and-rebound nor an overshoot is observed. Moreover, the response of uncertainty to its own shock is more persistent and goes back to the pre-shock level relatively more slowly.

The response of the federal funds rate is key for our analysis. Such response is estimated to be insignificant conditional on the ZLB state. It is important to stress that this is a prediction of the model, and not an a-priori assumption. No ZLB technical constraint is mechanically imposed on this variable. Hence, this is a fully-data driven result that points to the model's ability to discriminate between monetary policy in normal times vs. in the ZLB regime. In fact, the estimated response of the policy rate in normal times is very different, i.e., the federal funds rate is predicted to fall in a temporary but persistent fashion after an uncertainty shock.

An interpretation of the bigger drop in real activity during the ZLB period is the missing fall in the short-term nominal and real interest rates in presence of the ZLB. As explained in Basu and Bundick (2015, 2017), in a model with nominal rigidities an exogenous increase in uncertainty exerts larger effects on real activity when conventional monetary policy is constrained by the ZLB. In normal times, an increase in uncertainty stimulates precautionary savings and labor supply. Given sticky prices, lower wages do not fully translate in lower prices at an aggregate level. Hence, the price markup increases while real activity falls. However, the central bank tackles the contractionary effects of the uncertainty shock by lowering the nominal interest rate and, consequently, the real ex-ante interest rate. Differently, when the policy rate is at the zero lower bound, the central bank can offset only sufficiently positive shocks, but not negative ones. Consequently, a contractionary bias is in place because, given that the distribution of possible realizations of the policy rate is bounded below, the ex-ante real interest rate is higher than what it would be in absence of the zero lower bound. Given the persistence of the uncertainty shock, rational agents expect also future real rates to be higher than what would occur in normal times. These expectations imply a stronger current negative effects of an uncertainty shock on real activity as well as a more persistent response to the shock.

Our impulse responses offer support to the theoretical predictions proposed in Basu and Bundick (2015, 2017) and Leduc and Liu (2016) on the fall of real and nominal variables after an increase in uncertainty. We also find a different shape of the responses of real activity indicators to uncertainty shocks when exploring normal times vs. ZLB times, a finding in line with the evidence produced with linear VARs estimated over different samples by Johannsen (2014), Nodari (2014), Caggiano, Castelnuovo, and Groshenny (2014), and Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015). In spite of the deeper recession estimated to follow an uncertainty shock in the ZLB state, inflation is predicted to remain at levels comparable to the normal times ones, something resembling the "missing disinflation" of the 2007-2009 crisis.

Figure 2 documents the difference in the point estimates of the impulse responses computed in the two regimes.[16] A negative difference points to stronger contractionary effects at the ZLB. Two main results emerge. First, the negative real effects of uncertainty shocks are confirmed to be statistically stronger in presence of the ZLB for all three measures of real activity we consider in our analysis. Second, the difference in the response of the federal funds rate is positive, and it is basically the mirror image of the reaction of the policy rate in normal times documented in Figure 2. This is exactly what one should expect by an analysis comparing the response of the federal funds rate in normal times, in which the rate is expected to drop after an increase in uncertainty, and in ZLB times, in which the policy rate is bound to stay at zero.

The differences documented in Figure 2 are economically relevant. As documented

[16]We compute differences between the impulse responses in the two states conditional on the same set of bootstrapped simulated samples. In this way, the construction of the test accounts for the correlation between the estimated impulse responses. The empirical density of the difference is based on 1,000 realizations for each horizon of interest.

in Table 2, the peak negative response of investment in ZLB is about 3% larger relative to the one estimated in normal times, and 37% larger in cumulative terms over a five-year span, while the cumulative relative loss in output and consumption is about 12% and 13%, respectively.[17] Overall, this differences point to a large economic cost related by a binding ZLB. Wrapping up, our results point to substantially larger real effects of uncertainty shocks in the ZLB state, above all as regards investment.

The previous results show that uncertainty shocks generate a significant negative response in real activity, and that such response is magnified by the zero lower bound on policy rates. We then investigate how important uncertainty shocks are in explaining business cycle fluctuations in the two regimes. Table 3 reports the results of a Generalized Forecast Error Variance Decomposition (GFEVD) exercise for a forecast horizon of three years computed by adopting the algorithm proposed by Lanne and Nyberg (2016).[18] Three main findings emerge. First, uncertainty shocks are more important when the economy is at the ZLB. The contribution of uncertainty shocks is estimated to be 12%, 16%, and 13% for the volatility of real GDP, investment, and consumption, respectively. In normal times, these shares drop to 8%, 12%, and 6%. Second, uncertainty shocks are relatively more important for investment than for consumption and output. Third, the forecast error variance of the VIX is largely explained by its own shock in both regimes (85% in normal times and 83% at the ZLB, respectively).[19] All these results are in line with the predictions offered by the theoretical model by Basu and Bundick (2017).

The empirical findings discussed above are robust to a variety of perturbations of the baseline I-VAR model. These perturbations are: i) the employment of the LMN measure of financial uncertainty; ii) a different ordering of the variables in the vector

[17]These figures are computed by considering a rescaled version of the differences between normal times and ZLB plotted in Figure 2. Such responses are computed under the assumption of an equally sized uncertainty shock in the two regimes. However, the empirical distribution of the uncertainty shocks estimated via our I-VAR points to a volatility 1.93 times larger in the ZLB regime than in normal times. To take this "scale effect" into account when quantifying the relevance of the ZLB for the response of real activity, we calibrate the size of the uncertainty shock in a regime-specific fashion and re-compute the aforementioned differences with our I-VAR.

[18]Lanne and Nyberg (2016) focus on GFEVD analysis conducted by considering the residuals of a reduced-form VAR. We are interested in computing the contribution of structural (orthogonalized) shocks to the variance of the forecast errors of the endogenous variables in our VAR. Hence, we modify their algorithm to calculate the GFEVD to a one-standard deviation shock to all variables included in our analysis. Our Appendix provides further details on our application of Lanne and Nyberg's (2016) algorithm.

[19]Interestingly, these numbers remain mostly unchanged if the VIX is ordered last. In such a case, the volatility of the VIX is explained by its own shock for a fraction of 81.5% and 80% in the two regimes, respectively.

featuring uncertainty last; iii) the estimation of richer vectors including financial indices, measures of credit, house prices, fiscal stance, and hours. These results are documented in our Appendix.

4.2 The ZLB, the Great Recession and the Great Financial Crisis

Our I-VAR analysis aims at quantifying the effects of uncertainty shocks in two different regimes, normal times and the ZLB. This is the reason why our baseline framework models an interaction term involving a measure of uncertainty and the policy rate. However, some contributions in the literature point to nonlinearities unrelated to the ZLB. Uncertainty shocks may exert stronger effects in recessions (Caggiano, Castelnuovo, and Groshenny (2014), Nodari (2014), Caggiano, Castelnuovo, and Nodari (2017), Caggiano, Castelnuovo, and Figueres (2017)). This may occur because of a lower effectiveness of monetary policy in tackling negative shocks (see, e.g., Mumtaz and Surico (2015) and Tenreyro and Thwaites (2016)), and/or because of a stickier labor market during downturns (Cacciatore and Ravenna (2015)). Moreover, the interaction between uncertainty shocks and financial frictions may intensify during periods of high financial stress (Alessandri and Mumtaz (2014), Gilchrist, Sim, and Zakrajšek (2014), Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016)). Indeed, the 2007-2009 period was characterized by the joint presence of the ZLB, an exceptionally severe real crisis, and the Great Financial Crisis, which featured unprecedented levels of financial stress. As a consequence, the results documented above could be assigning an exaggerated role to the ZLB because of the omission of other channels which were contemporaneously at work, i.e., the business cycle channel and the financial cycle.

We tackle this identification issue by estimating two different versions of the I-VAR model (1)-(2). These two alternative frameworks are characterized by alternative interaction terms which are modeled to capture the nonlinearities due to the business cycle channel and the financial channel.[20] Formally, we capture the role played by the

[20]In principle, the I-VAR could be estimated by allowing for multiple interaction terms simultaneously. However, as anticipated in Section 3.1, the estimation of I-VARs featuring more than one interaction term to jointly model more than one of the channels discussed in the text failed to deliver stable models.

business cycle stance by estimating the following model:

$$\mathbf{y}_t = \boldsymbol{\alpha} + \sum_{j=1}^{k} \mathbf{A}_j \mathbf{y}_{t-j} + \left[\sum_{j=1}^{k} \mathbf{c}_j unc_{t-j} \times \Delta \ln GDP_{t-j} \right] + \mathbf{u}_t \tag{4}$$

$$E(\mathbf{u}_t \mathbf{u}_t') = \boldsymbol{\Omega} \tag{5}$$

where $\Delta \ln GDP_{t-j} \equiv \ln GDP_{t-j} - \ln GDP_{t-j-1}$ is the quarterly growth rate of GDP, which we take as a proxy of the stance of the business cycle. We estimate this model over the sample 1962Q3-2015Q4 and compute GIRFs conditional on the ZLB period 2008Q4-2015Q4, which is the one of interest for our discussion. If the driver of our baseline results is not the stance of monetary policy but rather business cycle conditions, we would expect to find the responses in this period to be similar to those associated to the very same ZLB period in our baseline analysis. If, instead, such responses turn out to be different, then our baseline impulse responses are not "observationally equivalent" to those produced with the alternative model (4)-(5). Such evidence would lead us to conclude that the key driver of the more recessionary responses in presence of the ZLB is the ZLB *per se*, and not the contemporaneous occurrence of the Great Recession. Notice that this exercise assumes the growth rate of real GDP to be a good proxy for the stance of the business cycle. Chauvet (1998) and Chauvet and Piger (2008) obtain smoothed recession probabilities for the United States from a Dynamic-Factor Markov-Switching model applied to coincident business cycle indicators such as non-farm payroll employment, industrial production, real personal income excluding transfer payments, and real manufacturing and trade sales. Reassuringly, the correlation between the growth rate of real GDP we use in this exercise and their smoothed recession probability - available on the Federal Reserve Bank of St. Louis' website - is as large as -0.60.

Figure 3 - top row reports the point estimates and the 68% confidence bands obtained with our baseline model as well as the GIRFs obtained with the alternative framework (4)-(5). The responses estimated with this model and conditional on the ZLB initial conditions are remarkably similar to those produced with the baseline model in normal times, i.e., real activity displays a quick drop and rebound and a temporary overshoot. Interestingly, the responses are included for all real activity indicators within the 68% confidence bands associated to normal times by our baseline I-VAR. This result suggests that the macroeconomic dynamics documented with our baseline framework as regards the ZLB phase are not driven by the contemporaneous occurrence of the Great Recession.

The second check looks at the role played by financial stress during the ZLB period.

Alessandri and Mumtaz (2014) work with a nonlinear FAVAR framework and show that uncertainty shocks exert stronger effects in periods of high financial strain. The same result is present in the empirical investigations proposed by Gilchrist, Sim, and Zakrajšek (2014) and Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016). As already mentioned, the ZLB period we focus on is characterized by an exceptionally high level of financial stress. To take into account the possible asymmetry due to financial strain, we then estimate the following I-VAR specification:

$$\mathbf{y}_t = \boldsymbol{\alpha} + \sum_{j=1}^{k} \mathbf{A}_j \mathbf{y}_{t-j} + \left[\sum_{j=1}^{k} \mathbf{c}_j unc_{t-j} \times GZ_{t-j} \right] + \mathbf{u}_t \tag{6}$$

$$E(\mathbf{u}_t \mathbf{u}_t') = \boldsymbol{\Omega} \tag{7}$$

where GZ_t indicates the measure of credit spread proposed by Gilchrist and Zakrajšek (2012) (GZ henceforth). As before, we estimate this model over the sample 1962Q3-2015Q4 and compute GIRFs by integrating over the period 2008Q4-2015Q4.[21] We order the GZ spread second in our vector to capture the effect that financial markets are likely to play in transmitting the impact of an uncertainty shock on the economy (Gilchrist, Sim, and Zakrajšek (2014), Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016)).

The logic of this exercise is the same as the one in the previous exercise. If the driver of our baseline results is not the stance of monetary policy but rather the financial strain, model (6)-(7) should return impulse responses which are similar to the baseline ZLB and different from the ones that the baseline model associates to normal times.

Figure 3 - bottom row shows that this is not the case. In fact, if we let the interaction between uncertainty and the GZ credit spread capture the nonlinearity of the effects of uncertainty shocks, we get a response of real activity in the ZLB sample which is actually very similar to the one that our baseline model associates to normal times. Noticeably, as in the previous case, the responses of all real activity measures lie within the 68% confidence bands estimated for normal times in the baseline I-VAR.

Our results should be seen as complementary with respect to those proposed by papers that study the effects of uncertainty shocks in good and bad times (Caggiano, Castelnuovo, and Groshenny (2014), Nodari (2014), Caggiano, Castelnuovo, and Nodari

[21] The original version of the GZ spread is available from 1973. Our baseline analysis starts in 1962. Then, we regress the GZ spread against the difference between i) the AAA corporate bonds and the 10-year Treasury yield; ii) the BAA corporate bonds and the 10-year Treasury yield; iii) the 6-month T-Bill rate and the 3-month T-Bill rate; iv) the 1-year Treasury yield and the 3-month T-Bill rate; v) the 10-year Treasury yield and the 3-month T-Bill rate. We do this for the sample 1973-2015, and then we use the fitted values of the regression to backcast the GZ spread and match our baseline sample. All data are taken from the Federal Reserve Bank of St. Louis' database.

(2017), Caggiano, Castelnuovo, and Figueres (2017)) or in periods of high financial stress (Alessandri and Mumtaz (2014), Gilchrist, Sim, and Zakrajšek (2014), and Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016)). In fact, these papers and ours tackle different research questions. Our paper explicitly deals with the ZLB, which is quite a peculiar event in the U.S. post-WWII economic history. Hence, a correct reading of our findings is that the Great Recession and the high levels of financial stress occurred during the global financial crisis would not be enough to explain the bigger impact on real activity documented by our impulse responses during the 2008Q4-2015Q4 period. Differently, the ZLB is able to generate significantly different responses during the ZLB as opposed to the pre-2008Q4 period. Our conclusion is that heightened uncertainty in presence of the ZLB makes things even worse than they would be in a world in which the policy rate is away for its bound.

A different question regards the role played by first moment shocks which may have originated before the ZLB period, led the U.S. economy to the ZLB, and had a large and negative impact during the ZLB period. In this case, such shocks could be behind our results, and the larger response of real activity to uncertainty shocks would not be caused by the ZLB, but simply correlated to it. We check for this possibility by running an exercise in which we compute the GIRFs by shutting down future non-uncertainty shocks one at a time. In conducting this exercise, we focus on shocks to prices, output, investment, and consumption. If one of these shocks (or a combination of them) is actually behind the results documented in the previous Section, we should observe a drastic change in our GIRFs and, in particular, more similar responses between regimes. The outcome of this exercise, reported in the Appendix for the sake of brevity, confirms that our main conclusion on the deeper recession opened by an uncertainty shock during the ZLB regime remains unaffected.

4.3 Fixed interest rate regime in Normal times

Another way to gauge the empirical relevance of the ZLB regime is to "plant a fixed interest rate regime" in Normal times.[22] The idea is the following. The ZLB is problematic because it impedes the conventional monetary policy response that a central bank would otherwise engineer in presence of a recessionary uncertainty shock, which is, a reduction in the policy rate. Rather than having the interest rate fixed at zero, the problematic component of conventional policy at the ZLB might be that the policy

[22]We thank two anonymous referees for suggesting this exercise and the one presented in the next Section.

rate is "fixed" or, in other words, not reactive to negative macroeconomic shocks. Our flexible nonlinear VAR can be used to empirically verify this statement. Suppose that, in spite of the arrival of a recessionary uncertainty shock, the policy rate remained fixed to its pre-shock level in Normal times: How would the response of real activity look like?[23] If the inability of the central bank to lower the interest rate is the key element behind the difference between our baseline GIRFs in Normal times vs. the ZLB period, then this counterfactual exercise should return responses in Normal times that look like our baseline responses in the ZLB regime.

The GIRFs plotted in Figure 4 confirm that this is exactly the case.[24] In spite of being in Normal times, the switch in policy regimes - from a reactive monetary policy, whose response in Normal times can be seen in the bottom-right panel, to a fixed one - clearly induces very different reactions of real activity, which are close to our baseline responses during the ZLB.

4.4 Role of the Volcker regime

The evidence provided so far points to stronger and more persistent effects of uncertainty shocks when the federal funds rate is at its lower bound, or when it is counterfactually kept fixed. Our interpretation of this evidence is that the effects of uncertainty shocks are more severe for the economic system when conventional monetary policy cannot be employed to tackle them because of the ZLB. However, the ZLB is not the only period in our sample where interest rates take extreme values. Indeed, during the Volcker era

[23] As underlined by an anonymous referee, this exercise is similar to the counterfactual experiment conducted by Del Negro, Giannoni, and Patterson (2015) in the context of their investigation of the power of forward guidance. They run a counterfactual experiment by simulating the effects of the annoucement of a future policy rate equal to 25 basis points for three years followed by a return to the historical Taylor rule. They show that a standard medium-scale DSGE model in which agents are infinitely lived predicts implausibly large expansionary effects in response to this policy. Differently, a modified version of the model featuring an overlapping generations structure delivers predictions in line with the data. Our focus is on the power of constrained and unconstrained versions of conventional monetary policy. We see our exercise as complementary to Del Negro et al.'s (2015).

[24] The counterfactual responses are conditional on a fixed interest rate imposed by setting all coefficients in the federal funds rate equation to zero apart from the one related to the first lag of the federal funds rate, which is set to one, and by setting to zero the coefficient regulating the contemporaneous response of the federal funds rate to an uncertainty shock. Notice that different historical values (initial conditions) of the federal funds rate in Normal times translate into different interest rate levels the federal funds rate is fixed at. The response depicted in Figure 4 is the average across all responses conditional on different initial conditions in Normal times. The impulse response of the policy rate under the fixed interest rate regime is zero at all horizons because it is computed as the different between a non-zero, fixed interest rate in presence of the uncertainty shock and the same non-zero, fixed interest rate in absence of it.

the federal funds rate was abnormally high. Then, a possible alternative interpretation for our main finding is that, for some reasons, uncertainty shocks during the Volcker period were scarcely effective. If so, the difference between the impulse responses at the ZLB versus those in Normal times documented with our baseline model might be driven by the existence of two distinct regimes within the Normal times period: the "Volcker regime", when interest rates were exceptionally high and uncertainty shocks scarcely effective, and the "Non-Volcker regime", characterized by uncertainty shocks whose real effects were similar to those we found for the ZLB regime. Hence, one may wonder if the driver of our empirical findings is the ZLB or, instead, the Volcker regime.

We address this issue by re-estimating the model excluding the ZLB sample, i.e., over the period 1962Q3-2008Q3, and then integrating the impulse responses of real activity to an uncertainty shock over two different sets of initial conditions: the "Volcker regime" (1979Q3-1987Q3), and the "Non-Volcker regime" (1962Q3-1979Q2, 1987Q4-2008Q3). If our baseline results are mainly driven by the scarce effectiveness of uncertainty shocks in the "Volcker regime", then the "Volcker"/"Non-Volcker" regimes should return different responses of real activity, and the impulse responses in the "non-Volcker" regime should be similar to those obtained for the ZLB period with our baseline model. If instead the ZLB is the main driver of the previously documented differences, the responses of real activity in the "Volcker"/"Non-Volcker" regimes should be similar, and not different from what obtained in "Normal times" with our baseline I-VAR model.

Figure 5 plots the GIRFs obtained in the "Volcker"/"Non-Volcker" regimes, along with those obtained with the baseline model. No matter what set of initial conditions one considers (Volcker/Non-Volcker), the GIRFs computed with the nonlinear VAR estimated by excluding the ZLB period look very similar to the Normal times ones in the baseline scenario. This result corroborates our interpretation of the relevance of the ZLB per se as a driver of the stronger response of real activity to uncertainty shocks during the 2008Q4-2015Q4 period.

4.5 Unconventional monetary policy

The analysis conducted so far has dealt with the effects of uncertainty shocks and their dependence on the stance of conventional monetary policy. As a matter of fact, a number of unconventional monetary policy interventions have been implemented by the Federal Reserve since December 2008 (when the ZLB became binding), including large-scale asset purchases and forward guidance. Such interventions are likely to have influenced long-term interest rates and, therefore, helped the economy out of the 2007-2009 recession also by mitigating the contractionary effects of heightened uncertainty. Our baseline VAR does not feature any variable modeling unconventional monetary policy. This form of misspecification of our model could therefore inflate the differences documented with our previous exercises.

We tackle this issue by estimating three different versions of our baseline framework. The first version takes into account unconventional monetary policy by considering the "shadow rate" introduced by Wu and Xia (2016). They estimate a multifactorial shadow rate term structure model and show that it provides an excellent empirical description of the evolution of the U.S. term structure in presence of the ZLB.[25] The idea is that, because of a mix of unconventional monetary policy interventions, the effective rate - which is, the shadow rate - might have been lower than the actual federal funds rate. We then run a version of our VAR which features the shadow rate produced by Wu and Xia (2016) *in lieu of* the federal funds rate.

The second experiment considers the possibility that the Federal Reserve could have been able to affect longer term rates via forward guidance while the policy rate was at its lower bound. Swanson and Williams (2014) conduct an empirical exercise focused on the response of interest rates at different maturities to macroeconomic announcements. They show that, during the ZLB period, Treasury yields with one- and two-year maturity were responsive to macroeconomic news throughout the 2008-2010 period in spite of the federal funds rate being stuck at its lower bound. To allow unconventional monetary policy to play a role in our model via the effects on longer term rates, we then replace the federal funds rate with the 1-year Treasury Bill rate and re-estimate the model.

Our third check specifically looks at the balance sheet of the Federal Reserve. Following Gambacorta, Hofmann, and Peersman (2014), we consider the adjusted monetary base as a measure of liability.[26] Gambacorta, Hofmann, and Peersman (2014) show with a panel VAR for eight advanced economies that unconventional monetary pol-

[25] The idea of the shadow rate has also been explored by, among others, Krippner (2013) and Christensen and Rudebusch (2015). For an extensive analysis, see Krippner (2015).

[26] We use the adjusted monetary base taken from the Federal Reserve Bank of St. Louis' website. Gambacorta, Hoffmann and Peersman (2014) also use a measure of assets. To our knowledge, a measure of total assets related to all Federal Reserve banks covering our sample 1962Q3-2015Q4 is not available at quarterly frequencies. The series "All Federal Reserve Banks: Total Assets" is available at quarterly frequencies starting from 2003Q1 (source: Federal Reserve Bank of St. Louis). Total assets and the adjusted monetary base display a remarkably similar behavior in the 2003Q1-2015Q4 period, i.e., they share a distinct upward trend and they are highly correlated - degree of correlation: 0.95 - at cyclical frequencies as identified by the Hodrick-Prescott filter (smoothing weight: 1,600).

icy shocks identified by using such a measure had expansionary effects on real activity while the policy rate was stuck at its effective lower bound. Given its nature of "fast moving variable", we order the adjusted monetary base last in the VAR to allow for contemporaneous responses to an uncertainty shock.

Our results are reported in Figure 6. The top row plots the impulse responses to uncertainty shocks in ZLB obtained with the model with the shadow rate over the responses obtained with our baseline framework and the corresponding 68% confidence bands. No sizeable differences with respect to our baseline results are detected in ZLB. The middle row of the same figure reports the results from the framework that models the 1-year Treasury Bill rate as the policy rate. As in the previous case, no sizeable differences can be detected with respect to the responses obtained in our baseline scenario featuring the federal funds rate as policy variable. The bottom row reports the response of real activity to an uncertainty shock produced with the model with the adjusted monetary base measure. Two results stand out. First, the baseline finding that real activity reacts more to an uncertainty shock at the ZLB is largely confirmed. Second, the presence of liquidity suggests some positive effect on real activity when the economy is at the ZLB. In particular, relative to the baseline case, all real activity indicators display a less pronounced trough and a faster recovery to the pre-shock level.[27] We speculate that liquidity measures could add relevant information to models featuring (official or shadow) policy rates when it comes to quantifying the responses of real activity to an uncertainty shock (and, possibly, to macroeconomic shocks in general). However, these responses are statistically in line with those obtained with our baseline model as regards the ZLB phase. Wrapping up, controlling for the shadow rate, longer term rates, and measures of liquidity does not lead to a significant change in our impulse responses.

5 Conclusions

This paper works with a nonlinear Interacted-VAR framework and post-WWII U.S. data and shows that uncertainty shocks triggered a deeper recession during the zero lower bound period than in times of unconstrained monetary policy. This result is shown not to be driven by other macroeconomic shocks that occurred during the Great

[27] Unsuprisingly, the responses estimated with these three models accounting for unconventional monetary policy display virtually no difference with respect to our baseline ones in normal times, when unconventional policies were not in place.

Recession or by the presence of more severe financial conditions, and it is robust to different ways of modeling unconventional monetary policy.

From a modeling standpoint, our results support the employment of general equilibrium frameworks i) which predict a larger response of real activity to an uncertainty shock in presence of the ZLB, and ii) are able to generate macroeconomic comovements after an uncertainty shock. Models by Johannsen (2014), Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), and Basu and Bundick (2015, 2017) are promising proposals along these lines.

Our results call for studies focusing on optimal monetary policy in presence of the ZLB when uncertainty shocks hit an economic system. Contributions like Basu and Bundick (2015), Evans et al. (2015), and Seneca (2016) represent relevant starting points for this research agenda.

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Unc. indic.	*Period*	$\Delta Y/Y$	$\Delta I/I$	$\Delta C/C$
VIX	Normal times	-0.22	-0.19	-0.23
	ZLB	*-0.75*	*-0.63*	*-0.79*
LMN	Normal times	-0.29	-0.26	-0.28
	ZLB	*-0.60*	*-0.55*	*-0.67*

Table 1: **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. Uncertainty proxied by the VIX and by the financial uncertainty index estimated by Ludvigson, Ma, and Ng (2016) (LMN in the Table). LMN's proxy refers to an uncertainty horizon equal to one month.

Variable	Peak	Cumul.
GDP	-0.87%	-11.72%
Investment	-2.87%	-37.21%
Consumption	-0.91%	-13.10%

Table 2: **Impact of the ZLB on real activity: Percentage deviations with respect to normal times.** Peak and cumulated percentage deviations of the responses of real activity indicators in ZLB and normal times. Responses computed by calibrating the standard deviations of the shocks in the two regimes to replicate the standard deviation of the empirical densities of the uncertainty shocks estimated by our model. Cumulated responses refer to a 5-year span.

Variable	Normal times	ZLB
GDP	0.08	0.12
Investment	0.12	0.16
Consumption	0.06	0.13
FFR	0.14	0.00
Price	0.01	0.02
VIX	0.85	0.83

Table 3: **Generalized Forecast Error Variance Decomposition: Contribution of uncertainty shocks in the two regimes.** GFEVD computed according to Lanne and Nyberg (2016)'s algorithm for a 1-standard deviation shock to all variables. Forecast horizon: 12 quarters.

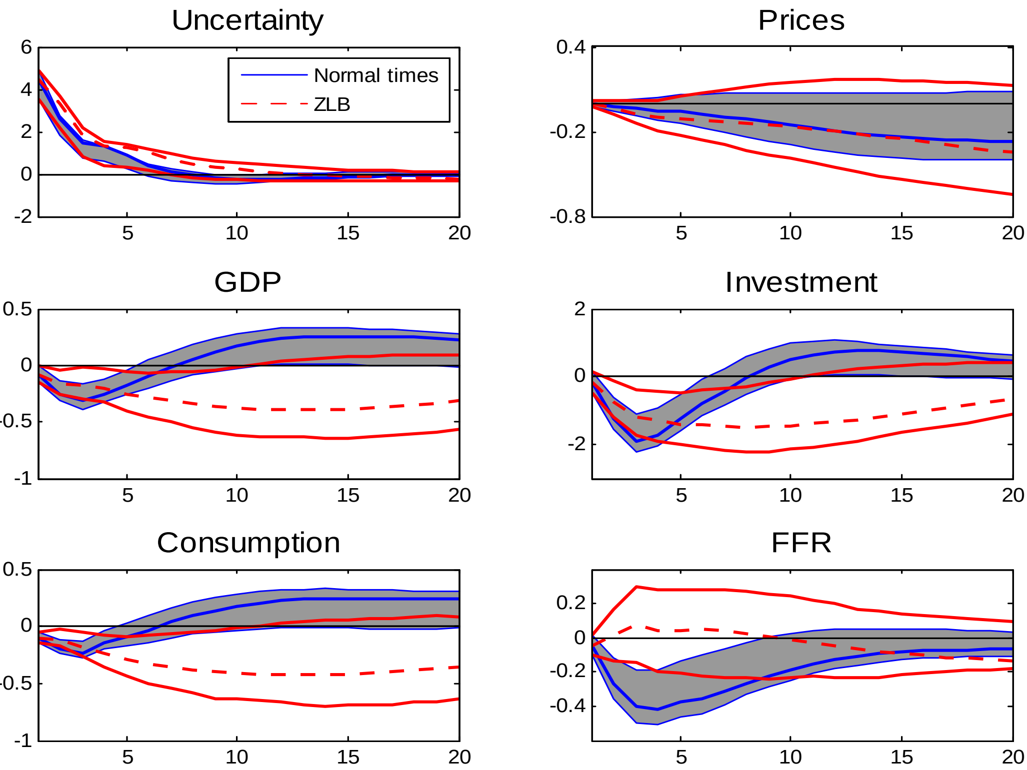

Figure 1: **Uncertainty shocks and the ZLB: Generalized Impulse Responses to a one-standard deviation uncertainty shock.** Uncertainty proxied by the VIX. Dashed-red line: ZLB regime. Solid-blue line: Normal times. Solid-red lines and gray areas: 68% confidence bands.

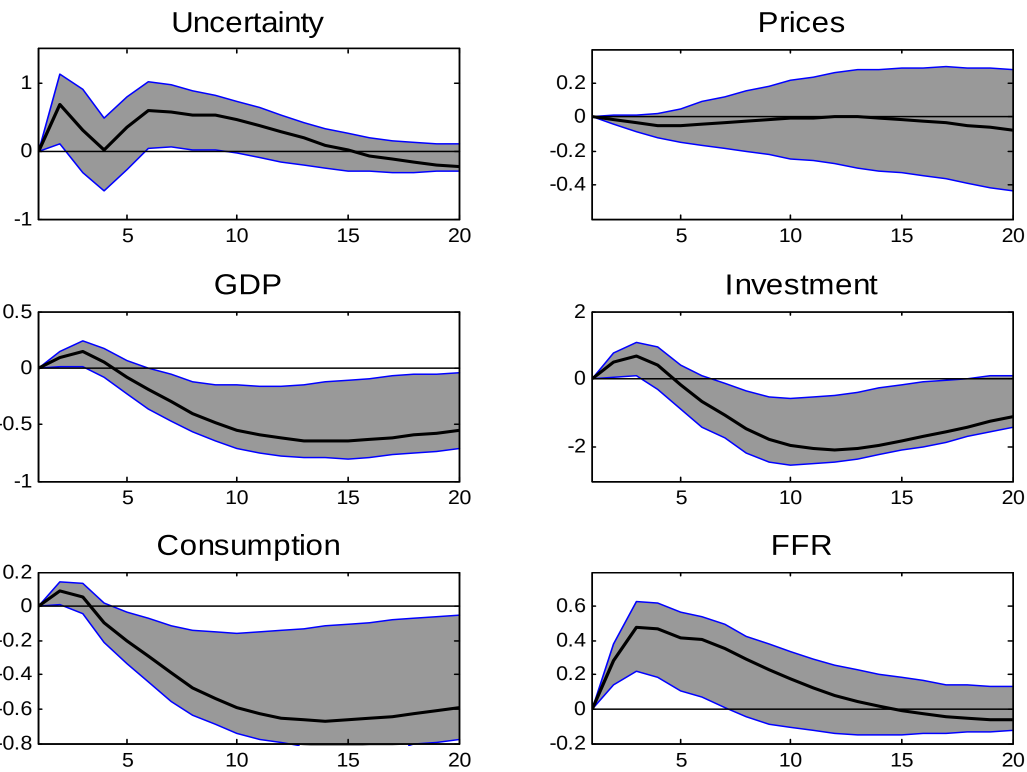

Figure 2: **Differences in Generalized Impulse Responses between ZLB and Normal times**. Uncertainty proxied by the VIX. Solid black line: Difference between the average GIRF to a one-standard deviation uncertainty shock in the ZLB state and in the Normal times state. Grey areas: 68% confidence bands.

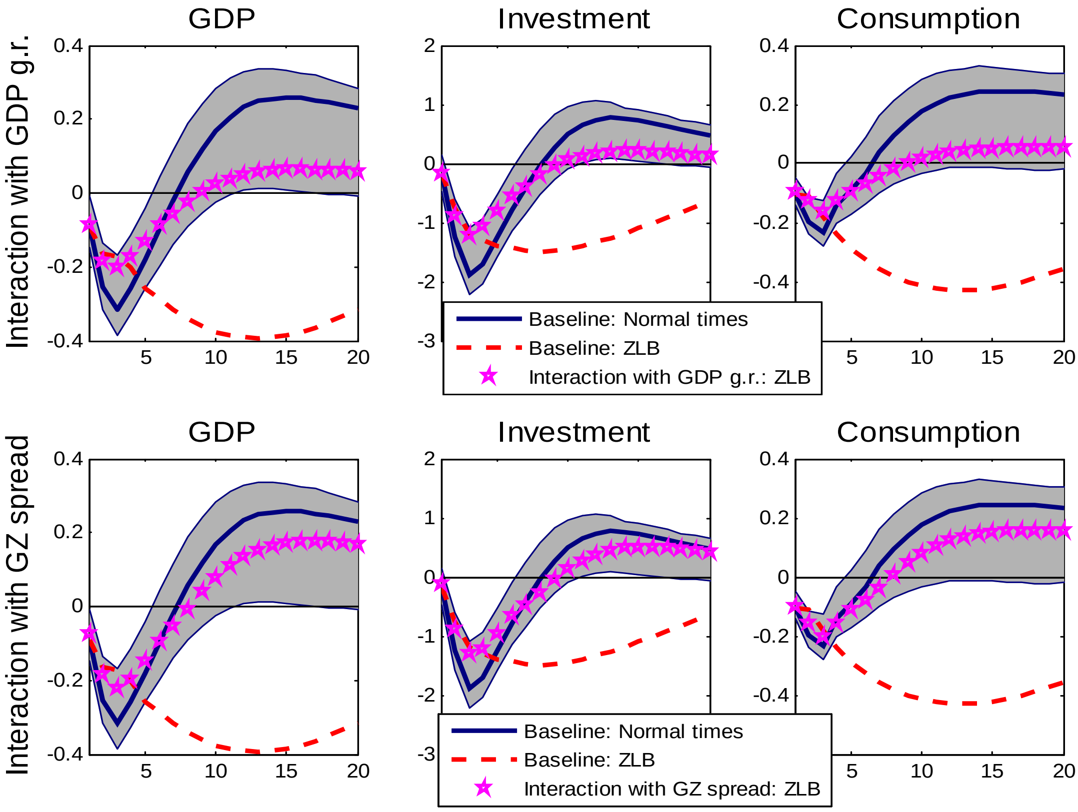

Figure 3: **Uncertainty shocks during the ZLB period: Role of the business cycle and financial frictions**. GIRFs to a one-standard deviation uncertainty shock in the ZLB state and in the Normal times state according to our baseline model and to models featuring alternative interaction terms. Solid-blue line: Baseline GIRF to a one-standard deviation uncertainty shock in the Normal times state. Dashed-red line: Baseline GIRF to a one-standard deviation uncertainty shock in the ZLB state. Starred-magenta lines refer to models featuring alternative interaction terms. Top row: Interaction terms involving uncertainty and real GDP growth rate. Bottom row: Interaction terms involving uncertainty and the GZ spread. Grey areas and solid-red lines: 68% confidence bands relative to the baseline case. Uncertainty proxied by the VIX.

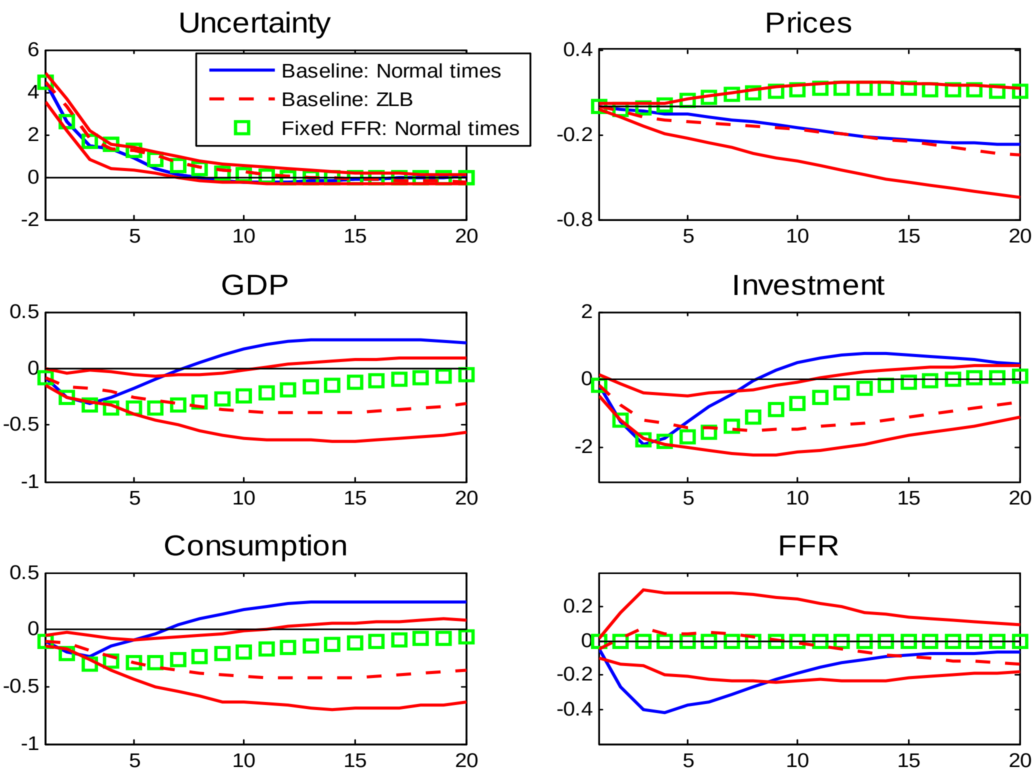

Figure 4: **Uncertainty shocks and Response of Real Activity: Effect of a Fixed Nominal Interest Rate in Normal Times**: **Generalized Impulse Responses to a one-standard deviation uncertainty shock**. Uncertainty proxied by the VIX. Dashed-red line: ZLB regime, baseline VAR. Solid-blue line: Normal times, baseline VAR. Solid-red lines: 68% confidence bands, baseline VAR. Green squares: Normal times conditional on a fixed interest rate regime.

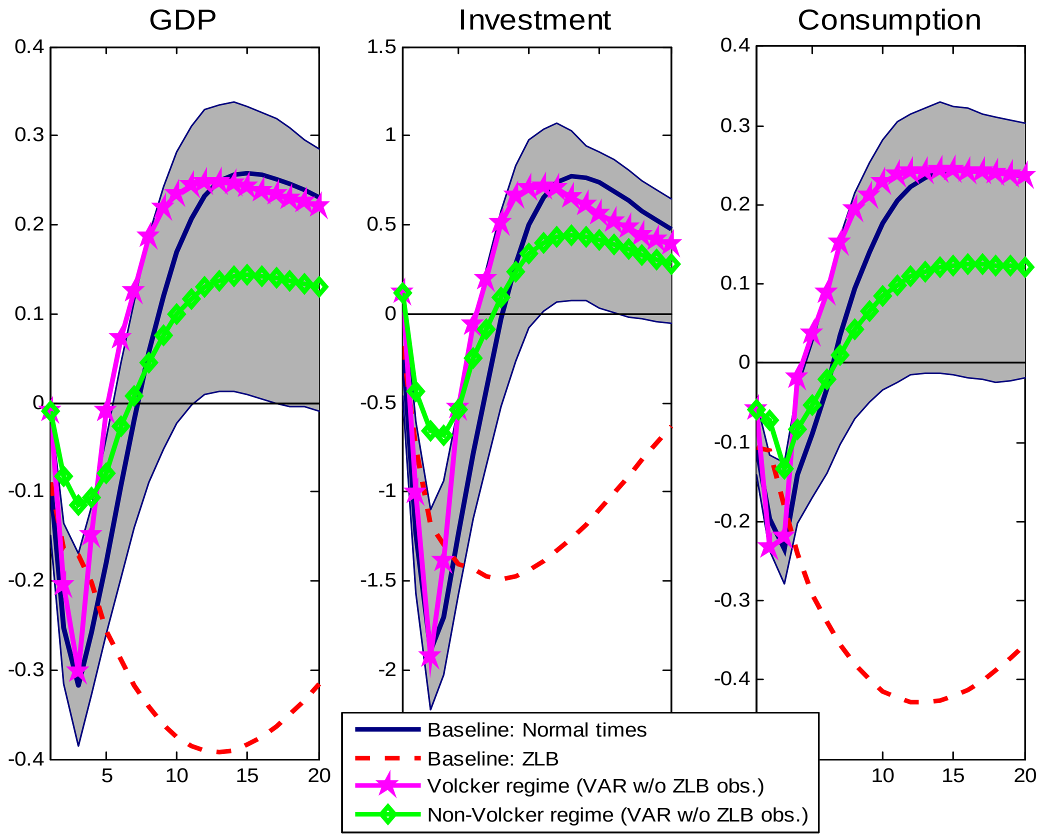

Figure 5: **Uncertainty shocks and Response of Real Activity: Role of the Volcker regime: Generalized Impulse Responses to a one-standard deviation uncertainty shock**. Uncertainty proxied by the VIX. Dashed-red line: ZLB regime, baseline VAR. Solid-blue line: Normal times, baseline VAR. Solid-red lines and gray areas: 68% confidence bands, baseline VAR. Magenta stars: Volcker regime, VAR estimated over the 1962Q3-2008Q3 sample. Green squares: Non-Volcker regime, VAR estimated over the 1962Q3-2008Q3 sample.

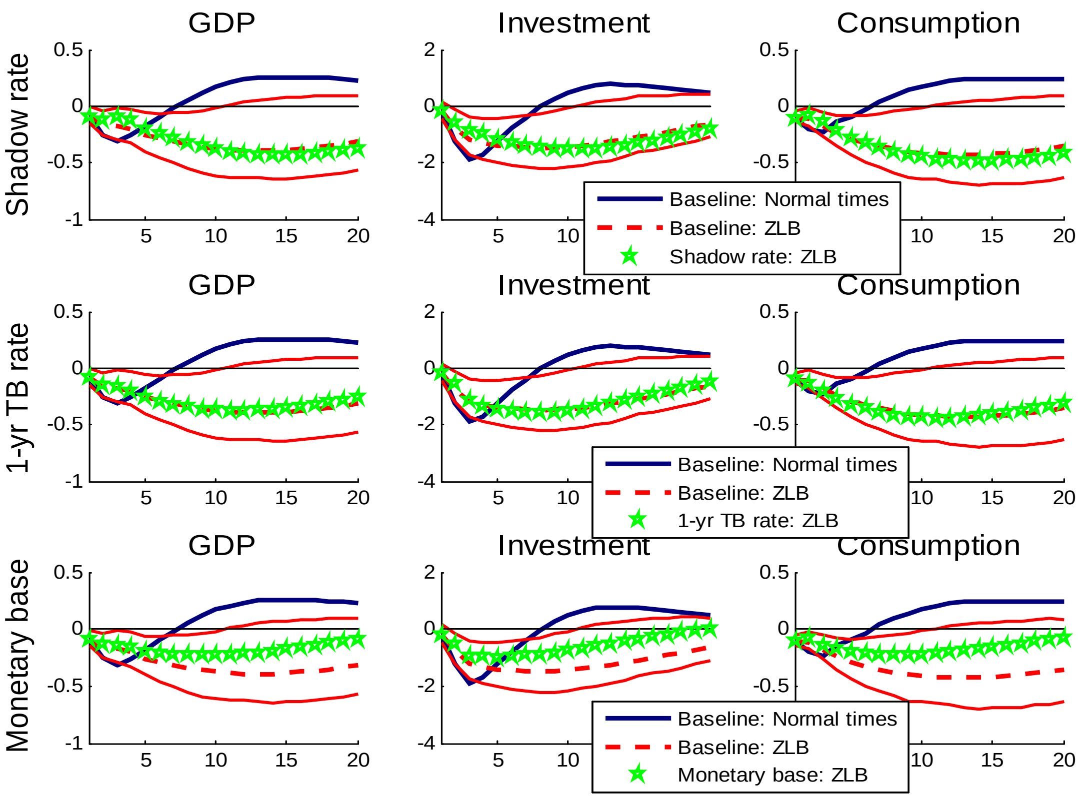

Figure 6: **Uncertainty shocks and the ZLB: Unconventional monetary policy.** Solid-blue line: Baseline GIRF to a one-standard deviation uncertainty shock in the Normal times state. Dashed-red line: Baseline GIRF to a one-standard deviation uncertainty shock in the ZLB state. Uncertainty proxied by the VIX. Solid-red lines: 68% confidence bands for the ZLB regime. Starred-green lines refer to unconventional monetary policy scenarios. Top row: GIRF to a one-standard deviation uncertainty shock in the ZLB state when the federal funds rate is replaced by the shadow rate in the otherwise baseline VAR. Middle row: GIRF to a one-standard deviation uncertainty shock in the ZLB state when the federal funds rate is replaced by the 1-year Treasury Bill rate rate in the otherwise baseline VAR. Bottom row: GIRF to a one-standard deviation uncertainty shock in the ZLB state when adjusted monetary base is added to the VAR as last variable of the vector.

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 $GIRF_{\mathbf{y}}(h, \delta, \boldsymbol{\omega}_{t-1})$ of the vector of endogenous variables $\mathbf{y}_t$, h periods ahead, for a given initial condition $\boldsymbol{\omega}_{t-1} = \{\mathbf{y}_{t-1}, ..., \mathbf{y}_{t-k}\}$, k is the number of VAR lags, and δ is the structural shock hitting at time t. Following Koop, Pesaran, and Potter (1996), such GIRF can be expressed as follows:

$$GIRF_{\mathbf{y}}(h, \delta, \boldsymbol{\omega}_{t-1}) = E[\mathbf{y}_{t+h} \,|\delta, \boldsymbol{\omega}_{t-1}] - E[\mathbf{y}_{t+h} \,|\boldsymbol{\omega}_{t-1}]$$

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

2. conditional on $\boldsymbol{\omega}_{t-1}$ and the structure of the model (1)-(2), we simulate the path $[\mathbf{y}_{t+h} \,|\boldsymbol{\omega}_{t-1}]^r$, $h = [0, 1, ..., 19]$ (which is, realizations up to 20-step ahead) by loading our VAR with a sequence of randomly extracted (with repetition) residuals $\widetilde{\mathbf{u}}^r_{t+h} \sim d(0, \widehat{\boldsymbol{\Omega}})$, $h = 0, 1, ..., H$,where $\widehat{\boldsymbol{\Omega}}$ 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 $\boldsymbol{\omega}_{t-1}$ and the structure of the model (1)-(2), we simulate the path $[\mathbf{y}_{t+h} \,|\delta, \boldsymbol{\omega}_{t-1}]^r$, $h = [0, 1, ..., 19]$ by loading our VAR with a perturbation of the randomly extracted residuals $\widetilde{\mathbf{u}}^r_{t+h} \sim d(0, \widehat{\boldsymbol{\Omega}})$ obtained in step 2. In particular, we Cholesky-decompose $\widehat{\boldsymbol{\Omega}} = \widehat{\boldsymbol{C}}\widehat{\boldsymbol{C}}'$, where $\widehat{\boldsymbol{C}}$ is a lower-triangular matrix. Hence,

we recover the orthogonalized elements (shocks) $\widetilde{\boldsymbol{\varepsilon}}_t^r = \widehat{\boldsymbol{C}}^{-1}\widetilde{\mathbf{u}}_t^r$. We then add a quantity $\delta > 0$ to the $\widetilde{\varepsilon^r}_{unc,t}$, where $\widetilde{\varepsilon^r}_{unc,t}$ is the scalar stochastic element loading the uncertainty equation in the VAR. This enable us to obtain $\widetilde{\boldsymbol{\varepsilon}}_t^r$, which is the vector of perturbed orthogonalized elements embedding $\widetilde{\varepsilon^r}_{unc,t}$. We then move from perturbed shocks to perturbed residuals as follows: $\widetilde{\mathbf{u}}_t^r = \widehat{\boldsymbol{C}}\widetilde{\boldsymbol{\varepsilon}}_t^r$. These are the perturbed residuals that we use to simulate $[\mathbf{y}_{t+h} \,|\delta, \boldsymbol{\omega}_{t-1}]^r$;

4. we compute the difference between paths for each simulated variable at each simulated horizon $[\mathbf{y}_{t+h} \,|\delta, \boldsymbol{\omega}_{t-1}]^r - [\mathbf{y}_{t+h} \,|\boldsymbol{\omega}_{t-1}]^r$, $h = [0, 1, ..., 19]$;

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., $\widehat{GIRF}_{\mathbf{y}}(h, \delta_t, \boldsymbol{\omega}_{t-1}) = \widehat{E}[\mathbf{y}_{t+h} \,|\delta, \boldsymbol{\omega}_{t-1}] - \widehat{E}[\mathbf{y}_{t+h} \,|\boldsymbol{\omega}_{t-1}]$, $h = [0, 1, ..., 19]$. If a given initial condition $\boldsymbol{\omega}_{t-1}$ leads to an explosive response (namely if this is explosive for most of the R sequences of residuals $\widetilde{\mathbf{u}}_{t+h}^r$, 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 $\boldsymbol{\omega}_t$ 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., $\boldsymbol{\omega}_{t-1}^s$ and $\boldsymbol{\Omega}_t^s$. 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

[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 $\boldsymbol{\omega}_{t-1}$ and a forecast horizon of interest z, the $GFEVD_{ij}$ that refers to a variable i and a shock j whose size is δ_j is given by:

$$GFEVD_{ij}(z, \boldsymbol{\omega}_{t-1}) = \frac{\sum_{h=1}^{z} GIRF_{y_i}(h, \delta_j, \boldsymbol{\omega}_{t-1})^2}{\sum_{j=1}^{n} \sum_{h=1}^{z} GIRF_{y_i}(h, \delta_j, \boldsymbol{\omega}_{t-1})^2} \qquad i, j = 1, ..., n \qquad \text{(A1)}$$

where h is an indicator keeping track of the forecast errors, and n denotes the number of variables in the vector $\mathbf{y}$.[4] Differently from Lanne and Nyberg (2016), in our case the object $GIRF_{y_i}(\cdot)$ 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 $\mathbf{y}$. 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:

[3] If dealing with a shorter sample, this reference is modified accordingly.

[4] Expression (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.

[5] The object $GIRF_{y_i}(\cdot)$ 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 $(\delta_1, \delta_2, ..., \delta_n) = (1, 1, ..., 1)$ in our algorithm in the previous Section;[6]

2. pick a history $\boldsymbol{\omega}_{t-1}$ from the set of all histories;

3. compute the $GIRF_{\mathbf{y}}(\cdot, \cdot, \boldsymbol{\omega}_{t-1})$ for each δ_j $(j = 1, ..., n)$ 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 $GFEVD_{ij}(z, \boldsymbol{\omega}_{t-1})$ for the particular forecast horizon z and history $\boldsymbol{\omega}_{t-1}$ 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 $GFEVD_{ij}(z, \cdot)$ 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 (2018) 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 (2018) 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]

[7] The 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.

[8] We 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.

[9] The 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 conducing an exercise in which the public debt-to-GDP ratio is embedded in our vector.[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 countercylicality in firms' markups.

inflation-output trade-off in that period. An exercise (available upon request) conducted by adding oil prices to our baseline vector confims the solidity of our findings.

[10] The debt-to-GDP ratio is taken from the Federal Reserve Bank of St. Louis' website and it is ordered first 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.[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).[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 (2017), Basu and Bundick (2015, 2017)). However, other contributions suggest

[11] Born and Pfeifer (2017) 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 (2017).

[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.[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".[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

[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.

[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, Castelnuovo, 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.

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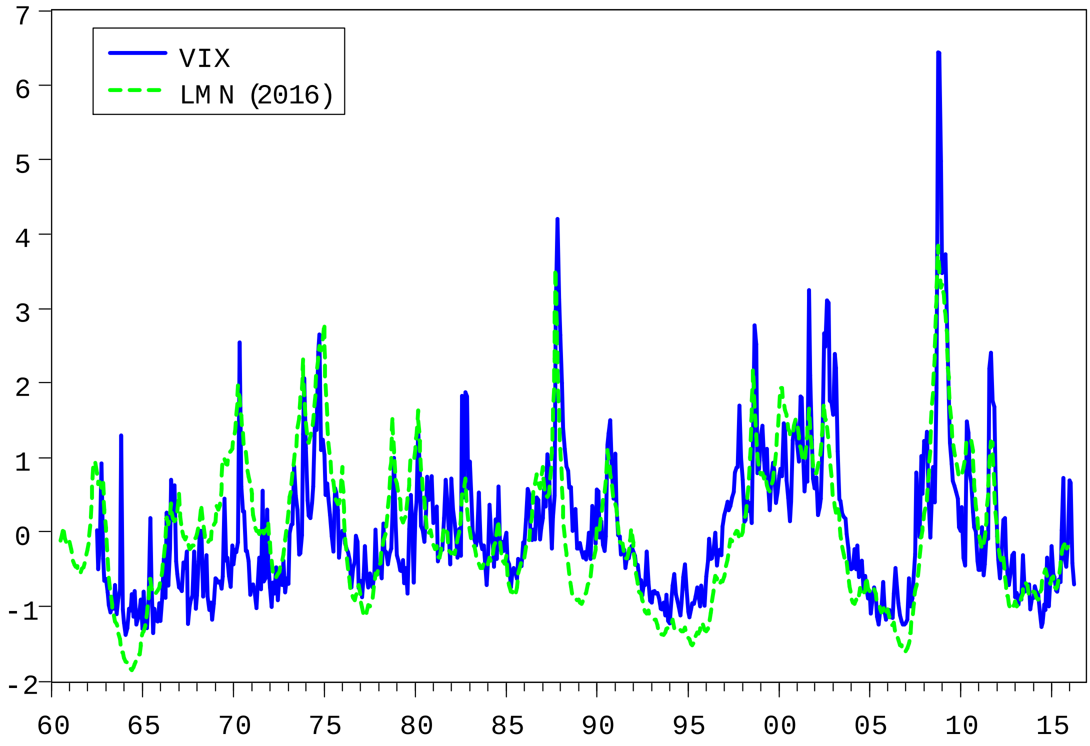

Figure A1: **Proxies for financial uncertainty.** VIX: Measure of implied volatility of stock market returns over the next 30 days commonly used in literature. LMN: Measure of financial uncertainty proposed by Ludvigson, Mah, and Ng (2016). The measure we consider refers to forecasts for the next month. Both measures are standardized (zero mean, unitary variance) to enhance comparability.

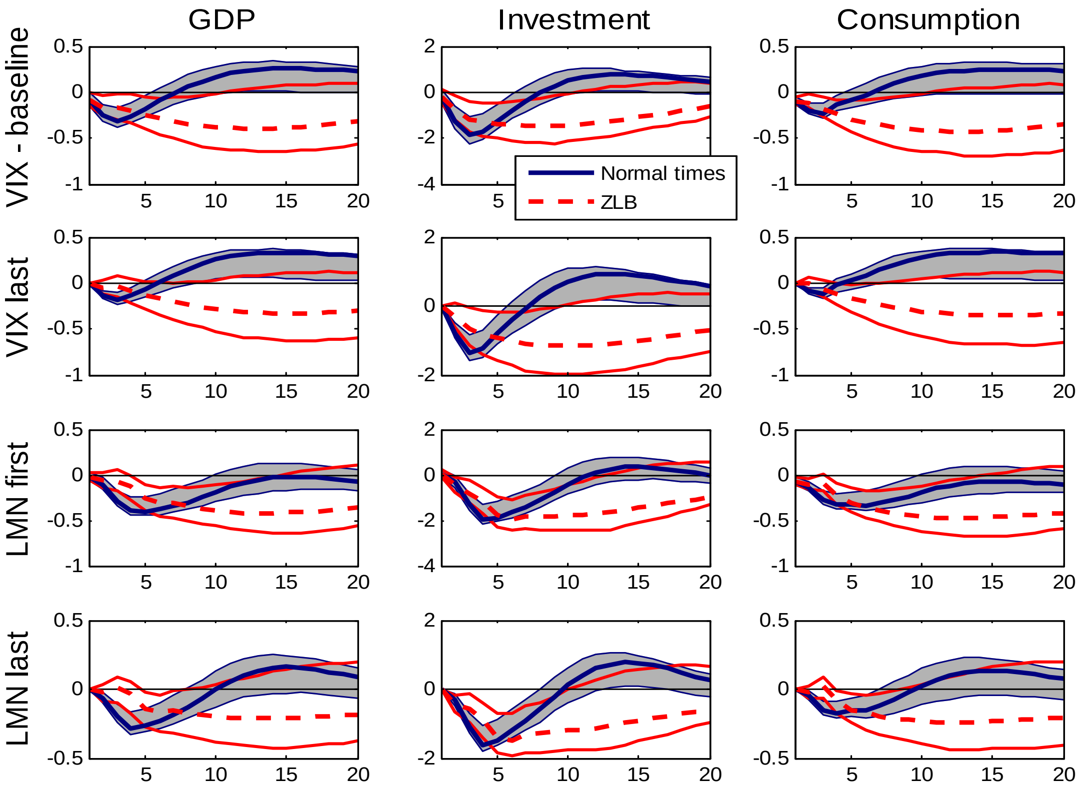

Figure A2: **Uncertainty shocks and the ZLB: Alternative measures/ordering of uncertainty.** GIRFs to a one-standard deviation uncertainty shock. Proxies of uncertainty: VIX and LMN (measure proposed by Ludvigson, Ma and Ng (2016)). Row 1: VIX ordered first. Row 2: VIX ordered last. Row 3: LMN ordered first. Row 4: LMN ordered last.

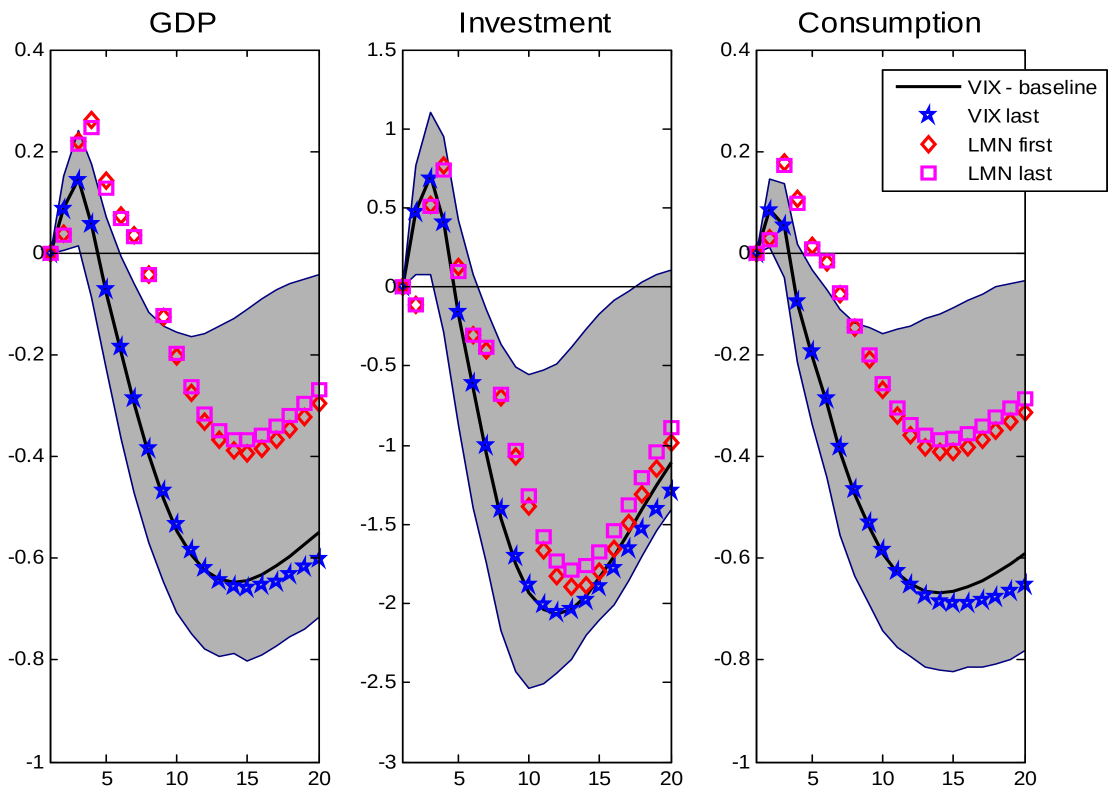

Figure A3: **Alternative measures/ordering of uncertainty: Differences in GIRFs between ZLB and Normal times**. Differences between the average GIRF to a one-standard deviation uncertainty shock in the ZLB state and in the Normal times state for different empirical models. Uncertainty proxied by the either the VIX or the LMN financial uncertainty proxy. Grey areas: 68% confidence bands relative to the baseline case.

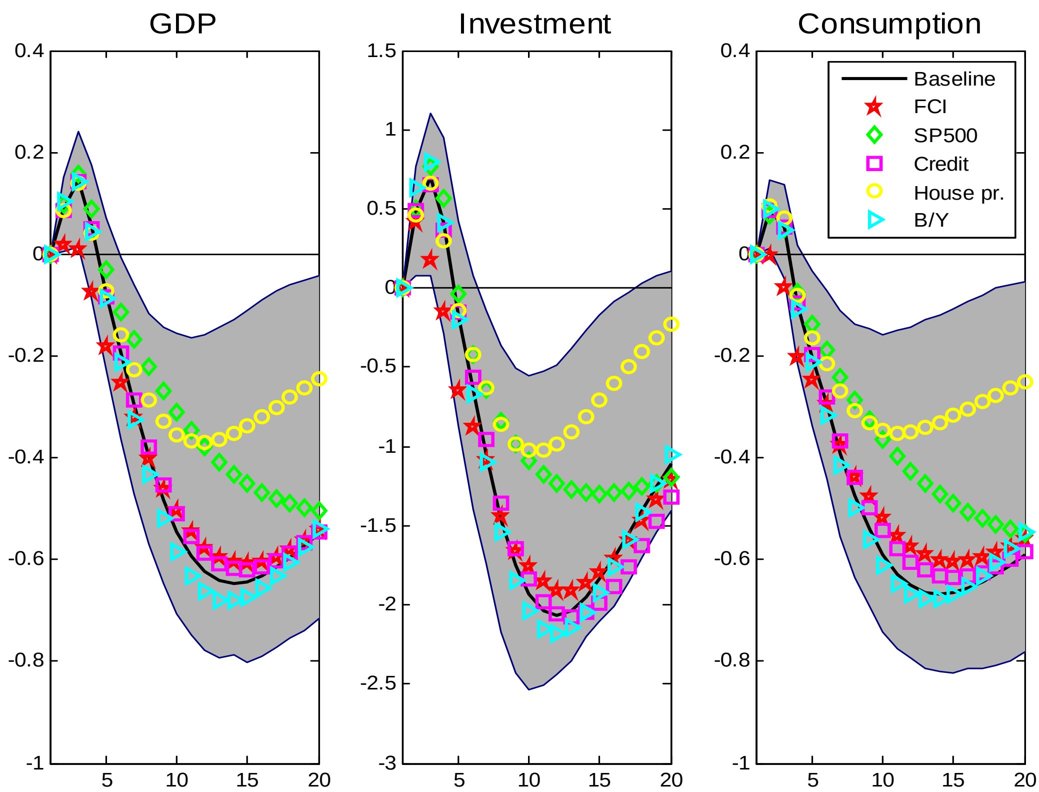

Figure A4: **Uncertainty shocks and the ZLB: Differences: Robustness checks**. Differences between the average GIRF to a one-standard deviation uncertainty shock in the ZLB state and in the Normal times state for different empirical models. Uncertainty proxied by the VIX. Grey areas: 68% confidence bands relative to the baseline case.

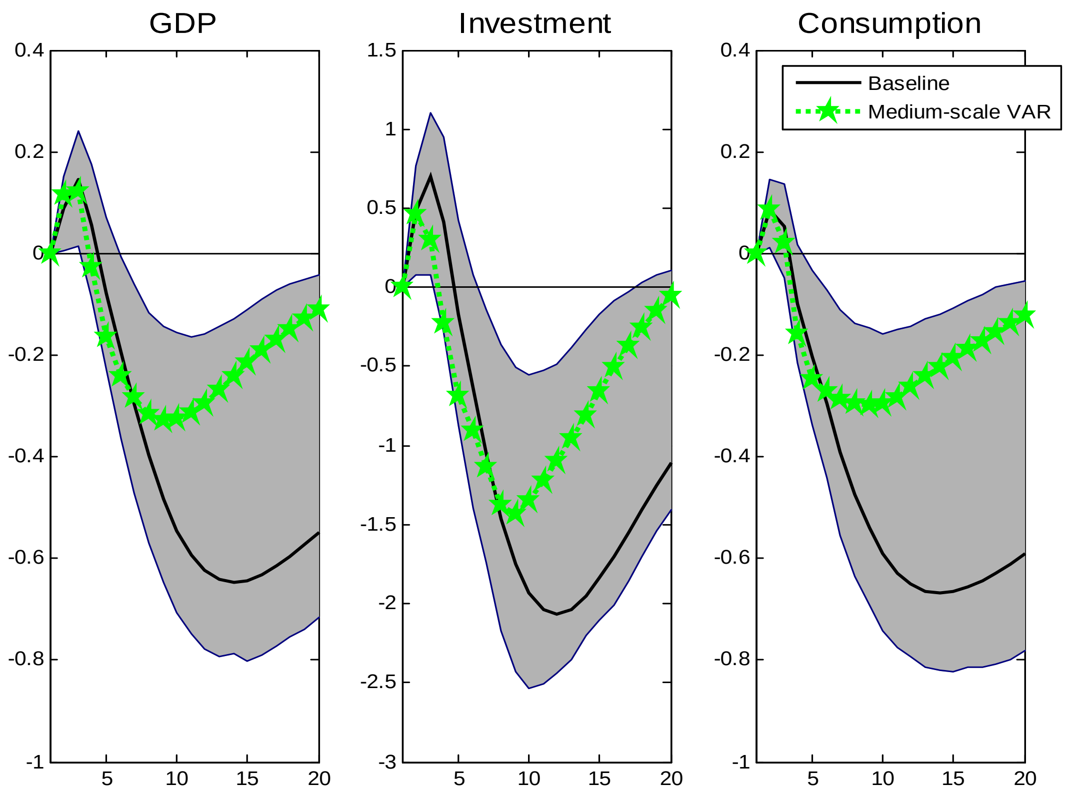

Figure A5: **Medium-scale VAR with credit, house prices, and debt/GDP ratio**. **Alternative measures/ordering of uncertainty: Differences in GIRFs between ZLB and Normal times**. Differences between the average GIRF to a one-standard deviation uncertainty shock in the ZLB state and in the Normal times 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.

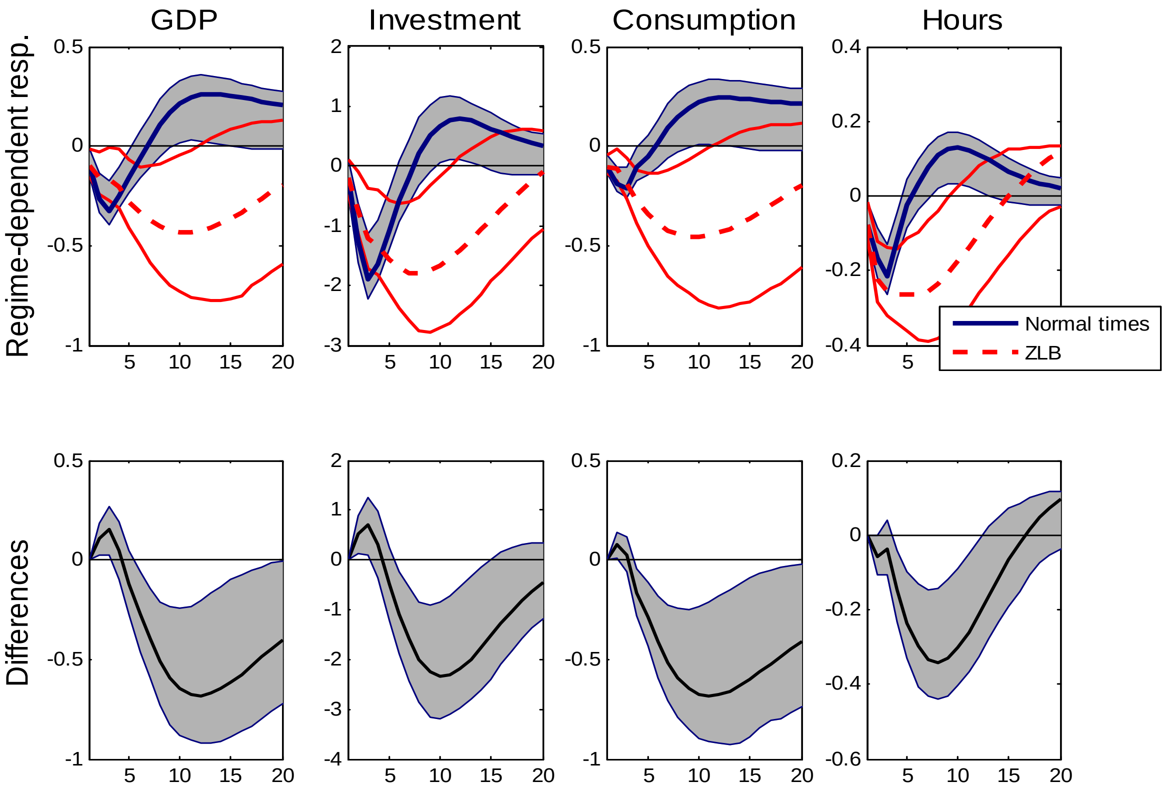

Figure A6: **Uncertainty shocks and Comovements: Generalized Impulse Responses to a one-standard deviation uncertainty shock**. Uncertainty proxied by the VIX. Upper panels: Dashed-red line: ZLB regime; solid-blue line: Normal times. Solid-red lines and gray areas: 68% confidence bands. Lower panel: 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.

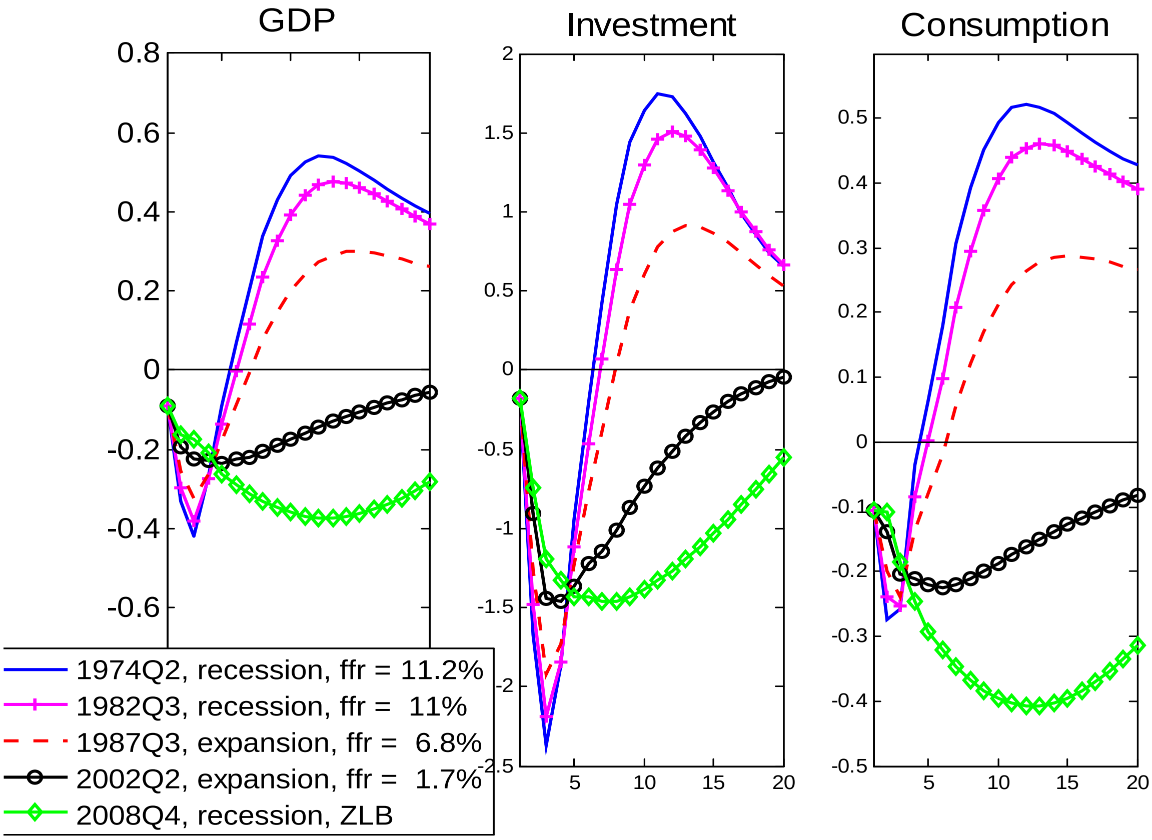

Figure A7: **Real effects of uncertainty shocks: Role of the monetary policy stance.** Uncertainty proxied by VIX. Impulse responses to a one standard deviation uncertainty shock for selected histories differing because of different levels of the federal funds rate.

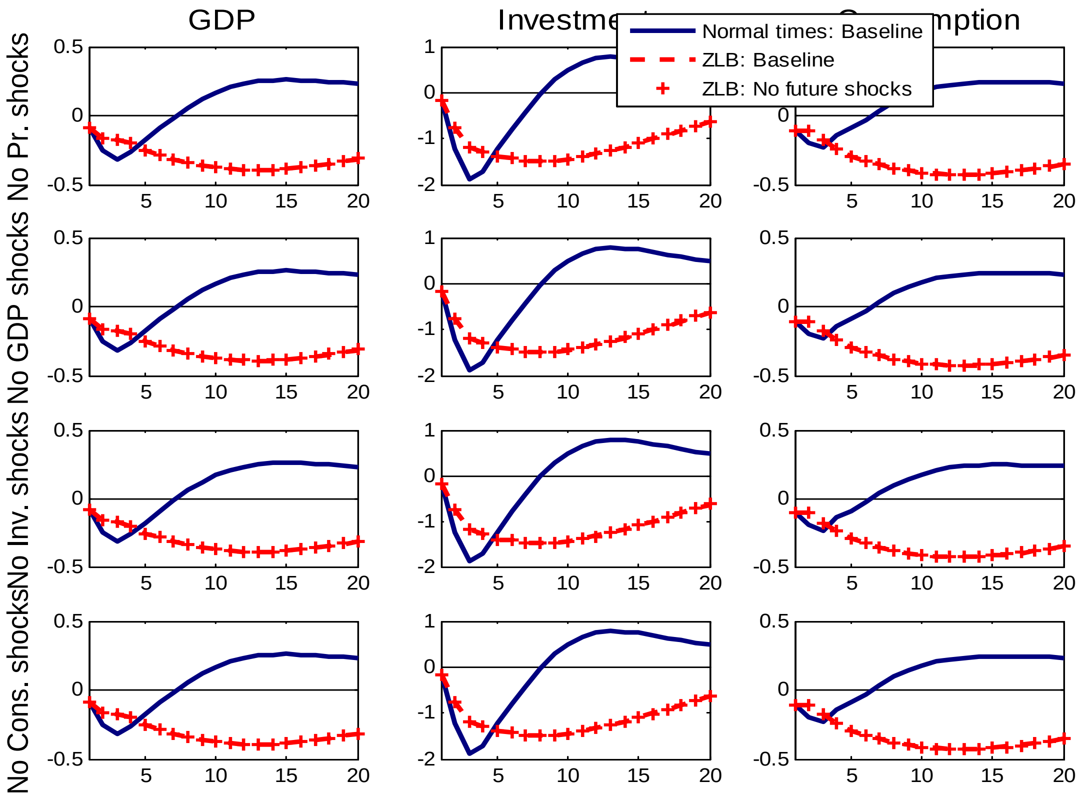

Figure A8: **GIRFs during the ZLB: Role of non-uncertainty shocks.** Comparison between GIRFs computed for the ZLB phase as in our baseline exercise and GIRFs computed by muting four non-uncertainty shocks one at a time. Muted shocks: "No Pr. shocks" refers to the case in which shocks to prices are muted: "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 whch shocks to consumption are muted.

Classific.	*Unc. indic.*	*Period*	$\Delta Y/Y$	$\Delta I/I$	$\Delta C/C$
Financial uncertainty	VIX	Normal times	-0.22	-0.19	-0.23
		ZLB	*-0.75*	*-0.63*	*-0.79*
	LMN	Normal times	-0.29	-0.26	-0.28
		ZLB	*-0.60*	*-0.55*	*-0.67*
Macroecon. uncertainty	JLN	Normal times	-0.46	-0.36	-0.47
		ZLB	*-0.74*	*-0.69*	*-0.75*
	RS	Normal times	-0.13	-0.12	-0.11
		ZLB	*-0.21*	*-0.36*	*-0.11*
	BBD	Normal times	-0.17	-0.14	-0.15
		ZLB	*-0.50*	*-0.45*	*-0.33*

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).