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Uncertainty, Financial Markets, and Monetary Policy over the Last Century

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Abstract

What has been the effect of uncertainty shocks in the U.S. economy over the last century? What are the historical roles of the financial channel and monetary policy channel in propagating uncertainty shocks? Our empirical strategies enable us to distinguish between the effects of uncertainty shocks on key macroeconomic and financial variables transmitted through each channel. A hundred years of data further allow us to answer these questions from a novel historical perspective. This paper finds robust evidence that financial conditions have played a crucial role in propagating uncertainty shocks over the last century, supporting many theoretical and empirical studies emphasizing the role of financial frictions in understanding uncertainty shocks. However, heightened uncertainty does not amplify the adverse effect of financial shocks, suggesting an asymmetric interaction between uncertainty and financial shocks. Interestingly, the stance of monetary policy seems to play only a minor role in propagating uncertainty shocks, which is in sharp contrast to the recent claim that binding zero-lower-bound amplifies the negative effect of uncertainty shocks. We argue that the contribution of constrained monetary policy to amplifying uncertainty shocks is largely masked by the joint concurrence of binding zero-lower-bound and tightened financial conditions.

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I. Introduction

Since the global financial crisis of 2008-09, there has been renewed attention to time-varying uncertainty as an emerging source of business cycles and a threat to financial stability. To the extent to which investors are risk-averse or financial frictions exist, the negative impact of heightened uncertainty on the macroeconomy is amplified through an increased cost of external financing or a decline in funds available to the economy. Therefore, recent studies in this rapidly growing area have highlighted the role of financial markets in amplifying the adverse effects of uncertainty shocks (Christiano et al., 2014; Gilchrist et al., 2014; Bordo et al., 2016; Caldara et al., 2016; Popp and Zhang, 2016; Alfaro et al., 2018; Choi et al., 2018; Alessandri and Mumtaz, 2019; Arellano et al., forthcoming), in addition to the so-called "real options channel" proposed by Bernanke (1983) and Bloom (2009). While most studies generally agree with the role of the financial channel in amplifying uncertainty shocks, its quantitative importance varies over the sample periods and the empirical methods used in each study.

The recent literature has also paid special attention to whether the contractionary effects of uncertainty shocks are amplified when monetary policy is constrained by the zero-lower-bound (ZLB) constraint (Nakata, 2017; Basu and Bundick, 2017; Caggiano et al., 2017; Plante et al., 2018). However, as argued by Bloom (2009), heightened uncertainty tends to make fiscal/monetary policies less effective by inducing a strong insensitivity to other economic stimuli via an increased real-option value of inaction. Indeed, Aastveit et al. (2017) and Castelnuovo and Pellegrino (2018) find that monetary policy becomes less effective when uncertainty is high. If the monetary policy becomes ineffective in response to uncertainty shocks anyway, constrained monetary policy may not necessarily exacerbate the adverse effect of uncertainty shocks on the macroeconomy. Thus, testing the monetary policy channel of uncertainty shocks also becomes an interesting empirical task.

Nevertheless, identifying the role of financial market conditions and monetary policy stance in propagating uncertainty shocks is not a trivial task. First, although a majority of the previous empirical studies used a proxy for time-varying uncertainty constructed from financial market data, such as the VIX, a high correlation between the VIX and various measures of financial market distress makes it difficult to separate the effect of uncertainty shocks from that of financial shocks (Caldara et al., 2016). Moreover, the recent ZLB period coincided with severe financial market distress and the unprecedentedly high level of uncertainty regardless of their empirical proxy. A potential endogenous interaction among uncertainty, financial markets, and monetary policy makes it difficult to identify their effects on the economy and the channel through which uncertainty shocks are propagated.

We overcome this identification issue by employing two alternative empirical methods taking account of the interaction effects among uncertainty, financial market conditions, and monetary policy. We test the role of financial market conditions and monetary policy stance in transmitting and amplifying the effect of uncertainty shocks by considering (i) counterfactual Vector Autoregressions (VARs) as used by Sims and Zha (2006) that allow the statistical isolation of the direct effect of uncertainty shocks on output from the indirect effect operating through financial and monetary policy channels and (ii) regime-dependent local projections as used by Auerbach and Gorodnichenko (2012) that allow for differential responses of the economy to uncertainty shocks depending on the underlying financial conditions or the ZLB constraint.

To minimize the direct influence of financial conditions when identifying a propagation channel and maximize the sample period for our analysis, we use a historical measure of economic policy uncertainty (EPU, henceforth) developed by Baker et al. (2016) that is not directly constructed from financial market data.[4] As a robustness check, we also use an alternative uncertainty measure based on stock market volatility and confirm that the main qualitative results still hold. To identify the role of financial conditions in transmitting the adverse effect of uncertainty shocks, we add a specific measure of financial market distress to our empirical models and investigate its interaction with uncertainty shocks.

This paper contributes to the literature on the macroeconomic effect of uncertainty shocks in a fundamental way by extending the VAR analysis by employing macroeconomic and financial data as well as a measure of uncertainty spanning almost a century (January 1919 to December

[4] The EPU index is based on the news coverage frequency of words related to "economic", "policy", and "uncertainty". By estimating the monthly structural VARs with the U.S. data from 1985, Baker et al. (2016) found that innovations in EPU reduce investment, output, and employment. Among the existing empirical proxies for uncertainty, the coverage of the historical EPU index is most comprehensive. For example, one of the most popular measures of uncertainty constructed by Jurado et al. (2015) covers about 50 years.

2017). This span of the data covers well beyond the period analyzed by any of the existing studies on the quantitative effect of uncertainty shocks (e.g., Bloom, 2009; Born and Pfeifer, 2014; Fernández-Villaverde et al., 2015; Jurado et al., 2015; Leduc and Liu, 2016; Basu and Bundick, 2017; Mumtaz and Surico, 2018) and includes the Great Depression and the subsequent period during which the U.S. economy is effectively in the liquidity trap. This particular historical episode resembles the recent episode of the Great Recession and the binding zero-lower-bound (ZLB) constraint, thereby providing another opportunity to study the interaction among uncertainty, financial markets, monetary policy, and economic activity from a novel historical perspective. To the best of our knowledge, none of the existing studies have investigated the role of financial conditions and monetary policy stance jointly in explaining the effect of uncertainty shocks with such an extensive historical sample as ours.

The main findings of the paper are summarized as follows. First, historical data reveals interesting inflation dynamics in response to uncertainty shocks. Unlike the recent studies by Leduc and Liu (2016) and Basu and Bundick (2017) who found a disinflationary effect of uncertainty shocks using shorter-duration U.S. macroeconomic data, incorporating historical data yields an inflationary effect of uncertainty shocks, implying that the aggregate demand interpretation of uncertainty shocks does not always hold. From a policy perspective, this finding suggests that uncertainty shocks might not be readily mitigated by monetary authorities due to a negative trade-off between output and inflation.

Second, from the counterfactual VARs, we find that the negative effect of uncertainty shocks on output is substantially mitigated by shutting down the financial channel. While output measured by industrial production declines by 0.4% six months after the one standard deviation of the uncertainty shock in the baseline analysis, it declines by only 0.2% in the counterfactual analysis where the endogenous response of financial conditions measured by credit spread is shut down, and this decline is no longer statistically significant. From regime-dependent local projections, we find that the adverse effect of uncertainty shocks on U.S. output diminishes and becomes statistically insignificant when financial conditions are relaxed, consistent with the financial channel of uncertainty shocks emphasized in recent literature. Moreover, once the financial channel is shut down, uncertainty shocks explain only a minor share of the U.S. output fluctuations and inflation dynamics over the last century, which corroborates the findings from Born and Pfeifer (2014) using a different approach.

Third, we evaluate the role of uncertainty in amplifying a financial shock, measured by a shock to credit spread. Interestingly, counterfactual VARs indicate an asymmetric interaction between uncertainty and financial shocks. The uncertainty channel does not affect the response of macroeconomic variables to financial shocks in any material way and financial shocks still explain most U.S. output fluctuations and inflation dynamics over the last century even after the uncertainty channel is shut down.

Lastly, we investigate the relationship between constrained monetary policy reflected in the binding ZLB constraint and uncertainty shocks. Shutting down the endogenous response of the federal funds rate to the uncertainty shock in the counterfactual VAR exercises does not amplify the adverse effect of uncertainty shocks. Moreover, the use of nearly 100 years of the data provides another interesting episode during which the U.S. economy is effectively in the liquidity trap (1934-1939). We find that the amplified adverse effect of uncertainty shocks during the binding ZLB constraint is largely masked by the joint occurrence of tightened financial conditions during the same period, which is in sharp contrast to the recent theoretical and empirical studies highlighting the independent role of the binding ZLB constraint in amplifying the effect of uncertainty shocks.

The remainder of the paper is organized as follows. Section II describes the data used in the empirical analysis. Section III proposes the econometric methodology used in this paper to isolate the financial and monetary channel, then presents the empirical results using counterfactual VARs and regime-dependent local projections, respectively. Section IV concludes with policy implications.

II. DATA

We choose the variables in our empirical analysis in a similar fashion as Baker et al. (2016) for comparability, except for the explicit consideration of financial market conditions in the propagation of uncertainty shocks. The EPU index has been widely used in recent studies as an alternative to the VIX, which measures implied volatility of the U.S. equity market. In constructing the index, Baker et al. (2016) mainly took a narrative approach that utilized the news coverage of policy-related economic uncertainty; in each newspaper, they counted the articles containing the terms related to economic and policy uncertainty.[5] To meet the criteria for inclusion, any article should include terms in all three categories pertaining to uncertainty, economy, and policy. For example, an article containing the words 'uncertain', 'Congress', and 'economic' meets the criteria.

In addition to the news coverage, they also computed an intermediate index by summing up the discounted value of expiring tax provisions in each year over a 10-year horizon. Since Congress often extends expiring tax provisions at the last minute, temporary tax measures can heighten the uncertainty for businesses and households. Baker et al. (2016) also considered the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. Since this quarterly survey provides the forecasts for various macroeconomic variables, such as the consumer price index and purchases of goods and services by the federal government, they used the dispersion in the forecasts of those variables as a proxy for uncertainty about the policy. To construct an overall index of economic policy uncertainty, Baker et al. (2016) normalized the intermediate indices of the three components (newspaper coverage, tax code expiration date, and economic forecaster disagreement) and computed the weighted average of each.

Along with the index covering the period after 1985, Baker et al. (2016) also provided a separate series of the U.S. historical EPU index for 1900-2012. This series was based solely on the narrative approach using news coverages. In our analysis, we combine the two EPU series of different periods (1985-2017 and 1900-2012) to construct a single time series of the economic policy uncertainty index for 1900-2017. For this, we normalize the shorter series to have the same mean as that of the longer series during the overlapping period from 1985 to 2012. Then we augment the values of the normalized series from 2013 to 2017 to the original historical EPU series.

Following previous studies (Gilchrist et al., 2009 and Gilchrist et al., 2014), we use the spread between the Baa-graded and the Aaa-graded nonfinancial firms to measure the external finance premium and the tightness of financial conditions. Although there are alternative measures

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[5] For the U.S. index, they refer to the ten largest newspapers: the USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicles, the Dallas Morning News, the Houston Chronicle, and the Wall Street Journal.

to this credit spread, we use the spread between Moody's Aaa and Baa corporate bond yields due to their long time-series availability at a monthly frequency since 1919.[6] Figure 1 shows the time series of the EPU index and the Baa-Aaa spread from January 1919 to December 2017. Not surprisingly, the two variables tend to co-move, but their correlation is far from perfect (0.37).[7] On the other hand, the correlation between the Baa-Aaa spread and stock market volatility—measured by the realized volatility of daily S&P500 returns—from January 1928 and December 2017 is 0.65, implying the difficulty of identifying uncertainty shocks from financial shocks when using an uncertainty measure based on financial data.[8]

As a measure of the price level, we use the monthly consumer price index. We then use the industrial production index as the measure of output in the economy for two reasons. First, the data on industrial production is available since January 1919, while GDP data (non-interpolated) are typically available after World War II. Second, its monthly frequency mitigates the identification issue when including financial data in the recursively identified VARs. We combine several kinds of interest rates to measure the monetary policy stance over the last century. We use the effective federal funds rate from July 1954, while we use the Federal Reserve Bank of New York's discount rate for November 1914–June 1954, during which period the effective federal funds rate is not available. When the federal funds rate was stuck at the ZLB since the global financial crisis, we use the shadow policy rate constructed by Wu and Xia (2016). Although the interest rate we employ is a combination of three different rates, we still call it the federal funds rate for simplicity's sake. Overall, the sample period adopted in this paper is determined by the availability of data on credit spread and output.

III. EMPIRICAL ANALYSIS

[6] We also test the robustness of our findings using a newspaper-based Financial Stress Indicator (FSI) developed by Püttmann (2018), which is available from 1889 to 2016. See Püttmann (2018) for further details of the construction of the FSI.

[7] The correlation between the two variables since January 1985 is also 0.37, suggesting their unconditional relationship is quite stable over time and not particularly sensitive to the sole reliance on newspaper coverage in constructing the historical EPU index.

[8] We take the monthly historical stock market volatility from Choi (2017) who constructed this index using daily stock returns from Global Financial Data.

A. Structural Vector Autoregressions

We now discuss the methodology for isolating the role of financial conditions and monetary policy stance in the transmission of uncertainty shocks. Our methodology stems from Sims and Zha (2006) who analyze the role of the systematic component of monetary policy in the transmission of other shocks in structural VARs. Such methodology has been adopted by many empirical studies to study the effect of oil price shocks (Kilian and Lewis, 2011), fiscal policy shocks (Bachmann and Sims, 2012), and also uncertainty shocks (Carrière-Swallow and Céspedes, 2013; Popp and Zhang, 2016).

Structural VAR model. Our baseline VAR model includes five variables: the uncertainty index, the measure of financial conditions (the Baa-Aaa spread), the consumer price index (CPI), the industrial production index, and the federal funds rate. Our model is parsimonious but contains adequate information on output, price, financial conditions, the monetary policy stance, and the measure of uncertainty over a long period of time, including 17 NBER recessions—the data spans from January 1919 to December 2017, the longest timespan for which all five variables of interest are available. We impose structural assumptions on the variables, which are equivalent to the Cholesky identification arranging the variables in the order of the uncertainty index, credit spread, industrial production, CPI, and the federal funds rate.

This assumption implies that a variable is affected by the contemporaneous changes in the variables listed before it, while it is exogenous to the variables listed after it. For example, at time t, the UNC, which is ordered first, does not respond to the concurrent innovations in the other variables, but it has contemporaneous impacts on the other four variables. Thus, the uncertainty variable is the most exogenous variable under this identifying assumption, which is in line with many of the earlier VAR studies (Bloom, 2009; Caggiano et al., 2014; Fernández-Villaverde et al., 2015; Leduc and Liu, 2016; Basu and Bundick, 2017).[9] Our identifying assumption is also similar to that of Baker et al. (2016) except we placed the federal funds rate after CPI and output. Such an

[9] While the emerging literature questions the exogeneity of uncertainty shocks and argues that uncertainty could increase as an "endogenous" response to aggregate fluctuations (Ludvigson et al., 2015; Fajgelbaum et al., 2017; Carreiro et al., 2018; Plante et al., 2018), we adopt the most commonly used identification here to facilitate comparisons with many existing empirical studies, as well as to give the uncertainty shock the best chance as a business cycle driver.

identifying assumption about the policy interest rate is standard in monetary VAR literature, such as in Christiano et al. (2005).

To simplify the notation, let $Y_t = [unc_t \ spread_t \ ip_t \ cpi_t \ ffr_t]'$ be a 5×1 column vector of the five time-series of interest observed at time *t*. Each element indicates the uncertainty index, credit spread, the log of industrial production, the log of CPI, and the federal funds rate, respectively. We model the data in (log) levels to preserve the cointegrating relationships among the variables.[10] Then the baseline VAR model can be represented in a matrix form as follows.

$$A_0 Y_t = \sum_{j=1}^{p} A_j Y_{t-j} + \epsilon_t, \tag{1}$$

where, A_0 is the lower triangular matrix that reflects the structural assumptions we imposed on the variables. p is the lag length and six lags have been chosen in our baseline model. ϵ_t is a 5×1 column vector of structural shocks at time *t* and each element in it is uncorrelated with each other.

Counterfactual structural VAR model. Our main focus is to examine how significant the role of financial conditions is in propagating the effect of uncertainty shocks on real activity.[11] For this, it is conceptually necessary to shut down the dynamic response of financial conditions to the uncertainty shocks in the VAR and compare the results to those of the baseline model without any restrictions. In isolating and restricting the role of the financial conditions, we take a similar approach as that of Sims and Zha (2006), Kilian and Lewis (2011), and Bachmann and Sims (2012).

Let us first consider how financial conditions can influence the transmission of uncertainty shocks into the other variables, especially output. Suppose, at time *t*, there occurs an uncertainty shock of one unit ($\epsilon_{1,t} = 1$). Then under our specification, it immediately influences output both directly and indirectly via the other variables. The third element in the first column of A_0, a_{31}, captures the direct impact of the uncertainty shock on output at time *t*. At the same time, the

[10] A large body of the literature on this issue suggests that it is still desirable to estimate a VAR model in levels, even if the variables have unit roots (Sims et al., 1990).

[11] In the later part of the paper, we further investigate the role of monetary policy in amplifying the effect of uncertainty shocks and the role of uncertainty channel in transmitting financial shocks in a similar way. For convenience, however, we here introduce our methodology focusing on studying the role of financial conditions in transmitting uncertainty shocks as an example.

financial conditions also respond to the shock as much as a_{21} and output, in turn, responds to the shock as much as a_{32}. Thus, the total impact of the uncertainty shock on output is $a_{31} + a_{21} \times a_{32}$, consisting of the direct impact (a_{31}) and the indirect impact via the changes in financial conditions ($a_{21} \times a_{32}$). Similarly, we can compute the indirect impact of uncertainty shock at time *t* on output at time *t+h* by taking into account the coefficients of the lagged variables. To shut down this propagation mechanism via the financial conditions, we construct a hypothetical sequence of the shocks that exactly offset the response of the financial conditions to the uncertainty shock in each horizon.

Once all the restrictions on the elements of A_0 have been identified and A_0^{-1} has been recovered, the matrix form specified above can be modified as

$$Y_t = \sum_{j=1}^{p} A_0^{-1} A_j Y_{t-j} + A_0^{-1} \epsilon_t. \tag{2}$$

Defining a $5p \times 1$ column vector $Z_t = [Y_t \ \ Y_{t-1} \ Y_{t-2} \ldots Y_{t-p+1}]'$, we can represent the above VAR(*p*) model more compactly as a VAR(1) model with a companion matrix as follows.

$Z_t = \Lambda Z_{t-1} + \widetilde{\epsilon_t}$, where,

$$\Lambda = \begin{pmatrix} A_0^{-1}A_1 & A_0^{-1}A_2 & \Lambda & \Lambda & A_0^{-1}A_p \\ I & 0 & 0 & \Lambda & 0 \\ 0 & / & 0 & \Lambda & 0 \\ \mathrm{M} & \mathrm{M} & \mathrm{O} & \mathrm{M} & \mathrm{M} \\ 0 & \Lambda & \Lambda & / & 0 \end{pmatrix}$$

$$\text{and } \widetilde{\epsilon_t} = \begin{bmatrix} A_0^{-1}\epsilon_t \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

The size of Λ and $\widetilde{\epsilon_t}$ is $5p \times 5p$ and $5p \times 1$ respectively. Let e_i be the selection row vector of dimension $1 \times 5p$, with a one in the i_{th} place and zeros elsewhere. Let $\widetilde{A_0^{-1}}(c)$ be the c_{th} column of A_0^{-1} with $5(p-1) \times 1$ zero vectors augmented below it. Then, the impulse response of variable *i* to the structural shock in variable *c* in horizon *h=0,1,2,…,H* is

$$\Phi_{i,c,h} = e_i \Lambda^h \widetilde{A_0^{-1}}(c)$$

To hold the financial condition fixed in response to a change in uncertainty, it is required to set $\Phi_{2,1,h} = 0$ in each forecast horizon. To force this to hold, we construct a hypothetical series of financial condition shocks $\{\epsilon_{2,h}\}$. For a unit shock to the uncertainty index, it requires $\epsilon_{2,0} = a_{21}$ to hold credit spread fixed in horizon 0. It can be equivalently represented in a matrix notation as follows.

$$\widetilde{A_0^{-1}}(2,1) + \widetilde{A_0^{-1}}(2,2)\epsilon_{2,0} = 0 \Rightarrow \epsilon_{2,0} = -\frac{\widetilde{A_0^{-1}}(2,1)}{\widetilde{A_0^{-1}}(2,2)} \tag{3}$$

Similarly, the subsequent financial shocks should satisfy the following equation in each horizon.

$$\Phi_{2,1,h} + \sum_{j=0}^{h-1} e_2 \Lambda^{h-j} A_0^{-1}(2)\epsilon_{2,j} + e_2 A_0^{-1}(2)\epsilon_{2,h} = 0,\ \ h = 1,2,\dots,H. \tag{4}$$

In turn, $\epsilon_{2,h}$ can be calculated recursively as

$$\epsilon_{2,h} = -\frac{\Phi_{2,1,h} + \sum_{j=0}^{h-1} e_2 \Lambda^{h-j} A_0^{-1}(2)\epsilon_{2,j}}{e_2 A_0^{-1}(2)}. \tag{5}$$

With this sequence, the adjusted impulse responses of the variables in the model to the uncertainty shock can be computed as

$$\widetilde{\Phi}_{i,1,h} = \Phi_{i,1,h} + \sum_{j=0}^{h} e_i \Lambda^{h-j} A_0^{-1}(2)\epsilon_{2,j}\,,\ \ i = 1,2,\dots,5 \tag{6}$$

The resulting impulse response functions show the pure response of each variable to the uncertainty shock with the propagation mechanism by the financial conditions shut down. By comparing them to the impulse response functions of the baseline model without such constraints, we can identify the role of the financial conditions in transmitting uncertainty shocks to the other variables.

Baseline results from a hundred years of data. Figure 2A and 2B illustrate the responses of the four endogenous variables to a one standard deviation increase in economic policy uncertainty under our baseline VAR specification with sample period starting from January 1985 and January 1919, respectively. Although our baseline specification employs the historical sample from January 1919 to December 2017 as shown in Figure 2B throughout the paper, we also include

Figure 2A to check whether our identification specification delivers findings consistent with those from previous studies using the EPU index dating from January 1985, such as Baker et al. (2016).

Before discussing the role of financial conditions in propagating the effect of uncertainty shocks, a few novel observations from using historical data are worth to mention. While the responses in Figure 2A are fully consistent with Baker et al. (2016), the response of CPI in Figure 2B changes its sign from Figure 2A. This finding is in sharp contrast to the recent studies by Leduc and Liu (2016) and Basu and Bundick (2017), among others, who found a disinflationary effect of uncertainty shocks using a shorter span of U.S. macroeconomic data and concluded that uncertainty shocks are a negative aggregate demand shock. However, the sign-varying response of CPI over time is indeed consistent with the recent VAR evidence by Meinen and Roehe (2018) and Alessandri and Mumtaz (2019) who show that the effect of uncertainty shocks on prices is indeterminate.

Theoretically, uncertainty shocks can also be inflationary through the so-called “inverse Oi-Hartman-Abel effect” (Born and Pfeifer, 2014; Fernández-Villaverde et al., 2015). Since firms must satisfy demand given their prices and sticky prices create a convex marginal profit function, firms raise markups in response to heightened uncertainty to insure themselves against being stuck at too low a price. Consequently, the aggregate output decreases, while inflation increases. Using the U.S. data starting from the first quarter of 1950, Mumtaz and Theodoridis (2018) also found that uncertainty shocks are inflationary and suggested this pricing bias channel as a rationale. Fasani and Rossi (2018) considered the effect of uncertainty shocks under different Taylor rules and found that with a less active Taylor rule,uncertainty shocks look more like aggregate supply shocks rather than demand shocks. Since the U.S. monetary policy was less active during the pre-1985 period than the post-1985 period analyzed in Figure 2A, the inflationary effect of uncertainty shocks and the aggregate supply shock interpretation are also consistent with Fasani and Rossi (2018). Thus, our findings call for caution on the negative demand shock interpretation of uncertainty shocks by Leduc and Liu (2016) and Basu and Bundick (2017).

The third panel depicts the response of output to the uncertainty shock. Figure 2B indicates a significant decline in output on impact and the maximum decline occurs after six months, indicating that heightened economic policy uncertainty has a significant detrimental effect on real activity. A similar pattern is observed in Figure 2A, but the magnitude of the decline is smaller, which is consistent with Choi (2013), Choi (2017), and Mumtaz and Theodoridis (2018) who found that the real effect of uncertainty shocks has decreased over time. The last panel shows the response of the monetary policy stance to the uncertainty shock. The central bank takes an expansionary monetary policy stance by lowering the policy rate to counter the negative effect of uncertainty shock on real activity. However, the inflationary response to uncertainty shocks in the full sample implies a potential policy dilemma faced by the central bank due to the negative trade-off between output and inflation.

Counterfactual exercises to infer the role of financial conditions. Figure 3 compares the impulse response functions of the baseline VAR model to those of the counterfactual exercise where propagation through the financial channel is shut down. The shaded area represents the 68% confidence bands for the impulse response functions, which is standard in the counterfactual VARs (e.g., Kilian and Lewis, 2011; Bachmann and Sims, 2012; Popp and Zhang, 2016). However, we also plot the 90% confidence bands in dashed lines, which is more common in standard VARs. The magnitude of the decline in output is significantly smaller when the financial channel is shut down and no longer statistically significant. While the response of CPI is more inflationary, the degree of monetary accommodation weakens slightly, probably because the monetary authorities do not need to lower the interest rate as much as in the baseline case. These findings corroborate the recent VAR studies employing a similar strategy but using much shorter periods (Carrière-Swallow and Céspedes, 2013; Bonciani and van Roye, 2016; Popp and Zhang, 2016).[12] Thus, we conclude that the role of financial markets in transmitting and amplifying uncertainty shocks is robust and not restricted to the recent period.

Robustness checks. We conduct several robustness tests to confirm the importance of the financial channel as a propagation mechanism of uncertainty shocks. To conserve space, we only discuss the results in the main text and present the relevant figures in the appendix. First, we run a

[12] Bonciani and van Roye (2016) analyzed the role of frictions in the banking sector in amplifying the adverse impact of uncertainty shocks in the euro area using stock market volatility data from 2000, while Popp and Zhang (2016) studied the interaction between uncertainty shocks and financial conditions in the U.S. using stock market volatility data from 1962, similar to Bloom (2009). Carrière-Swallow and Céspedes (2013) compared the effect of U.S. uncertainty shocks on a group of developed and emerging economies from 1990 and found that shutting down the credit channel has a much larger effect on emerging than developed economies.

parsimonious VAR model with only three variables (the uncertainty index, credit spread, and industrial production). Figure A.1 in the appendix shows the responses of credit spread and output to the uncertainty shock using the baseline and counterfactual specifications in the trivariate VARs. The change in the response of output after shutting down the financial channel is not qualitatively different from the results from the 5-variable VARs.

We then repeat the same counterfactual exercise but limit our sample period to January 1919—December 2012 during which only the historical EPU index is used. This is to avoid any potential structural break in combining the historical EPU index with the current EPU index that incorporates the information beyond the newspaper coverage used in constructing the historical EPU index. Figure A.2 confirms that slightly different methodologies in constructing the historical and current EPU index do not affect our results. Additionally, given the unprecedented increase in both economic policy uncertainty and credit spread during the Great Depression and the Great Recession periods, we dummy out these periods using the NBER recession dates. Figure A.3 shows that our findings are robust even after these outlier events are dropped from the analysis.

We also replace the EPU index with a stock market volatility index, which is available from January 1928, to confirm whether the financial channel measured by credit spread still plays an important role in amplifying the so-called financial uncertainty shock.[13] Figure A.4 compares the stock market volatility index constructed by Choi (2017) and the EPU index. Despite the moderate correlation between the two indices (0.4), Figure A.5 confirms that the adverse real effect of uncertainty shocks is substantially mitigated in this case as well, although the negative effect is still statistically significant in this case. Similar to the case of economic policy uncertainty, shutting down the financial channel makes the response more inflationary, although the baseline response is statistically insignificant.[14] While the use of the EPU index demonstrates the importance of the

[13] Since the VIX is available only after 1990, we cannot use an implied volatility measure for the historical sample. However, the correlation between a realized and implied volatility measure exceeds 0.9 during the post-1990 sample, suggesting that it is quite innocuous to use realized volatility for an empirical study.

[14] In the following section, we find that financial shocks are disinflationary, which is in contrast with the case of uncertainty shocks. In the sense that uncertainty measures based on financial data, such as VIX, tend to reflect both financial distress and other types of uncertainty to some extent, the statistically insignificant response of the CPI in this exercise seems plausible.

financial channel more clearly, the qualitative results still hold when using the historical extension of the VIX.

Lastly, we test the robustness of our findings by replacing the Baa-Aaa spread with the financial stress index (FSI) constructed by Püttmann (2018). This index is constructed in a similar manner to the EPU index by Baker et al. (2016) but focused on the article pertaining to financial markets. The correlation between the Baa-Aaa spread and the FSI is 0.37, suggesting that they might capture different dimensions regarding financial market conditions. Figure A.6 compares both indices. Figure A.7 confirms that our main findings from Figure 3 still hold when using an alternative measure of financial market conditions.

Uncertainty shocks vs. financial shocks as a business cycle driver. So far, we have found robust evidence that a financial channel, proxied by the Baa-Aaa spread or the financial stress index, plays a crucial role in amplifying the adverse effect of uncertainty shocks on the macroeconomy. Regarding the role of uncertainty shocks as a business cycle driver, Born and Pfeifer (2014) concluded that the so-called "pure uncertainty" effect of policy uncertainty is unlikely to play a major role in business cycle fluctuations. Ludvigson et al. (2015) also found that while uncertainty from financial markets is a dominant source of U.S. business cycle fluctuations, uncertainty about the rest of the economy is just an endogenous response to other shocks causing business cycle fluctuations. Their findings are in sharp contrast to those of Caggiano et al. (2014), Christiano et al. (2014), and Choi (2017) who found that uncertainty shocks, when measured using financial market data, are a major driver of business fluctuations.

Motivated by these contrasting findings, we conduct a similar counterfactual approach but estimate the effect of financial shocks this time after shutting down the so-called uncertainty channel. This exercise examines whether the uncertainty channel also amplifies an adverse financial shock, thereby shedding light on the endogenous interaction between uncertainty and financial shocks. For this exercise, we switch the ordering between the uncertainty index and the Baa-Aaa spread so that we treat credit spread as the most exogenous variable in the VAR system and allow uncertainty to respond to financial shocks, measured by an increase in credit spread. Thus, we give uncertainty and financial channels an equal opportunity to propagate shocks originated from each other.

Figure 4 shows the results from the baseline and counterfactual VARs under the new identifying assumption. When compared to Figure 3, two findings stand out. First, unlike uncertainty shocks, financial shocks have a disinflationary effect even in the full sample, implying that higher uncertainty is not simply a reflection of financial market distress if we take a more historical perspective. Such qualitatively different responses call for caution when treating the two shocks interchangeably, which is a common practice in some empirical studies. Second, financial shocks have a significantly negative impact on output, which is much larger than that of uncertainty shocks, and shutting down the uncertainty channel does not mitigate the adverse impact at all.[15]

Figure A.8 in the appendix shows the results using stock market volatility as a measure for the uncertainty channel. Although the importance of the uncertainty channel increases slightly, the strong asymmetry between the two channels still remains. In this sense, our finding is also related with Ludvigson et al. (2015) who found that uncertainty from financial markets is a dominant source of U.S. business cycle fluctuations, whereas uncertainty about the rest of the economy is just an endogenous response to other shocks causing business cycle fluctuations. To the extent to which their measure of financial uncertainty also reflects financial market distress, our finding is compatible with Ludvigson et al. (2015). Our finding in Figure A.5 that financial market-based uncertainty has a stronger real effect than policy-based uncertainty regardless of the transmission channel further supports this claim.

We further evaluate the role of uncertainty shocks in explaining the variation in output, the price level, and the policy interest rate when the financial channel is shut down. The top panel in Table 1 shows the share of variation in these variables explained by the uncertainty shock in different horizons when the financial channel is shut down. The bottom panel reports similar statistics corresponding to the exercise in Figure 4 where we shut down the uncertainty channel when evaluating the role of financial shocks. Consistent with the evidence presented in the impulse

[15] Our exercise is conceptually similar to the approach taken by Caldara et al. (2016) who found that uncertainty shocks are still an important driver of the U.S. output fluctuations after taking account of the effect of financial shocks. Although our findings seemingly contradict those of Caldara et al. (2016) using a penalty function approach, their conclusion is based on the analysis using the uncertainty measure of Jurado et al. (2015), which is a measure of dispersion in forecast errors constructed from a statistical model. When they used the EPU index by Baker et al. (2016) instead, they also found an economically and statistically insignificant effect of uncertainty shocks on industrial production, which is fully consistent with our findings.

response functions, a large share of macroeconomic variables, especially output, is still explained by the "pure" financial shocks, while only a very small share of these variables is explained by the "pure" uncertainty shocks. If anything, the role of pure uncertainty shocks in explaining output fluctuations diminishes even more, when we compare the historical sample to the recent sample. Again, the results from the forecast error variance decomposition highlight the importance of the financial channel in transmitting uncertainty shocks.[16]

Constrained monetary policy as an amplification channel of uncertainty shocks. We have established a strong asymmetry between uncertainty and financial shocks in propagating the effect of each other. Now we evaluate the role of constrained monetary policy in amplifying uncertainty shocks. The recent literature has investigated whether the contractionary effects of uncertainty shocks are amplified under the binding ZLB constraint (Nakata, 2017; Basu and Bundick, 2016; Caggiano et al., 2017; Plante et al., 2018). Leduc and Liu (2016) also argue that a much slower recovery from the Great Recession and the larger effect of uncertainty shocks on unemployment during this period is attributable to the binding ZLB constraint. While these studies often find that constrained monetary policy at the ZLB amplifies the adverse effect of uncertainty shocks on economic activity, the recent ZLB episode coincides with tightened financial market conditions, which are proven to be an independent driver of business cycles as well as a robust amplifying mechanism of uncertainty shocks.

Thus, identifying the role of constrained monetary policy in amplifying the adverse effect of uncertainty shocks crucially hinges on disentangling confounding factors, such as financial market conditions. To address this issue, we conduct a similar counterfactual exercise: we shut down the monetary policy channel through the federal funds rate but allowing the indirect effect of uncertainty shocks through credit spread. In other words, we construct a hypothetical sequence of the shocks that exactly offset the response of the federal funds rate to the uncertainty shock in each horizon, thereby nullifying the expansionary effect of monetary easing following the uncertainty shock.

[16] In a related study, Bachmann and Bayer (2013) also show that time-varying firm-level uncertainty through 'wait-and-see' mechanism cannot be a major source of business cycle fluctuations and suggest financial frictions instead as a potential mechanism using a heterogenous-firm dynamic stochastic general equilibrium model.

Interestingly, Figure 5 shows that shutting down the monetary policy channel does not have any material impact on the effect of uncertainty shocks, which is in sharp contrast to Caggiano et al. (2017) who find the amplified effect of uncertainty shocks under the binding ZLB using interacted-VARs. It is true that constructing any counterfactual of the policy response is subject to Lucas critique (Sims and Zha, 2006; Kilian and Lewis, 2011). While our empirical model cannot resolve this fundamental issue, we still provide the results from an alternative counterfactual exercise to enhance the credibility of our findings. As a robustness check, we shut down only the direct response to economic policy uncertainty while allowing for the Fed to react to fluctuations in other macroeconomic and financial variables as it normally would.[17] This alternative counterfactual exercise was used by Kilian and Lewis (2011) in identifying the role of monetary policy in transmitting oil price shocks.

Figure 6 summarizes the results from the alternative exercise. Whereas the Fed still lowers the policy rate in response to the aggravating macroeconomy, the response is smaller than the unrestricted VARs. However, even in this case, the effect of uncertainty shocks on other variables remains virtually the same, suggesting that constrained monetary policy is unlikely a major propagation channel of uncertainty shocks. Figure A.9 in the appendix shows the same exercise using stock market volatility as an alternative measure of uncertainty, which confirms that shutting down monetary policy response to uncertainty shocks does not amplify their effect on the macroeconomy.

While this finding seems puzzling at first glance, monetary policy ineffectiveness under heightened uncertainty might explain it. Bloom (2009) notes that uncertainty shocks induce a strong insensitivity to other economic stimuli via an increased real-option value of inaction, which makes monetary or fiscal policy particularly ineffective. Recently, Aastveit et al. (2017) and Castelnuovo and Pellegrino (2018) indeed find that monetary policy becomes less effective (i.e., its effect on output and inflation becomes smaller) when uncertainty is high, implying the absence of monetary policy channel following uncertainty shocks. If the monetary policy becomes ineffective following uncertainty shocks, shutting down this channel might not change the effect

[17] The baseline counterfactual exercise constructs a hypothetical path of the monetary policy shocks that fully offset any endogenous dynamics in the federal funds rate so that it remains unchanged over time.

of uncertainty shocks on the macroeconomy.[18] To better understand this novel but seemingly puzzling finding, we will revisit this issue in the following section by further exploiting another historical incidence of effective lower bound in the 1930s.

B. Local Projections

In this section, we estimate a regime-dependent effect of uncertainty shocks using Jordà's (2005) local projection method, thereby complementing the counterfactual VAR analysis conducted in the previous section. Estimating the regime-dependent effect of uncertainty shocks can shed further light on the importance of the financial and monetary policy channel in transmitting/amplifying the effect of uncertainty shocks without imposing potentially stringent restrictions used in the structural VAR analysis. Jordà (2005) argued that the local projection method can be a good approximation of a VAR model while allowing more flexibility.

The direct projection method is more robust to misspecification when calculating the impulse response functions compared with the iterated method in VARs. Thus, the local projection method has been advocated by Auerbach and Gorodnichencko (2012) and Ramey and Zubairy (2018), among others, as a flexible alternative to the VAR specifications. Moreover, the local projection method is particularly suited to estimating nonlinearities (for example, how the effect of uncertainty shocks is different during a period of financially tightened regime or the binding ZLB constraint from a normal period), as its application is much more straightforward than that of complex nonlinear structural VAR models and does not require taking a stand on how the economy switches from one regime to another.[19]

[18] However, the empirical VAR literature has not reached consensus on the effectiveness of monetary policy under heightened uncertainty. For example, Park (2019) finds that monetary policy becomes more effective under heightened uncertainty and explains this finding using rational inattention of economic agents.

[19] One should note that the local projection approach is not necessarily a panacea for computing the impulse response functions. The iterated model in standard VARs is more efficient if the one-period-ahead forecast is well specified. Moreover, the local projection method loses observations to be used for estimation as the estimation horizon increases, which results in wider confidence bands. However, this is not problematic for us given the hundred years of the data we have. Of course, the local projection method itself does not resolve an identification issue and it requires identifying assumptions as in structural VARs. See Plagborg-Møller and Wolf (2019) for the recent discussion about the properties of VARs and local projections.

Our regime-dependent local projection model is similar to the smooth transition autoregressive model developed by Granger and Teräsvirta (1993) and has the following advantages. First, unlike a model where each dependent variable interacts with a measure of the financial condition, it permits a direct test of whether the effect of uncertainty shocks varies across different regimes. Second, contrary to estimating structural VARs for each regime, it allows the effect of uncertainty shocks to change smoothly between two regimes by considering a continuum of states to compute the impulse response functions, thus making the response more stable and precise.

Baseline local projections. Jordà's method simply requires estimating a series of regressions for each horizon h for each variable. Following Auerbach and Gorodnichencko (2012) and Ramey and Zubairy (2018), we run a series of regressions for different horizons, $h = 1,2, \dots, H$ as follows:

$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h unc_t + \Sigma_{p=1}^{n} \gamma_h X_{t-p} + \epsilon_{t+h}, \tag{7}$$

where, y_t is the dependent variable of interest in time t, α_h is the vector of constants, unc_t is the identified uncertainty shock using the same Cholesky ordering from the structural VARs, and X_t is the set of control variables including the lags of the dependent variable y_t, the uncertainty index, and other macroeconomic variables. To be consistent with the structural VAR analysis in the previous section, we include the same five variables in the baseline model. We embed the same kind of an identifying assumption here so that uncertainty affects other variables simultaneously, but these variables affect uncertainty only with a lag.[20]

The coefficient β_h gives the response of y at time $t + h$ to the shock at time t. Thus, we can construct the impulse responses as a sequence of the values of β_h estimated in a series of single regressions for each horizon. This method stands in contrast to the standard method of estimating the parameters of the VAR for the horizon 0 and then using those parameters to iterate forward to construct the impulse response functions. The above equation is estimated for h=0, 1, 2, …, 24 so that we can trace the dynamic effect of uncertainty shocks over two years. In the baseline analysis,

[20] In other words, unc_t is the residuals from regressing the uncertainty index on its lags and the lags of other variables in the system. This identifying assumption is equivalent to the one used in the baseline structural VARs in the previous section where the uncertainty index is placed first in the Cholesky ordering so that uncertainty is treated the most exogenous variable in the system.

we use six lags of the control variables in X_t (i.e., n=6) but the selection of the lag length beyond six does not affect our findings in a meaningful way.

Figure 8 visualizes the dynamic responses of the four macroeconomic variables to the uncertainty shock using our baseline local projections. The responses of credit spread, industrial production, CPI, and the federal funds rate are consistent with our baseline 5-variable VAR model shown in Figure 2B, suggesting that the effect of uncertainty shocks does not depend on a particular estimation method.

Regime-dependent local projections. The local projection method is easily adapted to estimating a state-dependent model (for example, how the effect of uncertainty shocks differs during expansions and recessions), as its application is much more straightforward than that of complex non-linear structural VAR models, such as the Markov-switching, or the interacted/smooth transition/threshold-VAR models used in the empirical literature on the macroeconomic effect of uncertainty shocks (Bijsterbosch and Guérin, 2013; Caggiano et al., 2014; Caggiano et al., 2017; Alessandri and Mumtaz, 2019; Chatterjee, forthcoming).

We estimate a set of regressions for each horizon h as follows to account for smooth transitions between financially tightened and financially relaxed regimes:

$$y_{t+h} - y_{t-1} = F(z_{t-1})\left[\alpha_{B,h} + \Sigma_{p=1}^{n}\gamma_{B,h}X_{t-p} + \beta_{B,h}unc_t\right] + \left(1 - F(z_{t-1})\right)\left[\alpha_{G,h} + \Sigma_{p=1}^{n}\gamma_{G,h}X_{t-p} + \beta_{G,h}unc_t\right] + \epsilon_{t+h}, \tag{8}$$

where $F(z_{t-1})$ can be interpreted as the measure of the probability of being in a financially tightened regime at time t-1 based on a measure of financial market conditions. Following Auerbach and Gorodnichenko (2012), we lag z_t by one period to minimize contemporaneous correlations between uncertainty shocks and macroeconomic variables.

We still use the spread between Moody's Aaa and Baa corporate bond yields as the proxy for financial market conditions. To account for a long-run trend in credit spread, we control for both linear and quadratic trends. Moreover, we use the residuals from regressing credit spread on twelve lags of the monthly growth of industrial production, to distinguish our financial regimes from the regimes based on the state of business cycles when studying the asymmetric effect of uncertainty shocks (Caggiano et al., 2014; Chatterjee, forthcoming). As a result, Figure 7 demonstrates that our financial regimes are quite different from the NBER recessions and the regimes identified by Auerbach and Gorodnichenko (2012) or Caggiano et al. (2014). Since our local projection approach based on the financial regime is conceptually very similar to the nonlinear-VAR model by Alessandri and Mumtaz (2019), we pay special attention to how our results compare with theirs.

We construct $F(z_t) = \exp(-\theta z_t)/[1 + \exp(-\theta z_t)]$ and $\theta > 0$ where z_t is normalized to have unit variance. Thus, $F(z_t)$ becomes the transition function that ranges between 0 (most relaxed) and 1 (most tightened). We choose $\theta = 1.5$ following Auerbach and Gorodnichenko (2012)[21] and calibrate the mean of z_t such that the economy spends about 20 percent of the time in the financially tightened regime. The parameter $\theta > 0$ governs the smoothness of transition from the financially relaxed regime to a tightened regime. As θ increases, the transition becomes more abrupt between the regimes, while setting $\theta = 0$ is equivalent to the linear specification.

We allow all the coefficients in the model to vary according to the state of the economy when the shock occurs. The estimated parameters depend on the average behavior of the economy in the historical sample between t and $t+h$, given the shock, the initial state, and the control variables. The parameter estimates of the control variables explain the average tendency of the economy to evolve between states. Thus, the estimates incorporate both natural transitions and endogenous transitions from one state to the other, on average, in the data. The coefficients $\beta_{G,h}$ and $\beta_{B,h}$ trace the dynamic response to uncertainty shocks when the economy is in the financially relaxed and tightened regime, respectively.

Following Alessandri and Mumtaz (2019), Figure 9 compares the responses of macroeconomic variables to uncertainty shocks during the financially relaxed regime to the responses during the tightened regime. Despite the wider confidence intervals in the financially tightened regime due to the effectively smaller sample size, the adverse effect on output during that regime is much greater, especially in the short-run.[22] Moreover, the response of prices to

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[21] Our results hardly change when using alternative parameter values of θ between 1 and 6.

[22] While we observe a stronger rebound of output after one year during the financially tightened regime, it is likely to occur due to the shorter span of this regime compared to the financially relaxed regime. Existing empirical studies

uncertainty shocks switches its sign from positive during the financially relaxed regime to negative during the financially tightened regime and monetary accommodation is also stronger during the financially tightened regime. Figure A.10 confirms that the financial regime-dependent effect of uncertainty shocks still holds when using stock market volatility as an alternative measure of uncertainty. Indeed, the dramatic difference in the output effect between the two regimes is even more pronounced in this case.

Overall, all of these findings are perfectly consistent with the findings of Alessandri and Mumtaz (2019) who applied the nonlinear structural VAR with stochastic volatility to the U.S. data from 1973. Despite the different estimation method, the different measure of uncertainty, and the different sample period from Alessandri and Mumtaz (2019), we confirm that a strong asymmetric effect of uncertainty shocks depending on the underlying financial conditions is a robust phenomenon.

Uncertainty shocks and the zero lower bound. In the previous section, we find that shutting down the endogenous response of the policy rate to the uncertainty shock does not alter their effect on other variables in the system, which seems to be a sharp contrast to the recent theoretical and empirical findings that the contractionary effects of uncertainty shocks are amplified when the ZLB constraint is binding (Nakata, 2017; Basu and Bundick, 2017; Caggiano et al., 2017; Plante et al., 2018). To further elaborate on this puzzling finding, we employ a different estimation approach using regime-dependent local projections where the additional regime is based on whether monetary policy is constrained or not.

As argued before, identifying the role of the binding ZLB constraint in amplifying the effect of uncertainty shocks crucially hinges on disentangling confounding factors, such as deteriorating financial market conditions. Indeed, Figure A.11 in the appendix highlights the fact that the effective ZLB episodes in U.S. history are also characterized by tightened financial conditions. Again, the major advantage of the local projection method over nonlinear VARs is its straightforward extension toward a multi-regime situation. Thus, the local projection method allows us to investigate the effect of uncertainty shocks depending on the joint regime based on

using VAR also find a more abrupt drop and faster recovery in real activity during bad times than good times (e.g., Popp and Zhang, 2016; Caggiano et al., 2017; Alessandri and Mumtaz, 2019).

financial market conditions and whether or not the ZLB constraint binds. However, the estimation of the effect of uncertainty shocks based on the joint regime requires more data points to draw reliable inferences. If credit spread remained high during most of the ZLB period, the regime-dependent local projections must rely on only a handful of observations to disentangle the propagation mechanism of uncertainty shocks through the ZLB channel from that through the financial channel.

The use of nearly 100 years of the data is particularly helpful in identifying the effect of uncertainty shocks during the ZLB period since the long historical data offers another interesting episode during which the U.S. economy was effectively in the liquidity trap (1934-1939). Of course, since the federal funds rate was not a monetary policy instrument at the time, we do not define the ZLB episode solely based on the interest rate behavior. Instead, we define the earlier ZLB episode based on the historical perspective. For example, according to Krugman (1998), the U.S. interest rates were "hard up against the zero constraints." From 1934 through the outbreak of World War II in 1939, overnight rates were effectively zero and Treasury bill rates were usually below 25 basis points (Hanes, 2006).[23]

We first analyze whether the adverse effect of uncertainty shocks are amplified under the binding ZLB constraint. In so doing, we replace $F(z_t)$ in equation (8) with a binary indicator I_t, taking a value equal to one when the ZLB contraint binds (March 1934 to August 1939; December 2008 to November 2015) and zero otherwise. Figure 10 shows that the short-term interest rate does not respond to the uncertainty shock during the binding-ZLB regime, lending support to the correct identification of the ZLB episodes. Despite the wider confidence intervals due to the small sample size of the ZLB episodes, the adverese effect on output becomes much larger during the binding-ZLB regime. Unlike the baseline results, the uncertainty shock is disinflationary during the binding-ZLB regime, suggesting that they act as a negative aggregate demand shock when the

[23] The literature has not agreed on understanding of the liquidity trap during the 1930s. For example, Orphanides (2004) argued that "an incorrect understanding of the economy and flawed policy, rather than monetary-policy ineffectiveness, appear to have been behind the dismal outcomes of the period." However, for our purpose, it does not matter whether monetary policy was ineffective or flawed. If the short-term interest rate is not an adequate indicator of monetary policy during a low-interest rate environment, the binding ZLB constraint does not need to exacerbate the adverse effect of uncertainty shocks.

ZLB constraint binds. Figure A.12 in the appendix also confirms the amplified real effect of uncertainty shocks when using stock market volatility as an alternative measure of uncertainty.

While these findings corroborate the existing studies focusing on the recent ZLB episode, the documented responses of the macroeconomic variables resemble those during the financially tightened-regime (Figure 9), casting doubt on the independent role of the binding ZLB constraint in amplifying the effect of uncertainty shocks. Thus, we test this possibility by considering the following multi-regime local projection method, which extends equation (8) by augmenting a binary indicator variable I_t:

$$\begin{aligned} y_{t+h} - y_{t-1} = {} & I_t F(z_{t-1})\left[\alpha_{BZ,h} + \Sigma_{p=1}^{n} \gamma_{BZ,h} X_{t-p} + \beta_{BZ,h} unc_t \right] + \\ & (1 - I_t) F(z_{t-1})\left[\alpha_{BN,h} + \Sigma_{p=1}^{n} \gamma_{BN,h} X_{t-p} + \beta_{BN,h} unc_t \right] + \\ & I_t\left(1 - F(z_{t-1})\right)\left[\alpha_{GZ,h} + \Sigma_{p=1}^{n} \gamma_{GZ,h} X_{t-p} + \beta_{GZ,h} unc_t \right] + \\ & (1 - I_t)\left(1 - F(z_{t-1})\right)\left[\alpha_{GN,h} + \Sigma_{p=1}^{n} \gamma_{GN,h} X_{t-p} + \beta_{GN,h} unc_t \right] + \epsilon_{t+h}, \end{aligned} \tag{9}$$

where the *BZ*, *BN*, *GZ*, and *GN* regime denotes “the financially tightened and binding ZLB regime”, “financially tightened and non-binding ZLB regime”, “financially relaxed and binding ZLB regime”, and “financially relaxed and non-binding ZLB regime”, respectively.

To gauge the relative role between financial market conditions and the binding ZLB constraint in propagating uncertainty shocks, we compare the effect of uncertainty shocks during the *BN* regime to that during the *GZ* regime. The top panel in Figure 11 shows that the overall effect of uncertainty shocks during the *BN* regime is similar to the financially constrained regime: the adverse effect on output is still larger than the baseline and the price response is significantly inflationary. However, the bottom panel shows that the effects during the *GZ* regime differ sharply from those in the binding ZLB regime shown in Figure 10. Uncertainty shocks are no longer contractionary and their effect on prices become inflationary, which corroborates the evidence from the counterfactual VAR exercises. As long as financial conditions remain sound, the binding ZLB constraint alone fails to amplify the negative real effect of uncertainty shocks. Figure A.13 in the appendix confirms that this finding still holds when using stock market volatility as an alternative measure of uncertainty.

We conclude that the amplified adverse effect of uncertainty shocks during the binding ZLB constraint is largely masked by the simultaneous occurrence of tightened financial conditions during the same period. By no means, are we trying to disregard the recent theoretical and empirical attempt to understand a propagation mechanism of uncertainty shocks using the ZLB episode. The nature of our empirical analysis cannot rule out the endogenous interaction among uncertainty, financial conditions, and monetary policy such that the binding ZLB constraint tightens financial conditions, which eventually amplifies uncertainty shocks. However, we also observe that unconventional monetary policy, such as quantitative easing, was at least partly successful in alleviating financial market distress (Baumeister and Benati, 2013; Dell'Ariccia et al., 2018). In this regard, the new evidence from the historical data using nonlinear methods calls for developing a fully structural model, which allows the identification of the role of the binding ZLB constraint in propagating uncertainty shocks separately from the direct influence of financial conditions.

IV. CONCLUSION

We have analyzed the linear and nonlinear effects of uncertainty shocks on the U.S. economy using almost a hundred years of macroeconomic and financial data. To shed some light on the financial channel of uncertainty shocks, we apply two complementing methodologies (structural VARs with a counterfactual exercise and regime-dependent local projections). In identifying the role of the financial channel, we also use a measure of economic policy uncertainty in the baseline analysis, which does not rely on financial market data in its construction to avoid an inherent identification issue when using a proxy for uncertainty constructed from financial market data, such as the VIX. However, most of our findings still hold when using stock market volatility as an alternative measure of uncertainty, in the same spirit with Bloom (2009).

The historical data we use is longer than any of the data analyzed in the existing studies on the quantitative effect of uncertainty shocks and reveals interesting price dynamics in response to uncertainty shocks. We find that using data of a longer span yields an inflationary effect of uncertainty shocks on average, while the operation of the financial channel makes uncertainty shocks disinflationary. Since the channel is strong enough to change the sign of the response of the price level to the shock, the monetary authorities should closely monitor the underlying financial conditions when implementing monetary policy in response to uncertainty shocks.

From counterfactual VARs, we find that the negative effect of uncertainty shocks on output is substantially mitigated by shutting down the financial channel. From regime-dependent local projections, we also find that the adverse effect of uncertainty shocks on output becomes smaller and statistically insignificant when financial conditions are relaxed, consistent with the financial channel of uncertainty shocks emphasized in the recent literature. However, the uncertainty channel does not amplify financial shocks, suggesting a strong asymmetry between uncertainty and financial shocks. To sum up, the empirical evidence we have found using complementary approaches strongly suggests that the financial channel plays an important role in propagating the adverse effect of uncertainty shocks.

Lastly, nearly 100 years of the data provide another opportunity to investigate an interesting episode during which the U.S. economy was effectively in the liquidity trap (1934-1939), which helps identify the role of the binding ZLB constraint in amplifying the adverse effect of uncertainty shocks. While the adverse effect is amplified during the binding ZLB constraint, we find that it is largely masked by the simultaneous occurrence of tightened financial conditions during the same period. The binding ZLB constraint alone fails to amplify the adverse effect of uncertainty shocks. Thus, policymakers' priority concern regarding the negative consequence of heightened uncertainty should be placed on monitoring financial market conditions.

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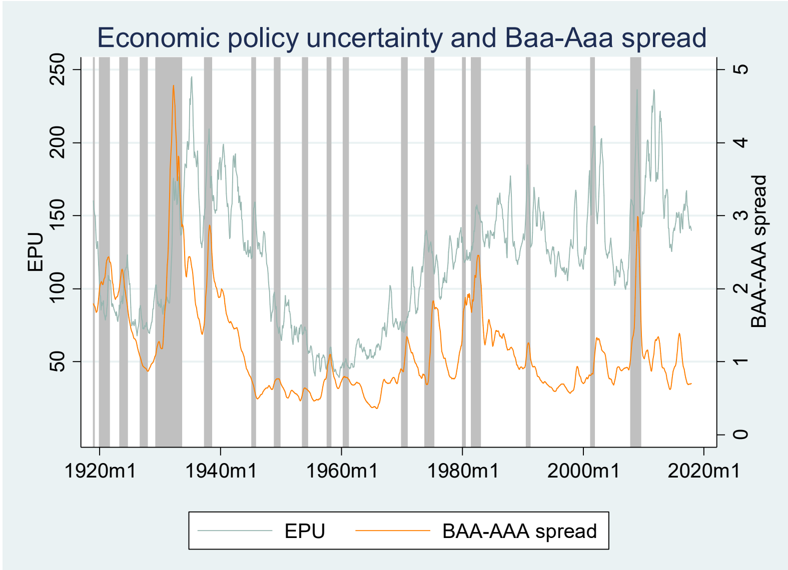
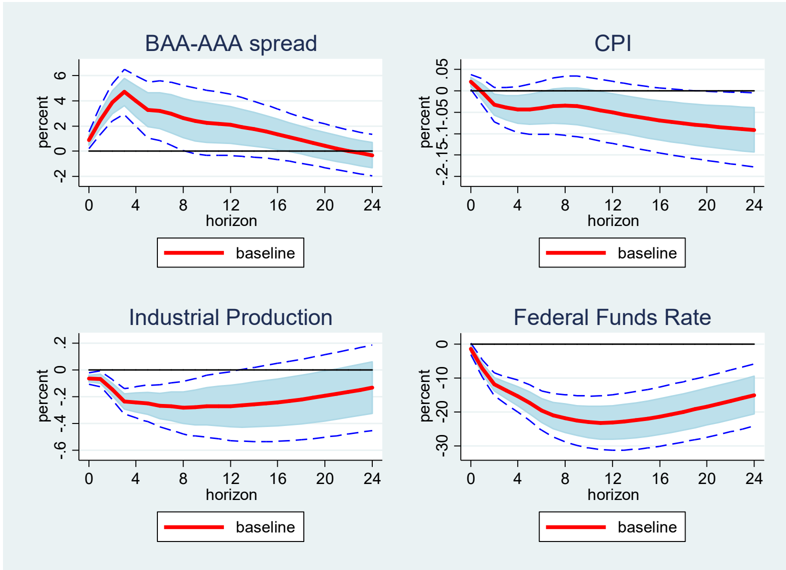
Figures and tables

Figure 1. Economic policy uncertainty and Baa-Aaa spread (1919M1 to 2017M12)



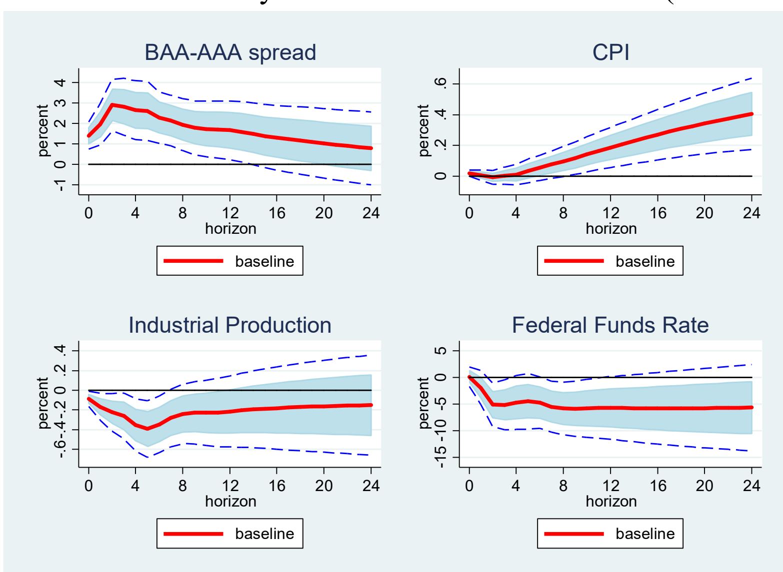
Note: The shaded region shows recessions as defined by the NBER. The EPU index is on the left axis, while the Baa-Aaa credit spread is on the right axis.

Figure 2A. Effect of uncertainty shocks: baseline VAR model (1985M1-2017M12)



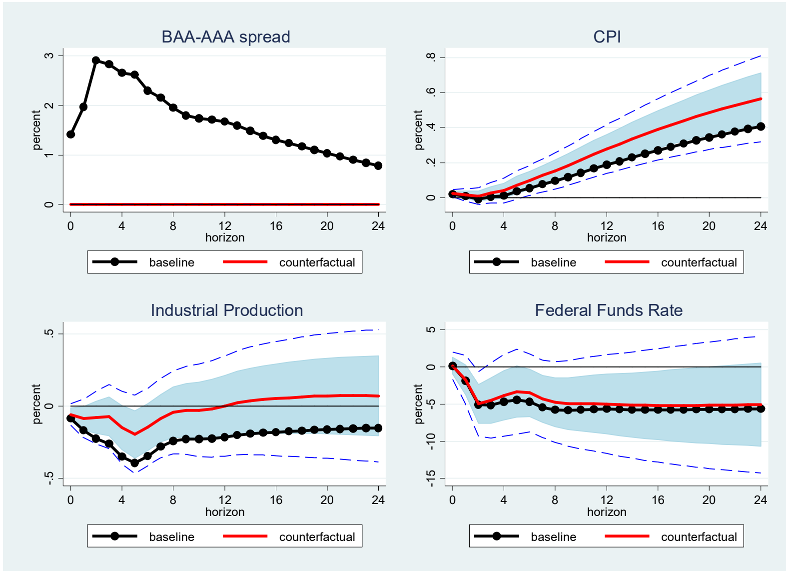
Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1985M1 and 2017M12. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure 2B. Effect of uncertainty shocks: baseline VAR model (1919M1-2017M12)



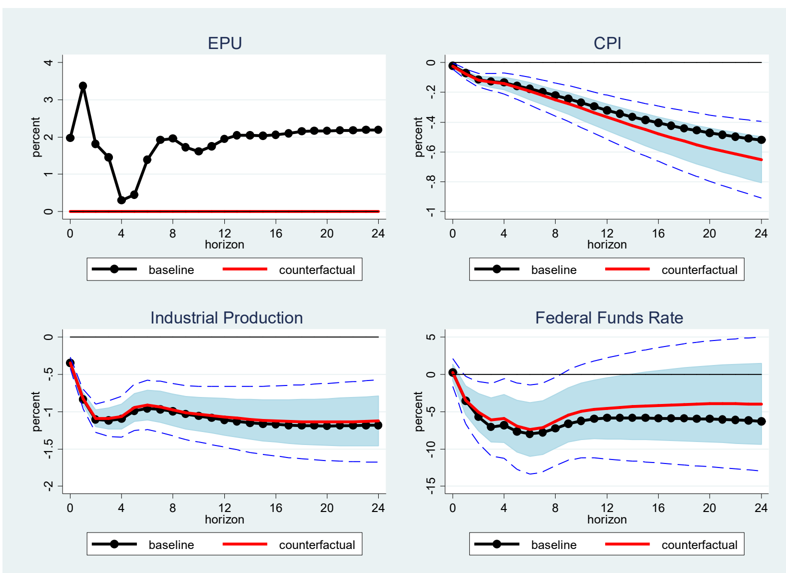
Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1919M1 and 2017M12. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure 3. Effect of uncertainty shocks: baseline vs. counterfactual



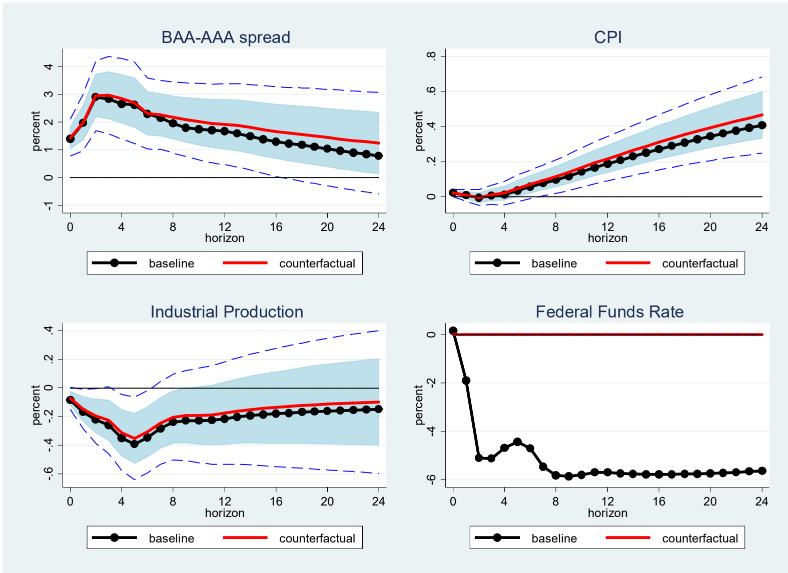
Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1919M1 and 2017M12 when the financial channel is shut down in the counterfactual exercise. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure 4. Effect of financial shocks: baseline vs. counterfactual



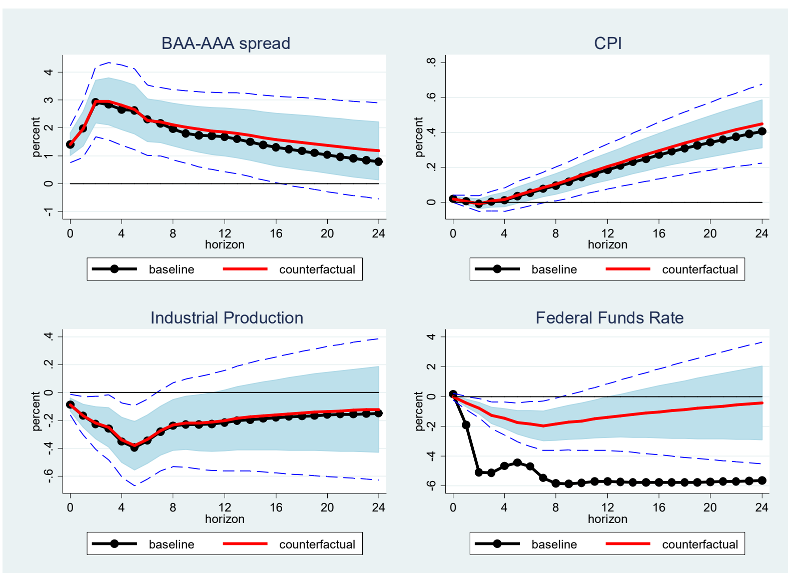
Note: This graph plots the effects of the one-standard-deviation financial shock and their 68% and 90% confidence bands for the sample period between 1919M1 and 2017M12 when the uncertainty channel is shut down in the counterfactual exercise. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure 5. Effect of uncertainty shocks: baseline vs. fully constrained monetary policy



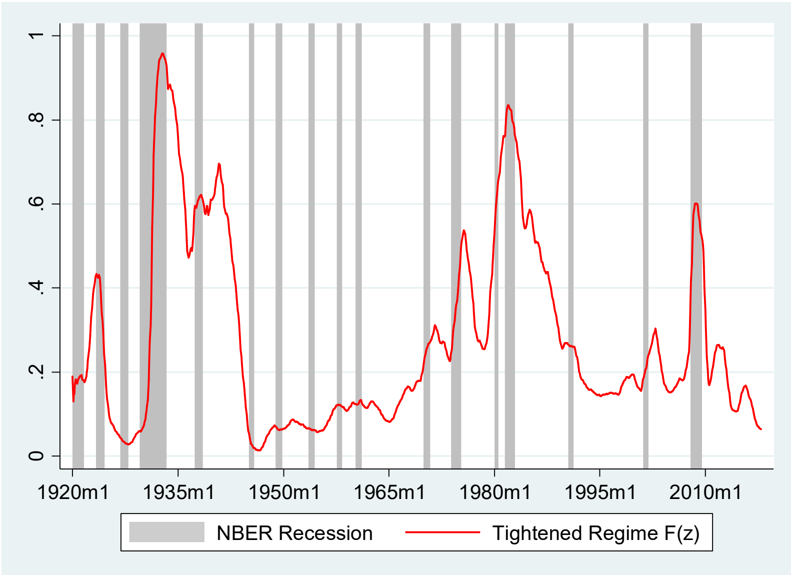
Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1919M1 and 2017M12 when the monetary policy channel is fully shut down in the counterfactual exercise. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure 6. Effect of uncertainty shocks: baseline vs. partially constrained monetary policy



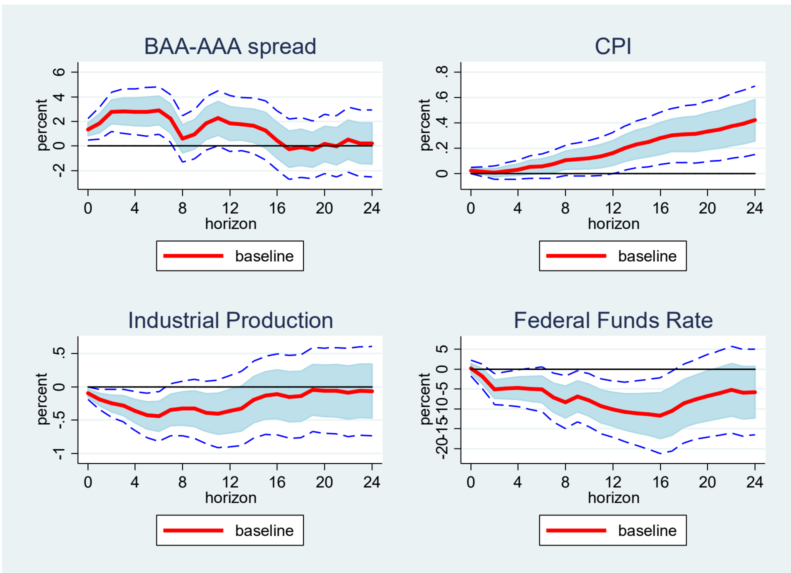
Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1919M1 and 2017M12 when only the direct monetary policy channel is shut down in the counterfactual exercise. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure 7. Financial regimes and the NBER recessions



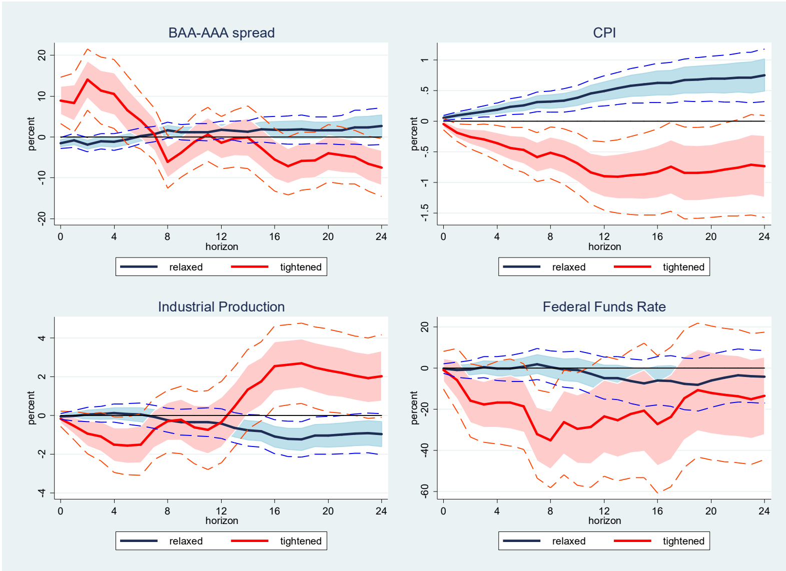
Note: The shaded region shows recessions as defined by the NBER. The solid red line shows the weight *F(z)* on the financially tightened regime.

Figure 8. Effect of uncertainty shocks: baseline local projection



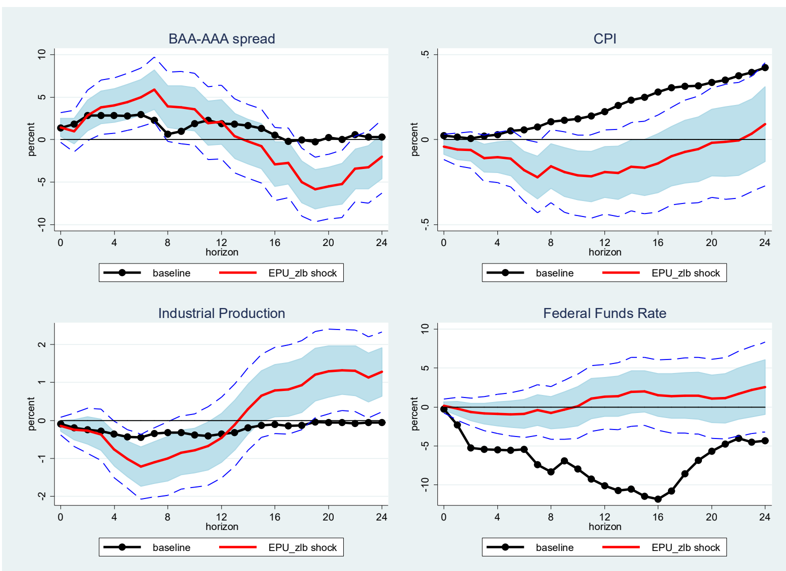
Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1919M1 and 2017M12 using the local projection method. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure 9. Effect of uncertainty shocks: financially relaxed vs. tightened regime



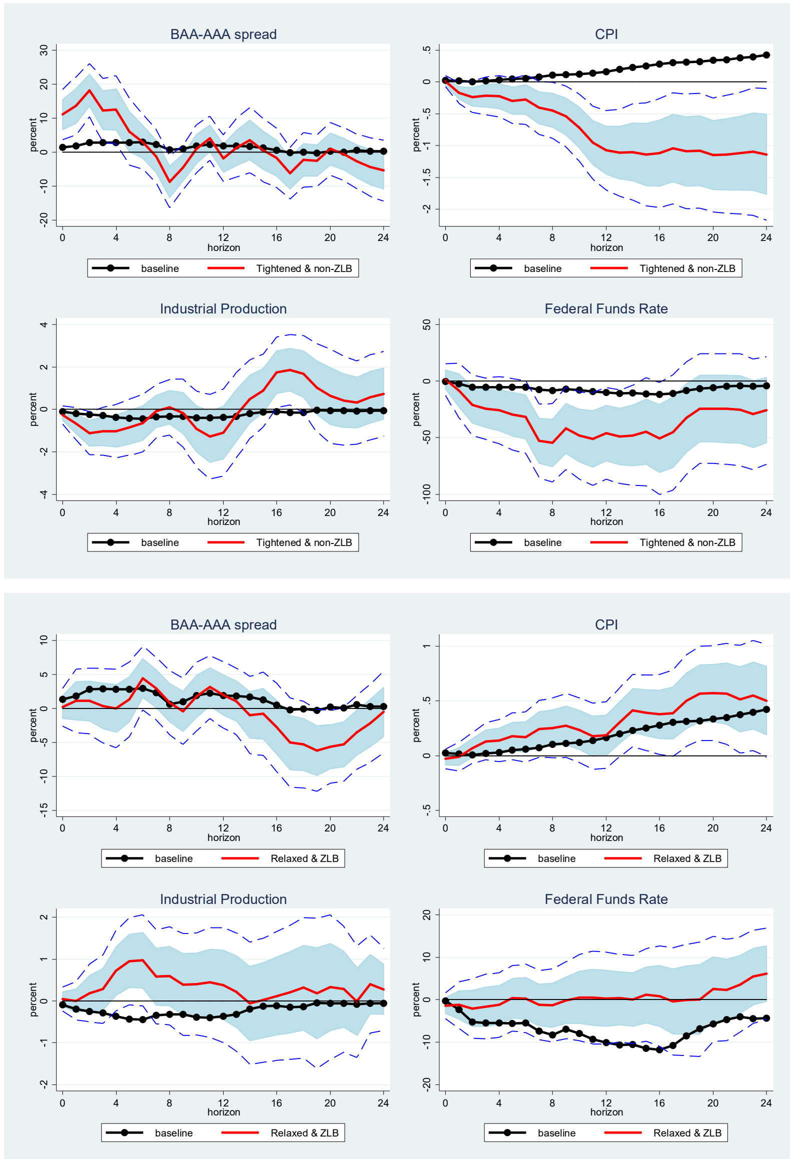
Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1919M1 and 2017M12 using the local projection method. The black (red) solid line denotes the response to uncertainty shocks during the financially relaxed (tightened) regime. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure 10. Effect of uncertainty shocks: baseline vs. binding ZLB constraint



Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1919M1 and 2017M12 using the local projection method. The black solid line denotes the response to uncertainty shocks in the baseline estimation, while the red solid line denotes the response during the binding ZLB constraint. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure 11. Effect of uncertainty shocks: financial tightened/non-ZLB regime (top panel) vs. financially relaxed/ZLB regime (bottom panel)



Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1919M1 and 2017M12 using the local projection method. The black solid line denotes the response to uncertainty shocks in the baseline estimation, while the red solid line denotes the response during the financial tightened/non-ZLB regime (top panel) and the financially relaxed/ZLB regime (bottom panel). The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Table 1. Forecast error variance decomposition from counterfactual VARs

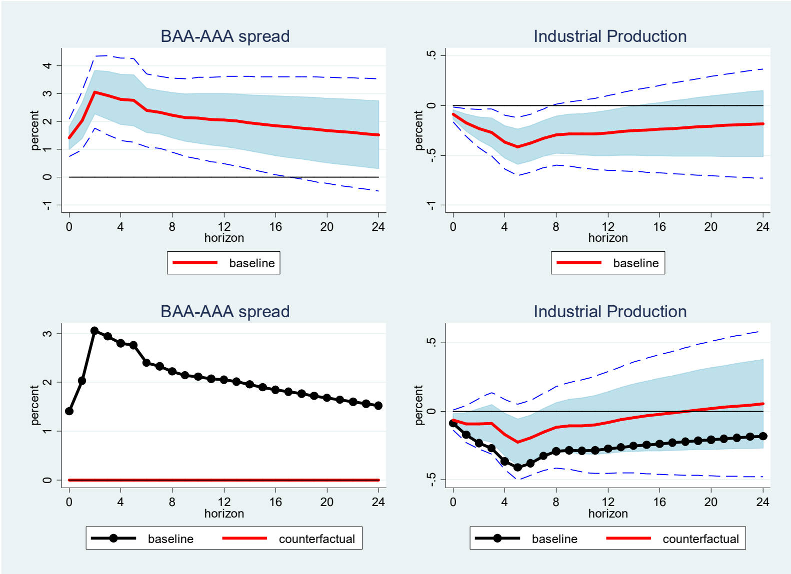
Horizon (month)	Share explained by uncertainty shocks after shutting down the financial channel					
	1919-2017			1985-2017		
	IP	CPI	FFR	IP	CPI	FFR
6	0.55	0.11	0.05	5.40	0.34	20.74
12	0.43	1.13	0.08	4.62	0.69	34.28
18	0.32	2.96	1.06	4.26	1.80	39.11
24	0.25	5.02	1.20	3.76	3.27	39.79
Horizon (month)	**Share explained by financial shocks after shutting down the uncertainty channel**					
	1919-2017			1985-2017		
	IP	CPI	FFR	IP	CPI	FFR
6	12.41	2.66	1.23	8.44	15.61	0.43
12	12.52	4.48	1.73	15.21	18.89	0.37
18	14.31	7.11	1.71	16.95	18.39	0.32
24	16.10	9.66	1.72	17.57	17.43	0.54

Note: This table summarizes the forecast error variance decomposition exercise. The top panel presents the share of variation in three macroeconomic variables explained by uncertainty shocks when the financial channel is shut down. The bottom panel presents the share of variation in three macroeconomic variables explained by financial shocks when the uncertainty channel is shut down. The units are percentage points.

Appendix

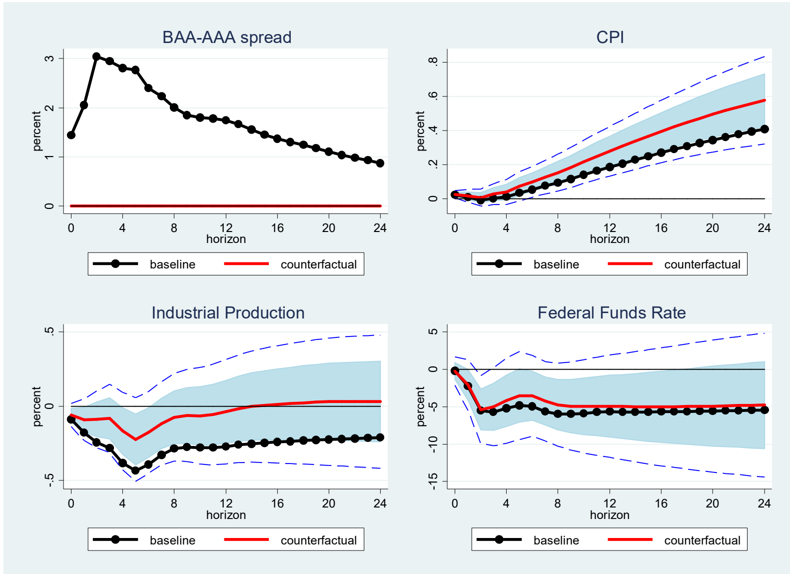
A. Additional figures and tables

Figure A.1. Effect of uncertainty shocks: 3-variable VARs



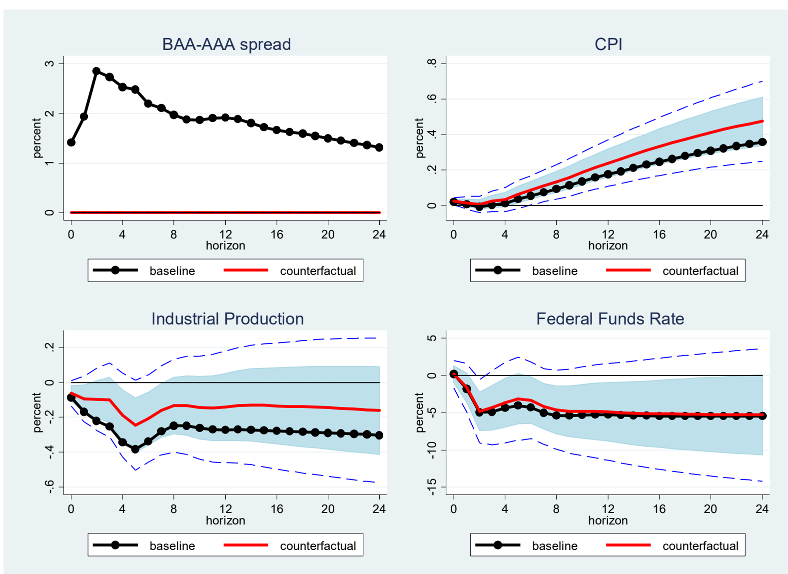
Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands from the trivariate VARs for the sample period between 1919M1 and 2017M12 (top panel) and when the financial channel is shut down in the counterfactual exercise (bottom panel). The units of the horizontal axes are a month and the units of the vertical axes are percentage points.

Figure A.2. Effect of uncertainty shocks: using the historical EPU index only



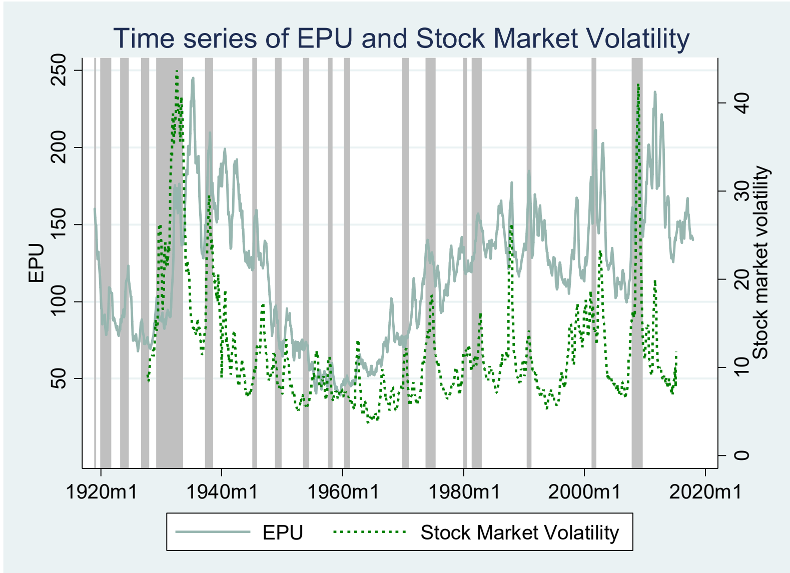
Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1919M1 and 2012M12 using the historical EPU index when the financial channel is shut down in the counterfactual exercise. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure A.3. Effect of uncertainty shocks: excluding the Great Recession and the Great Depression



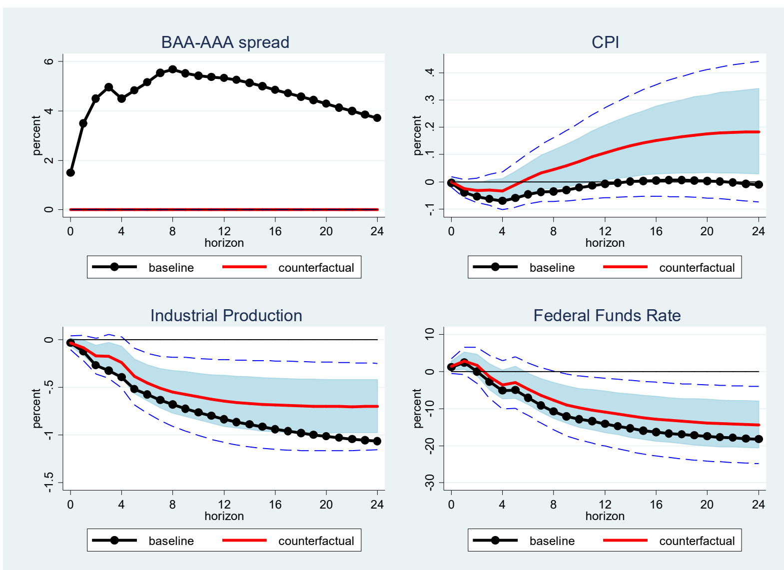
Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1919M1 and 2017M12 after dummying out the Great Depression and the Great Recession episodes when the financial channel is shut down in the counterfactual exercise. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure A.4. Economic uncertainty index and stock market volatility



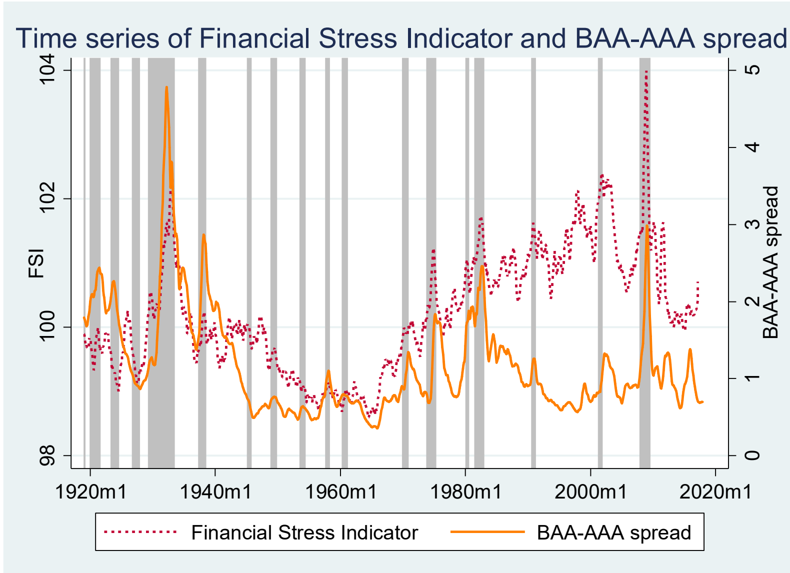
Note: The shaded region shows recessions as defined by the NBER. The EPU index is on the left axis, while realized stock market volatility is on the right axis.

Figure A.5. Effect of uncertainty shocks: using stock market volatility



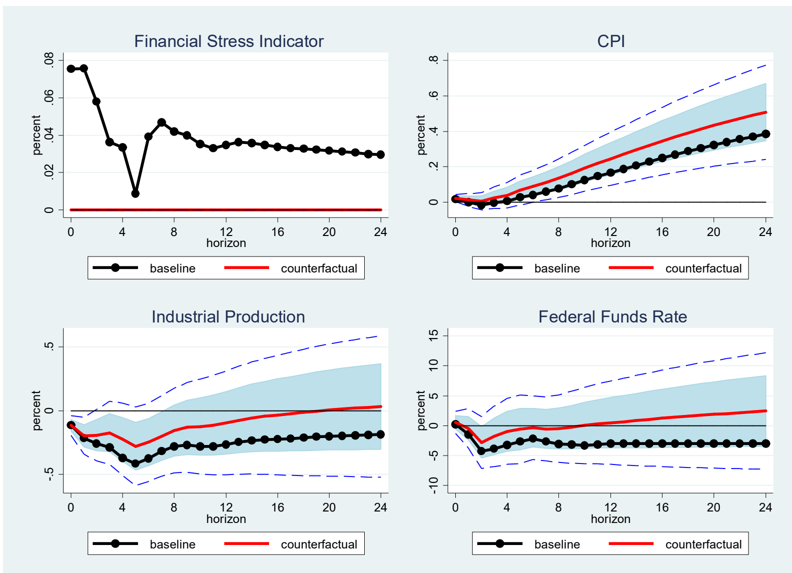
Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1928M1 and 2017M12 using stock market volatility as an alternative measure of uncertainty when the financial channel is shut down in the counterfactual exercise. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure A.6. Baa-Aaa spread and financial stress indicator



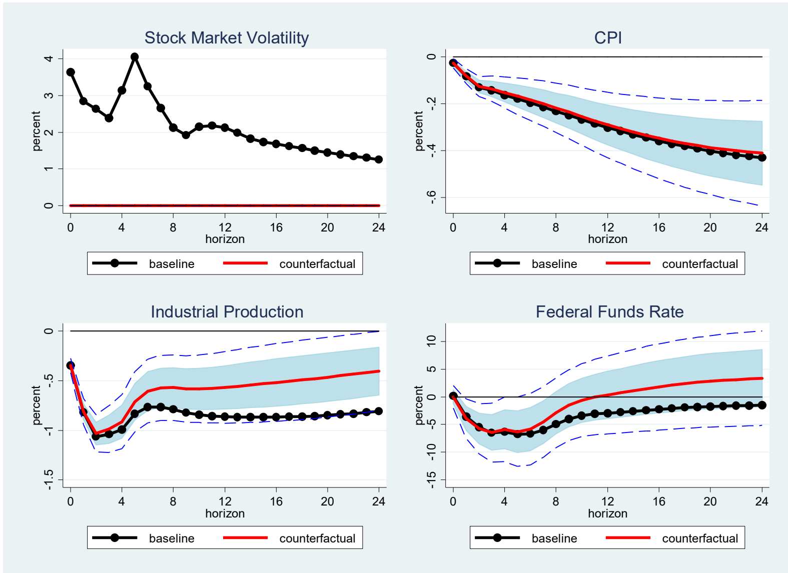
Note: The shaded region shows recessions as defined by the NBER. The financial stress indicator is on the left axis, while the Baa-Aaa credit spread is on the right axis.

Figure A.7. Effect of uncertainty shocks: using financial stress indicator



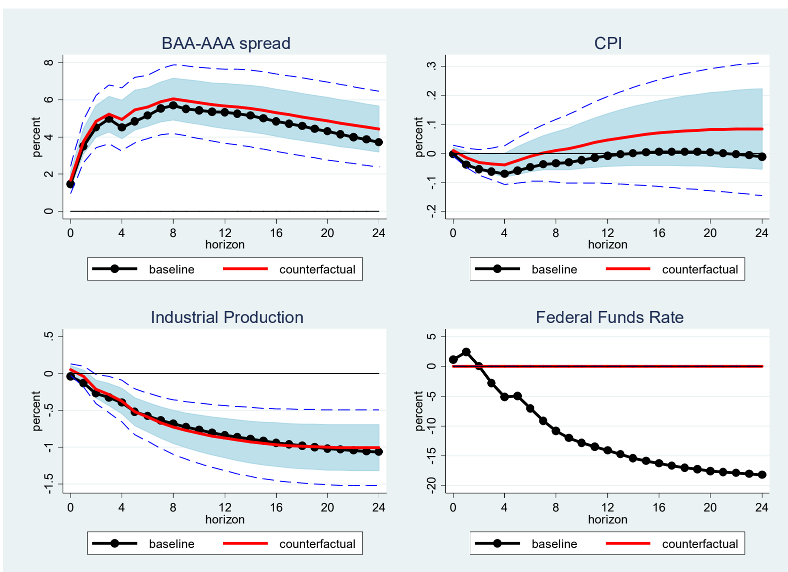
Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1919M1 and 2017M12 when the financial channel, measured by the FSI, is shut down in the counterfactual exercise. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure A.8. Effect of financial shocks: baseline vs. counterfactual using stock market volatility



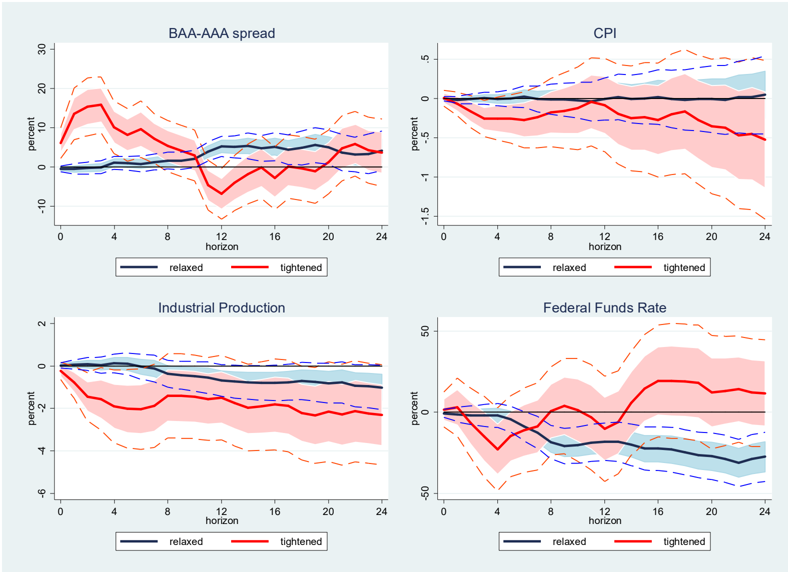
Note: This graph plots the effects of the one-standard-deviation financial shock and their 68% and 90% confidence bands for the sample period between 1928M1 and 2017M12 when the uncertainty channel, measured by stock market volatility, is shut down in the counterfactual exercise. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure A.9. Effect of uncertainty shocks using stock market volatility: baseline vs. fully constrained monetary policy



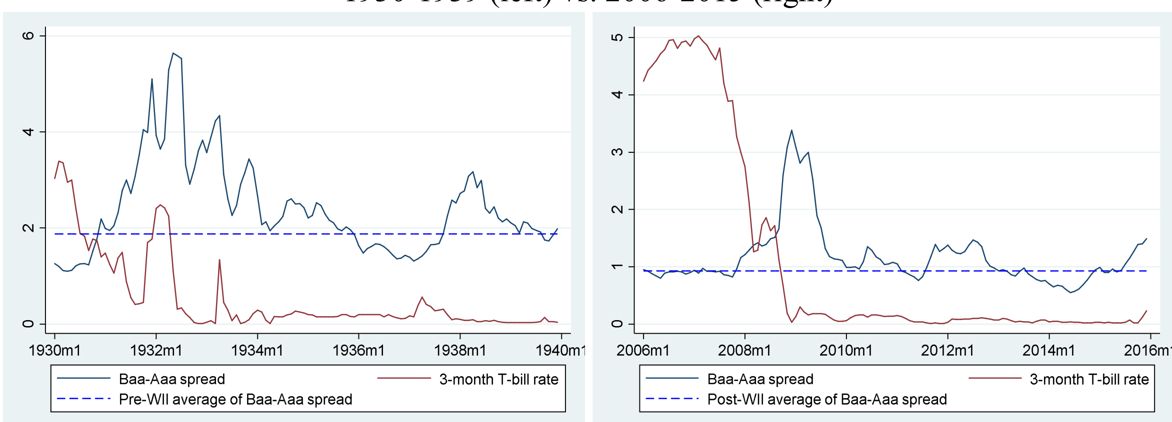
Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1928M1 and 2017M12 using stock market volatility as an alternative measure of uncertainty when the monetary policy channel is shut down in the counterfactual exercise. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure A.10. Effect of uncertainty shocks: financially relaxed vs. tightened regime using stock market volatility



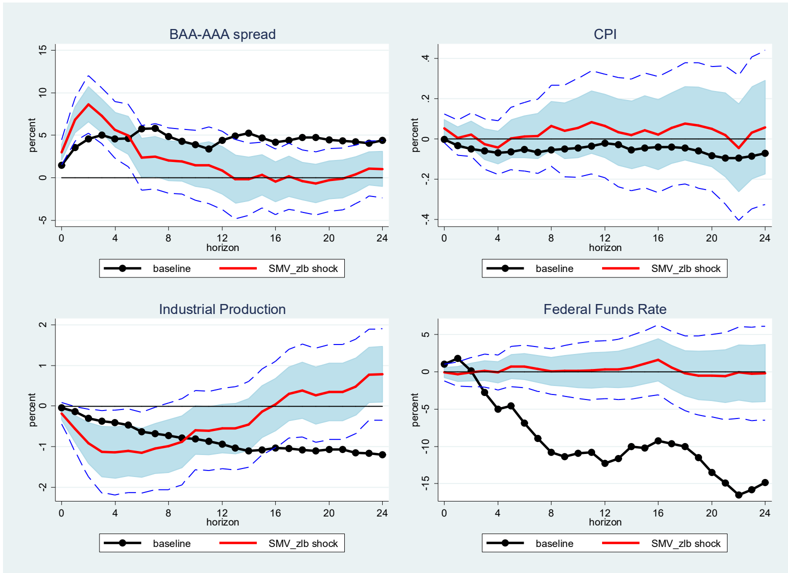
Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1928M1 and 2017M12 using the local projection method. The black (red) solid line denotes the response to uncertainty shocks using stock market volatility as an alternative measure of uncertainty during the financially relaxed (tightened) regime. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure A.11. Financial conditions and the interest rates from the two historical episodes: 1930-1939 (left) vs. 2006-2015 (right)



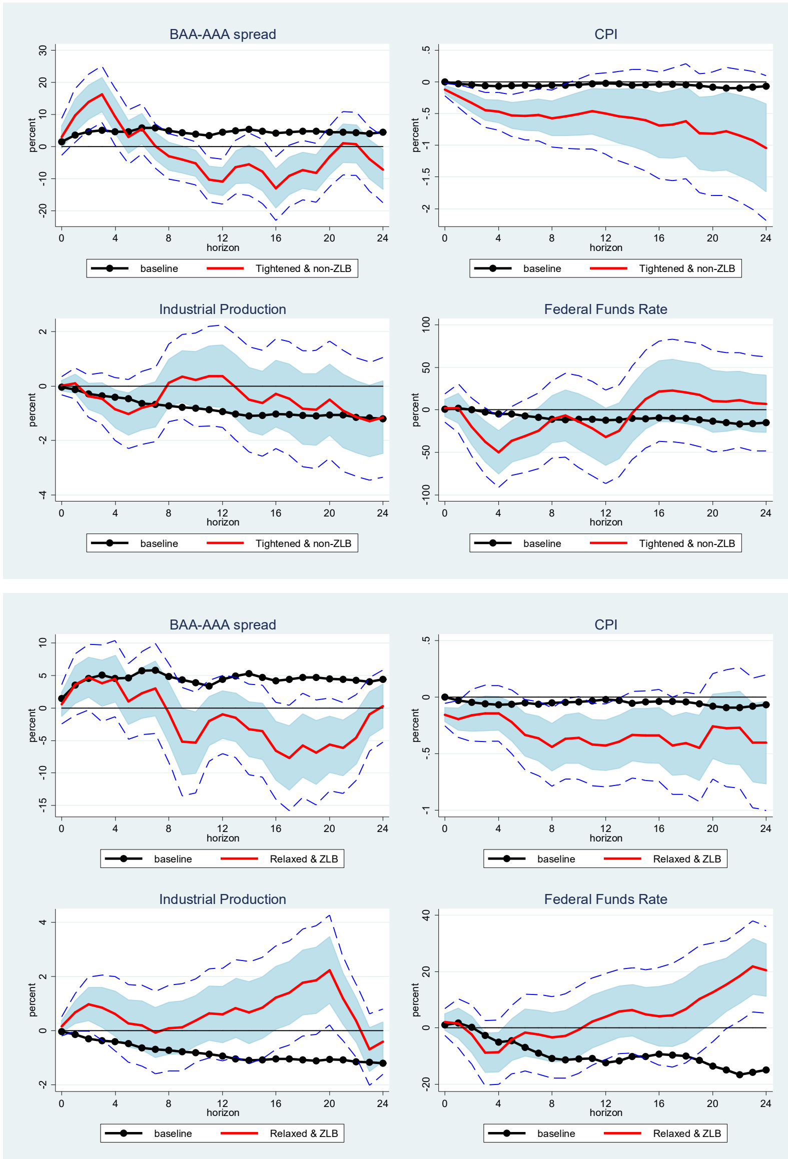
Note: This graph plots financial conditions measured by the Baa-Aaa spread and the monetary policy stance measured by the three-month U.S. treasury bill rate during the two historical episodes when the short-term interest rates were near zero.

Figure A.12. Effect of uncertainty shocks: baseline vs. binding ZLB constraint using stock market volatility



Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1928M1 and 2017M12 using the local projection method. The black solid line denotes the response to uncertainty shocks in the baseline estimation using stock market volatility as an alternative measure of uncertainty, while the red solid line denotes the response during the binding ZLB constraint. The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).

Figure A.13. Effect of uncertainty shocks: financial tightened/non-ZLB regime (top panel) vs. financially relaxed/ZLB regime (bottom panel) using stock market volatility



Note: This graph plots the effects of the one-standard-deviation uncertainty shock and their 68% and 90% confidence bands for the sample period between 1928M1 and 2017M12 using the local projection method. The black solid line denotes the response to uncertainty shocks in the baseline estimation using stock market volatility as an alternative measure of uncertainty, while the red solid line denotes the response during the financial tightened/non-ZLB regime (top panel) and the financially relaxed/ZLB regime (bottom panel). The units of the horizontal axes are a month and the units of the vertical axes are percentage points except for the federal funds rate (basis points).