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

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Estimating the Real Effects of Uncertainty Shocks at the Zero Lower Bound*

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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. Our results show that the contractionary effects of uncertainty shocks are statistically larger when the ZLB is binding, with differences that are economically important. Such differences are shown not to be driven by the contemporaneous occurrence of the Great Recession. 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 codes: C32, E32.

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1 Introduction

Uncertainty is widely recognized as one of the major 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.[1] Theoretically, uncertainty can exert contractionary effects on real activity via different channels, including "real option" effects affecting investment in presence of adjustment costs or partial irreversibilities, and "precautionary savings" effects influencing consumption if agents are risk averse (for a survey, see Bloom, Fernández-Villaverde, and Schneider (2013)).

Unsurprisingly, fluctuations in uncertainty represent a major challenge for policymakers.[2] Focusing on monetary policy, an increase in uncertainty naturally calls for a cut in the policy rate. Since December 2008, however, the U.S. federal funds rate has hit the zero lower bound (ZLB henceforth).[3] Table 1 documents the correlation between different business cycle indicators (real GDP, investment, and consumption, all expressed in quarterly growth rates) and the VIX (a commonly used proxy of uncertainty). It does so for two different phases of the U.S. post-WWII economic history, i.e., "Normal times", in which the federal funds rate was unconstrained below, and "Zero Lower Bound", in which the federal funds rate hit and stayed at its bottom value. A clear fact arises. The negative correlation between these business cycle indicators and uncertainty just tripled since the end of 2008 (for a similar evidence, see Plante, Richter, and Throckmorton (2014)). This stylized fact holds true even if alternative proxies for uncertainty such as those recently proposed by Jurado, Ludvigson, and Ng (2015) and Rossi and Sekhposyan (2015) are considered.[4] Interestingly, these

[1] See, among others, Bloom (2009), Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011), Gourio (2012), Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2013), Baker, Bloom, and Davis (2013), Bachmann, Elstner, and Sims (2013), Leduc and Liu (2013), Gilchrist, Sim, and Zakrajsek (2013), Colombo (2013), Mumtaz and Surico (2013), Mumtaz and Zanetti (2013), Nodari (2014), Caggiano, Castelnuovo, and Groshenny (2014), Christiano, Motto, and Rostagno (2014), Born and Pfeifer (2014), Orlik and Veldkamp (2014), Istrefi and Piloiu (2015), and Mecikovsky and Meier (2015).

[2] 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."

[3] This has also forced the Federal Reserve to implement a set of unconventional policy moves. This paper focuses on conventional monetary policy in normal times and at the zero-lower bound. For a discussion on the effectiveness of unconventional policy interventions, see Bernanke (2012) and the literature cited therein.

[4] Jurado, Ludvigson, and Ng (2015) develop a measure of uncertainty which is the common compo-

correlations are in line with the predictions coming from the theoretical contributions by Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2013), Johannsen (2013), Nakata (2013), and Basu and Bundick (2014, 2015). These papers employ New Keynesian general equilibrium models and reach the same conclusion, i.e., when monetary policy is constrained by the ZLB, uncertainty shocks generate a much larger and persistent drop in real activity.

In spite of the obvious relevance of this issue from a policy and modeling standpoints, no empirical analysis explicitly modeling the nonlinearity of the real effects of uncertainty shocks due to the ZLB has been proposed so far.[5] This paper addresses this issue by estimating a nonlinear Interacted-VAR (I-VAR) with post-WWII quarterly U.S. data. Relative to alternative nonlinear specifications, the I-VAR is particularly appealing in this context. First, it parsimoniously captures the nonlinearity we are interested in, i.e., the possibly different responses of real variables to uncertainty shocks in normal vs. ZLB times. A parsimonious approach is desirable here, given the limited amount of observations belonging to the ZLB state. Second, the I-VAR is a simpler framework than those typically used in the literature. In fact, it does neither require the estimation of transition functions, unlike Smooth Transition VARs, nor latent factors, which are a feature of Regime-Switching VARs. Relative to Time-Varying Parameters VARs, it does not require setting priors, and it is less computationally intensive.

We use the I-VAR framework to model a standard set of macroeconomic variables including measures of real activity (real GDP, consumption, investment), prices (the GDP deflator), and the policy rate as well as a widely used proxy of uncertainty, the VIX, which is a measure of implied stock market volatility.[6] Put it simply, our I-VAR model augments an otherwise standard linear VAR with an interaction term that captures a proxy for uncertainty, which is the variable we want to shock, and the federal funds rate, which is the one that identifies the two states we want to model, i.e., the

nent of the volatility of the forecast errors computed for a large set of U.S. macroeconomic variables. Rossi and Sekhposyan (2015) employ Survey of Professional Forecasters data to construct an index based on the location of a given real GDP forecast error over its empirical distribution. Section 4 deals with these measures in greater detail.

[5] Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2013), Johannsen (2013), Basu and Bundick (2014), Nodari (2014), and Caggiano, Castelnuovo, and Groshenny (2014) propose VAR investigations dealing with impulse responses estimated over different samples including or excluding the ZLB.

[6] 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.

"Normal times" and "ZLB" states. Crucially, the federal funds rate is endogenously modeled in our analysis. This implies that the dynamic responses of the endogenous variables to uncertainty shocks must be computed as fully nonlinear Generalized Impulse Response Functions (GIRFs) à la Koop, Pesaran, and Potter (1996) and Kilian and Vigfusson (2011).

Our main results can be summarized as follows. First, in line with most empirical papers on the real effects of uncertainty shocks, we find that heightened uncertainty induces a contraction in real activity. This holds true in both states of the economy, a finding which suggests that uncertainty should be a concern for policymakers also in tranquil times. 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. This stronger effect is particularly evident in the response of investment. This result nicely squares with the theoretical literature that has proposed models in which the value of investment opportunities changes with the level of uncertainty because of some form of adjustment costs or irreversibilities (see, e.g., Bernanke (1983), Hassler (1996), Bloom, Bond, and Reenen (2007), Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014)). Third, different proxies of uncertainty are found to lead to different shapes of the response of investment, consumption, and output. In particular, the VIX implies a drop-rebound-overshoot type of response in normal times but not in presence of the ZLB, while the proxies for uncertainty proposed by Jurado, Ludvigson, and Ng (2015) and Rossi and Sekhposyan (2015) imply a persistent, hump-shaped response of these variables in both states. Fourth, our main result, i.e., contractionary effects of uncertainty shocks are greater when the economy is at the zero lower bound, turns out to be robust to the inclusion of a number of financial and real variables in our otherwise baseline model (measures of financial stress, stock prices, house prices, and longer-term interest rates). Fifth, an exercise conducted by contrasting impulse responses to uncertainty shocks in different recessionary phases of the U.S. business cycle confirms the specificity of the ZLB period as the one associated to the largest real effects triggered by uncertainty shocks. A possible interpretation for this result is that longer-term interest rates are less sensitive to policy moves in the proximity of the ZLB.

The aforementioned findings are relevant both from a modeling standpoint and from a policy perspective. From a modeling standpoint, our contribution offers support to the theoretical models recently designed to understand the effects of uncertainty shocks in presence of the ZLB (Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-

Ramírez (2013), Johannsen (2013), Nakata (2013), and Basu and Bundick (2014, 2015)). Policy-wise, Bloom (2009) advocates policies and reforms designed to respond to (or avoid the occurrence of) second-order moment shocks. 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) 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 non-linear framework and the data employed in the empirical analysis. Section 4 documents our main results and a number of robustness checks. Section 5 concludes.

2 Relation to the literature

Our paper joins other contributions that have recently investigated the role of uncertainty in a regime-specific fashion. Enders and Jones (2013) work with univariate nonlinear models to isolate potentially different effects of uncertainty shocks in presence of high vs. low uncertainty. Bijsterbosch and Guérin (2013) follow a two-step approach, i.e., they first identify episodes of high uncertainty in the U.S. modeling measures of uncertainty via a Markov-Switching approach, and then regress a number of macroeconomic and financial indicators on a "high uncertainty dummy" constructed in the first step. Caggiano, Castelnuovo, and Groshenny (2014) use a Smooth-Transition VAR to estimate the response of unemployment to uncertainty shocks in recessions. Caggiano, Castelnuovo, and Nodari (2015) 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) use the Chicago Fed's Financial Condition Index as transition variable to isolate periods in which financial markets are in distress, with the aim of checking whether the real effects of uncertainty shocks depend on the level of financial markets' strain. Ricco, Callegari, and Cimadomo (2014) use a Threshold-VAR to study the effects of fiscal policy shocks in presence of fiscal policy uncertainty. Our paper is complementary to those cited here in that it focuses on the nonlinearity implied by the policy rate near the ZLB.

Methodologically, I-VARs have recently been employed to study nonlinear interactions along a variety of dimensions. Towbin and Weber (2013) study a panel of open-economy countries to investigate how the reaction of output and investment to foreign shocks is influenced by variables such as external debt, import structure, as well as the exchange rate regime in place. Aastveit, Natvik, and Sola (2013) investigate the effectiveness of monetary policy shocks in high vs. low uncertainty scenarios. Sá, Towbin, and Wieladek (2014) focus on the effects of capital inflows. They study how such effects are affected by the mortgage market structure and the different securitization in place in different countries. To our knowledge, ours is the first paper that fully endogeneizes the conditioning variable which determines the switch between the states of interest. The closest paper to ours is Pellegrino (2014). He studies the real effects of monetary policy shocks in presence of time-varying uncertainty by computing fully nonlinear GIRFs. Our paper shares the same methodology as Pellegrino's (2014) but tackles a different research question, i.e., the effects of uncertainty shocks in normal times vs. when the ZLB is binding.

The interaction between uncertainty shocks and the ZLB in new-Keynesian frameworks has recently been studied by Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2013), Johannsen (2013), Nakata (2013), and Basu and Bundick (2014, 2015). Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2013) show that fiscal policy uncertainty shocks trigger a larger negative effect on a number of real activity indicators due to sticky prices and countercyclical markups. In presence of a binding ZLB, the real interest rate cannot fall enough to fully tackle the recessionary effects of a spike in fiscal policy uncertainty. Johannsen (2013) shows that short-run and long-run fiscal policy uncertainty has large adverse effects on investment and consumption only when the economy is near the ZLB. This is because of the deflationary effects of fiscal policy uncertainty. An increase in fiscal policy uncertainty leads risk averse households to increase their desire to work and save, which in turn reduces inflation. When the ZLB is binding, the deflation cannot be not fully tackled by a Taylor-rule type of systematic monetary policy. As a consequence, a higher equilibrium real interest rate is expected, which depresses investment and consumption and generates a stronger contraction. Nakata (2013) studies the role played by increases in the variance of shocks to the discount factor process, which he interprets as increases in uncertainty. He finds a substantially larger reduction in consumption, output, and inflation when the ZLB is in place due to a higher expected real interest rate and lower expected marginal costs. Basu and Bundick (2014) compare the predictions of RBC and new-Keynesian models regarding consumption, investment, and output in response to an uncertainty shocks over technology and preferences. They show that uncertainty shocks have contractionary effects that are magnified by the constraint imposed by the ZLB on stabilizing conventional monetary policy. They also show that flexible prices RBC models with constant markups are ill-suited to replicate business-cycle comovements among these variables generated by uncertainty shocks because of workers' willingness to supply extra-hours to keep their consumption level up. Differently, countercyclical markups due to sticky prices predict lower equilibrium hours worked, therefore enabling new-Keynesian models to capture those comovements. Basu and Bundick (2015) use a New Keynesian model with nominal rigidities to explore the interaction involving uncertainty shocks, a Taylor rule-type of policy conduct, and a binding ZLB. They show that uncertainty shocks can generate a substantial, and potentially catastrophic, contraction in real activity in presence of a binding ZLB if a central bank sticks to a Taylor rule. This is due to the central bank's inability to face negative shocks, which contrasts its ability to face positive ones. Such an asymmetry implies that the future expected mean of target variables will be lower, whereas their volatility will be magnified. This enhances precautionary savings, therefore lowering even more consumption, output, and inflation. As a result, agents expect a high real interest rate, something which creates a "contractionary bias", whose size is magnified by heightened uncertainty. Basu and Bundick (2015) show that optimal monetary policy can attenuate the effects of the endogenous volatility generated by the ZLB by committing to a lower path of future nominal interest rates. Such a state-contingent policy stabilizes the household's expected distribution of consumption and importantly limits the recessionary effects of uncertainty shocks. Evans, Fisher, Gourio, and Krane (2015) work with AD/AS models and study two channels which make risk management by the central bank optimal, i.e., the "expectations" channel and the "buffer stock" channel. The expectations channel arises when a non-zero likelihood of a binding ZLB in the future leads to lower expected inflation and output today, therefore calling for a counteracting policy easing today. The buffer stock channel arises when persistent processes for output and inflation suggest the opportunity to induce an output and inflation boom today to reduce the likelihood and severity of a binding ZLB tomorrow. Then, in presence of an already binding ZLB and expectations of a future build up of output and inflation, a delayed liftoff of the policy rate is the optimal strategy to implement. Evans, Fisher, Gourio, and Krane (2015) also find a number of proxies for uncertainty added to an otherwise standard Taylor rule estimated with U.S. data to be statistically significant. Hence, uncertainty is found to be important to explain the evolution of the federal funds rate in the U.S. over and above the impact that uncertainty may have had directly on expected inflation and output.

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, an otherwise standard linear VAR including measures of real activity, prices, monetary policy stance, and a proxy for uncertainty is augmented with an interaction term. The interaction term involves two endogenously modeled variable, i.e., uncertainty, which is the variable whose exogenous variations we want to identify, and the federal funds rate, which is the proxy for the monetary policy stance.[7] This latter variable is used as a conditioning variable to discriminate between the "Normal times" state (in which the ZLB is not binding) and the "ZLB" state (in which the ZLB is *de facto* binding as regards downward movements of the policy rate).

Our Interacted-VAR reads as follows:

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

$$\mathbf{u}_t \sim N(0, \boldsymbol{\Omega}) \tag{2}$$

where $\mathbf{y}_t$ is the $(n \times 1)$ vector of endogenous variables, $\boldsymbol{\alpha}$ is the $(n \times 1)$ vector of constant terms, $\mathbf{A}_j$ are $(n \times n)$ matrices of coefficients, and $\mathbf{u}$ is the $(n \times 1)$ vector of error terms, whose covariance matrix is $\boldsymbol{\Omega}$. The term in brackets makes an otherwise standard linear VAR a nonlinear I-VAR. The interaction terms include the $(n \times 1)$ vectors of coefficients, $\mathbf{c}_j$, a measure of uncertainty, unc, and the federal funds rate ffr, which is our measure of policy stance.[8] The equations are estimated in levels to preserve

[7] The use of the federal funds rate as an indicator of monetary policy stance has been established by Bernanke and Mihov (1998), and it is widespread in the applied macroeconomic literature (see, e.g., Christiano, Eichenbaum, and Evans (1999)).

[8] The federal funds rate takes values close to zero in 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

the cointegrating relationships among the modeled variables. However, our results are virtually unchanged when estimating our VAR in growth rates (evidence available upon request).

Our I-VAR can be seen as a special case of a Generalized Vector Autoregressive (GAR) model (Mittnik (1990)). As pointed out by Granger (1998) and, more recently, Aruoba, Bucola, and Schorfheide (2013), GAR models might feature instability of the impulse responses when squares or higher powers of the interactions terms are included among the covariates. Our nonlinear framework appears not to suffer from instabilities. This is confirmed by our GIRFs, which are clearly non-explosive. This is due to the fact that we model interaction terms in a parsimonious manner, and have no squares or higher powers among our regressors.

Relative to alternative nonlinear specifications (e.g. Smooth-Transition VARs, Threshold-VARs, Time-Varying Parameters VARs, nonlinear Local Projections), the I-VAR presents several advantages in our context. First, STVAR models are well-suited for modeling regime changes that are not abrupt. The effective federal funds rate in the U.S. moved from 5.25% in July 2007 down to 0.15% in December 2008, a quite abrupt change indeed. In a VAR context, abrupt changes can be modeled by T-VARs. However, in our case one problem with estimating T-VARs is the relatively small number of observations available for one of the two states, i.e., the ZLB state. The I-VAR allows instead to use all available observations for estimation while preserving nonlinearities in the impulse responses. An alternative specification that would allow us to deal with unbalanced observations between the two states would be the TVP-VAR model. Although a TVP-VAR framework can effectively be used to model the Zero Lower Bound (see Chan and Strachan (2014) for a recent application), the I-VAR has the advantages of not requiring setting priors for estimation and being less computationally intensive. Finally, a competing framework to nonlinear VARs that would allow for abrupt regime changes would be the nonlinear local projection model à la Jordà (2005). Nonlinear Local Projections have been recently used by Ramey and Zubairy (2014) in a related context, i.e., to examine the role of the ZLB for government spending shocks. Relative to nonlinear local projections, the I-VAR model has four main advantages. First, it allows to endogenously model the federal funds rate (our conditioning variable) and hence to obtain

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, something that ensures that ZLB observations are also theoretically nonzero) returns results virtually equivalent to those documented in this paper.

proper (generalized) impulse responses. Second, it allows to obtain impulse responses that are not erratic at long horizons. Third, it enables us to model the predictable part of uncertainty and isolate the exogenous, unpredictable one. Fourth, and most importantly in our context, local projections allow to obtain only the average reaction of the economy to an exogenous shock in a given state, whereas our I-VAR allows us to obtain dynamic responses to a shock for each given initial quarter in the sample. This is particularly important to disentangle the role played by the ZLB in transmitting an uncertainty shock to real activity from the role played by other potentially relevant initial conditions, e.g., the stance of the business cycle.

3.2 Generalized Impulse Response Functions

Relative to the standard specification of I-VAR models, ours implies an important generalization. I-VARs typically used in the literature employ interaction terms which include variables that are not endogenously modeled. In such a context, the dynamic responses of the endogenous variables to the shock of interest in a given state are conditionally linear, i.e., they can be calculated by keeping the interaction variables fixed to a given value for the horizon of interest. Such an approach is sensible in absence of endogeneity of the interaction variables. However, this simplifying assumption would clearly be ill-suited for our analysis, given that the policy rate is likely to react to uncertainty shocks. This implies that the economy can endogenously switch from one regime to the other, within the horizon of interest. Consider as an example the response of real activity to heightened uncertainty. Even though the economy starts in normal times, the contraction that follows the negative shock might induce monetary authorities to lower the interest rate enough to drive the economy in a ZLB-regime.

We correctly account for the intrinsic nonlinearity of the model by computing Generalized Impulse Response Functions (GIRFs) à la Koop, Pesaran, and Potter (1996). GIRFs enable us to keep track of the dynamic responses of all the endogenous variables of the system as well as the evolution of the value of the interaction terms in our framework. Importantly, in computing GIRFs, we follow Kilian and Vigfusson (2011) and work with orthogonalized residuals, which enable us to talk about "uncertainty shocks". With respect to previous contributions dealing with I-VARs, this is a modeling novelty which, to our knowledge, we share with Pellegrino (2014).

Our dynamic responses allow us to fully take into account the nonlinearity of the system we deal with. This means that, on top of the size and the sign of the shock, GIRFs will depend on the initial conditions of the system (Koop, Pesaran, and Potter (1996)). We unveil the importance of initial conditions in Section 4.[9] 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, all taken in logs. Prices are measured by (the log of) 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 (FRED2 database).[10] The sample size is 1962Q3-2014Q3. 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. Our baseline measure of uncertainty is the VIX, which is a measure of implied stock market volatility.[11] This choice is justified by a number of reasons. First, it is a standard choice in the literature, something which ensures that our results are not driven by peculiarities of the selected proxy for uncertainty (see, e.g., Bloom (2009) and Leduc and Liu (2013)). Second, stock market volatility is highly correlated with micro-based, theoretically-relevant measures of dispersion such as establishment-level TFP dispersion (Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014)), macro-based proxies such as GDP growth forecasters' disagreement (Bloom (2014)), and economic policy uncertainty (Baker, Bloom, and Davis (2013)). Third, while being partly endogenous (see, e.g., Bekaert, Hoerova, and Lo Duca (2013)), the bulk of the stock market volatility is driven by exogenous components (Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014)). Section 4 shows that our results are robust to the employment of alternative measures of uncertainty such as

[9]Some experiments (not shown here for the sake of brevity) conducted with differently signed and sized uncertainty shocks suggest that changes in the sign and the magnitude of such shocks play a very minor role in our empirical application.

[10]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.

[11]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).

those recently proposed by Jurado, Ludvigson, and Ng (2015) and Rossi and Sekhposyan (2015).

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.[12] 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 as first is quite common in reduced-form models used to study the real effects of uncertainty shocks, since it allows real variables to react on impact. In the robustness checks section, we will consider also the case in which uncertainty is ordered last., which shows that our results are robust to this variation of our baseline case.

Since any nonlinear model would be misspecified if the true data generating process is linear, we provide some empirical evidence at the multivariate level in favor of non-linearity, 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 $\chi_{18} = 29.58$ with an associated p-value of 0.04.[13]

The interaction term involving the proxy for uncertainty and the federal funds rate is meant to capture in a parsimonious manner the possible nonlinearities in the impulse responses to an uncertainty shock due to different states identified via, and indexed by, different values of the federal funds rate. In principle, the I-VAR could be enriched by including several other interaction terms involving the federal funds rate, i.e., the

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

[13] Similar results are obtained with alternative measures of uncertainty. In particular, the Jurado, Ludvigson, and Ng (2015) and Rossi and Sekhposyan (2015) measures imply, respectively, a $\chi_{24} = 80.14$ and a $\chi_{18} = 44.32$, 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 first measure (four lags) and the second one (three lags), respectively.

variable that defines the two regimes we are interested in, or the proxy of uncertainty, i.e., the variables whose exogenous variations we want to isolate. Additional interaction terms involving the federal funds rate made our VARs unstable. Differently, exercises conducted with additional interaction terms featuring the proxy for uncertainty led to richer VARs delivering impulse responses very similar to those documented in this paper (and available upon request). Then, to maximize the number of degrees of freedom in estimating the I-VAR while minimizing the likelihood of handling an unstable VAR, we decided to stick to the parsimonious I-VAR described by eq.s (1)-(2).

4 Normal times vs. ZLB: Empirical evidence

4.1 Baseline results

Figure 1 plots our impulse responses to a one-standard deviation uncertainty shock identified with the VIX along with 68% confidence bands. We focus on normal times first. In line with the empirical literature cited in the Introduction, an uncertainty shock triggers a temporary recession. Real GDP falls by about 0.25% after two quarters, while consumption and investment drop respectively of about 0.25% and 2%. Interestingly, all three variables follow the same dynamics after the uncertainty shock: a quick drop, followed by a rapid recover and then an overshoot (though this latter phase is not statistically significant). Such a dynamic pattern is in line with the theoretical predictions offered by Bloom (2009). 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, though their response is not significant from a statistical viewpoint.

When we turn to the ZLB state, the responses to an uncertainty shock are estimated to be quite different. Two features are worth pointing out. First, all real activity indicators are predicted to experience a much deeper fall. Real GDP reaches its through after about two years, equal to about 0.5%. Consumption and investment both drop substantially, by about 0.5% after two years and 2% after one year respectively. Second, they all follow a much slower and persistent recovery path, with no overshoot. After five years, real GDP is still below its pre-shock level, though from a statistical viewpoint it takes about three years to go back to that level. The same dynamics holds for consumption, while investment recovers relatively more rapidly, remaining significantly below the pre-shock level for about two years. In all cases, neither a quick drop-and-rebound nor an overshoot is observed. A possible interpretation for this absence of overshoot is the missing fall in the short-term nominal and real interest rates in presence of the ZLB, which implies higher factor prices and a lower expected stream of firms' profits. Consequently, the reallocation of resources from low- to high-productivity firms behind the overshoot documented by Bloom (2009) is less likely to occur, or at least to have a large effect, in presence of a binding ZLB. Interestingly, the response of uncertainty turns out to be more persistent in the ZLB state, a finding in line with Basu and Bundick's (2015) theoretical model in which the ZLB concurs to create endogenous uncertainty.

The response of the federal funds rate is key for our analysis. In line with a binding ZLB, such response is estimated to be insignificant conditional on the ZLB state. This is very relevant in our context, since no ZLB technical constraint is put a priori on this variable. Hence, we find no reaction of the policy rate in a fully-data driven fashion, which is a result *per se*. Differently, the response of the policy rate to an uncertainty shock occurring in normal times is negative and persistent. While not necessarily pointing to a response of the policy rate to movements in uncertainty per se, this result is consistent with the one documented by Evans, Fisher, Gourio, and Krane (2015), who find that movements in uncertainty are important to describe the evolution of the federal funds rate in the pre-ZLB period.

Our impulse responses offer support to the theoretical predictions proposed in Leduc and Liu (2013) and Basu and Bundick (2014, 2015) 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 Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2013) and Caggiano, Castelnuovo, and Groshenny (2014). 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 states.[14] Two main results emerge. First, the negative real effects of uncertainty shocks are confirmed to be stronger in presence of the ZLB for all three measures of real activity we consider in our analysis. Second, the difference in the

[14] 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.

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 1. 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.

Wrapping up, our results point to significantly larger real effects of uncertainty shocks in the ZLB state, above all as regards investment.

4.2 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; ii) a different identification scheme; iii) omitted variables. We present our checks below.

Alternative measures of uncertainty. The use of the VIX as a proxy of uncertainty has recently been challenged by Jurado, Ludvigson, and Ng (2015) and Rossi and Sekhposyan (2015). Jurado, Ludvigson, and Ng (2015) propose an uncertainty index based on the common factor of the time-varying volatility of the estimated h-steps-ahead forecast errors of a large number of macroeconomic time-series. Their key point is that uncertainty is a latent variable related to unexpected future dynamics. Differently, movements in the VIX are partly forecastable. Hence, while the VIX has been employed in a variety of studies on the effects of uncertainty shocks, the results coming from VIX-based analysis may be affected by the endogeneity of the movements of the VIX. In a similar spirit, Rossi and Sekhposyan (2015) construct an uncertainty index aimed at quantifying how unexpected the mistakes in predicting relevant macroeconomic outcomes, namely the growth rate of real GDP taken as a summary measure of the business cycle stance, are relative to their historic distributions.[15] The correlation between the VIX and these alternative proxies of uncertainty reads 0.48 when the Jurado, Ludvigson, and Ng (2015) measure is considered, and0.24 when the Rossi and Sekhposyan (2015) is taken into account. While being positive, these correlations suggest that these two alternative proxies are likely to carry a different information on the evolution of uncertainty in the U.S. with respect to the VIX.

We then repeat our analysis by replacing the VIX with, alternatively, the Jurado,

[15] Baker, Bloom, and Davis (2013) develop a measure of economic-policy uncertainty which aims at capturing the fraction of uncertainty due to policymakers' actions and statements. Our research question focuses on a broad definition of uncertainty, which includes both policy-related uncertainty and uncertainty unrelated to policy actions.

Ludvigson, and Ng (2015) (JLN) and the Rossi and Sekhposyan (2015) (RS) indices in our vector.[16] Figure 3 reports the impulse responses of our real activity measures to an uncertainty shock identified using these two alternative proxies. Two main considerations are in order. First, uncertainty shocks are recessionary both in normal and in ZLB times. Second, normal times are not associated with a quick drop and rebound followed by an overshoot of real activity. Instead, uncertainty shocks here lead to a very persistent, hump-shaped response of real GDP, investment, and consumption. This evidence lines up with that in Jurado, Ludvigson, and Ng (2015) and Rossi and Sekhposyan (2015) on the effects of uncertainty shocks in a linear VAR, but it stands in stark contrast with the results we obtained conditional on the VIX.[17] Figure 4 reports the difference between the impulse responses in the ZLB regime and in normal times. The analysis of the differences between states reveals that, in fact, not all results obtained with the VIX go through. In particular, while the point estimates signal a deeper and longer lasting recession for output and consumption in ZLB times, the uncertainty surrounding such differences is so large that they turn out to be insignificant. Importantly, however, the response of investment is still documented to be significantly stronger in the ZLB state. This is perhaps not surprising, given that investment is the component of GDP which is more likely to be affected by "wait-and-see" behavior as a response to heightened uncertainty, as documented by a large theoretical and empirical literature (see, e.g., the survey by Pindyck (1991) and the papers by Bernanke (1983), Hassler (1996), Bloom, Bond, and Reenen (2007), Bloom (2009), and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014). Going back to the proxy proposed by Rossi and Sekhposyan (2015), we find our results to be robust to the employment of their downside uncertainty index, which focuses on news or outcomes that are unex-

[16] We employ the JLN index constructed with the macro dataset as described in Jurado, Ludvigson, and Ng (2015) and referring to a forecasting horizon equal to three months, which is consistent with a one-quarter-ahead forecast. The index is downloadable from Sydney Ludvigson's webpage, i.e., http://www.econ.nyu.edu/user/ludvigsons/MacroUncertainty_update.zip . The RS index has been downloaded from http://www.tateviksekhposyan.org/RS_SPFUncertaintySeriesOutputGrowth.xlsx?attredirects=0. We use the four-quarters-ahead "overall uncertainty" revised measure, which appears to be less noisy then the "nowcast" version.

[17] Notice that, even if the variables in our VAR are not Hodrick-Prescott filtered as in Bloom (2009), we find evidence in favor of the "drop-rebound-overshoot" dynamics when the VIX is employed, but we do not find such evidence when either of the other two proxies is employed. One possible explanation of this fact is that the VIX is an imperfect proxy of uncertainty. Interestingly, Carriero, Mumtaz, Theodoridis, and Theophilopoulou (2013) employ a proxy structural VAR approach to control for the possible impact of measurement errors in the VIX as a proxy for uncertainty shocks. They find that, after controlling for measurement errors, the impulse responses of real activity are larger in magnitude and more persistent than those obtained from a standard recursive VAR.

pectedly negative (results not shown here for the sake of brevity, but available in our on-line Appendix).

Uncertainty ordered last. Our baseline results are obtained with a VAR in which uncertainty is ordered first. Given that we identify exogenous variations in uncertainty by orthogonalizing the residuals of our VAR via a standard Cholesky-decomposition of the variance-covariance matrix, in our baseline analysis we assume the one-step ahead forecast error variance of uncertainty to be fully explained by uncertainty shocks. If other shocks are behind movements in uncertainty within a quarter, then the recessionary power assigned to uncertainty shocks in our baseline analysis is over-estimated. A way to check for the relevance of this choice is to move uncertainty last in our VAR and recompute our GIRFs. Figure 5 collects the response of the difference in real activity between ZLB and Normal times. Our main result is clearly robust to placing uncertainty last in the vector.

Financial conditions. Stock and Watson (2012) point out that financial strains lead to higher uncertainty, which in turn increases financial risk. Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2014) and Alessandri and Mumtaz (2014) find evidence in favor of stronger real effects of uncertainty shocks in periods of high financial stress. It is then important to control for measures of financial stress in order to distinguish the role played by uncertainty from that played by the financial cycle. Following Alessandri and Mumtaz (2014), we then add to our VAR a broad measure of financial stress, i.e., the Financial Conditions Index (FCI). The aim of this index is to offer a synthetic measure of financial stress based on a broad coverage (i.e., more than 100 series) of measures of risk, liquidity, and leverage (for a detailed explanation on the construction of this index, see Brave and Butters (2011)). We then add the FCI as first variable in our VAR, a strategy that we follow also when we consider the possibly omitted variables we discuss below, and re-estimate our VAR over the period 1973Q1-2014Q3 (the choice of the first quarter being driven by the availability of the FCI).[18] Figure 5 collects the difference of the response in real GDP, investment, and consumption in the two states obtained with our (financial) Factor-Augmented VAR. This evidence confirms our baseline findings.

S&P500. The baseline specification is based on the implicit hypothesis that our VAR contains enough information to isolate second moment shocks. Given the correla-

[18] We consider the Chicago Fed National Financial Conditions Index, one of the data which is available at 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.

tion between the VIX and the S&P500 index, there is however the risk of confounding first and second moment financial shocks. Following Bloom (2009), we then add the log of S&P500 index to our VAR and (as anticipated above as regards our controls for omitted variables) include it as first in the vector of endogenous variables. Again, the evidence shown in Figure 5 confirms the solidity of our results.

House prices. Since Iacoviello (2005), there has been a revamped attention towards the relationship between housing market dynamics and the business cycle. This is particularly important in light of the development of the 2007-09 financial and real crisis. The housing market is particularly important for us in light of a recent paper by Furlanetto, Ravazzolo, and Sarferaz (2014), who show that uncertainty shocks may play a minor role 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.[19] Figure 5 suggests that our results are robust to the inclusion of house prices in our vector.[20]

1-year Treasury Bill rate. Swanson and Williams (2014) conduct an empirical exercise focused on the responses of interest rates at different maturities to macroeconomic announcements. They show that, during the ZLB period, Treasury yields with one or two years to maturity were surprisingly responsive to news throughout the 2008-2010 period, despite the federal funds rate being essentially zero over this period. The absence of one such rate in our VAR may therefore importantly underestimate the ability of the Federal Reserve to influence the term structure of interest rates in the ZLB state. In order to model possibly important downward variations of Treasury yields in response of uncertainty shocks in the ZLB state, we then add the 1-year Treasury Bill rate as possibly omitted variable. As shown in Figure 5, the inclusion of a longer-term interest rate leaves our results unchanged.

Shadow rate. A number of monetary policy interventions alternative to changes in the federal funds rate target have been implemented by the Federal Reserve since December 2008, when the ZLB became binding. These include large-scale asset purchases, forward guidance, and the formalization of a 2 percent inflation objective. Such moves are likely to have influenced long-term interest rates and, therefore, helped the economy out of the 2007-2009 recession. Hence, the mere presence of the federal funds rate in our vector is likely insufficient to capture the expansionary power of these unconventional policy moves. A number of proposals focusing on the construction of a

[19] The index is available here: http://www.econ.yale.edu/~shiller/data/Fig2-1.xls.

[20] Differently with respect to house prices, oil prices are typically associated to high inflation in the 1970s and seen as one of the drivers of the inflation-output trade-off in that period. An exercise (available upon request) conducted by adding oil prices to our baseline vector left our results unchanged.

"shadow rate", a theoretical negative nominal interest rate consistent with the rest of the term structure of interest rates (see, among others, Krippner (2013), Christensen and Rudebusch (2015), and the extensive analysis in Krippner (2014)). Wu and Xia (2014) propose an analytical representation for bond prices in the 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. Moreover, they show that such shadow rate exhibits similar dynamic correlations with a number of macroeconomic variables in the pre-crisis and post-2009 periods, and that the Federal Reserve has managed to lower the shadow rate with unconventional policies. We then run a regression with a version of our VAR featuring the shadow rate produced by Wu and Xia (2014) in lieu of the federal funds rate. Figure 5, again, suggests that our results are robust to the inclusion of such shadow rate.

As pointed out above, the response of all measures of real activity to an uncertainty shock is significantly stronger in the ZLB regime for all robustness exercises. It is possible to make contact with other papers in the literature via these robustness checks. Bekaert, Hoerova, and Lo Duca (2013) show that uncertainty shocks induce business cycle fluctuations even when controlling for indicators of time-varying risk aversion. To the extent that changes in risk-aversion may be approximated by variations in financial stress indexes and/or fluctuations in the stock market, are results are consistent with Bekaert et al.'s (2013). Our results are also consistent with those in Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2014) and Alessandri and Mumtaz (2014), who show that uncertainty shocks working via credit frictions may lead to a persistent decline in real and financial variables. Our robustness checks also show that house prices, at least to some extent, do appear to moderate the response of real activity. This latter result is consistent with Furlanetto, Ravazzolo, and Sarferaz (2014), who show that controlling for house prices reduces the share of variance of real variables usually attributed to uncertainty shocks. The results obtained with the regression including Wu and Xia's (2014) shadow rate are not necessarily in contrast with their results on the effectiveness of unconventional monetary policy during the ZLB period. In fact, monetary policy may have very well limited the recessionary effects due to negative shocks, financial and uncertainty shocks, among others. However, our results point to a lower power by monetary policy to stabilize the economy when uncertainty shocks hit and the ZLB is binding. Overall, the main message of our robustness checks is that the main result obtained with the baseline specification continues to hold.[21]

[21] Further robustness checks considering the debt/GDP ratio and the monetary aggregates (MZM

It is worth noting that, as regards macroeconomic shocks in general, this result is corroborated by some recent monetary policymakers' statements. As pointed out by William C. Dudley, President and Chief Executive Officer of the Federal Reserve Bank of New York, in a speech held on May 21, 2013 at the Japan Society (New York City): *"[...] the constraints imposed by the zero bound limit what monetary policy can accomplish by itself."* Consistently, Evans, Fisher, Gourio, and Krane (2015) stress that the effects of unconventional policy moves and forward guidance are likely not to be on an equal footing with traditional policy instruments due to the fact that they are complicated functions of private sector expectations, which are by themselves highly uncertain, and because of the costs associated to unconventional moves. Such costs include possibly inflationary large increases in reserves, difficulties by the Federal Reserve to increase interest rates when needed due to a large balance sheet and large losses by the Federal Reserve itself caused by quick increases in the federal funds rate, and an inefficient allocation of credit and financial fragility due to a prolonged period of low interest rates.

A look at the labor market. Basu and Bundick (2014) show that competitive, one-sector, closed-economy models are in general unable to generate business cycle comovements in response to uncertainty shocks. In such frameworks, when uncertainty increases, households increase their savings and reduce their consumption due to precautionary motives. Then, two scenarios may arise. If labor supply is inelastic, total output remains unaltered (the assumption being that uncertainty shocks exert zero effects on technology and, at least in the short run, capital). Then, due to the decrease in consumption, investment must increase. If labor supply is not inelastic, instead, households react to an uncertainty shock by reducing consumption and increasing the supply of hours worked for a given level of real wage. Labor demand remains unaltered due to the fact that capital and technology do not react to uncertainty shocks. Then, in equilibrium, consumption decreases, but hours worked increase, and output and investment increase too. A key force behind these correlations is hours worked, which either stay put (when labor supply is inelastic) or increase (when "precautionary labor supply" is at work). As shown by Basu and Bundick (2014), a strikingly different prediction regarding macroeconomic comovements arise when a non-competitive, one sector model is considered where prices are assumed to be sticky. A jump in uncertainty decreases consumption (due to precautionary savings) and induces an increase in

money stock) as omitted variables confirm the solidity of our main findings (evidence omitted for brevity but available upon request).

labor supply. Given labor demand, this pushes the real wage down, therefore increasing hours worked in equilibrium. The reduction in firms' marginal costs puts a downward pressure on prices, which however do not fully adjust due to price stickiness. Hence, firms' markup increases over marginal costs. Hence, given the fall in demand, output falls. This fall in output implies a fall in hours worked and investment. As a result, according to this model, uncertainty shocks cause fluctuations that look qualitatively like a business cycle.[22]

Importantly, each of these three different models generate a different prediction for the response of hours worked to uncertainty shocks. The competitive model with inelastic labor supply predicts no response of hours worked. The version of the competitive model with precautionary labor supply predicts an increase of hours worked in equilibrium. Differently, the sticky-price model predicts a decrease of hours worked after a spike in uncertainty. It is then of interest to check if the comovement of the real activity indicators detected so far in response to an uncertainty shock is confirmed by a VAR including hours worked, and what response of hours worked is generated by such VAR.

We then estimate a version of the VAR enriched with hours worked.[23] Figure 6 displays the state-dependent responses of hours, output, investment, and consumption, along with the differences in these responses in the two regimes considered. Our responses clearly support the predictions of Basu and Bundick's (2014) model featuring sticky prices and countercyclical markup. In particular, hours worked fall in both regimes after an uncertainty shock, and the same occurs to output, investment, and consumption. Interestingly, and again in line with Basu and Bundick's (2014) predictions, the drop in real activity indicators is significantly more marked in the ZLB regime.

4.3 Time-varying GIRFs

The results we have shown so far are related to the average response of real activity to an uncertainty shock. This is obtained by integrating out the initial conditions within each regime. Initial conditions might, however, play an important role in the transmission

[22] Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014) show that comovements can be obtained as a combination of negative first moment shocks and exogenous increases in uncertainty. Leduc and Liu (2013) show that a model with real matching frictions and price rigidity predicts an increase in unemployment and a decrease in inflation following a spike in uncertainty. Pinter, Theodoridis, and Yates (2013) find rule-of-thumb consumers to be an important ingredient in a model with risk shocks and financial frictions to replicate the effects of uncertainty shocks suggested by a VAR analysis.

[23] We consider the series "average weekly hours of production and nonsupervisory employees for the manufacturing sector" (source: Federal Reserve Bank of St. Louis' database).

of uncertainty shocks. We then turn to the examination of the role played by histories (initial conditions) to investigate the time-dependence of our dynamic responses to an uncertainty shock. Histories are dated by considering the first lag of the VAR as the reference quarter. For instance, a history dated 2008Q4 refers to an uncertainty shock hitting in the 2009Q1 quarter and whose impulse responses are conditional on the values (initial conditions) for the quarters 2008Q4, 2008Q3, and 2008Q2, which correspond to the three lags of our VAR.

Figure 7 reports the evolution of the point estimates of our GIRFs over histories within each regime to a (constant-size) standard deviation shock. Several things are worth noticing. First, there is an evident within-state heterogeneity. In particular, looking at normal times, the evidence of overshoot changes substantially over histories. The impulse responses in the late 1970s are those with the highest overshoot realizations, while those in 2000s, even before the ZLB, are associated with the weakest evidence of overshoot. Second, dispersion in the ZLB regime is much lower, a result possibly due to the lower number of observations in the ZLB subsample, which amounts to about 10% of all observations in our full sample. Third, despite some similarities between the two regimes emerge, we still find that the mass depicted by the bundle of GIRFs in normal times tends to be quite distinct with respect to that in ZLB times. This confirms our main finding, i.e., the real effects of uncertainty shocks are estimated to be stronger when the economy is at the ZLB. Fourth, while being in general different, some responses in normal times are actually quite similar to some of the responses we estimate for the ZLB period. In particular, the absence of overshoot realizations for the quarters in early 2000s resembles the one we observe for the ZLB phase. Intriguingly, a correlation between the absence of overshoot and low interest rates appears to emerge, with the early 2000s being characterized by low interest rates (the response of Alan Greenspan to the burst of the dot-com bubble) and the aftermath of Lehman Brothers' collapse being characterized by a quick reduction in the federal funds rate which rapidly hit the ZLB. This is information that may be relevant to discriminate between the real effects of uncertainty shocks in presence of the ZLB, or low interest rates in general, and the effects of the same shocks in recessions. We elaborate on this point in the next Section.

4.4 Recessions or ZLB?

Our 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 (2013), Nakata (2013), Basu and Bundick (2014, 2015)). However, other contributions have suggested that monetary policy is likely to be less effective in recessions, regardless of a binding ZLB (Tenreyro and Thwaites (2013), Mumtaz and Surico (2014)). 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.[24] 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".[25] 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

[24] 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.

[25] 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).

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 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.

Figure 8 shows the GIRFs relative to the selected histories. A clear indication arises. 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 in the on-line Appendix).

A possible interpretation for this result, i.e. uncertainty shocks have stronger negative real effects at low levels of the policy rate, is that longer-term interest rates are less sensitive to policy moves in the proximity of the ZLB. Swanson and Williams (2014) find that the Federal Reserve's ability to influence the term structure has been time-varying and often limited in presence of low, but non-necessarily "zero", values of the federal funds rate. We then scrutinize whether the ability of the Federal Reserve to influence the term structure of interest rate along the "policy rate cycle" is a key factor behind our result by adding longer-term interest rates to our VAR and computing their impulse responses to an uncertainty shock. We alternatively consider the 1-year, 5-year, and 10-year Treasury Bill rates.

Figure 9 displays the response of the real GDP (to keep a reference of the response of real activity to an uncertainty shock) along with the GIRFs of the various interest rates alternatively modeled in our VARs.[26] The most evident finding is that, in the proximity of the ZLB, a weaker response of the term structure occurs after an uncertainty shock. Consistently with a lower reduction of the longer-term rates, the reaction of the real GDP (as well as investment and consumption, which are shown in Figure 8) is stronger. This result corroborates the message by Swanson and Williams (2014) on the weak ability of the Federal Reserve to influence the term structure of interest rates in the early 2000s as well as after the ZLB has kicked in.[27]

Importantly, our result contradicts neither those contributions who find different effects of uncertainty shocks in good and bad times (Caggiano, Castelnuovo, and Nodari (2015)) nor those that find that central banks are less effective in stabilizing the business cycle in recessions (Tenreyro and Thwaites (2013), Mumtaz and Surico (2014)). None of these papers explicitly deals with the ZLB, which is a quite peculiar event in the U.S. post-WWII economic history. What this exercise shows is that, in presence of the ZLB, heightened uncertainty would make things even worse than they would have been if the economy were not close to such a bound. This conclusion is in line with the prediction of Bloom (2009), who shows that the effects of uncertainty shocks on real activity can be offset only by very bold moves of monetary authorities, which are obviously possible only if the initial level of the interest rate is far enough from its lower bound.[28]

5 Conclusions

While evidence on the empirical relevance of heightened uncertainty for the business cycle has been provided by a number of recent studies, less is known on the role played

[26] The response of real GDP displayed in this Figure is the one obtained with our benchmark VAR. No substantial changes occur in the I-VAR augmented with any of the three interest rates we deal with in this exercise.

[27] To be precise, Swanson and Williams (2014) find that interest rates with a year or more to maturity were surprisingly responsive to news throughout 2008 to 2010. Our ZLB regime includes observations from 2008 to 2014. Our conjecture is that the 2011-2014 observations in our ZLB regime are those driving our main results. The estimation of our Iteracted VAR with data until 2010 would severely undermine the ability of our model to capture the dynamics in the ZLB regime due to lack of degrees of freedom.

[28] Bloom (2009) calculates that a one standard deviation uncertainty shock would generate no contractionary effects whatsoever only if the central bank lowered the interest rate by 700 basis points.

by the monetary policy stance in driving the transmission mechanism of uncertainty shocks to the real economy. This paper asks whether uncertainty shocks have different real effects when the economy is near the zero lower bound. Working with a nonlinear Interacted-VAR framework and post-WWII U.S. data, we find that they trigger deeper recessions than in normal times. This is particularly true regarding investment, a variable whose response to uncertainty shocks has been object of theoretical investigations for long time.

Our finding is relevant both for the construction of theoretical macroeconomic models and for their policy implications. From a modeling standpoint, our result supports the employment of general equilibrium frameworks that explicitly model the interaction between uncertainty shocks and the zero lower bound of the nominal interest rate, and the consequent state-dependent transmission of uncertainty shocks. Policy-wise, our paper lends support to theoretical studies advocating the implementation of the switch from Taylor-type rules to a policy forward guidance-type of policies able to stabilize the real interest rate when the zero lower bound constraint is binding.

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Unc. indic.	*Period*	*GDP*	*Invest.*	*Cons.*
VIX	Normal times	-0.22	-0.19	-0.23
	ZLB	-0.80	-0.66	-0.83
JLN	Normal times	-0.45	-0.35	-0.47
	ZLB	-0.81	-0.75	-0.83
RS	Normal times	-0.14	-0.13	-0.11
	ZLB	-0.28	-0.41	-0.16

Table 1: **Uncertainty-Real activity correlations: Normal times vs. ZLB.** Real activity indicators expressed in quarterly growth rates. Correlation coefficients conditional on the following periods: 1962Q3-2014Q3 - uncertainty proxied by the VIX, 1962Q3-2013Q3 - uncertainty proxied by the Jurado, Ludvigson, and Ng (2015) index (JLN in the Table), and 1968Q4-2013Q1 - 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.

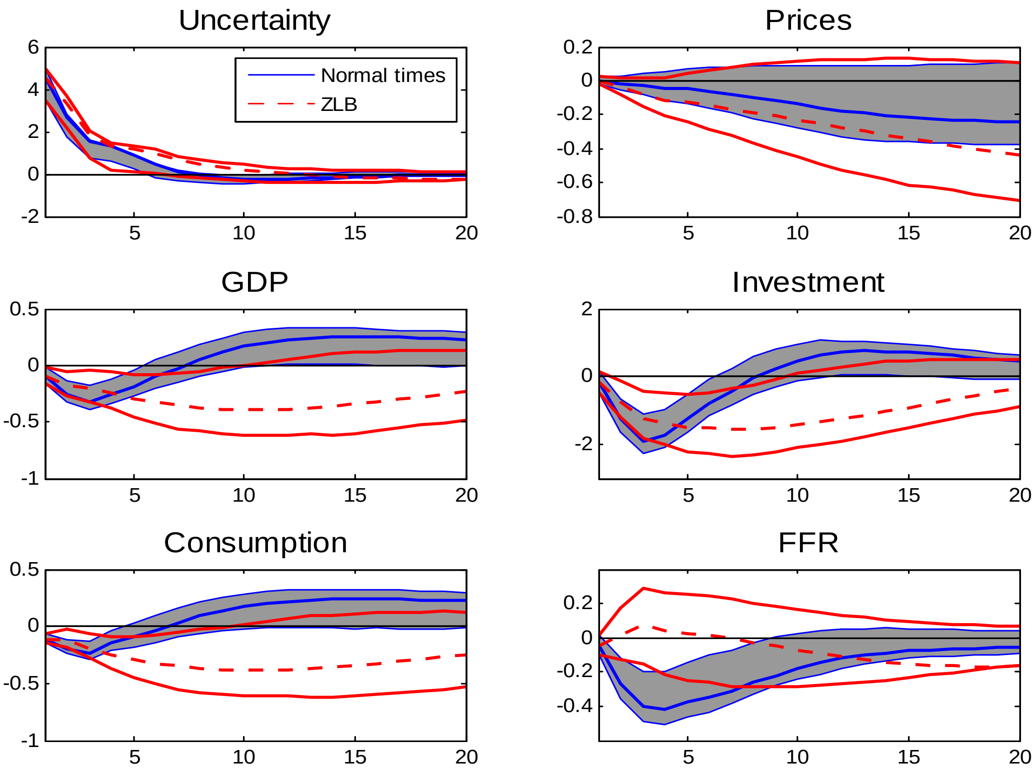

Figure 1: **Uncertainty shocks and the ZLB**: **Generalized Impulse Responses to a one-standard deviation uncertainty shock**. Uncertainty proxied by the VIX. Dashed-red line: ZLB regime. Solid blue line: Normal times. Solid red lines and gray areas: 68% confidence bands.

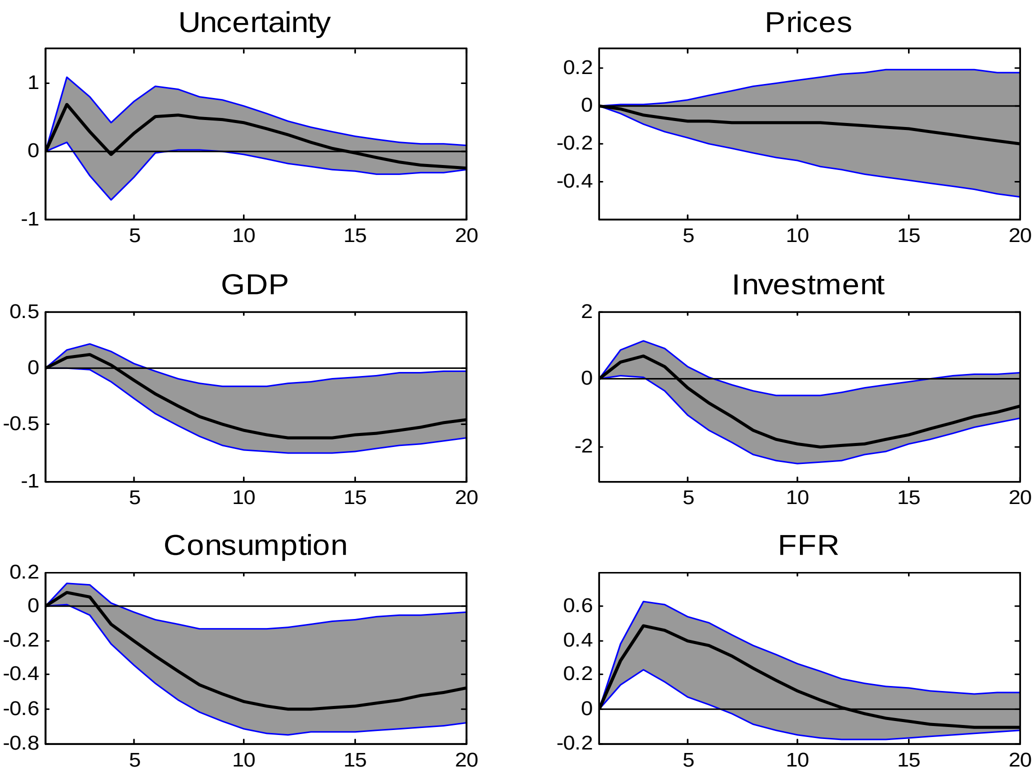

Figure 2: **Differences in Generalized Impulse Responses between ZLB and Normal times**. Uncertainty proxied by the VIX. Solid black line: Difference between the average GIRF to a one-standard deviation uncertainty shock in the ZLB state and in the Normal times state. Grey areas: 68% confidence bands.

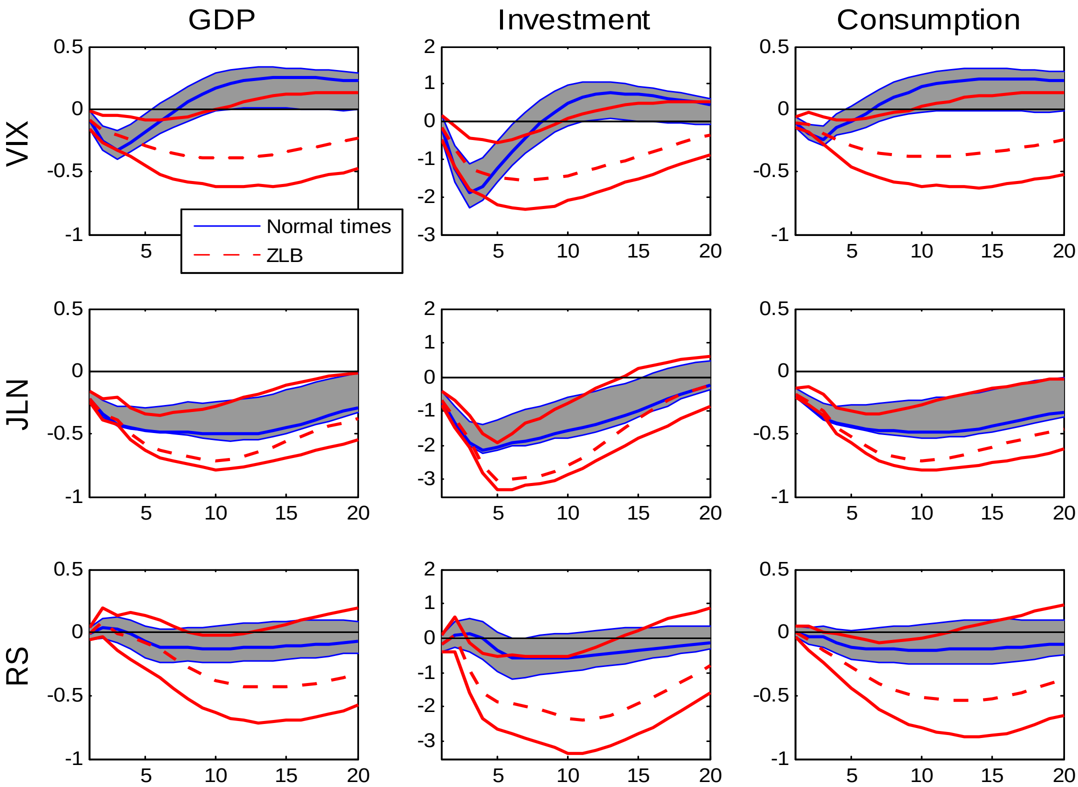

Figure 3: **Uncertainty shocks and the ZLB: Alternative measures of uncertainty.** GIRFs to a one-standard deviation uncertainty shock. Proxies of uncertainty: VIX (sample: 1962Q3-2014Q3), JLN (measure proposed by Jurado, Ludvigson, and Ng (2015), sample: 1962Q3-2013Q3), and RS (measure proposed by Rossi and Sekhposyan (2015), sample: 1968Q4-2013Q1). Differences in samples due to differences in the availability of the uncertainty proxies.

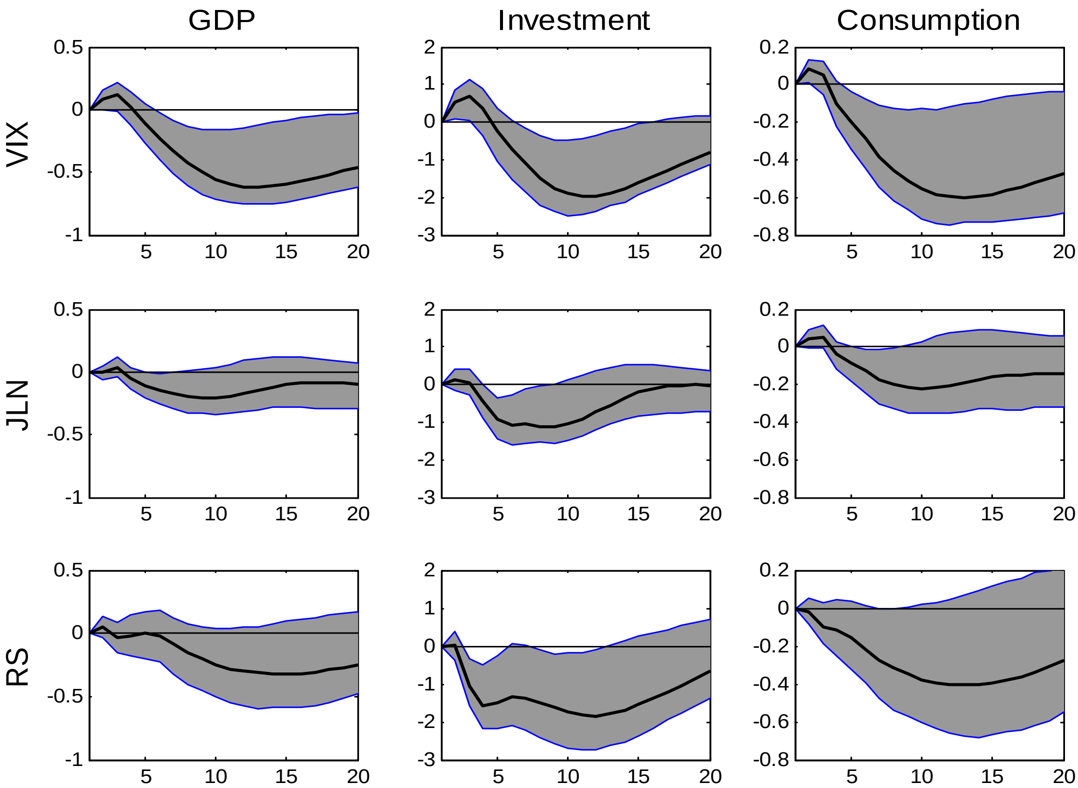

Figure 4: **Differences in Generalized Impulse Responses between ZLB and Normal times**. Uncertainty proxied by the VIX. Solid black line: Difference between the average GIRF to a one-standard deviation uncertainty shock in the ZLB state and in the Normal times state. Grey areas: 68% confidence bands. Proxies of uncertainty: VIX (sample: 1962Q3-2014Q3), JLN (measure proposed by Jurado, Ludvigson, and Ng (2015), sample: 1962Q3-2013Q3), and RS (measure proposed by Rossi and Sekhposyan (2015), sample: 1968Q4-2013Q1). Differences in samples due to differences in the availability of the uncertainty proxies.

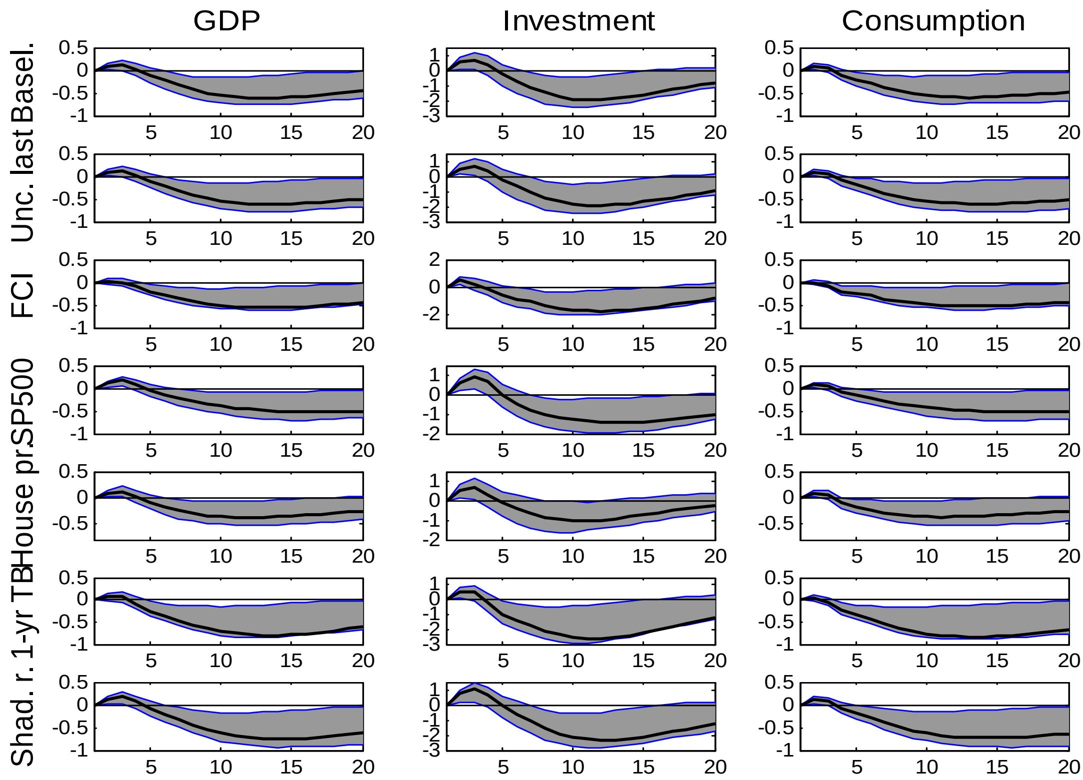

Figure 5: **Uncertainty shocks and the ZLB: Differences, Robustness checks**. Solid black line: Difference between the average GIRF to a one-standard deviation uncertainty shock in the ZLB state and in the Normal times state. Uncertainty proxied by the VIX. Grey areas: 68% confidence bands.

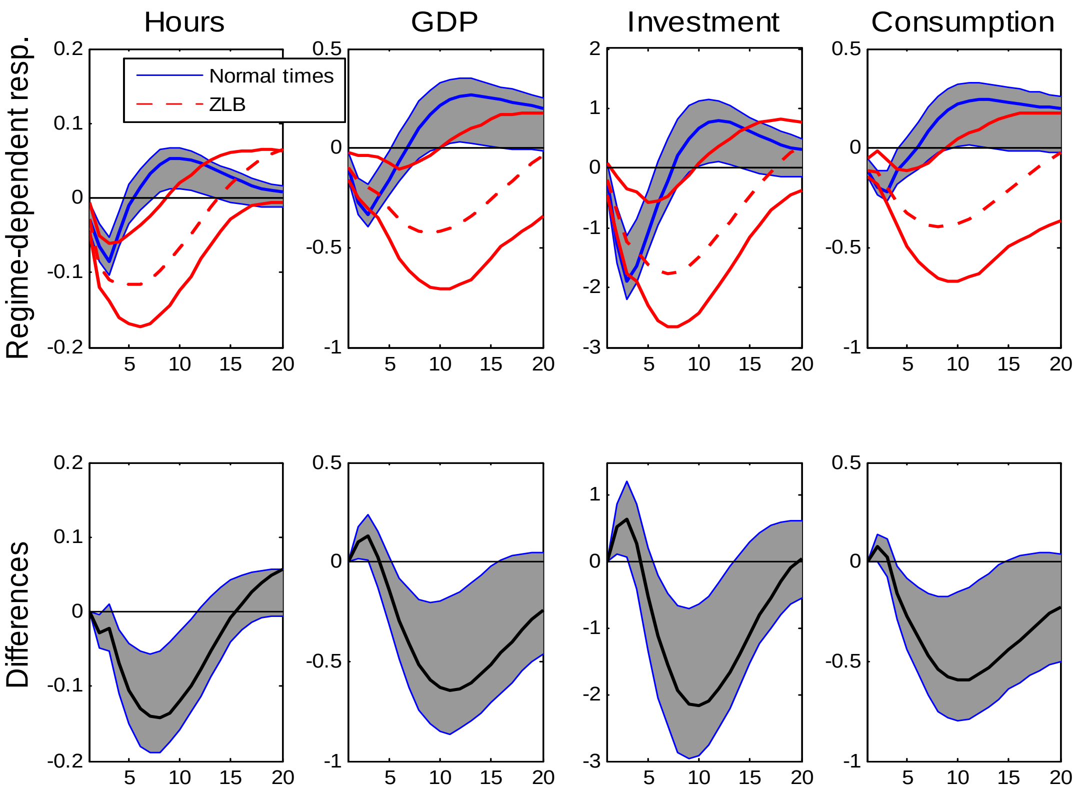

Figure 6: **Uncertainty shocks and the ZLB: Response of hours and comovements.** Top panels. Dashed-red line: ZLB regime. Solid blue line: Normal times. Solid red lines and gray areas: 68% confidence bands. Bottom panels. Solid black line: Difference between the average GIRF to a one-standard deviation uncertainty shock in the ZLB state and in the Normal times state. Uncertainty proxied by the VIX. Grey areas: 68% confidence bands.

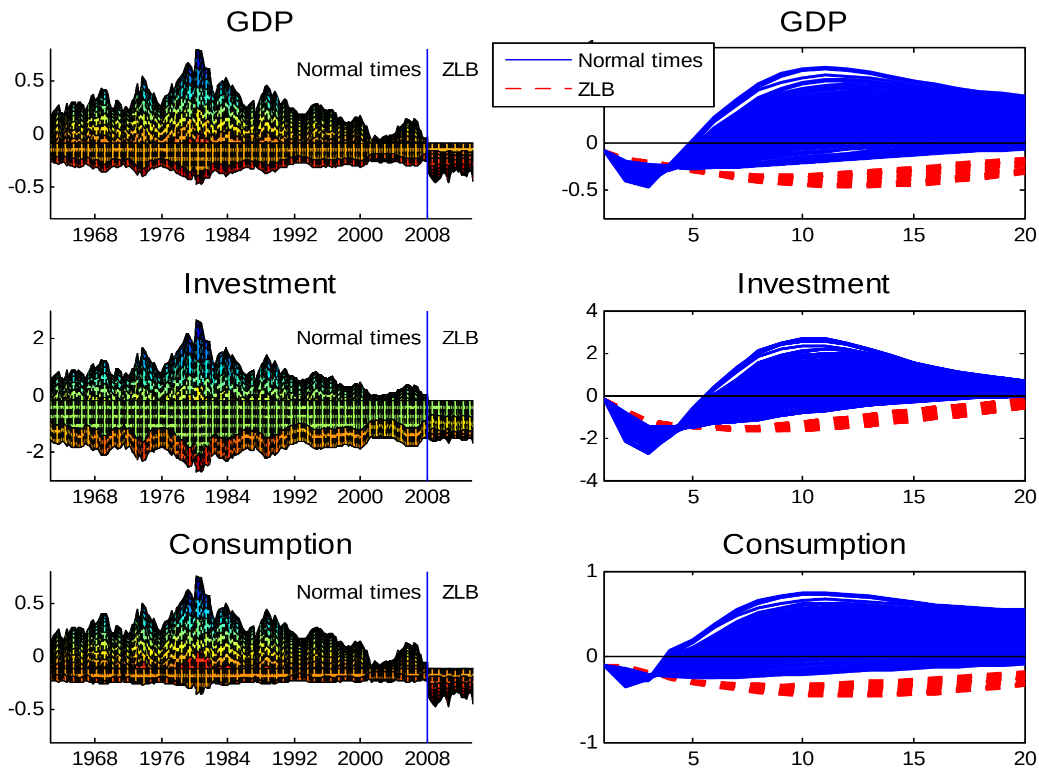

Figure 7: **Time-varying GIRFs: Normal times vs. ZLB.** Uncertainty proxied by VIX. Left column: Temporal evolution of the GIRFs. Colors ranging from blue (peak values per each given history) to red (trough values per each given history). Histories on the x-axis of the left-panels stand for the first lagged value of the quarter in which the uncertainty shock occurs. Right column: State-specific responses conditional on histories. Blue GIRFs: Point estimates related to Normal times. Red GIRFs: Point estimates related to the ZLB state.

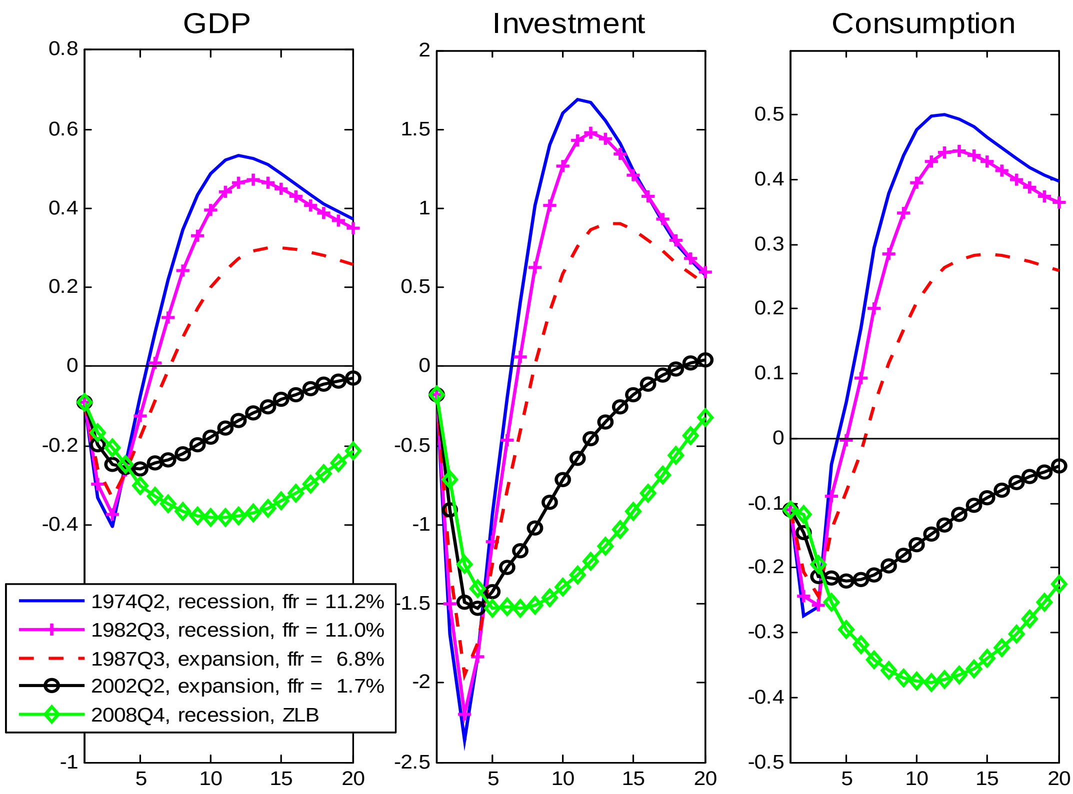

Figure 8: **Real effects of uncertainty shocks: Business cycle vs. interest rate cycle.** Uncertainty proxied by VIX. Impulse responses to a one standard deviation uncertainty shock for selected histories.

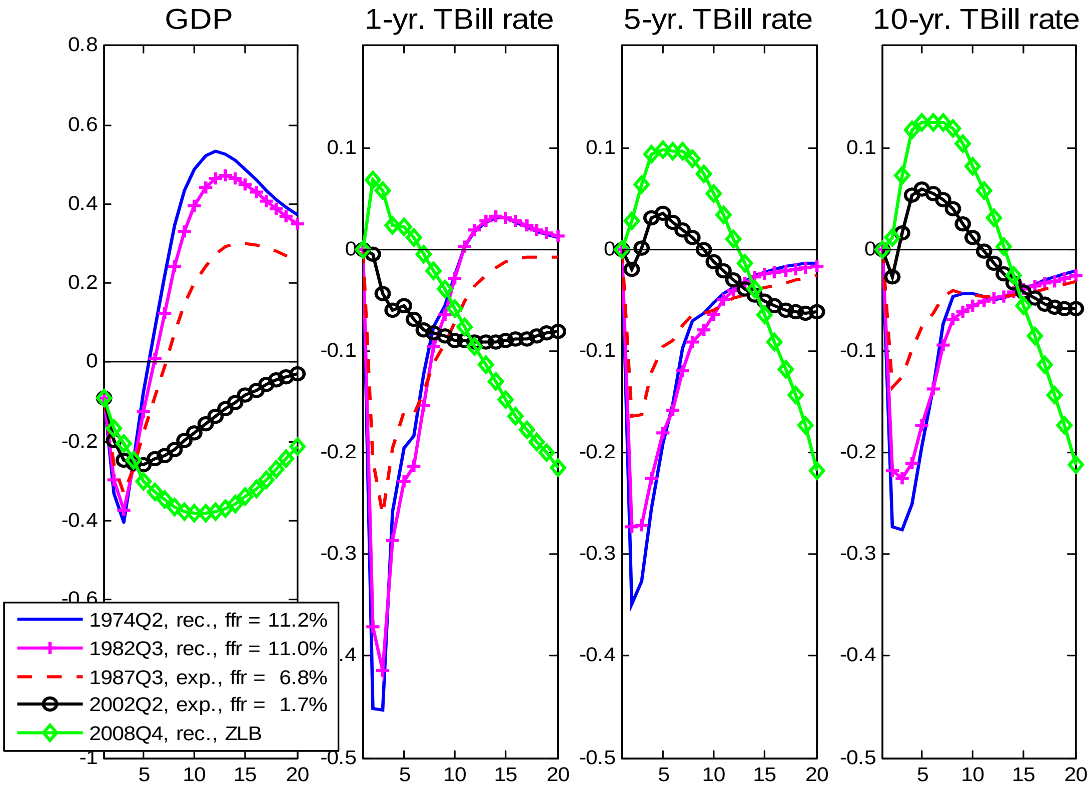

Figure 9: **Effects of uncertainty shocks on the term structure: 1-yr., 5-yr., and 10-yr. TBill rates.** Uncertainty proxied by VIX. Responses of the real GDP conditional on the baseline VAR without term-structure. Impulse responses to a one standard deviation uncertainty shock for selected histories.

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. This temporal reference calls for a 0.25% numerical reference for the federal funds rate. In fact, since 2008, the Federal Reserve has paid an annual interest rate of 0.25% on reserves. Hence, we consider 0.25% as our threshold for discriminating "Normal times" and "ZLB", a choice in line with Wu and Xia (2014).

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

[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 used 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 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 the randomness of the realization of the residuals, we classify as ZLB observations those corresponding to the lowest 10% realizations of the federal funds rate in each given simulated sample, 10% 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]

Extra results and material

Figure A1 shows the GIRFs obtained with different measures of uncertainty computed by Rossi and Sekhposyan (2015). The top row shows GIRFs conditional on an uncertainty shock (size: one standard deviation) estimated with a VAR modeling uncertainty with the overall index by Rossi and Sekhposyan (2015). Differently, the middle row depicts GIRFs computed with the downside version of such index, which accounts for uncertainty arising only from news or outcomes that are unexpectedly negative. Notably, this latter proxy of uncertainty is estimated to have a larger effect on the real activity indicators we are after, a result in line with the evidence found by Rossi and Sekhposyan (2015) with their VAR. The third row pictures the differences between the responses in ZLB and normal times. As in the case of the overall index (shown in the paper), also the downside measure of uncertainty predicts deeper and longer lasting recessions in presence of the ZLB.

Figure A2 shows selected GIRFs which are intended to shed light on the relevance of initial conditions and, in particular, on the role of the "interest rate cycle" (see discussion in the paper). This is the same figure plotted in the paper, which is here enriched by the presence of statistical bands. This evidence confirms that histories characterized by low values of the nominal interest rate are associated to deeper and longer lasting recessions, which are such also from a statistical standpoint.

Figure A3 displays three different proxies of uncertainty: the VIX, the measure developed by Jurado, Ludvigson, and Ng (2015), and the measure developed by Rossi and Sekhposyan (2015).

Finally, Figure A4 displays our time-varying GIRFs in a tri-dimensional fashion.

[3] This "10% rule" works as a good approximation in most of our analysis. We adopt instead a 14% rule when dealing with the shorter sample period available for the check that includes the FCI.

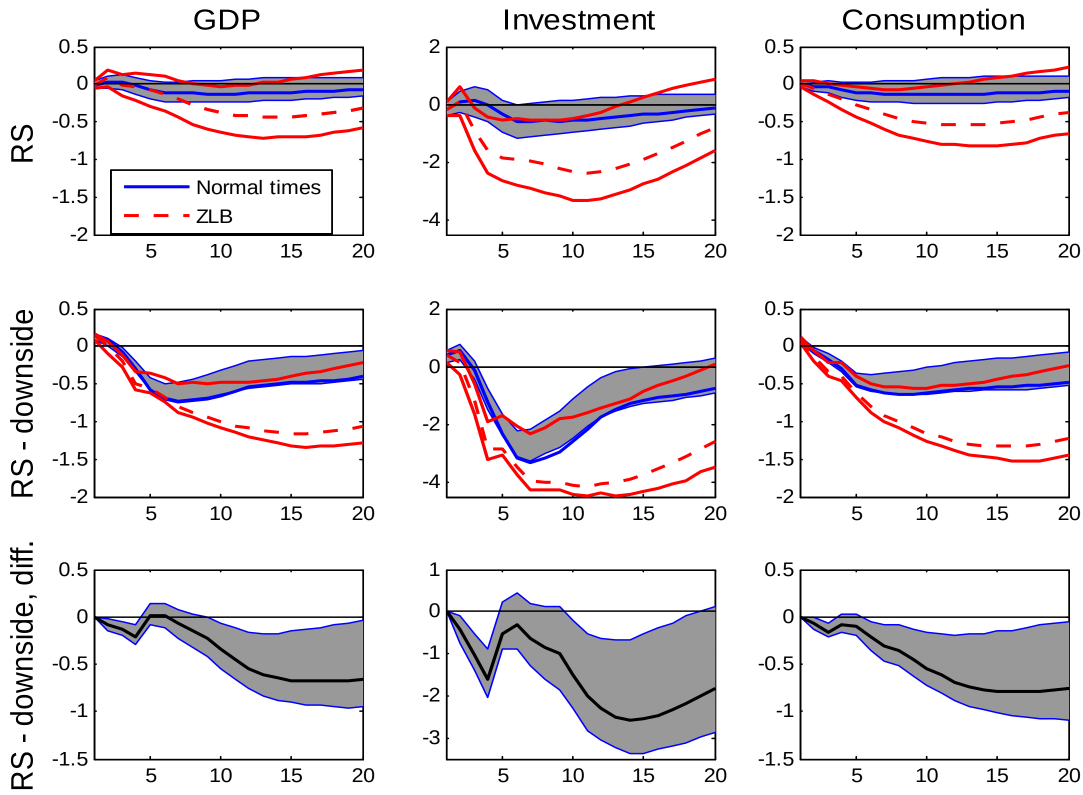

Figure A1. **Uncertainty shocks and the ZLB: Rossi and Sekhposyan's (2015) measures of uncertainty.** GIRFs to a one-standard deviation uncertainty shock. RS stands for overall Rossi and Sekhposyan's measure, RS - downside indicates GIRFs conditional on uncertainty arising only from news or outcomes that are unexpectedly negative, RS - downside, diff. stands for the difference between the average GIRF to a one-standard deviation uncertainty shock in the ZLB state and in the Normal times state.

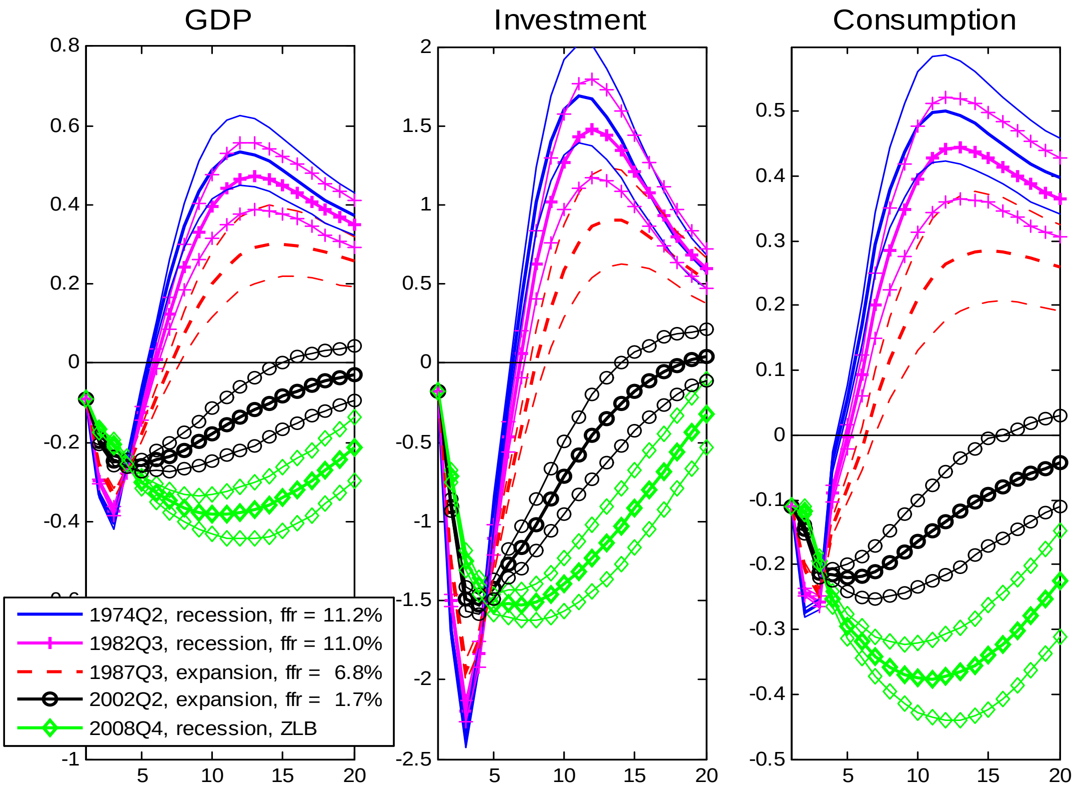

Figure A2. **Statistical relevance of the real effects of uncertainty shocks: Business cycle vs. interest rate cycle.** Uncertainty proxied by VIX. Impulse responses to a one standard deviation uncertainty shock for selected histories. 68% confidence bands computed by randomizing over the sequence of future shocks employed to compute the GIRFs.

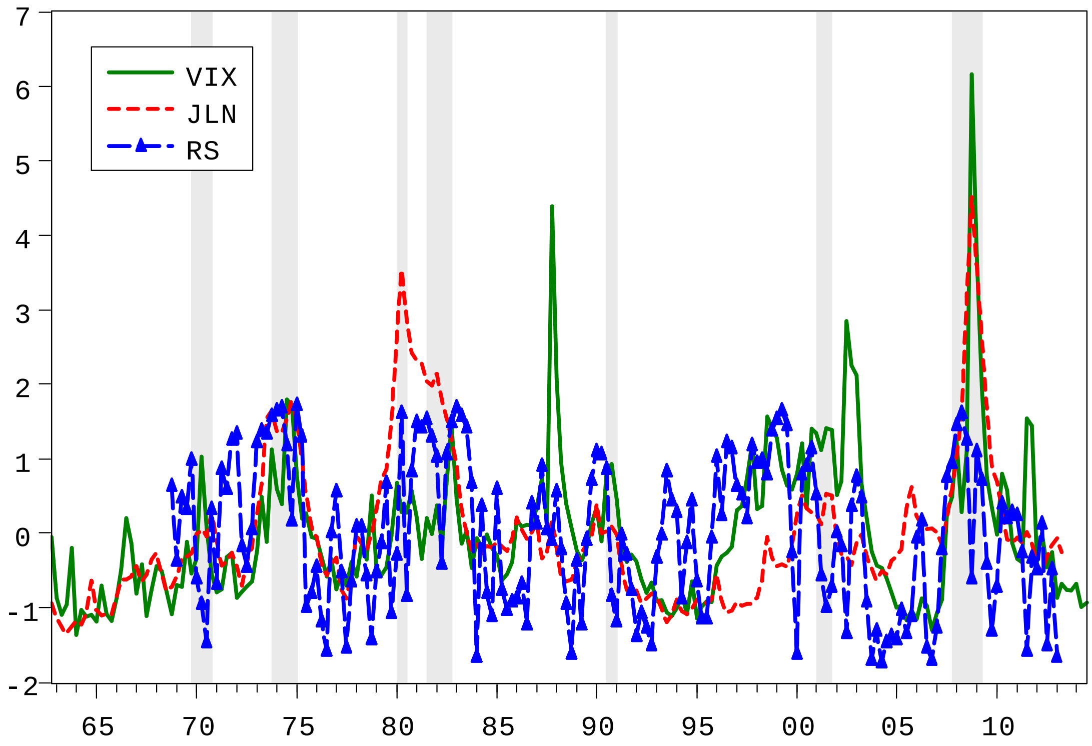

Figure A3. **Uncertainty proxies.** VIX: As in Bloom (2009). JLN: Jurado, Ludvigson, and Ng's (2015) uncertainty index based on the common factor of the time-varying volatility of the estimated h-steps-ahead forecast errors of a large number of macroeconomic time-series. RS: Rossi and Sekhposyan's (2015) uncertainty index quantifying how unexpected the mistakes in predicting relevant macroeconomic outcomes, namely the growth rate of real GDP taken as a summary measure of the business cycle stance, are relative to their historical distributions.

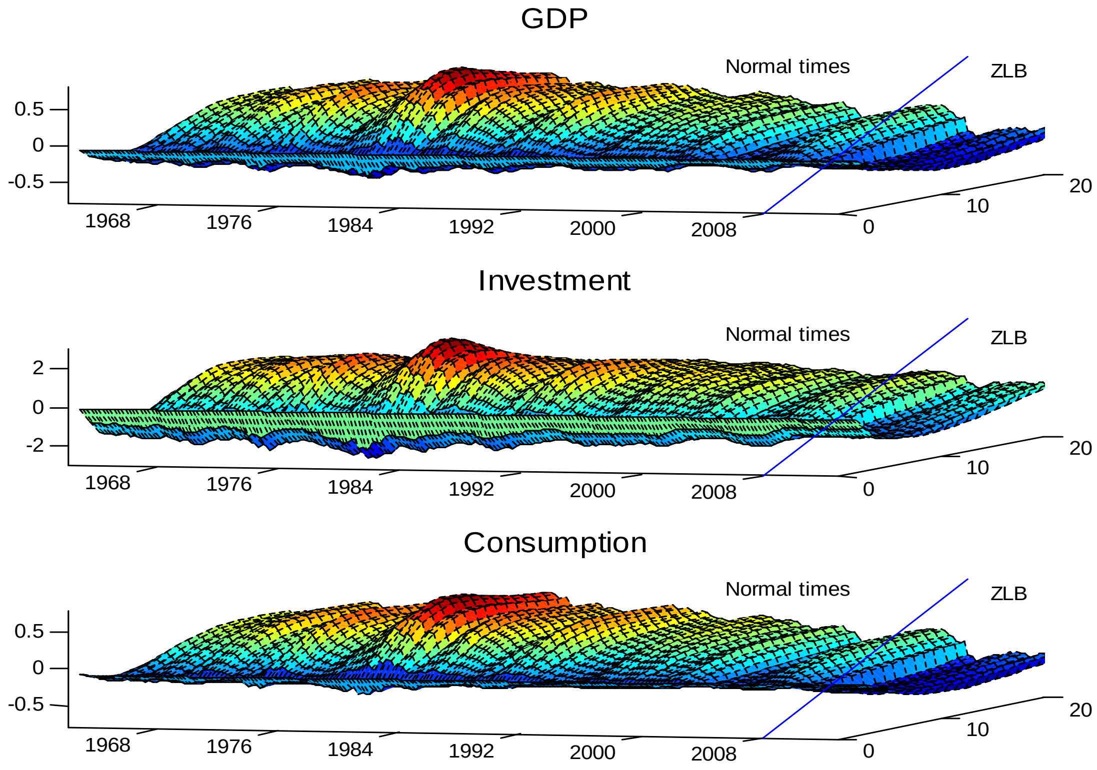

Figure A4. **Time-varying GIRFs: Normal times vs. ZLB.** Uncertainty proxied by VIX. Left column: Temporal evolution of the GIRFs. Colors ranging from blue (peak values per each given history) to red (trough values per each given history).

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