

Economic Policy Uncertainty and the Supply of Business Loans

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Abstract

Economic policy uncertainty creates frictions in the business loan market. Using a Bayesian VAR framework of analysis and data from the Survey of Terms of Business Lending on flows of spot loans and loans disbursed under commitment we show that, in response to an exogenous increase in economic policy uncertainty, bank business lending falls, partly as the consequence of a contraction in the supply of spot loans. Additional tests using data on credit line originations from DealScan help us describe a richer mechanism whereby banks further restrict their supply of credit by writing liquidity options that disincentivize the use of committed funds. The results, documented for the 1985–2017 period, are economically significant and robust to a large number of alternative specifications and considerations. Moreover, they carry a simple, yet clearly relevant policy implication – clarity and effective communication in policy-making can prove a powerful policy in itself.

Keywords: economic policy uncertainty, bank lending, business, credit.

JEL Classification: D80, E66, G18, G21.

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1 Introduction

“When confronted with uncertainty, especially Knightian uncertainty, human beings invariably attempt to disengage from medium to long-term commitments in favor of safety and liquidity.”

—Alan Greenspan, *Chairman of the Board of Governors*¹

The last decade has seen a burgeoning interest in understanding the ways uncertainty affects the dynamics of the economy. As a result, the literature has identified several meaningful effects on the real and financial markets. This paper contributes to this literature by documenting a bank lending channel through which uncertainty about economic policy affects the business sector. Specifically, we show that increasing economic policy uncertainty leads to lower levels of bank lending to businesses, and this fall in lending is partly driven by a contraction in the supply of credit.

“Uncertainty is an amorphous concept” (Bloom, 2014), and this has given rise to a number of related definitions and metrics over the years. Our focus here lies on economic policy uncertainty (EPU henceforth), which refers to unknown future paths of action to be taken by policy makers. In Baker, Bloom, and Davis (2016), EPU relates to decisions to be made by Congress, the White House, or the Federal Reserve, and it is primarily captured by the relative prevalence of EPU-related articles in the news media.² In other studies, policy uncertainty can stem from specific events like the unknown outcome of gubernatorial elections, as it is the case in Jens (2017) and Falk and Shelton (2018). Almost invariably, the evidence ultimately suggests that heightened EPU leads to a fall in economic activity, which can translate into lower levels of employment, industrial production, or business investment.³

The contractionary effects that economic policy uncertainty has on the business sector invite questions about the role banks play in the transmission of uncertainty shocks. A first question is whether and how aggregate bank business lending responds to shocks in economic policy uncertainty. A second related question is whether any observed change could be attributed to changes in the supply of credit. While answering the first question could be relatively straightforward, answering the second one could be less so. On one hand, financial theory suggests that banks would have incentives to preserve liquidity and curtail credit in response to increasing uncertainty (Caballero and Krishnamurthy, 2008). On the other, any fall in lending could be potentially attributed to a fall in the corporate demand for funds, as slowing business activity can reduce firms’ financial needs for purposes such as

¹Greenspan (2004).

²In this work, we adopt the baseline metric from Baker, Bloom, and Davis (2016). We will say more about this shortly.

³The literature has extensively documented the contractionary effects on the economy of a broader definition of uncertainty. A non-exhaustive list of works includes articles studying mainly the relation between uncertainty and economic activity, such as Bloom (2009); Bachmann, Elstner, and Sims (2013); Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016); Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018). Articles studying the impact of uncertainty on investment in particular, like Bernanke (1983); Leahy and Whited (1996); Bloom, Bond, and Reenen (2007); Baum, Caglayan, and Talavera (2008); Bloom (2009); Gilchrist, Sim, and Zakrajsek (2014); Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018); Smitanka, Bloom, and Mizen (2018). And works investigating the effect of uncertainty on employment, such as Bloom (2009); Caggiano, Castelnuovo, and Groshenny (2014); Leduc and Liu (2016); Schaal (2017); Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018).

investment. Thus, properly identifying the role of banks in a change of credit volumes would require disentangling supply- from demand-side effects.

In order to resolve this issue we adopt the empirical approach recently proposed by [Barraza, Civelli, and Zaniboni \(2019\)](#). This approach relies on a Bayesian VAR framework of analysis and exploits contractual differences between loans disbursed under commitment and spot loans to identify supply effects in bank business lending in response to monetary policy shocks.⁴ In the end, the answer to our first question is that aggregate business lending indeed falls in response to a shock that increases economic policy uncertainty. Arguably, this fall partly corresponds to a weaker demand for funds that accompanies slowing activity and corporate investment. However, the answer to the second question is that the first result is also the consequence of a contraction in credit supply. After controlling for demand-side effects and changing levels of credit spreads, the pace at which spot loan origination falls far exceeds the slowdown in drawdowns from pre-exiting commitments, evidencing a tightening. Moreover, banks further restrict their supply of credit by originating new credit lines carrying a pricing structure that disincentivizes drawdowns, which can slow down loan growth.

Our finding of a clear contraction in the supply of bank business lending in response to an increase in EPU is particularly relevant in light of recent research that studies the interactions between financial frictions and uncertainty, emphasizing the amplifying effects the financial system can have in the propagation of uncertainty shocks to the real economy. In the theoretical literature, [Bonciani and van Roye \(2015\)](#) propose a DSGE model with credit constrained entrepreneurs and frictions in the pass-through of the policy rate to the banking sector. They show that these frictions amplify the effects of uncertainty shocks on the economic activity. [Gilchrist, Sim, and Zakrajsek \(2014\)](#) explain their empirical result of a contractionary effect of uncertainty on investment using a model that exploits the interaction between non-convex capital adjustment costs and credit market frictions, which induce credit supply contractions in response to uncertainty shocks. [Arellano, Bai, and Kehoe \(2016\)](#) develop a general equilibrium model with imperfect financial markets in which entrepreneurs cannot fully insure against the risk of time separation between hiring of inputs and production. In their model, higher uncertainty triggers an endogenous contraction of credit conditions. Similarly, [Christiano, Motto, and Rostagno \(2014\)](#) propose a model with heterogeneous probability of success for entrepreneurial activity and financial frictions due to agency problems. Changes in the dispersion of this idiosyncratic risk across firms have persistent effects on credit spreads, output, and investment. The model in [Bianchi, Ilut, and Schneider \(2017\)](#), instead, relies on ambiguity averse shareholders, adjustment costs, and an upward sloping marginal cost of the debt of firms to link uncertainty to the optimal capital structure of firms and the shareholder payout. In their model, changes in uncertainty endogenously generate the comovement of stock prices, debt, and payout observed in the data.

The modern empirical literature frequently relies on VAR models to study the effects of different types of uncertainty on macroeconomic outcomes. For instance, [Baker, Bloom, and Davis \(2016\)](#) use VAR models to assess the effects of shocks on their EPU measure on industrial production and employment. [Gilchrist, Sim, and Zakrajsek \(2014\)](#) use VAR

⁴The identification strategy, which we discuss at length below, builds on works from [Sofianos, Melnik, and Wachtel \(1990\)](#), [Kashyap, Stein, and Wilcox \(1993\)](#), and [Morgan \(1998\)](#).

models to gauge the effects on the economy of a financial measure of uncertainty based on firm stock returns volatility. [Leduc and Liu \(2016\)](#) define uncertainty shocks using the Michigan Survey of Consumers data to show, within a VAR framework of analysis, that uncertainty increases unemployment and lowers inflation. [Caggiano, Castelnuovo, and Groshenny \(2014\)](#) explore non-linear effects on the transmission of uncertainty in a smooth transition VAR and show that shocks on VIX, their proxy for uncertainty, have larger effects on unemployment during recessions. And [Bachmann, Elstner, and Sims \(2013\)](#) use VAR models to compare the macroeconomic effects of uncertainty shocks based on business survey data for the U.S. and Germany and document striking differences across countries.

Our paper shares the focus on credit markets and the provision of liquidity with the strand of literature that investigates the effects of uncertainty on financial aggregates in different empirical setups. For instance, [Berger, Guedhami, Kim, and Li \(2018\)](#) study the effect of EPU on bank liquidity creation. They show that higher EPU is associated with a decrease in asset-side and off-balance sheet liquidity creation, which accompanied by increases in spreads suggests that banks actively pursue liquidity hoarding. Our work neatly complements theirs in at least two ways. First, we document a specific mechanism through which banks can create or hoard liquidity, namely the supply of business loans. Second, the results from our empirical strategy – which is designed to uncover the structural effect of EPU innovations on the supply of credit – lend support to their claim that in the face of increases in EPU banks actively respond by altering their supply of liquidity.

[Alessandri and Bottero \(2017\)](#) use loan application and rejection data from commercial banks in Italy between 2003 and 2012 to assess the effects of multiple measures of economic uncertainty on credit conditions. They find a substantial reduction in the acceptance probability of new credit applications and smaller responsiveness of banks to the short-term interest rate during periods of heightened uncertainty. This paper empirically documents the role of frictional capital markets in the transmission channel devising an identification strategy based on heterogeneous capitalization across lenders. In our work, we exploit frictions arising from contractual differences between spot loans and loans under commitment instead.

Lastly, [Bordo, Duca, and Koch \(2016\)](#) show that policy uncertainty has a negative effect on loan growth and this is observable both at aggregate- and bank-level. Moreover, their cross-sectional analysis shows that economic policy uncertainty has heterogeneous effects across banks. Specifically, large banks and banks with lower levels of capital seem more sensitive to uncertainty. Our paper is also complementary to their work, as we find different responses of business loans across bank types and we tailor our identification strategy of the credit supply-side effects in response to uncertainty shocks around the association of large banks with large firms. Our results also lend support to theirs.

The paper proceeds as follows. Section 2 introduces an overview of our empirical VAR model, estimation methodology and identification assumptions. Section 3 summarizes the characteristics of the business lending data and the EPU measures used in the analysis. Section 4 introduces the main findings of the paper from the baseline VAR model and structural identification scheme. Section 5 discusses further insights and presents an extensive robustness analysis of the main results. Finally, Section 6 concludes.

2 Empirical Framework

In this work, we rely on a Bayesian VAR framework of analysis that uses a recursive orthogonalization scheme to identify the EPU shock. In our setting, the economy is described by a vector of endogenous variables Y_t , whose reduced-form dynamics are modeled as a p th-order VAR

$$Y_t = \sum_{i=1}^p B_i Y_{t-i} + \varepsilon_t \quad (1)$$

where B_i is a matrix of parameters and the VAR residuals ε_t follow a distribution $\varepsilon_t \sim \mathcal{N}(0, \Sigma_\varepsilon)$ such that $\mathbb{E}(\varepsilon_t \varepsilon_t') = \Sigma_\varepsilon$ and $\mathbb{E}(\varepsilon_t \varepsilon_s') = 0 \forall t \neq s$.

In defining Y_t , we borrow from two main strands of literature. On one hand, on the strand of literature that studies the interaction between monetary policy and the business lending sector (den Haan, Sumner, and Yamashiro, 2007; Barraza, Civelli, and Zaniboni, 2019). On the other, on the strand that uses VAR models to study the effects of uncertainty on the economy (Bachmann, Elstner, and Sims, 2013; Gilchrist, Sim, and Zakrajsek, 2014; Baker, Bloom, and Davis, 2016; Leduc and Liu, 2016). Thus, Y_t is formed to include a block X_t of variables that represent the real sector, a measure of economic policy uncertainty epu_t , and a block Z_t of monetary policy and financial variables, in that order. Accordingly,

$$Y_t = \begin{bmatrix} X_t \\ epu_t \\ Z_t \end{bmatrix} \quad (2)$$

where, in our baseline specification, X_t includes the log of real GDP, the log of the price deflator, and the log of real gross business investment, epu_t is the U.S. Baseline Overall EPU Index from Baker, Bloom, and Davis (2016), and Z_t includes the Wu-Xia shadow rate (Wu and Xia, 2016), the 10-year Baa-Treasury credit spread, and a measure of the flow of bank business lending from the Survey of Terms of Business Lending.⁵ The flow of business lending is alternatively considered in aggregate, separating loans extended under commitment from spot loans, or as a ratio between these two categories. We say more about this shortly, in Section 2.1.

In order to identify the EPU shock, we follow a standard practice in the literature of monetary policy (see, for instance, Christiano, Eichenbaum, and Evans, 1999) to assume a linear relation between the reduced-form residuals ε_t and the fundamental structural innovations of the model u_t

$$\varepsilon_t = A_0 u_t \quad (3)$$

⁵We use the Wu-Xia shadow rate as a measure of the true monetary policy stance. This rate is virtually the same as the Federal Funds rate throughout the sample period, except between the December 2008 and December 2015, when the Federal Funds rate reaches the zero lower bound. We leave for Section 5 a more thorough discussion of this issue.

where $\mathbb{E}(u_t u_t') = V$ is diagonal, implying that the structural shocks are orthogonal, and V is normalized so as to represent unit-variance structural shocks. Moreover, A_0 , the structural impact multiplier matrix, has a block-recursive structure and can be recovered as the lower-triangular Cholesky factor of Σ_ε .

It is also a well-established practice in empirical monetary VAR analysis (see, again, [Christiano, Eichenbaum, and Evans, 1999](#)) to identify monetary policy shocks by placing the monetary policy instrument between the real block X_t and the financial block Z_t within Y_t . This setting embodies the assumption that the Federal Reserve incorporates information on the current state of the real sector to form its policy decision, but information about the current state of the financial sector is not part of the decision process. At the same time, the financial sector is allowed to respond on impact to the policy innovation, while the real sector only responds with a lag. Our baseline identification strategy similarly pivots on the central position of epu_t within Y_t and the block-recursive structure of A_0 . Thus, our identification strategy boils down to assuming two main restrictions on the contemporaneous effects of the structural innovations in the model. First, epu_t is affected by the contemporaneous state of the real sector, X_t , but not by the contemporaneous state of the financial sector, Z_t . And, second, while the financial sector can respond on impact to an epu_t innovation, the real sector is assumed to respond with a lag. It is worth mentioning finally that, given the block-recursive structure of A_0 , the impulse response functions corresponding to an EPU shock are invariant to the specific ordering of the variables within each of the blocks X_t and Z_t .

The results we present in Section 4 correspond to VAR(2) models (i.e. $p = 2$) estimated with Bayesian methods using Minnesota priors ([Litterman, 1979, 1986](#); [Doan, Litterman, and Sims, 1984](#)).⁶ In Section 4 we use different specifications of Z_t , centering our attention on alternative measures of bank businesses lending that help us identify the transmission mechanism of economic policy uncertainty. In Section 5 we run a host of robustness checks that span from the inclusion of additional variables to changes in the lag order to changes in the recursive ordering. The main estimation sample period is 1985:Q1-2017:Q1, which includes the Great Recession and the era of unconventional monetary policy that followed the 2007–2009 financial crisis. We address possible implications of this period for the transmission mechanism of policy uncertainty by adopting a shadow rate in our benchmark specifications and considering alternative monetary policy rates in Section 5. We discuss

⁶Bayesian estimation methods are particularly suitable for models with a large number of parameters with respect to the data available, as they help avoiding overfitting of the data. In Bayesian VAR models, the coefficient matrix B_i and the reduced-form error variance-covariance matrix Σ_ε are the two key blocks of parameters of interest. The Minnesota prior method assumes that Σ_ε is known – in this study, it takes its value from its OLS counterpart – and that each endogenous variable has a unit root, which allows thinking the VAR model as a multivariate random walk process. Thus, in defining the prior distribution of B_i , each endogenous variable is modeled to have a gaussian prior mean coefficient of one on its own first lag, and gaussian prior mean coefficients of zero on larger own lags and all cross-variable lags. Furthermore, the priors on the coefficient variances also reflect the belief that shorter lags are more informative than larger lags, and that own lags are more informative than lagged values of the other variables in the model. As the method smoothly combines prior information with the likelihood in the data, the Minnesota prior method produces parsimonious models, characterized by analytically tractable, gaussian posterior distributions of the parameters. For an introduction to Bayesian VAR analysis see [Canova \(2007\)](#) and [Kilian and Lütkepohl \(2017\)](#).

then these aspects in greater detail.

2.1 Discussion of the Identification Approach

Our benchmark identification strategy reflects the underlying assumption that financial markets clear immediately after the observation of the macroeconomic and policy stances within the same quarter, but their feedback to the real sector and the uncertainty of the policy outcomes takes place with a lag. This rationale clearly reflects the same type of argument used in the monetary literature to place the monetary policy instrument between macro and financial blocks in the recursive ordering. However, it must be noted that neither the theoretical nor the empirical principles justifying such an approach have been unambiguously established in the literature yet.

In choosing our baseline identification ordering, we follow to some extent [Gilchrist, Sim, and Zakrajsek \(2014\)](#) who study a VAR model with a real sector and a financial block that includes a credit spread and the short-term interest rate. Their measure of uncertainty captures common variations in volatility of daily firm-specific stock returns, and their identification assumption hinges on the interaction between this form of uncertainty and credit spreads. By ordering the uncertainty measure before the credit spread, but after the real block, they assume financial uncertainty is exogenous to movements in the spread, while responding on-impact to macroeconomic fundamentals. In our model, we add business loans to the credit spread and the policy rate and focus on the effects of policy uncertainty instead. However, we maintain the assumption that the policy decision-making process that determines policy uncertainty is endogenous to the macroeconomic block, thus ensuring the impact of the real sector is already controlled for when looking at the impact of EPU shocks on the financial variables.

In some respect, this identification scheme allows us to at least in part distinguish between unexpected innovations to policy uncertainty and bad news about future economic stance already embedded in the contemporaneous shocks to output and inflation. Nevertheless, as noted by [Baker, Bloom, and Davis \(2016\)](#) and [Stock and Watson \(2012\)](#), identification in this context remains a difficult and open issue. Despite being a plausible choice, hence, the validity of this recursive ordering remains quite debatable. For these reasons, we check for the robustness of our results in Section 5 by employing two alternative, and opposite, recursive orderings in which the EPU measure is included either as first or last in the vector of endogenous variables.

An EPU ordered first implies the uncertainty variable is the most exogenous possible in the model and does not respond to any other shocks, neither from the real nor the financial side, in the impact period, while the other variables are allowed to respond to an uncertainty shock. This assumption has been used in their empirical models by [Leduc and Liu \(2016\)](#) for a consumer uncertainty measure based on the Michigan Survey, by [Baker, Bloom, and Davis \(2016\)](#) for EPU, and by [Caggiano, Castelnuovo, and Groshenny \(2014\)](#) for the VIX stock market volatility index (Chicago Board Options Exchange Market Volatility Index).⁷ It is probably better suited for data at the monthly frequency, and it has a practical justification

⁷All these papers consider small or mid-size VAR models, with slightly different variable specifications that include both macroeconomic and financial variables as in our model.

for survey-based consumer uncertainty in which survey data is collected during the month before new macroeconomic information is released.

These papers, however, also explicitly consider Cholesky schemes in which uncertainty is put after any other variable, and so do we. In this case, movements due to past or contemporaneous shocks affecting the economic system are fully removed from the uncertainty shocks, while the variables in the real and financial blocks of the model are not allowed to respond to EPU on impact. This option might be especially relevant, for instance, in a sample that extends to the post-Great Recession period when the economy is subject to large financial shocks and the monetary authority promptly reacts to prevent the collapse of credit markets. In these circumstances, the EPU measure could indirectly pick up the effects of expected credit market future uncertainty or the endogenous response of the financial sector to future uncertainty reflected in contemporaneous movements of business loans in our model, and it becomes important to properly separate these feedback components from the structural innovation to uncertainty.

A second crucial identification assumption we exploit in this paper is necessary to disentangle supply-side from demand-side effects in the responses of business loans to EPU shocks. The empirical strategy we use relies on a strand of literature showing that changing credit market conditions can result in changes in the mix of corporate bank borrowing. This literature includes [Sofianos, Melnik, and Wachtel \(1990\)](#), [Kashyap, Stein, and Wilcox \(1993\)](#), [Morgan \(1998\)](#) and, more recently, [Barraza, Civelli, and Zaniboni \(2019\)](#).

We test for these effects by including the ratio of loans extended under commitment to spot loans in the Z_t block of the VAR. This approach is grounded in an argument similar to others in the extant literature, such as in [Kashyap, Stein, and Wilcox \(1993\)](#). Intuitively, provided that banks are contractually bound to serve pre-existing commitments in the absence of material adverse changes, upon exogenous innovations they can only operate immediately on the supply of spot loans. Therefore, assuming common movements across the two types of loans to reflect demand-side factors, a positive response of the ratio would indicate a slower expansion of spot loans and suggest the a supply-side loan contraction.

The key assumption for the validity of this identification strategy is that demand for both types of loans has uniform cyclical properties. This is arguably plausibly satisfied in our setup, as we limit the analysis to loans originated by large banks and, by association, large firms ([Berger, Miller, Petersen, Rajan, and Stein \(2005\)](#)). Large firms face relatively fewer financial constraints and can be more confident regarding their ability to roll over loans, regardless of the type, thus maintaining comparable demands for both types of loans across the business cycle. By restricting our comparison to banks within the same size category we also follow an insight in [Demiroglu, James, and Kizilaslan \(2012\)](#), who show that controlling for firms characteristics is critical in the identification of bank loans supply-side effects. We shall, finally, add that in Section 5 we relax this assumption to show that our results are robust to allowing the two types of loans to face independent demands.

3 Data

We turn now to a more detailed discussion of our data. We distinguish four main groups of data: data that relate specifically to the measurement of economic policy uncer-

tainty, data on flow of business loans from the Survey of Terms of Business Lending, data on loan originations from Thomson Reuters DealScan, and, lastly, the macroeconomic data that are standard in this strand of literature. We discuss them in that order.

Our benchmark measure of economic policy uncertainty is the *U.S. Baseline Overall EPU Index* from [Baker, Bloom, and Davis \(2016\)](#) and in a robustness test we use the *U.S. News-Based Policy Uncertainty Index*, which is the main component of the former index. In what follows, when we refer to metrics, we use the term *EPU* to refer to the former and the term *EPU News* to refer to the latter. EPU is the weighted-average of four measures, with EPU News accounting for half the weight of EPU. The remaining three components of EPU are the *Tax Expiration Index*, the *CPI Forecast Disagreement Measure*, and the *Federal/State/Local Purchases Disagreement Measure*, which are all equally-weighted. While we kindly refer the reader to [Baker, Bloom, and Davis \(2016\)](#) for a thorough discussion on the methodological aspects behind the construction of these measures, we describe here the main elements that are crucial to our identification strategy and the interpretation of our results.

EPU News compiles search results among news articles published in ten major newspapers in the U.S.⁸ This metric is designed to reflect the relative prevalence of articles that are suggestive of economic policy uncertainty. A given article is deemed to reflect economic policy uncertainty if it contains at least one term from each one of the following three sets of terms: (i) “uncertainty” or “uncertain”; (ii) “economic” or “economy”; (iii) “Congress”, “legislation”, “White House”, “regulation”, “Federal Reserve”, or “deficit”. The Tax Expiration Index compiles every year temporary federal tax code provisions from the Congressional Budget Office and reflects provision expirations that can create uncertainty in the business environment. The CPI Forecast Disagreement and the Federal/State/Local Purchases Disagreement measures rely on data from the Survey of Professional Forecasters run by the Federal Reserve Bank of Philadelphia. Both measures reflect, at a quarterly frequency, the dispersion of forecasts among professional forecasters, which is indicative of uncertainty about the future state of the economy. This metric follows a well-established practice in the literature that uses forecast disagreements as proxies for uncertainty – see [Bloom \(2014\)](#) for a discussion and [Bachmann, Elstner, and Sims \(2013\)](#) for an example. Both the Baseline Overall EPU Index and the News-Based Policy Uncertainty Index are available at monthly frequency. In building our quarterly data set, we use data points corresponding to the last month of each quarter. As can be expected from the construction, EPU News is the true driver of EPU, and this is readily apparent from observation of both data series plotted together in [Figure 1](#).

Our data on flows of bank loans to businesses come from the Survey of Terms of Business Lending (STBL). Between 1977 and 2017 the Board of Governors of the Federal Reserve System ran this quarterly survey among roughly 350 banks. The survey responses were extrapolated to represent the population of banks and the Board published the main results through the E.2 Release. A portion of the historical data is publicly available through the Board’s website. In this work, nonetheless, we use some portions of the data kindly made

⁸The newspapers are the Boston Globe, the Chicago Tribune, the Dallas Morning News, the Houston Chronicle, the Los Angeles Times, the Miami Herald, the San Francisco Chronicle, USA Today, the Wall Street Journal, and the Washington Post.

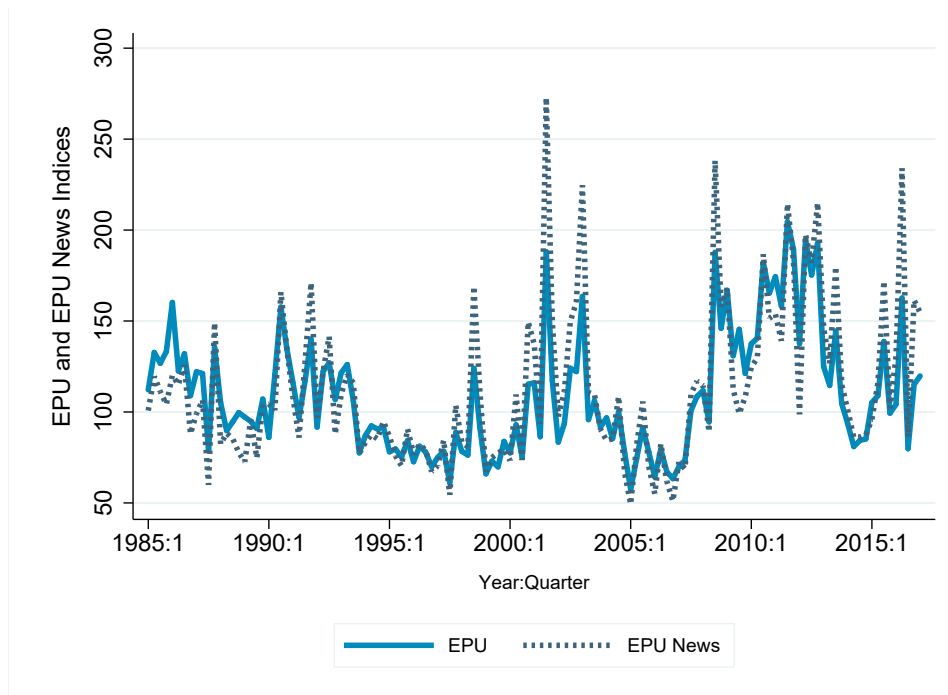


Figure 1: EPU and EPU News, from [Baker, Bloom, and Davis \(2016\)](#).

available to us by the Board upon request. We are particularly interested in the series of business loans that partition the amounts of loans disbursed by large and small banks via two different types of contractual agreements, namely loans disbursed under commitment and spot loans – which are not part of commitments.^{9,10} These series represent “*gross loan extensions made during the first full week in the middle month of each quarter*” ([Board of Governors of the Federal Reserve System, 2017](#)) and, thus, constitute outstanding sources of information in what regards *flows* of bank credit to businesses. In different specifications of our models we use the separate series of loans disbursed under commitment and spot loans, their sum, or the ratio of loans disbursed under commitment to spot loans. The data show that commitments are a widely used contractual agreement, as they historically represent roughly 80% of the flows of loans. As discussed in Section 2.1, we focus our analysis on lending by large banks, which dominate the business loan market and drive the aggregate dynamics. This is clearly illustrated by Figure 2. Our STBL data set runs from 1982:Q3 through 2017:Q1, yet in their use we are generally constrained by the earliest available data on EPU, which starts in 1985:Q1.

We also use data on loan volumes and spreads on originations recorded in Thomson Reuters LPC DealScan. DealScan tracks loan originations in the syndicated loan market,

⁹Throughout the paper, we use the term business loans to refer to commercial and industrial loans.

¹⁰To give a sense of what the distinction between *large* and *small* bank entails, the E.2 Release of April 2017 – which publishes results for the February 2017 survey – states that “*As of December 31, 2016, assets of the large banks were at least \$5.5 billion. Median total assets for all insured banks were roughly \$202 million. Assets at all U.S. branches and agencies averaged \$10.5 billion*” ([Board of Governors of the Federal Reserve System, 2017](#)).

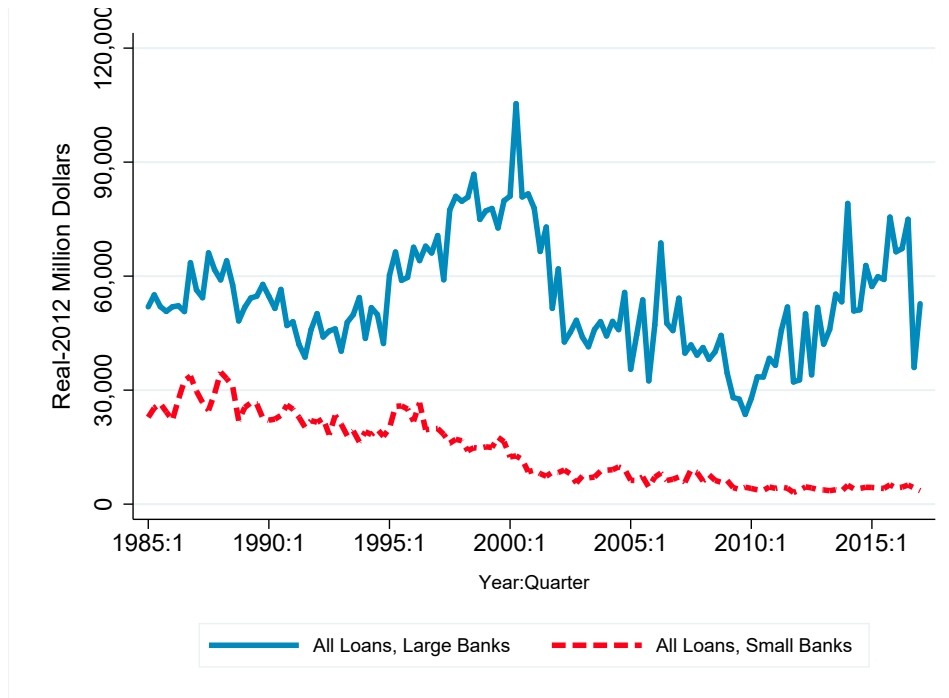


Figure 2: Total Loans issued by Large and Small Banks in the STBL Data Set, in Real Terms, Seasonally Adjusted.

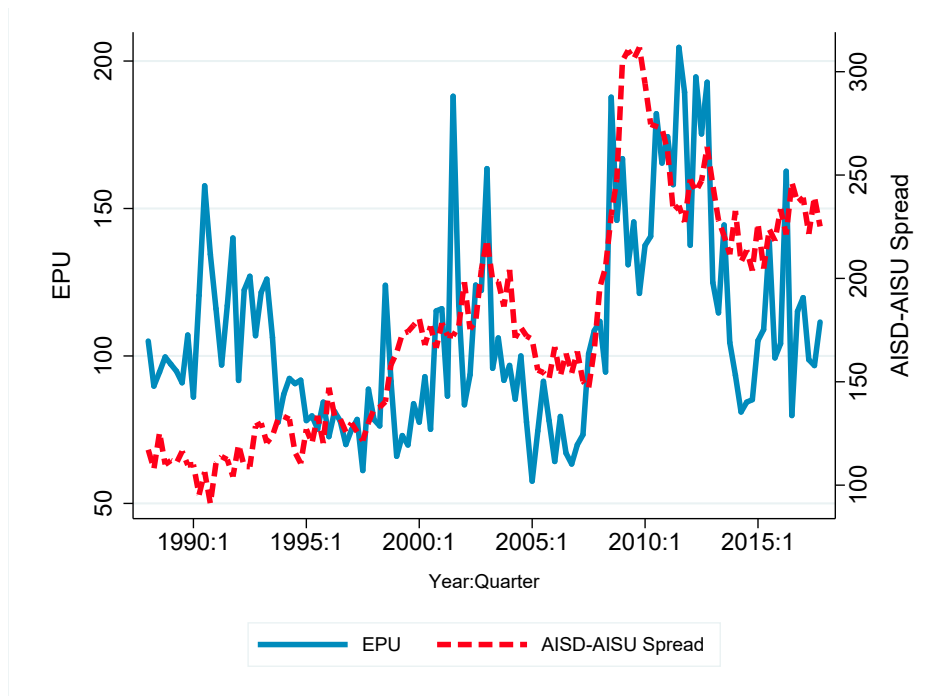


Figure 3: EPU and the Spread between All-In Spread Drawn and All-In Spread Undrawn from Credit Lines in DealScan.

where large banks originate a significant portion of their business loans (Ivashina, 2009).¹¹ In this market, banks finance portions of loans originated to mid-size and large borrowers, which allows them to efficiently diversify their lending portfolios. In a typical syndicated loan transaction, a borrower appoints a lead arranger, or a group of lead arrangers, and gives it a mandate to arrange the credit transaction. This mandate generally includes a term sheet setting the basis of the credit conditions sought. The lead arranger will invite other financial institutions to participate in the syndicate and, usually upon a negotiation process, the final terms of each facility in the package will be defined and the distribution among participants will be determined. Each facility will typically belong to one of two main types of loans: term loans or revolver loans.¹² The data series we use in our analysis are based on two subsets of the 123,295 facilities originated in U.S. dollars, to non-financial U.S. firms, and syndicated in the U.S. market between 1988 and 2017.¹³

In Section 4.3 we study the spreads on revolvers, which are lines of credit whereby banks offer businesses liquidity on demand.¹⁴ Under a revolver agreement, a borrower is typically entitled to draw down on and repay the line on one or multiple occasions for a pre-specified period of time. Since this contract essentially offers the borrower an option to secure liquidity on demand, banks charge this service via a commitment fee, which is a fee on the unused amount on the line. Banks can also charge borrowers an annual facility fee, which is independent of the use of funds, yet in credit lines commitment fees appear twice as frequently as facility fees and seldom does a single contract carry both commitment and facility fees at once (Berg, Saunders, and Steffen, 2016). The sum of commitment fee and facility fee is commonly referred to as the all-in-spread-undrawn (AISU henceforth). Naturally, banks also charge on the effective use of funds. Thus, should the borrower draw down on the credit line, she will be charged a fee in the form of a spread over a reference rate.¹⁵ This spread added to the facility fee is usually referred to as the all-in-spread-drawn (AISD henceforth).

It is evident, hence, that AISU and AISD represent costs associated to two distinctly different services. On one hand, AISU represents the cost of an insurance granting access to liquidity on demand – an access that might or might not materialize – or the price of an option to access liquidity on demand. On the other, AISD represents the actual cost of

¹¹The E.2 Release of April 2017 is also informative on this point. The release reports that loans made under participation or syndication represent 61.5% of the loans extended by large domestic banks, 27.7% of loans made by small domestic banks, and 59.7% of those made by all domestic banks.

¹²For the sake of space, we maintain the description of this market concise. Sufi (2007) offers a detailed description of this market. Strahan (2010) includes an excellent discussion on the workings and economic rationales in this market.

¹³Non-financial firms are defined as those with Standard Industrial Classification (SIC) code less than 6000 or more than 6999 among the firms with non-missing codes.

¹⁴Credit lines are defined as facilities whose loan type is “Revolver/Line < 1 Yr.”, “Revolver/Line ≥ 1 Yr.”, or “Revolver/Term Loan” in DealScan, and they represent 62,925 facilities, or 51% of all qualifying facilities. Notice that we use the terms commitments, revolvers, and credit lines interchangeably, as they conceptually represent very close definitions.

¹⁵In our data set, LIBOR is overwhelmingly the preferred base rate, and this is one of the reasons we focus our analysis on facilities whose base rate is LIBOR. The other reason is that this is also the choice of reference in the literature (e.g. Berg, Saunders, and Steffen, 2016). It is worth mentioning that only a marginal number of facilities bear a fixed rate instead of a spread over a variable rate. This regularity has long been recognized in the literature (for instance, in Shockley and Thakor, 1997).

tapping the funds. In Section 4.3 we elaborate further on this option view of credit lines and posit that, in response to increasing policy uncertainty, banks become wary of giving up liquidity and write options of liquidity on demand carrying high cost of access to liquidity with respect to the cost of securing the line. In Figure 3 we illustrate the spread between AISD and AISU on credit lines together with EPU to make apparent that the spread widens as policy uncertainty increases, suggesting that the cost of outright liquidity increases with respect to the cost of liquidity insurance as policy uncertainty heightens.

In Section 5.1 we also estimate a model using data on term loan originations from DealScan.¹⁶ A term loan gives the borrower a short availability period to borrow up to a maximum amount agreed on the package. After drawdown, the loan will be due for repayment either following an amortizing schedule or as a bullet payment at maturity, when repayment in full is due. Two comments are relevant at this point. First, as the main service these loans offer is outright liquidity, the spread of associated to these loans that becomes relevant is the AISD, or the cost of outright liquidity. Second, given that terms loans are originated for prompt disbursement and use, they are conceptually comparable to spot loans from the STBL data set. We will come back to this point.

The main source of our macroeconomic data is FRED, the online repository maintained by the Federal Reserve Bank of St. Louis. We obtain from FRED the real GDP, the GDP deflator, gross business investment, the Federal Funds rate, and the 10-year Baa-Treasury credit spread.¹⁷ Additionally, we also use two alternative shadow rates that proxy for the effective monetary policy stance during the period in which the Federal Funds rate reached the zero lower bound (ZLB), between December 2008 and December 2015. These measures derive from Wu and Xia (2016) and Krippner (2013, 2015) and we obtain them from the websites of the Federal Reserve Bank of Atlanta and the Reserve Bank of New Zealand, respectively. To conclude this section, we shall add that dollar-denominated series are expressed in real terms and series are seasonally adjusted following standard practices in the literature.¹⁸

4 Main Results

In this section, we present the main results of our analysis. Subsections 4.1 and 4.2 present results for the analysis based on STBL data on flows of business loans extended by large domestic banks in the U.S. By association, this analysis primarily refers to the dynamics of business lending to large firms (Berger, Miller, Petersen, Rajan, and Stein, 2005).¹⁹ Section 4.3 presents results for the analysis based on credit line originations in the

¹⁶These loans are defined as those whose loan type is “Term Loan” or “Term Loan A” through “Term Loan K”, and they represent 41,041 loans, or 33% of the qualifying facilities. In what follows, we refer to these loans as spot loans or term loans interchangeably.

¹⁷The corresponding series ids are as follows. Real GDP: gdp1; GDP deflator: gdpdef; Gross Business Investment: gdpdib; Federal Funds rate: fedfunds; 10-Year Baa-Treasury Constant Maturity: baa10ym.

¹⁸That is, all series are seasonally adjusted, except measures of interest rate or spreads and the EPU, EPU News and S&P 500 indices.

¹⁹In Section 5, we will extend this analysis to all banks combined and small banks separately. As we discuss in detail then, the results from all banks considered as a single group resemble those presented in this section, as large banks drive the aggregate dynamics of the business loan market. The results for small

syndicated loan market which, again, is closely associated to relatively large firms.

The first result of the analysis shows that total business lending falls in response to an exogenous increase in EPU. Part of this fall can be plausibly explained by a contraction in loan demand accompanying the slowdown in economic activity and the fall in investment resulting from the shock. Signs of this contraction in loan demand are apparent from the moderate use firms make of existing credit lines. The second result of the analysis shows that the negative response of total lending also reflects a contraction in the supply of loans. This is observable in the sharp decline of funds extended as spot loans, which far exceeds the slowdown in the pace at which borrowers draw down funds on their credit lines. The third result we present reinforces the notion of a loan supply contraction. In response to the EPU shock, banks originate new credit lines carrying a pricing structure that heavily penalizes drawing funds from the lines. Thus, the overall evidence of a supply contraction substantiates the existence of a bank lending channel in the transmission of economic policy uncertainty shocks to the rest of the economy through business lending.

In Section 5, we extend our study to a rich set of robustness checks of our main results in order to discuss additional insights about the workings of the transmission channel we describe in this section.

4.1 Total Business Lending

We first document that aggregate business lending falls in response to an exogenous increase in EPU. This is illustrated in Figure 4, where we report the response functions of the variable of our model to a one-standard-deviation innovation to the EPU index, which roughly corresponds to an increase in the uncertainty index of 25 points. The size of this innovation is relatively moderate. As a reference, consider that the EPU index was about 60-70 points during the first part of 2007, before the financial crisis unraveled, and reached 190 points in October 2008, at the apex of the crisis. In this figure, and all the following ones, the solid lines correspond to the response of a variable to the shock, whereas the dashed lines represent the 14/86th percentile bands of the posterior distribution of the responses.²⁰ The variables included in this first model are GDP, the GDP deflator, gross business investment, the EPU index, the Wu-Xia shadow rate, the credit spread, and the amount of all C&I loans originated by large banks. This ordering of variables defines the baseline identification scheme of the structural innovations as well. The estimation sample is 1985:Q1-2017:Q1 and the x-axis represents years from the shock.

The last panel of Figure 4 illustrates the response of loans. The response is slightly positive on impact, but it rapidly turns negative for the rest of the response horizon. The response is inversely hump-shaped and significant for up to two years, with the EPU shock foreshadowing a maximum fall of 2% in total loans after one year. This result is robust to a number of unreported robustness checks and is consistent with some of the findings in [Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek \(2016\)](#). In order to study the response of total bank loans to an uncertainty shock, [Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek \(2016\)](#) rely on a penalty function approach to jointly identify financial and uncertainty

banks, in contrast, exhibit meaningful differences which we discuss in time.

²⁰This choice of bands is well-established in the literature of Bayesian VAR models (see, for instance, [Sims and Zha, 1998](#)).

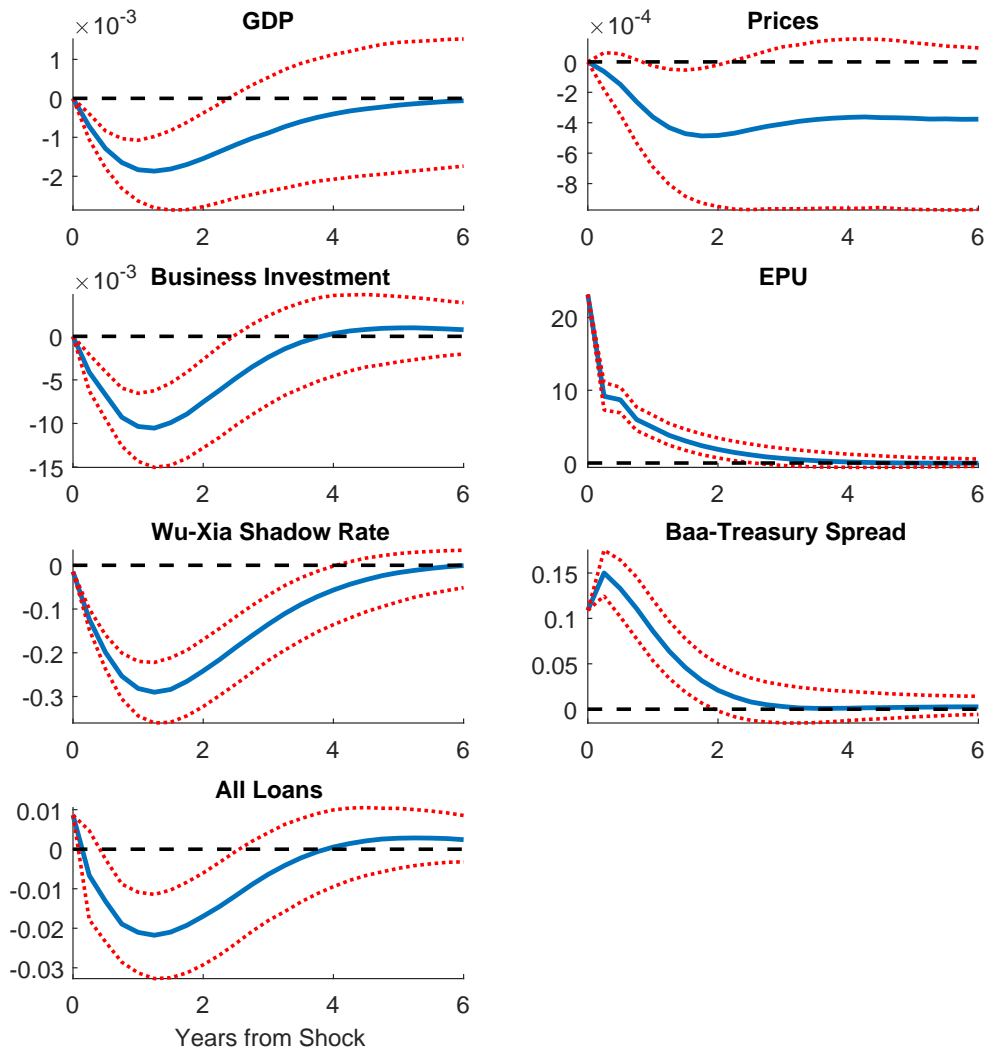


Figure 4: EPU and the Response of All Loans issued by Large Banks, 1985:Q1-2017:Q1. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross business investment, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, and the amount of all loans originated by large banks. VAR(2). Years from the shock on the x-axis.

shocks. While in their baseline identification strategy loans do not seem to respond to uncertainty shocks, the authors do find a negative and significant response of bank loans under their alternative specification, which penalizes less the response of financial variables to the uncertainty shocks.

The responses of the other variables of the model are in line with what has typically been found in the VAR literature on the effects of uncertainty on macroeconomic outcomes. GDP, prices, and the policy rate drop as well. The effects are an order of magnitude smaller than those observed for the loan aggregate, about two tenth of a percentage point, but

the responses are similarly hump-shaped and relatively persistent, especially for the price index. Output displays a sharper decline in the first year, with a gradual recovery within sixteen to twenty quarters after the impulse. This result is consistent with previous findings documenting falls in the level of activity, such as the fall in industrial production reported in [Baker, Bloom, and Davis \(2016\)](#).

We have included business investment in this model as both the theoretical and empirical literature have documented a link between changes in corporate investment and uncertainty (see, among others, [Bernanke, 1983](#); [Leahy and Whited, 1996](#); [Bloom, Bond, and Reenen, 2007](#); [Baum, Caglayan, and Talavera, 2008](#); [Jens, 2017](#); [Smietanka, Bloom, and Mizen, 2018](#); [Falk and Shelton, 2018](#)). The empirical literature, in particular, has convincingly documented that unanticipated increases in uncertainty hamper corporate investment and falling investment could naturally result in weaker demand for funds, making it necessary to control for them. As expected, we find a fall of business investment in response to an exogenous increase in EPU. The trough of the response corresponds to a fall in the order of 1.0% after about five quarters from the shock.

On the other hand, the credit spread increases in response to the higher uncertainty shock. This increase is economically and statistically significant, peaking after two quarters and converging to zero only after three years. The effect we find is in line with the impulse response function reported by [Gilchrist, Sim, and Zakrajsek \(2014\)](#) for an uncertainty measure of financial nature, and it is interpreted as an implicit outcome of a supply side contraction in the financial markets. We regard this response, jointly with the response of loans, as a first indication of the potential importance that the financial channel might have in the propagation of uncertainty shocks to the real economy. We further investigate this point in the next subsection.

We note that the response of the spread could raise questions as to whether the EPU shock could confound the effects of other forms of uncertainty, such as those stemming from the financial sector. In [Section 5](#), we further investigate this possibility by considering different orderings in the Cholesky scheme and by adding a stock price index to the financial block.

4.2 Identification of Supply Effect: Flows of Loans Extended under Commitment and Spot Loans

We now turn to specifications in which total loans are replaced by their component parts: loans disbursed under commitment and spot loans. The main purpose of this exercise is to exploit the different characteristics of pre-existing commitments and spot loans to disentangle supply side effects in the transmission mechanism of uncertainty shocks. We look at a model in which loans under commitment and spot loans are used separately to replace total loans. The response functions for this model are illustrated in [Figure 5](#).

This modification in the specification leaves the responses of the non-loan variables fundamentally unchanged. We find, however, very interesting differences in the responses of the two types of loans. Loans under commitment exhibit a generally negative response from the second quarter on, yet this response is smaller than that of total loans in [Figure 4](#). And, although reverting slowly back to zero, the response is relatively mild and muted by its

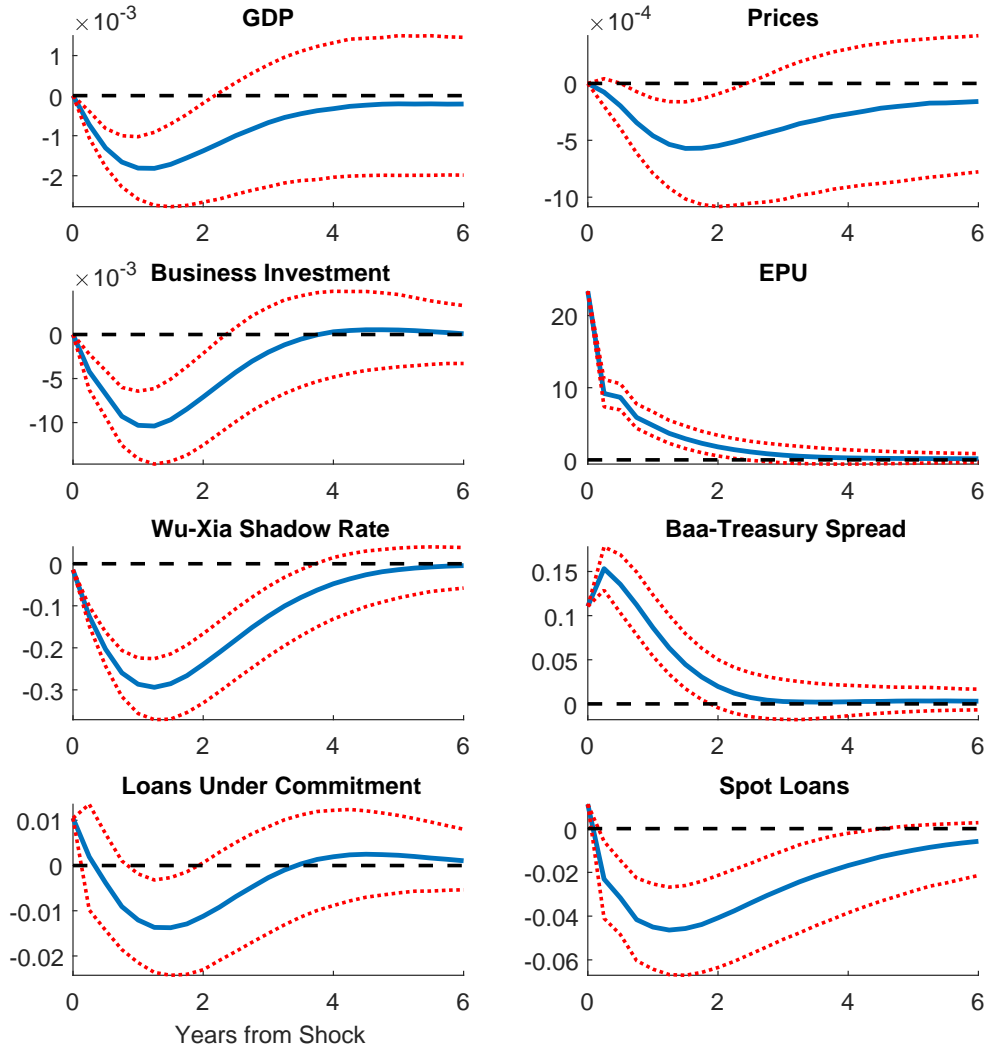


Figure 5: EPU and the Response of Loans extended under Commitment and Spot Loans by Large Banks and Business Investment, 1985:Q1-2017:Q1. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, and the amounts of loans extended under commitment and spot loans originated by large banks. VAR(2). Years from the shock on the x-axis.

statistical insignificance at virtually any horizon. In contrast, the EPU shock foreshadows a much larger and significantly negative response of spot loans, which reaches its trough about one year from the shock.²¹ We also notice that the maximum drop in loans disbursed under commitments is about four-fifths the maximum contraction of loans under commitment, and both troughs occur approximately at same time, five to six quarters from the shock. Moreover, the two responses display very similar shapes, which makes plausible to argue that a consider part of the demand-component in the reduction of loans discussed here finds a justification in the fall in investment that firms face.

While the slower drawdowns on commitments in response to the shock are suggestive of a slowdown in the demand for funds, the comparatively more pronounced fall in spot loans may suggest a concurrent contraction in the supply of credit as well. We explicitly test this hypothesis below using the ratio of loans disbursed under commitment to spot loans, which concludes the analysis in this section. The goal of this final exercise is to provide evidence of a supply-side restriction mechanism in the response of business loans to an exogenous increase in EPU. The literature has dedicated significant attention to the role financial frictions play in the transmission of uncertainty shocks to the real economy, especially investment. In the theoretical models of [Christiano, Motto, and Rostagno \(2014\)](#) and [Arellano, Bai, and Kehoe \(2016\)](#), for instance, financial frictions interact with uncertainty shock determining credit supply restrictions, and amplifying the effect of uncertainty on the economy in addition to the impact of the “wait and see” strategy that would normally arise at firm level. Finding evidence in support of this channel is of paramount interest then, and we present this evidence in [Figure 6](#) for a model in which the ratio of loans under commitment to spot loans replaces total loans in the specification of the model in [Figure 5](#).

In the face of increasing uncertainty and absent any material adverse change, firms have full access to their outstanding credit lines. Banks, on the other hand, have incentives to hoard liquidity in response to the same shock ([Caballero and Krishnamurthy, 2008](#)), and curtailing lending offers a means to do so. But they are contractually bound to honor pre-existing commitments, and hence can only adjust freely their supply of spot loans. Our identification strategy builds on these priors. Thus, a positive response of the ratio of loans disbursed under commitment to spot loans would reflect a supply-side loan contraction in response to a positive shock to uncertainty.

As discussed in [Section 2.1](#), this identification strategy relies on the assumption that loan demand has uniform cyclical properties across the two types of contracts. There are reasons to believe this assumption is plausibly satisfied in our setup. The main reason is that we limit the analysis to large banks and, by association, larger firms. Larger firms typically face fewer financial constraints and can secure alternative sources of financing, if needed. This makes them less likely to draw down or preserve lines strategically. After controlling for the changes in credit spreads, this should result in comparable demands across the two types of loans over the cycle. Smaller firms, in contrast, are more likely to be financially constrained, and have incentives to strategically manage open credit lines in response to different types of shocks, making untenable the premise of comparability of demand across

²¹We illustrate the impulse response functions of the same model for small banks sample in [Figure A11](#) in the Appendix. While most of the response set of the small-bank model remains unaltered, there is a clear difference in the response of loans under commitment between small and large banks. We discuss these differences in [5](#).

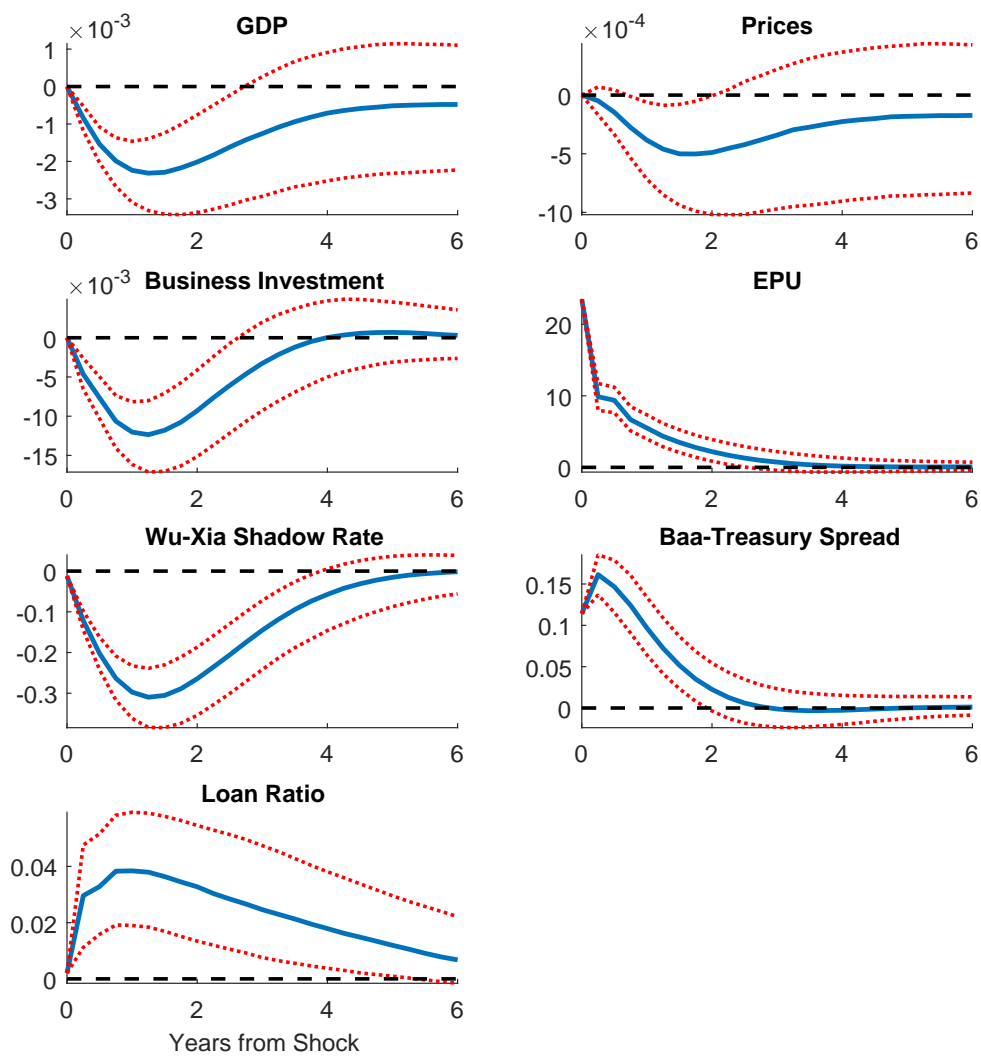


Figure 6: EPU and the Response of the Ratio of Loans extended under Commitment to Spot Loans by Large Banks, 1985:Q1-2017:Q1. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, and the ratio of loans extended under commitment to spot loans originated by large banks. VAR(2). Years from the shock on the x-axis.

the two types of loan contracts. The exclusion of small banks from our sample becomes important, then. Indeed, Figure A11 shows that the response of loans under commitment issued by small banks is significantly different from the response of loans under commitment issued by large banks, which suggests that both types of banks face different loan demands after an uncertainty shock.

The response of the loan ratio to an EPU innovation in Figure 6 is consistently positive. It is hump-shaped, persistent, with a peak between the third and fourth quarters, and is statistically significant up to six years from the shock. Comparing these results to those in Figure 5 for the model with separate loans, we can observe that the ratio response is driven by the fall in spot loans. This evidence offers corroborating signs of a concurrent contraction in supply of loans. The responses of the other variables in the model are very much unaffected, and the results presented here hold up well to an extensive set of robustness checks – as we show in Section 5.

In summary, our findings document a role of financial frictions in the transmission and amplification of uncertainty shocks through two types of effects that are consistent with a supply contraction in the financial sector. The first effect is an increase in credit spreads, an established result documented by Gilchrist, Sim, and Zakrajsek (2014) for their financial uncertainty measure as well. The second effect is a supply restriction in the business loan market, which results in limited access to new spot loans for firms. This is a new financial transmission channel of the effects of uncertainty to the real sector.

To conclude this section, we assess the relevance of EPU innovations in explaining variations in the loan variables. We resort to an analysis of forecast error variance decomposition (FEVD henceforth), which summarizes the relative importance of shocks on each one of the endogenous variables in explaining the deviations of a variable of interest from its observed value at different horizons. By means of this analysis, we can gauge the proportion of the error in forecasting values of, say, spot loans at a one-year horizon, that can be attributed to innovations of, say, EPU.

We have said that, in response to an exogenous increase in EPU, banks could only adjust immediately the amount of credit they offer as spot loans, as they are contractually bound to serve pre-existing credit lines. By the symmetry of the linear VAR models we use here, we could similarly argue that in the wake of an exogenous decrease in EPU, banks could rapidly augment their supply of credit by loosening the conditions on new spot loans beyond the (now relatively tight) conditions on pre-existing credit lines. An implication of this argument is that spot loans should be more responsive to EPU innovations than credit lines are. Figure 7 compiles the FEVD of loans extended under commitment and spot loans from the model reported in Figure 5 and the FEVD of the loan ratio from our benchmark model reported in Figure 6. Figure 7 neatly documents our point, as it shows that while EPU innovations explain about 11% of the long-run forecast errors in spot loans and 9% of the long-run forecast errors in the loan ratio, they only explain 3.5% of the forecast errors in loans extended under commitment, all of which is consistent with the preceding argument.

4.3 Banks as Providers of Liquidity on Demand

A key function of the banking system is the provision of liquidity on demand (Kashyap, Rajan, and Stein, 2002; Gatev and Strahan, 2006; Gatev, Schuermann, and Strahan, 2009;

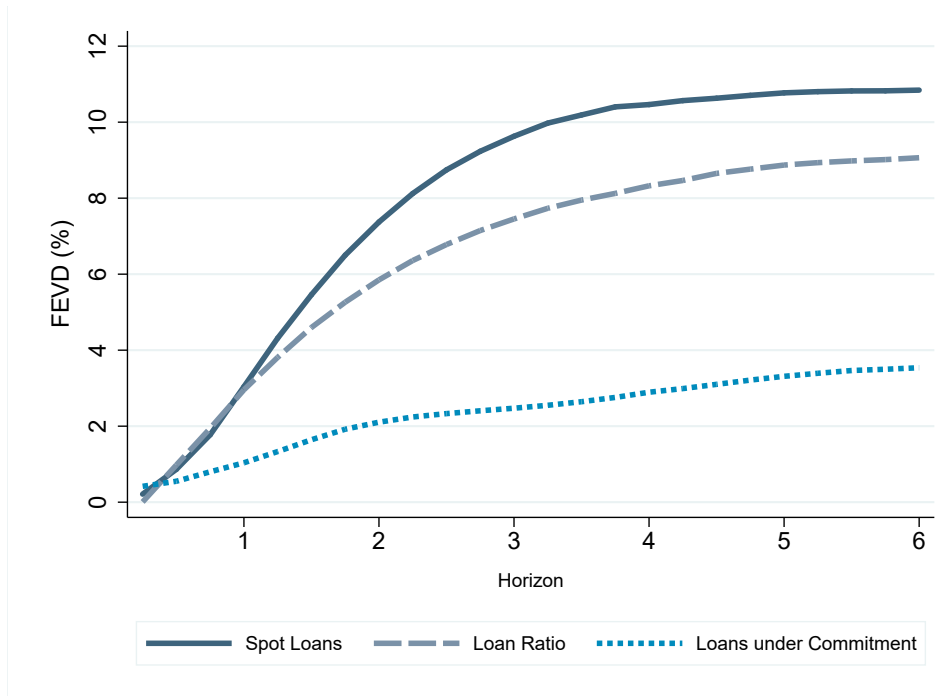


Figure 7: Forecast Error Variance Decomposition for Loans Extended under Commitment, Spot Loans, and the Loan Ratio. Horizon in Years.

Strahan, 2010). In relation to the business sector, this function is fundamentally implemented via commitments, which offer firms a form of liquidity insurance. The point we illustrate in this section relates to this primary function of banks and is very straightforward: in response to heightening economic policy uncertainty, banks originate new credit lines carrying steeper costs of effective access to liquidity on demand with respect to the cost of the insurance itself. By means of this strategy, banks disincentivize drawdowns on commitments, ultimately slowing down loan growth and extending the supply contraction to the new credit lines as well.

From an option theory standpoint, this equates to writing liquidity options carrying steeper striking prices with respect to the option price. *Ceteris paribus*, higher striking prices should translate into lower probabilities of the option ever being *in the money*, thus reducing the probability of exercise – i.e. drawdown. This notion is rooted in the intuition developed in previous works that see credit lines as options, including Thakor, Hong, and Greenbaum (1981), Shockley and Thakor (1997), and Berg, Saunders, and Steffen (2016).²²

²²In Thakor, Hong, and Greenbaum (1981) a commitment is deemed a put option whereby a customer is entitled to sell the bank a debt claim at a predetermined (exercise) price. The bank sells this option to the customer for a fee. The customer shall choose to exercise the option whenever the market price of her debt claim is lower than the price the bank is contractually bound to pay for it, which will occur when market spot rates are higher than the committed rate. Berg, Saunders, and Steffen (2016) call this option the drawdown option on credit lines. Shockley and Thakor (1997) emphasize that this put option on the customer’s debt claim is isomorphic to a call option on interest rate markups, as the total rate on funds drawn on commitments is typically set as a fixed spread or markup over a variable market rate (such as LIBOR). The customer will exercise her option to draw down on the line whenever that total committed rate is below the market spot rate on a comparable loan. Our discussion in this section of a credit lines as

Yet more specifically, it builds on the finding in [Berg, Saunders, and Steffen \(2016\)](#) showing that borrowers paying lower costs for securing and maintaining their credit lines with respect to the costs associated with drawing down on the lines are significantly less likely to draw down on their lines.

Credit lines in DealScan offer virtually ideal pieces of information to help us prove this point. On one hand, the AISU neatly approximates the notion of the cost of purchasing an option of liquidity on demand. On the other, AISD represents the cost of tapping the committed funds and can be thought of as the exercise price on the option.²³ The customer will exercise this option whenever the locked-in AISD is below the market spread on comparable spot loans. A quick glance at [Figure 3](#), which plots the spread between AISD and AISU on credit lines together with EPU, reveals that the exercise price on the liquidity option does rise with respect to the cost of the option as policy uncertainty rises.

We evaluate our conjecture formally. To this end, we estimate a VAR model that includes the ratio of AISD to AISU so as to emphasize the fact that exogenous increases in EPU foreshadow a relative increase in the cost of accessing liquidity with respect to the cost of securing the option.²⁴ We report the results in [Figure 8](#), which substantiates our point. The AISD/AISU ratio increases slightly on impact, yet it quickly rises to become significant and peak after about a year. Thus, this evidence of tightening on the margins of newly originated credit lines reinforces the notion of a supply contraction of bank lending we have observed on spot loans thus far.

A number of reasons could explain why banks could chose to implement a credit contraction by increasing the cost of drawdowns with respect to the cost of the credit lines. First, the increased credit risk can make it desirable to the bank to delay lending as much as possible, thus preserving the opportunity to reassess the convenience of lending in the future. Should the borrower present weakened creditworthiness, the bank could always resort to the non-compliance of the MAC clause and decline credit or, as it is often the case, reduce the amount it lends ([Shockley and Thakor, 1997](#)). Second, reducing the volume of drawdowns could allow, *ceteris paribus*, serving more clients than otherwise banks could. This would allow them to not only preserve, but also cherish the bank relationships with their clients. As banks develop relationships in expectation to capture future rents from their clients ([Sharpe, 1990](#); [Rajan, 1992](#)), harming these relationships by declining credit altogether during a period of heightened uncertainty could prove excessively costly in the long-run. Finally yet importantly, writing credit lines would allow them to preserve their sources of current and future income, even despite effectively providing less liquidity. Altogether, our empirical results are consistent with an interpretation grounded on sound economic principles.

an option goes along the lines of this second interpretation.

²³More precisely, the cost of tapping the committed funds would be the sum of a base rate (e.g. LIBOR) plus the AISD. Similarly, the cost of alternatively securing funds on the spot loan market would be determined as the sum of a base rate plus the prevailing spread on the spot market.

²⁴This is the inverse of the ratio [Berg, Saunders, and Steffen \(2016\)](#) use to test their Hypothesis 5. This choice is simply meant to facilitate the exposition here, as we want to stress that borrowers paying a *higher* cost to draw down on their lines with respect to the cost of securing and maintaining the lines are less likely to actually draw down the committed funds.

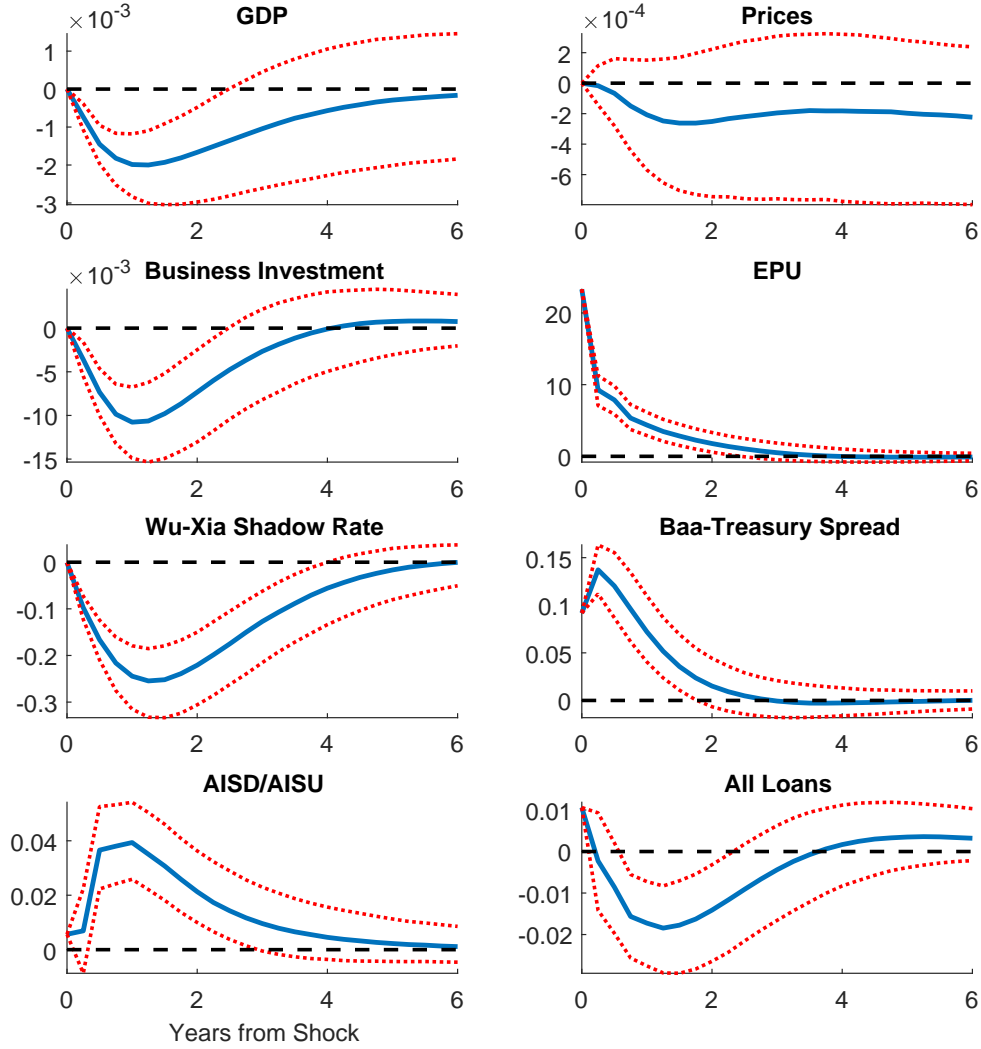


Figure 8: EPU and the Response of the AISD/AISU Ratio for Credit Lines in DealScan, 1988:Q1-2017:Q1. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, the ratio of all-in spread drawn to all-in spread undrawn from credit lines (DealScan), and the amount of business loans issued by large banks (STBL). VAR(2). Years from the shock on the x-axis.

5 Further Insights and Robustness Checks

In this section, we present some new insights and run a host of robustness checks on our main results. In the first part of Section 5.1, we take an alternative approach to document the supply contraction on spot loans using data from the syndicated loan market. Then, we show that the loan ratio results presented in Section 4.2 are not driven by the Financial Crisis of 2007–2009. Lastly, we present an analysis of lending by small banks in response to an EPU shock. In Section 5.2, on the other hand, we extensively check the robustness of the loan ratio results by adopting a variety of alternative model specifications. For reading convenience, we report in the Appendix the full sets of responses that accompany the responses of lending variables presented here.

An overarching message emerges clearly from these tests. Irrespective of the specification and data we consider, our analysis of large banks and, by association, large firms, reveals that an exogenous increase in EPU foreshadows a contraction in the supply of business loans. This is evident in the flows of spot loans falling at a significantly faster pace than the flows of loans extended under commitment and, also, in a concurrent spike in spreads accompanying the shrinking origination of new spot loan contracts.

5.1 The Role of Spreads on Spot Loans, the Financial Crisis, and Bank Size

Spreads on Spot Loan Originations. We interpret the increase in the Baa-Treasury spread in the benchmark model in Figure 6 of the Section 4 as evidence suggesting an overall tightening of the credit conditions of the business loan market in response to positive shocks to policy uncertainty. We argue banks implement this credit supply contraction mainly through the reduction of spot loans, as the increase in the ratio of loans extended under commitment to spot loans suggests in Figure 6. Additionally, in Section 4.3 we describe a second mechanism that banks can resort to implement a credit contraction. That is, the increasing penalization on draw downs on credit lines they originate following the shock.

We further corroborate our identification strategy of the credit supply-side transmission mechanism of the EPU shock, which primarily relies on the interpretation of the negative adjustments of spot loans as supply driven, by exploring a model that considers the volume of new term loans originated in DealScan and their corresponding AISD.²⁵ In this specification we opt for the use of both loan volumes and spreads from DealScan given obvious advantages of relying on a common source of data. However, using flows of spot loans from STBL in lieu of term loan originations from DealScan would yield very similar results. This is so because term loans recorded in DealScan are generally meant for prompt disbursement, which makes them conceptually very close to the flow of spot loans reported in STBL. We illustrate the responses of these two variables in Figure 9, while the full set of impulse response functions for this model can be found in Figure A10 of the Appendix.

If an overall supply contraction dominates the spot loan market equilibrium after the shock that increases EPU, the fall in spot loans must be accompanied by an increase in the

²⁵The use of loan spreads in this model is close in spirit to Berger, Guedhami, Kim, and Li (2018), who ultimately posit that increasing spreads are an indication of banks slowing down liquidity creation when faced with increasing economic policy uncertainty. The results we present here lend support to their claim.

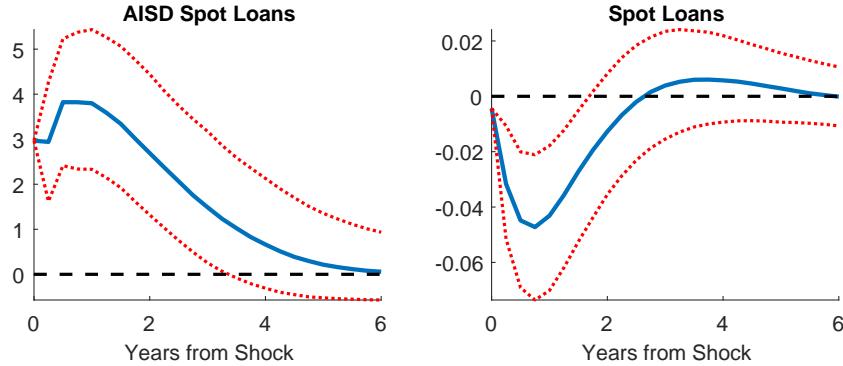


Figure 9: EPU and the Response of the AISD on Spot Loans and Spot Loan Volume from DealScan. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the DealScan AISD on Spot Loans, and the DealScan Spot Loans. VAR(2). Sample 1988:Q1–2017:Q1. Years from the shock on the x-axis.

price paid by firms to obtain the new loans as well. Figure 9 exactly illustrates this point. Spot loans drop by an amount similar to that of the baseline specifications (compare to Figure 5, for instance), with a sharp decline in the short-run after the shock, reaching a trough at about one year, and slowly recovering in the longer term. The response of the AISD, at the same time, is positive on impact continues with dynamics that mirror the response of loans. We regard this exercise as a useful empirical validation of our identification strategy.²⁶

The Financial Crisis, the Great Recession, and the Unconventional Monetary Policy Regime. The sample we use in our benchmark model includes the Financial Crisis, the Great Recession, and the post-recession period characterized by an unconventional monetary policy regime. This period not only entails persistently high levels of EPU, but it also includes a documented acute contraction in the supply of credit (see, for instance, Ivashina and Scharfstein, 2010; Cornett, McNutt, Strahan, and Tehranian, 2011; Santos, 2011; Adrian, Colla, and Shin, 2013; Chodorow-Reich, 2014). It becomes sensible, then, to assess whether the result of a supply-side contraction from the benchmark model could be driven by this period of unusually high levels of uncertainty and pronounced contraction in the supply of loans, or if the benchmark result would hold for the more standard regime as well. Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016) express a similar concern in their work, hence they replicate their baseline analysis using the more standard pre-crisis period. We follow their approach and estimate our benchmark model using the 1985:Q1-2007:Q2 sample.

Figure 10 illustrates the response of the loan ratio to a positive one-standard deviation uncertainty shock on this shorter sample. The hump-shaped behavior of the response is fully preserved, with a peak that arrives after about two years from the shock. This peak is

²⁶Similarly, in unreported exercises, available upon request, we find that the same type of result holds for the market of loans issued under new commitments and that the responses of AISD for spot loans and loans extended under new commitments closely comove.

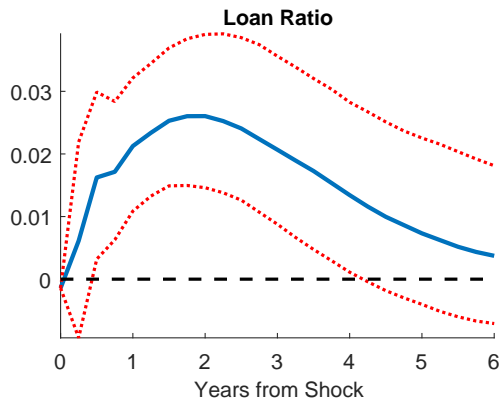


Figure 10: EPU and the Response of the Ratio of Loans extended under Commitment to Spot Loans by Large Banks. Sample 1985:Q1-2007:Q2. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, and the ratio of loans extended under commitment to spot loans originated by large banks. VAR(2). Years from the shock on the x-axis.

delayed by about one year with respect to the benchmark response in Figure 6, indicating a more conservative adjustment process of loan supply in the pre-crisis period. Similarly, the magnitude of the response decreases by about 1% at the peak with respect to the benchmark, and the response is not anymore significant after four years since the shock. Even though these elements altogether show that excluding the crisis, Great Recession, and unconventional monetary policy regime period leads to a mildly weaker effect of uncertainty on loan supply, we can conclude that the transmission mechanism we describe in Section 4 is a regular feature of the interaction between uncertainty and banking system which applies to the more standard pre-crisis regime as well.

We report the full set of impulse response functions for the pre-crisis sample in Figure A14 of the Appendix. All the other responses in the model are very similar to those of the benchmark model, especially for the variables in the macro block of the model.

The Role of Bank Size. The consolidation process of the banking industry (Berger, Demsetz, and Strahan, 1999; DeYoung, 2014) has given birth to larger banks, which have become increasingly more important players in the origination of business credit, as can be seen in Figure 2. While large banks originated about two thirds of the business loans before 1995, they currently originate well over 90% of them in our sample. Large and small banks embrace different business models and serve different clienteles – while large banks tend to serve larger firms, small banks specialize in serving smaller ones (Berger, Miller, Petersen, Rajan, and Stein, 2005). Smaller firms tend to be informationally more opaque and, partially as a result of that, more credit constrained. This naturally creates incentives for small firms to strategically administer their access to liquidity sources, such as open credit lines. Thus, in the face of increasing uncertainty, they could have pressing incentives to slow draw downs

and preserve access to open credit lines. This response would differ from that of larger firms, with access to alternative sources of funding.

Figure 11 illustrates the responses to uncertainty shocks to two models in which small bank loans are used to replace large bank ones. Figure 11a is for a model in which spot loans and loans under commitment are considered separately, paralleling Figure 5, while Figure 11b considers the loan ratio for small banks, as in our main specification in Figure 6 for large banks.²⁷ In the analysis for large banks-large firms we have seen that both loans extended under commitment and spot loans typically respond negatively to increases in EPU. Yet, while the response of loans extended under commitment is relatively mild, the response of spot loans builds up over time to become two to three times the size of the former. On the contrary, we observe a sharp decline of drawdowns on credit lines in the short and medium run for small banks in Figure 11a, which is comparable in size to that of their spot loans. These effects imply a much smaller and largely non-significant response of the ratio of loans under commitment to spot loans in Figure 11b as well.

This negative response of the loan ratio among small banks could be indicative of small firms more cautiously managing access to liquidity than larger firms in response to increasing EPU, slowing down their drawdowns on credit lines so as to preserve the liquidity insurance credit lines give them. The different response could arise from the different characteristics of the firms that typically borrow from small banks. These firms are smaller, more financially constrained, have limited access to alternative sources of funding such as the public capital markets and, possibly, display different funding needs over the business cycle. Also for these reasons, they must be considered separately from the large banks-large firms sample.

Finally, the response of all banks combined is virtually the same we observe when only large banks are studied. This is hardly surprising, since large banks issue the lion's share of all business credit. We report the impulse response functions for this model in Figure A13 of the Appendix.

5.2 Robustness Checks

VAR Order Selection. In the first robustness check we consider four lags instead of two in the baseline VAR model. The benchmark model lag order of two was based on the standard comparison criteria of the posterior probabilities of models with lag orders between one and four. Nevertheless, we run a series of robustness tests using alternative lag orders. Figure 12a illustrates the response of the loan ratio in the model with four lags, typically used with quarterly data in the literature in monetary policy. Clearly, this response is consistent with the response in our benchmark model. In unreported tests of models using lag order one and three, we find similar results.

Structural Identification Ordering. The benchmark identification strategy reflects the belief that, while credit markets clear immediately in response to an uncertainty shock, the real economy adjusts with a delay of a lag.²⁸ We check the robustness of the results to the

²⁷The full set of impulse response functions for these two models can be respectively found in Figures A11 and A12 of the Appendix.

²⁸As we mentioned before, this is consistent with the baseline identification scheme in Gilchrist, Sim, and Zakrajsek (2014) and it is also in line with the schemes broadly used in the literature on transmission of

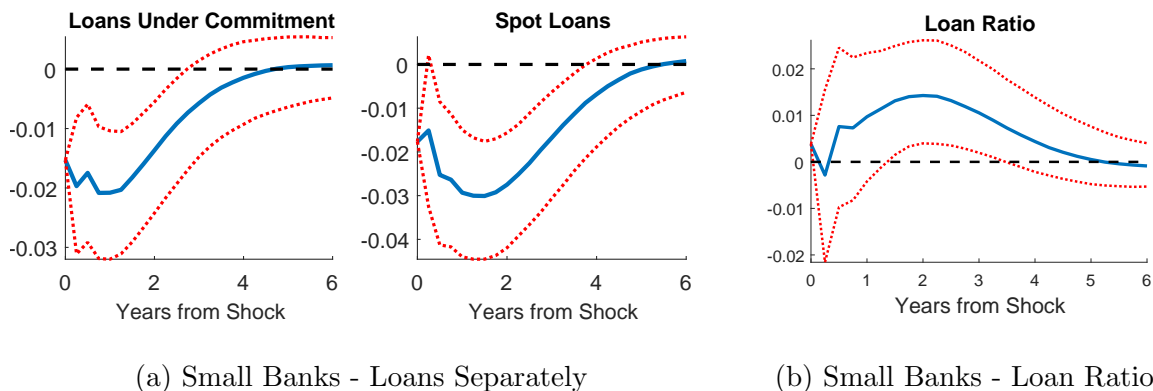


Figure 11: EPU and the Response of the Ratio of Loans extended under Commitment to Spot Loans for *Small* Banks. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, and either the amount of loans extended under commitment (a) and spot loans or the ratio of loans extended under commitment to spot loans (b). VAR(2). Sample 1985:Q1–2017:Q1. Years from the shock on the x-axis.

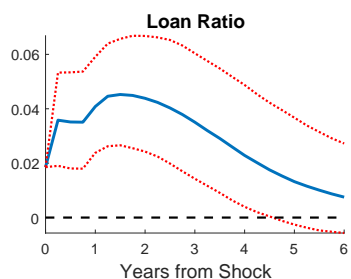
following two alternative identification schemes.

First, as in [Baker, Bloom, and Davis \(2016\)](#), we assume that EPU is the most exogenous variable in the system and both the real economy and the financial markets adjust immediately to an uncertainty shock. In the block-recursive identification model we adopt, this is achieved by placing EPU first in the vector of endogenous variables. The response of the ratio of loans extended under commitment to spot loans for this model is reported in [Figure 12b](#) shows this causal ordering of the variables does not affect our results.

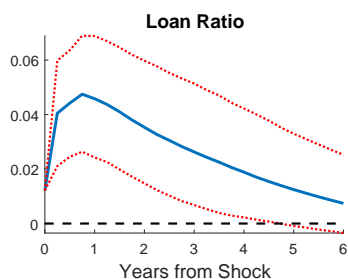
Second, we place EPU last in the identification ordering. In doing so, both past and contemporaneous shocks that affect the real economy, the financial sector, and even the monetary policy stance are controlled for in the uncertainty innovations. This ordering resembles the second identification scheme in [Gilchrist, Sim, and Zakrajsek \(2014\)](#), for instance. This ordering choice could be plausible in cases where it becomes important to assess the impact of EPU innovations on other variables conditional on the information on both the real and financial sectors of the economy. While the magnitude of the loan ratio response for this model is slightly reduced, [Figure 12c](#), the shape of the response clearly follows that of the benchmark result.

Alternative Measures of Monetary Policy Stance. We now assess the possible implications of two alternative measures of monetary policy stance for our results. In the benchmark specification we use the Wu-Xia shadow rate to capture the monetary policy stance during the period of unconventional monetary policy that followed the 2007–2009

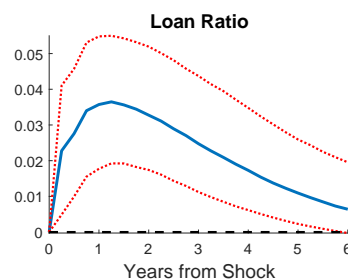
monetary policy ([Morgan \(1998\)](#); [den Haan, Sumner, and Yamashiro \(2007\)](#); [Barraza, Civelli, and Zaniboni \(2019\)](#)) with the uncertainty variable taking the place of the monetary policy instrument.



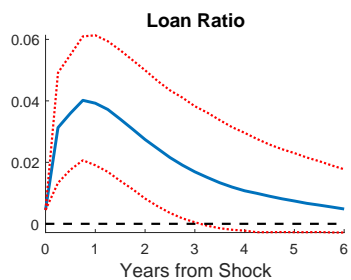
(a) VAR(4)



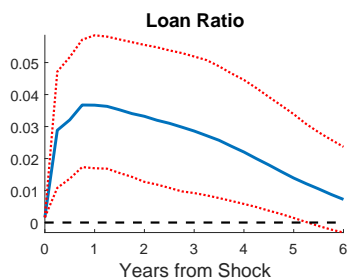
(b) EPU first in the identification ordering



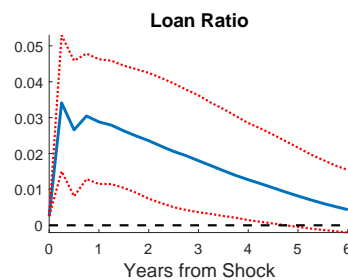
(c) EPU last in the identification ordering



(d) Federal Funds Rate



(e) S&P Index



(f) EPU News

Figure 12: Robustness Checks: Response of the Ratio of Loans extended under Commitment to Spot Loans at Large Banks to a one s.d. structural innovation to EPU. The benchmark model is modified in each robustness exercise as described in the panels. Sample 1985:Q1–2017:Q1. Years from the shock on the x-axis.

financial crisis, when the Federal Reserve resorted to large-scale asset purchases and forward guidance to further ease the monetary conditions and the federal funds rate reached the zero bound.²⁹ As a first check, then, Figure 12d illustrates the response of the loan ratio when the actual federal funds rate replaces the Wu-Xia shadow rate. A policy rate stuck at the lower bound during a significant part of the sample could, in principle, affect the identification of the policy uncertainty shocks in the model. However, the response of the loan ratio remains relatively unaltered also in this case, with a significantly positive response from impact until roughly the third year after the shock.

In the second check, the Wu-Xia rate is replaced with the Krippner shadow rate Krippner (2013, 2015). While conceptually similar, these two measures of the shadow rate bear some important differences in the modeling and estimation procedures, which could have an impact on the identification of the EPU shock as well.³⁰ Moreover, recent literature on monetary policy (see, for instance Wu and Xia, 2016) has pointed out that these subtle differences somewhat matter in the VAR framework of monetary policy analysis. This new response of the loan ratio is very similar to the benchmark one as well; we hence leave the illustration of this result for Figure A3 in the Appendix. Overall, we conclude that our results are robust to alternative measures of the monetary policy stance.

Changes to the Financial Block. Two changes to the financial block can be introduced to better characterize the financial sector of the model. As a first change, we add the log of the S&P 500 stock market index to the Z_t block as in Baker, Bloom, and Davis (2016), and report the response of the loan ratio in Figure 12e. Business decisions are typically forward looking. Firms respond to expected economic conditions and their willingness to take credit reflects their expectations regarding future profitability of investment opportunities. Policy uncertainty is an important determinant of these expectations, but more in general different types of news would also affect them. Since stock market prices embed information from multiple sources, they provide a suitable control to help us disentangle specific policy uncertainty shocks from the effects of other news. Moreover, explicitly including a measure of market performance in the VAR could also improve the empirical modeling of elements of latent demand and supply of credit, as stock markets are, in turn, sensitive to policy uncertainty (Pastor and Veronesi, 2013; Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek, 2016; Kelly, Pastor, and Veronesi, 2016). As before, the ratio of loans extended under commitment to spot loans remains unchanged.

The second change is obtained by replacing the ten-year Baa-Treasury Credit Spread of the benchmark specification with the ten-year Aaa-Treasury Credit Spread. We have mentioned that choosing the sample of large banks allows the analysis to be primarily centered around large firms. There is also a well-established positive relation between firm size

²⁹See Bernanke (2012) for a description of these policies.

³⁰Both methodologies build on the shadow rate term structure model introduced by Black (1995) to find more suitable measures of the underlying policy stance. Wu and Xia (2016) propose an analytical approximation to the shadow rate term structure model that is easily tractable and can be applied directly to discrete-time data using an extended Kalman Filter. Krippner (2013, 2015) proposes a framework that relies on a continuous-time Gaussian affine term structure model where the estimation is performed using the iterated extended Kalman Filter. Accordingly, they also yield slightly different shadow rates, which is apparent in Figure A1 in the Appendix.

and creditworthiness. Thus, an equally plausible choice of credit spread would be Moody’s Seasoned Aaa Corporate Bond Yield Relative to Yield on Ten-Year Treasury Constant Maturity. The results for this model, reported in Figure A5 of the Appendix, shows that the response of the loan ratio to an EPU innovation is virtually unchanged by this modification.

EPU News. As discussed in Section 3, the main component of the baseline overall EPU index is the news-based EPU index. This index is built to gauge economic policy uncertainty through the relative prevalence of newspaper articles that include at least one term from each of the following three categories: (i) uncertainty or uncertain; (ii) economic or economy; (iii) Congress, legislation, White House, regulation, Federal Reserve, or deficit. Articles that satisfy this condition are deemed to reflect economic policy uncertainty. In Figure 12f, we substitute news-based uncertainty index for the baseline overall EPU index used in our benchmark model. The response of the loan ratio sharply increases in the very short run and monotonically reverts to zero over the usual horizon of five years. Besides this difference, however, the overall interpretation of the response once again remains the same.

Other Robustness Checks. We conclude this section with a few more simple specification checks, which for sake of brevity are displayed in the Appendix. These, once again, confirm the baseline loan ratio response. First we add, alternatively, the amount of loans extended under commitment or the amount of spot loans to our benchmark specification. The full sets of responses are respectively illustrated in Figures A15 and A16 in the Appendix. The responses of the loan ratio remain unchanged, and the separate responses of loans extended under commitment and spot loans closely follow their responses previously reported in Figure 5. Second, we restrict the estimation sample to the period from 1985:Q1 to 2014:Q4 in order to compare our results to the study by Baker, Bloom, and Davis (2016). The output for this model is reported in Figure A17. We obtain a response of GDP closely comparable to that of industrial production in Baker, Bloom, and Davis (2016), while the loan ratio response is the same as in the benchmark result.

6 Conclusion

We empirically document the responses of business lending in the U.S. to shocks to economic policy uncertainty. Our analysis is based on a Bayesian VAR empirical framework in which the EPU shocks are identified using a recursive Cholesky structure, where the EPU measure is ordered between the variables of a real macroeconomic block and those of a financial-monetary one.

We focus our analysis on large banks, which dominate the business loan market, in order to devise a strategy that allows us to tease out supply- from demand-side effects in the responses of loans to uncertainty shocks. Large banks are generally associated with large firms, and this allows our strategy to exploit contractual differences between commitments and spot loans to disentangle the effects of higher uncertainty on the supply of credit by controlling for common movements in demand for funds across loan types. We implement this strategy using data on flows of business loans from the Survey of Terms of Business Lending. This analysis yields two main results. First, in response to increasing economic

policy uncertainty, overall bank business lending falls. Second, this fall is partly driven by a contraction in the supply of credit. Further tests using originations of credit lines in the syndicated loan market show that banks not only contract their supply of loans by curtailing their origination of spot loans. They further tighten their supply of credit by using in the new credit lines a pricing structure that heavily penalizes drawdowns on commitments.

Our results provide evidence on the role the banking system plays in the transmission of uncertainty shocks to the real sector. In particular, they stress the potential implications of limited access to credit that firms may face, which reflects a financial friction in the economy. In light of the theoretical literature showing that financial frictions amplify the contractionary effects on the economy that result from heightened economic policy uncertainty, our analysis clearly identifies the source of one of such friction, thus contributing to the understanding of this transmission channel. Furthermore, they convey a relevant policy implication – clarity and effective communication in the policy-making process can prove a powerful policy in itself.

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Appendix

A Additional Figures

In this appendix, we present additional figures to accompany those presented in the main text, including the full sets of orthogonalized impulse-response functions for results presented in Section 5.

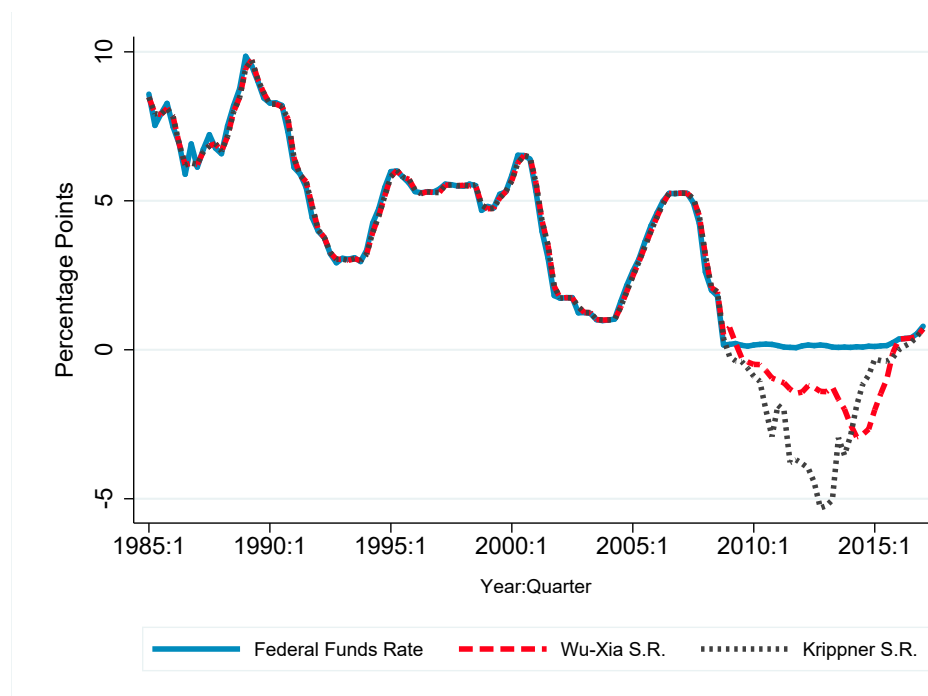


Figure A1: Monetary Policy Rates: Federal Funds Rate, Wu-Xia Shadow Rate, Krippner Shadow Rate.

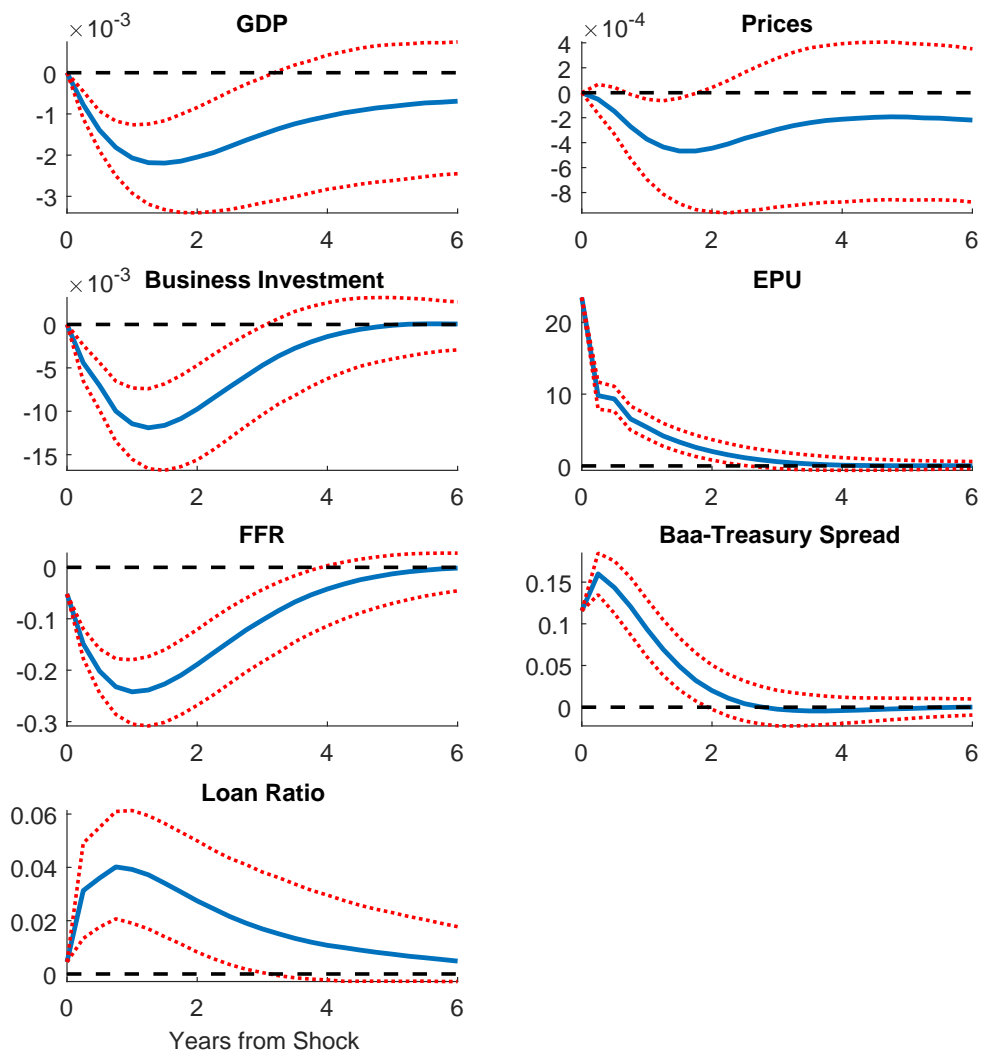


Figure A2: The Federal Funds rate replaces the Wu-Xia shadow rate in the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Federal Funds rate, the 10-year Baa-Treasury credit spread, and the ratio of loans extended under commitment to spot loans. VAR(2). Sample 1985:Q1–2017:Q1. Years from the shock on the x-axis.

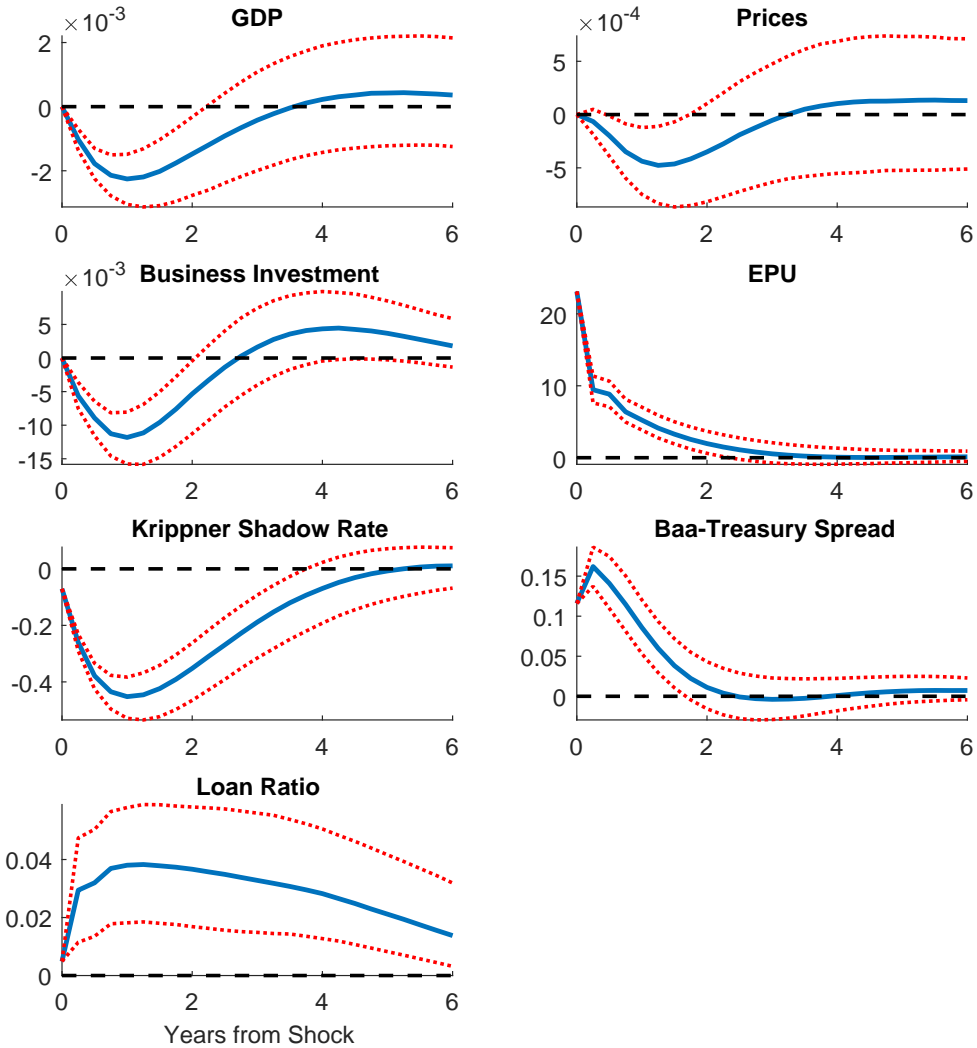


Figure A3: The Krippner shadow rate replaces the Wu-Xia shadow rate in the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Krippner shadow rate, the 10-year Baa-Treasury credit spread, and the ratio of loans extended under commitment to spot loans. VAR(2). Sample 1985:Q1–2017:Q1. Years from the shock on the x-axis.

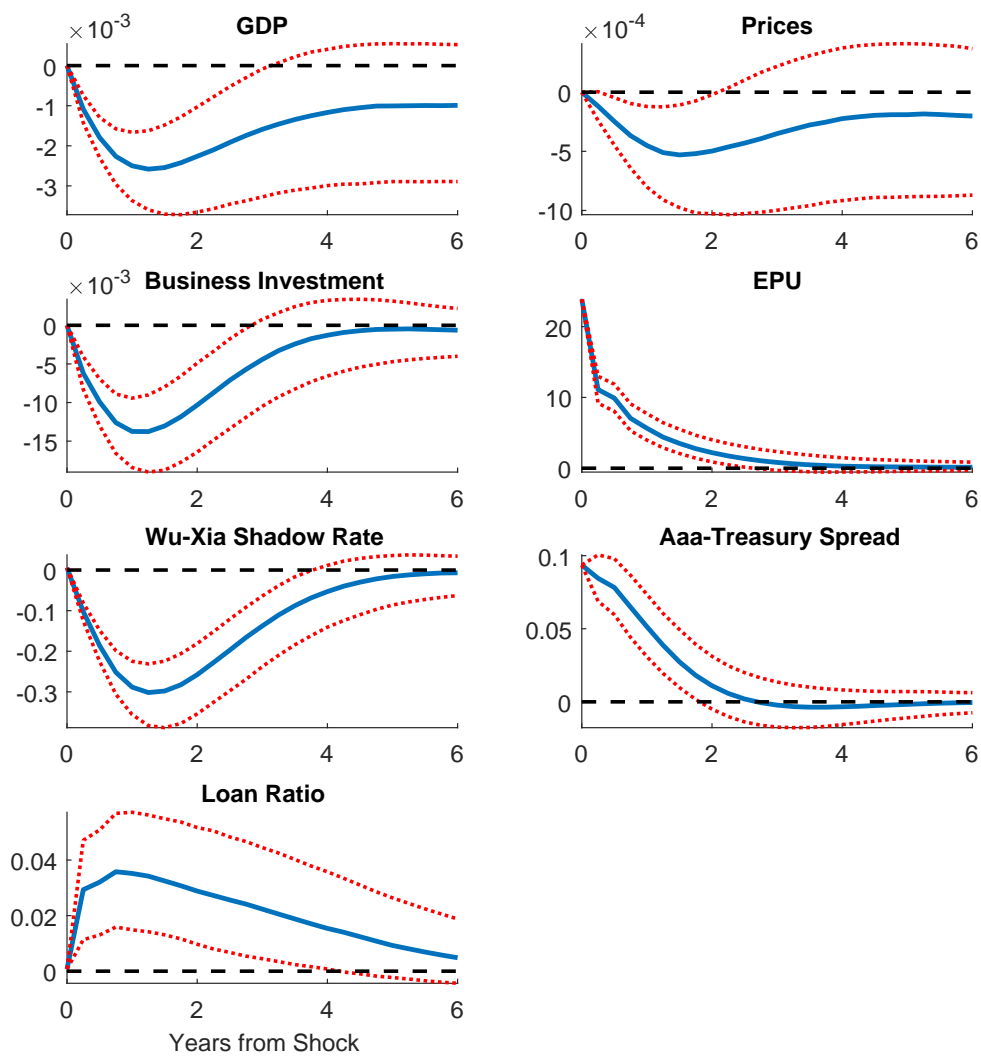


Figure A4: The 10-year Aaa-Treasury credit spread replaces the 10-year Baa-Treasury credit spread in the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Aaa-Treasury credit spread, and the ratio of loans extended under commitment to spot loans. VAR(2). Sample 1985:Q1–2017:Q1. Years from the shock on the x-axis.

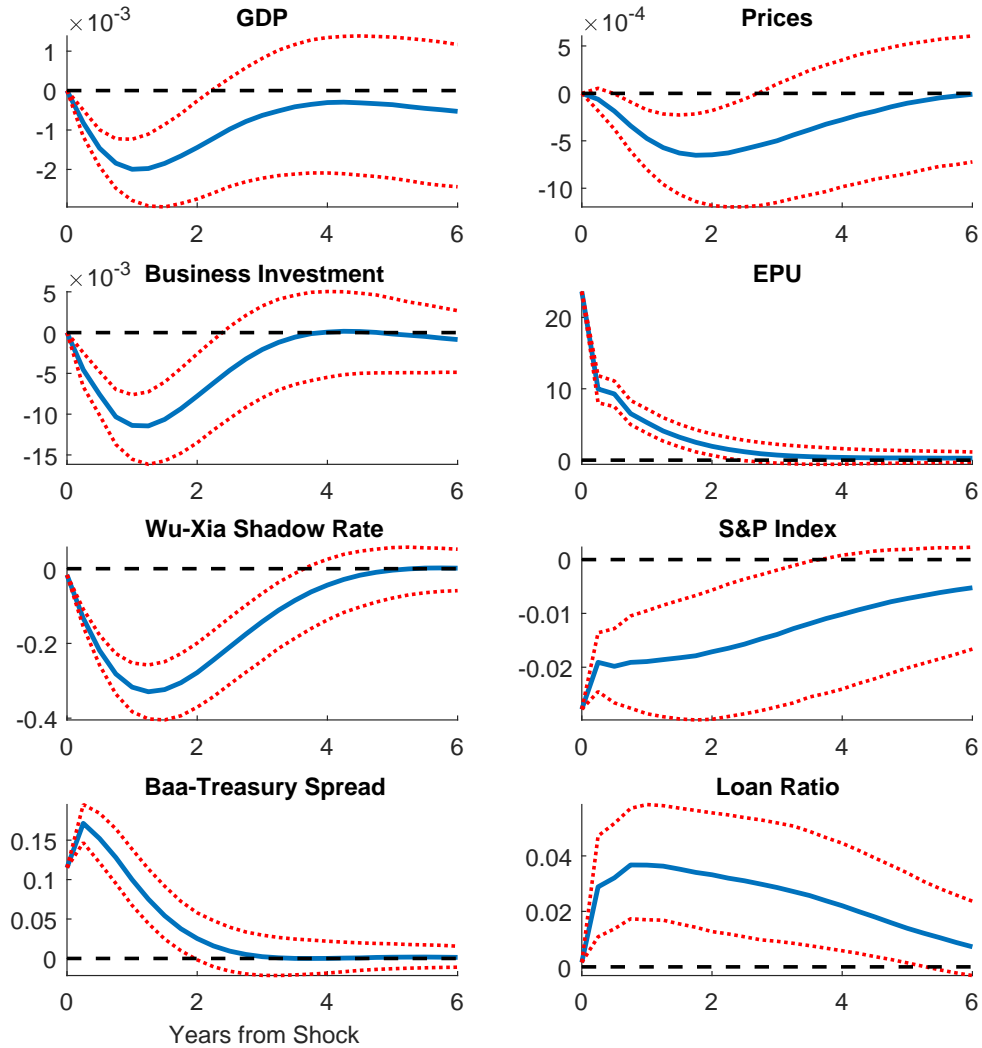


Figure A5: Adding the log of the S&P index to the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the log of the S&P index, the 10-year Baa-Treasury credit spread, and the ratio of loans extended under commitment to spot loans. VAR(2). Sample 1985:Q1–2017:Q1. Years from the shock on the x-axis.

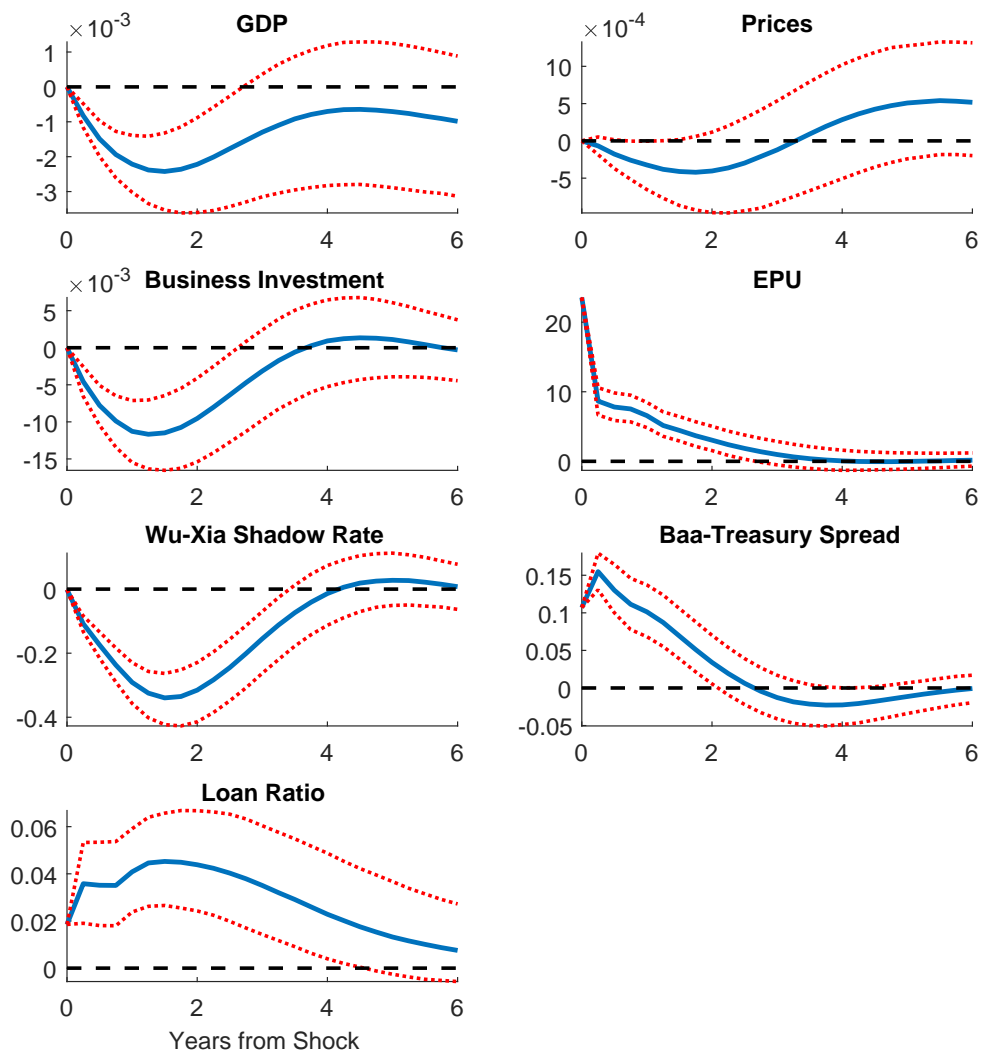


Figure A6: VAR(4) for the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the federal funds rate, the 10-year Baa-Treasury credit spread, and the ratio of loans extended under commitment to spot loans. VAR(4). Sample 1985:Q1–2017:Q1. Years from the shock on the x-axis.

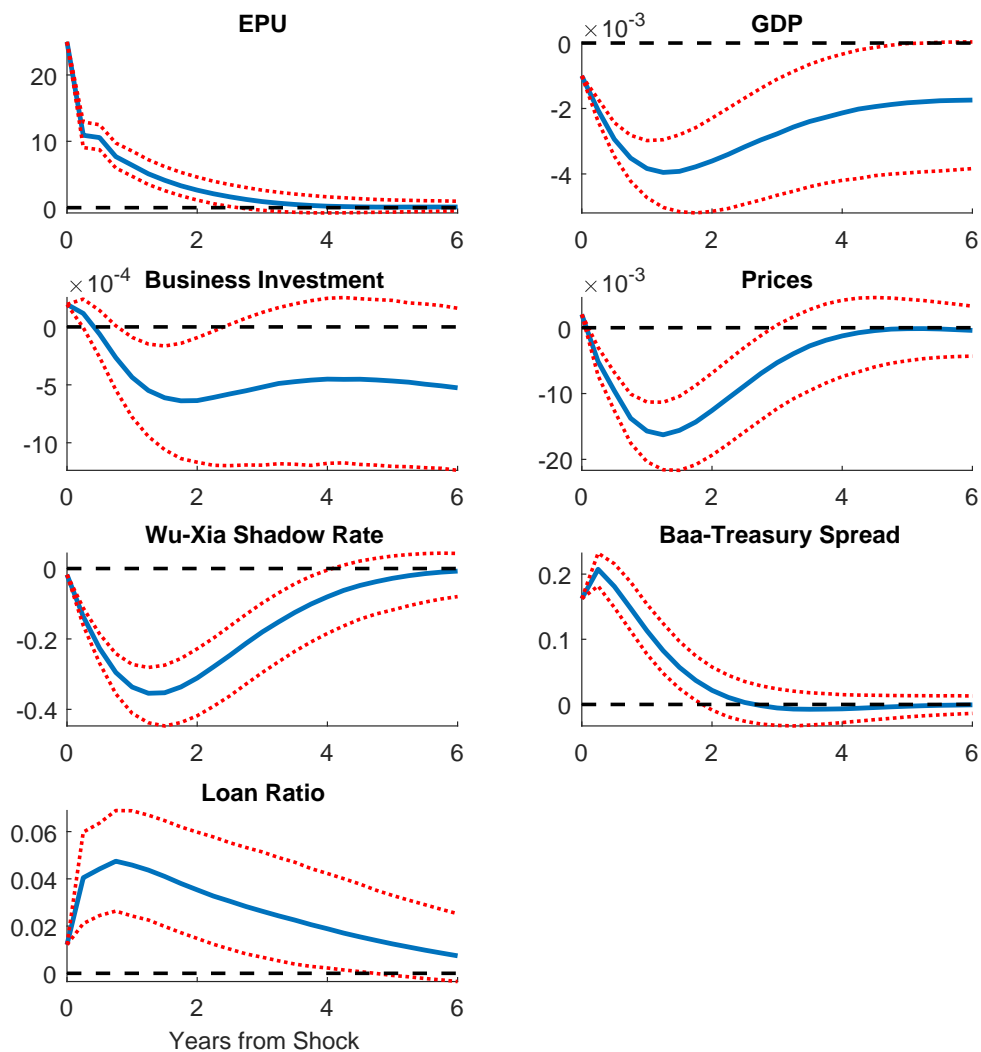


Figure A7: EPU First in the Recursive Ordering for the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the baseline overall EPU index, the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, and the ratio of loans extended under commitment to spot loans. VAR(2). Sample 1985:Q1–2017:Q1. Years from the shock on the x-axis.

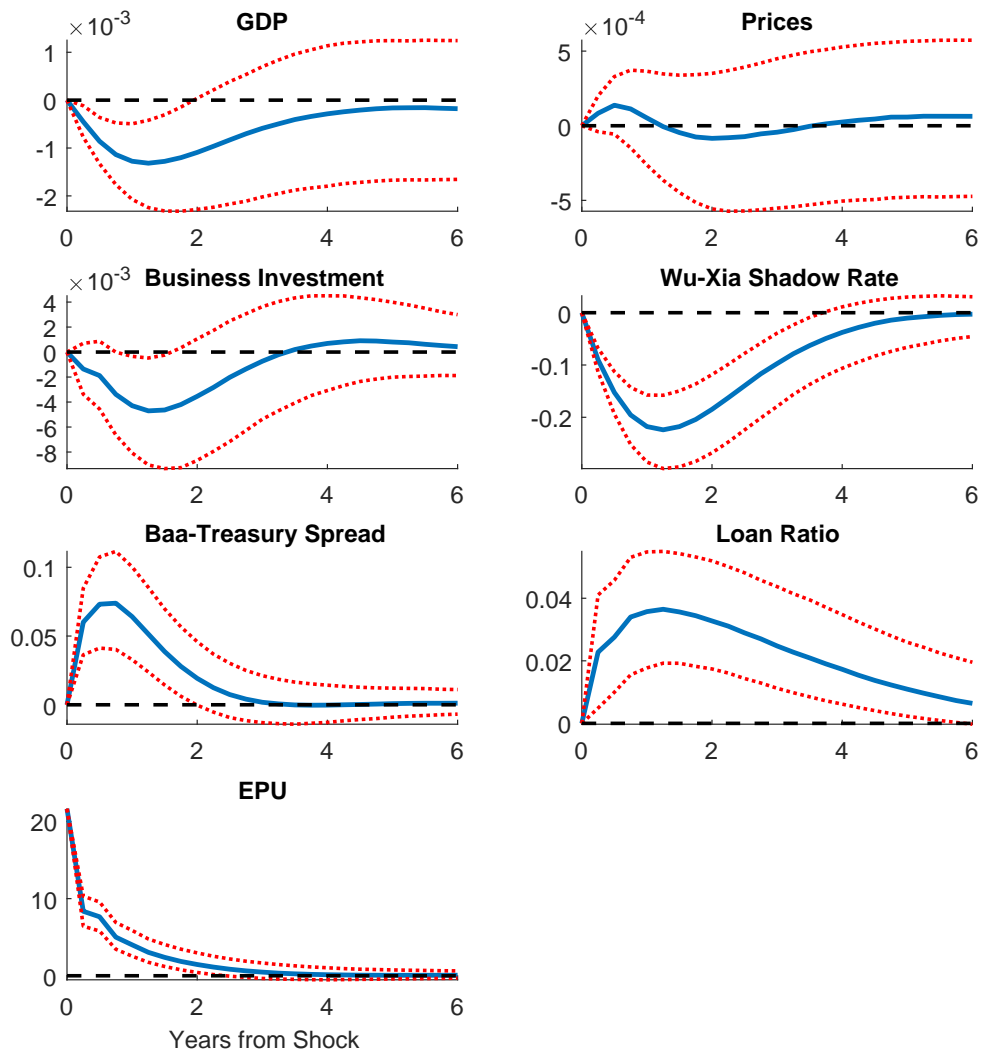


Figure A8: EPU Last in the Recursive Ordering for the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the Wu-Xia shadow rate, commitment to spot loans, and the baseline overall EPU index. VAR(2). Sample 1985:Q1–2017:Q1. Years from the shock on the x-axis.

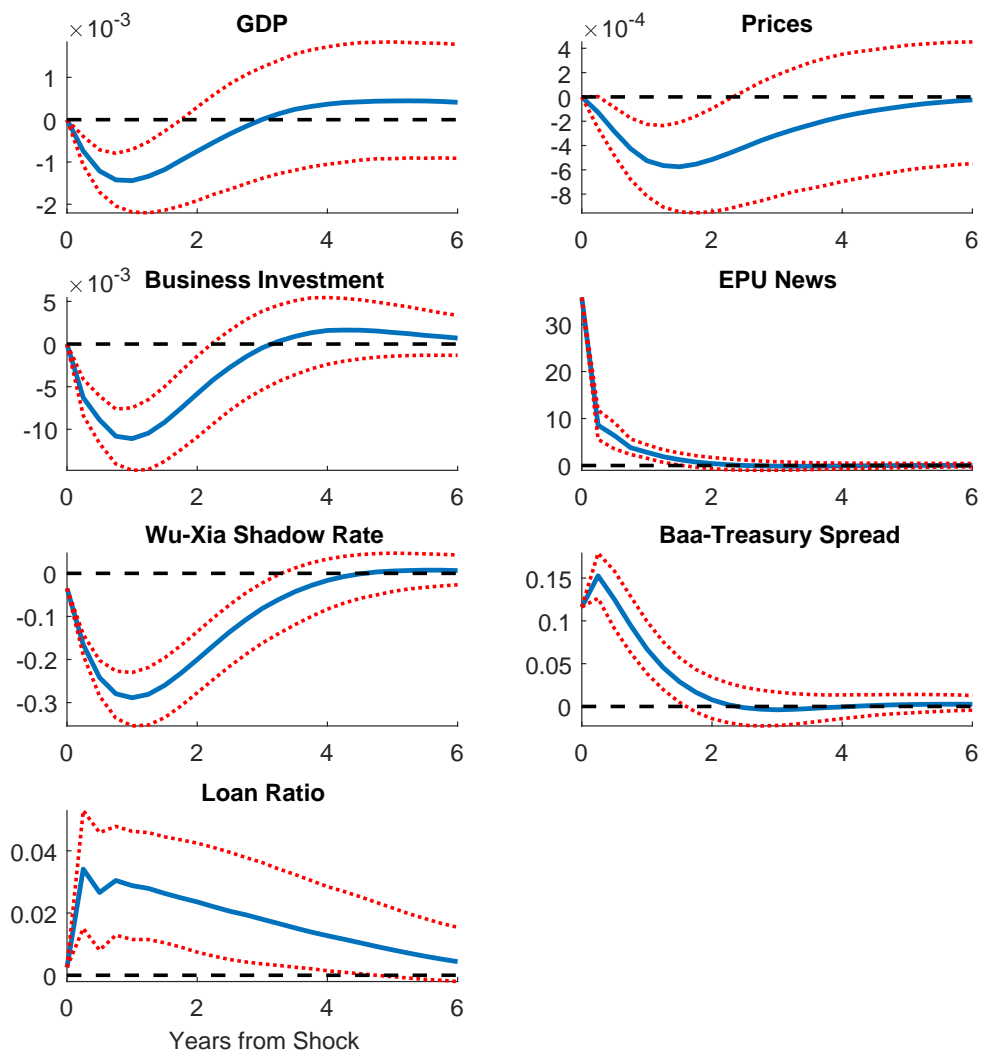


Figure A9: EPU *News* replaces EPU in the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the EPU *News* index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, and the ratio of loans extended under commitment to spot loans. VAR(2). Sample 1985:Q1–2017:Q1. Years from the shock on the x-axis.

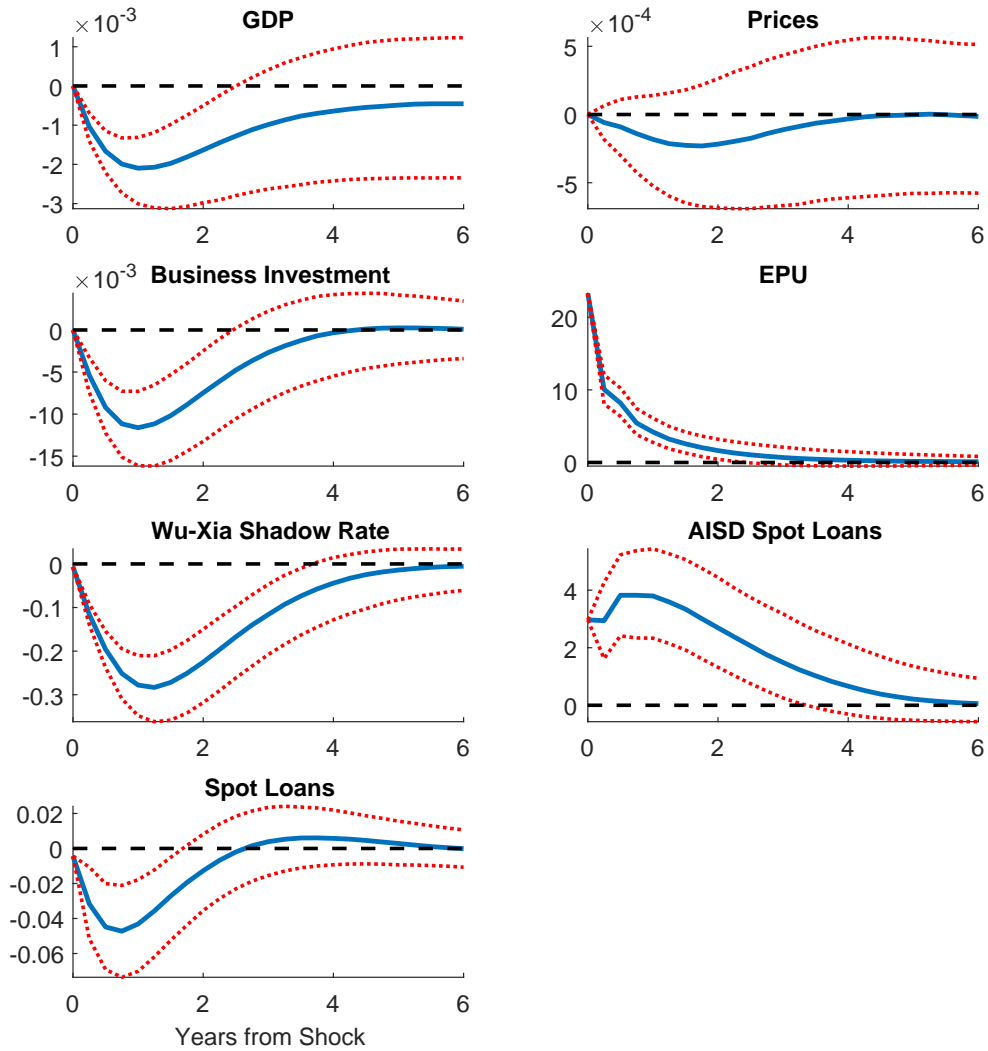


Figure A10: AISD on spot loans and Spot Loans for Large Banks replace the Baa-Treasury credit spread and the loan ratio in the benchmark model. Data from DealScan. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the DealScan AISD on Spot Loans, and the DealScan Spot Loans. VAR(2). Sample 1988:Q1–2017:Q1. Years from the shock on the x-axis.

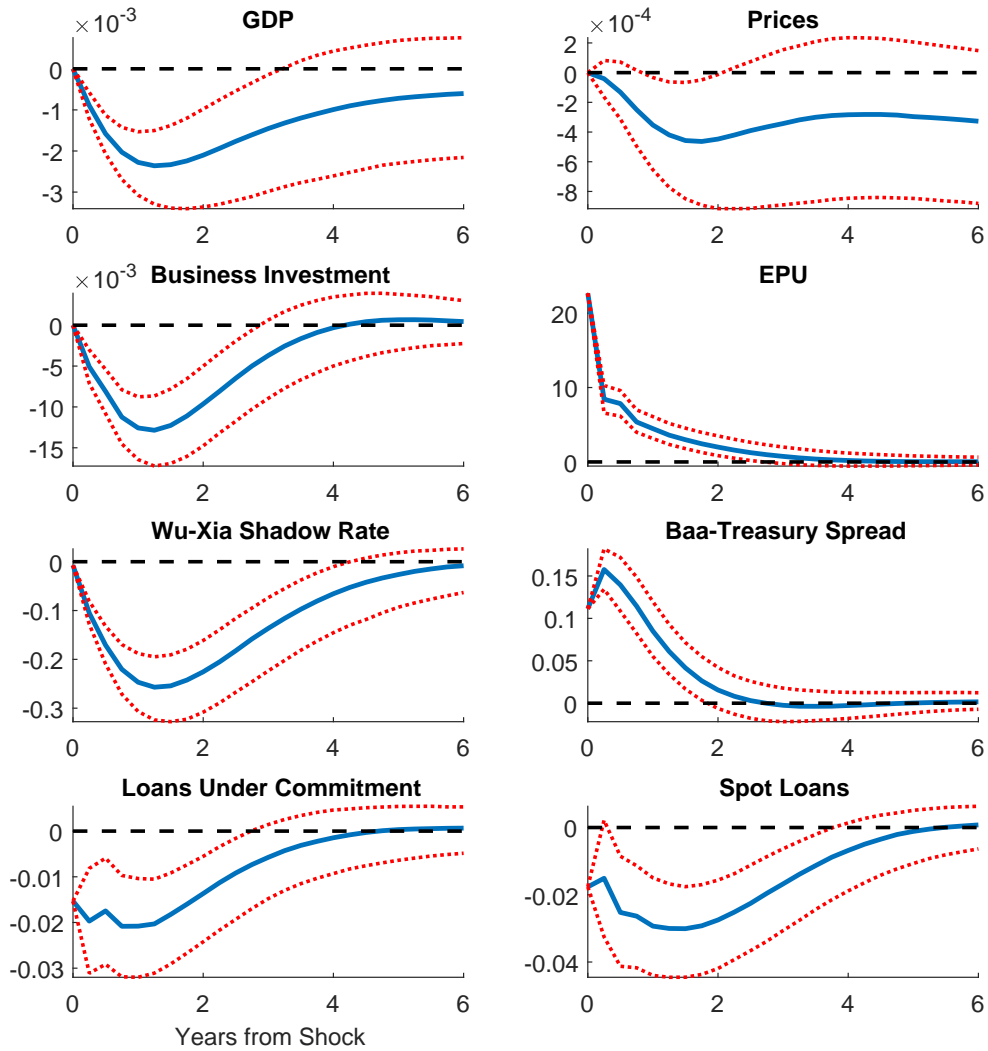


Figure A11: *Small* Bank loans replace Large Bank loans in the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, and the amounts of loans extended under commitment and spot loans originated by all banks. Sample 1985:Q1-2017:Q1. VAR(2). Years from the shock on the x-axis.

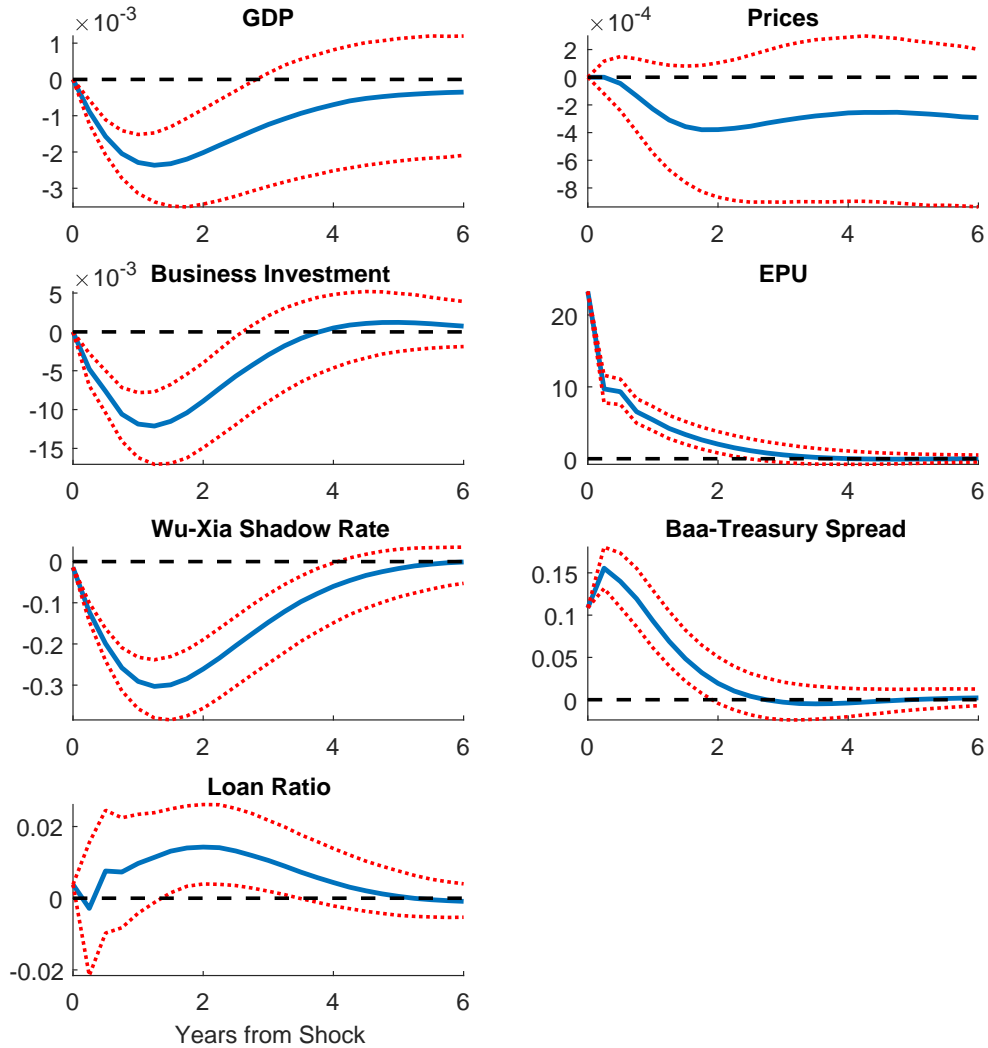


Figure A12: Loan Ratio for *Small* Banks replaces the ratio for Large Banks in the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, and the ratio of loans extended under commitment to spot loans. VAR(2). Sample 1985:Q1–2017:Q1. Years from the shock on the x-axis.

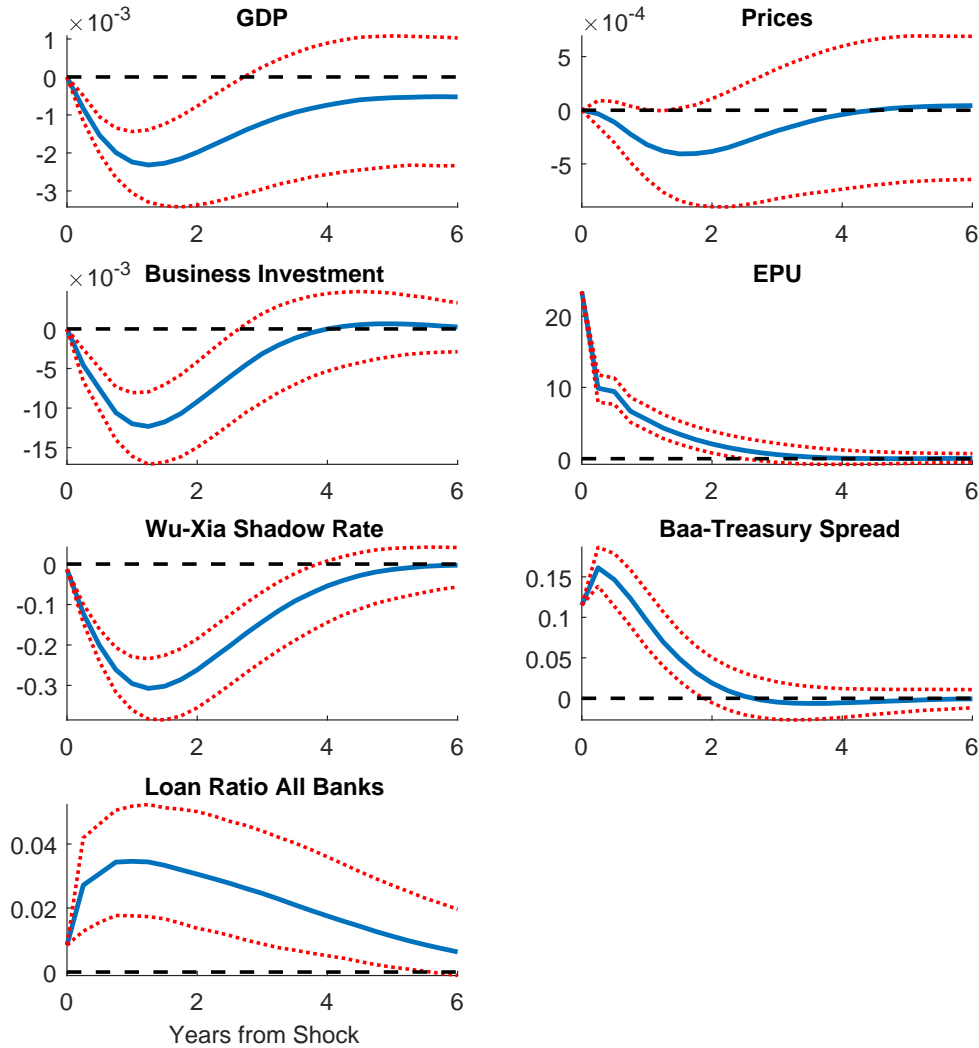


Figure A13: Loan Ratio for *All* Banks replaces the ratio for Large Banks in the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, and the ratio of loans extended under commitment to spot loans. VAR(2). Sample 1985:Q1–2017:Q1. Years from the shock on the x-axis.

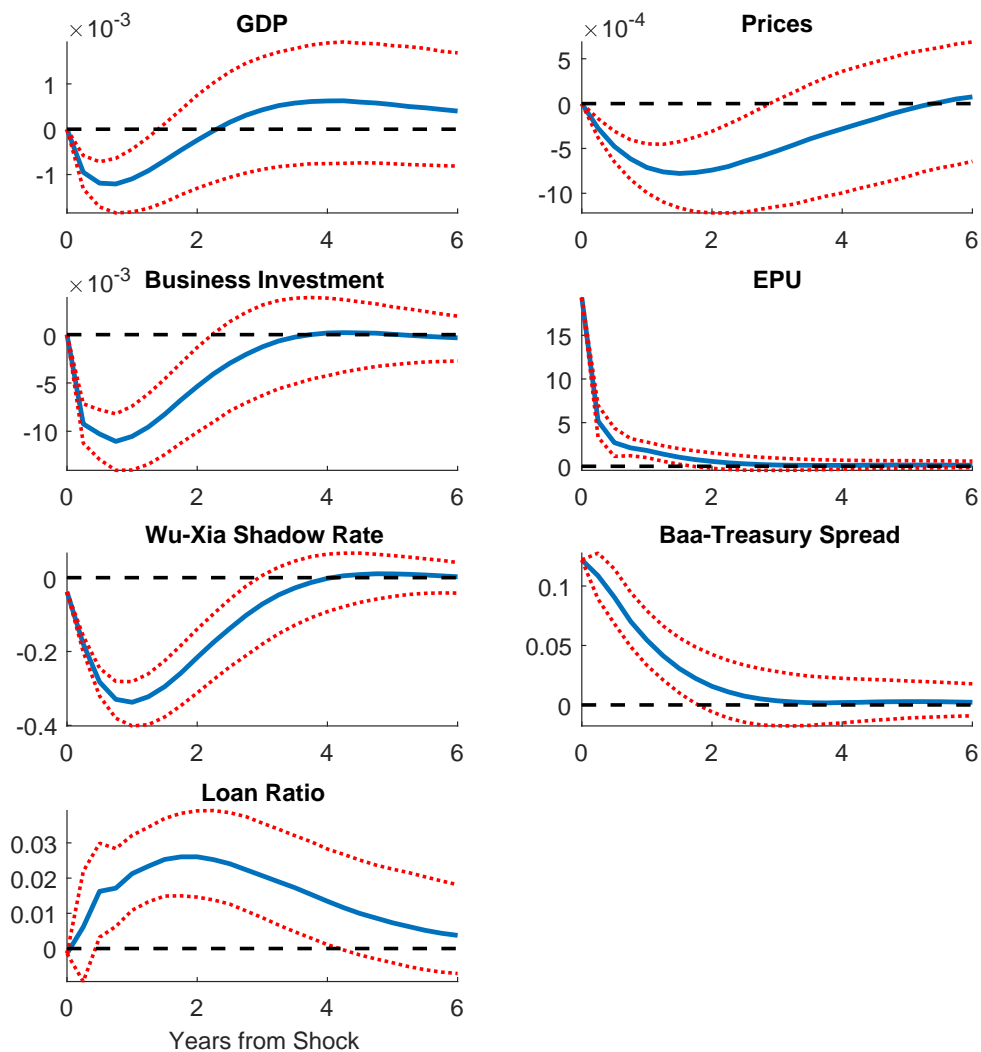


Figure A14: Excluding the Unconventional Monetary Policy Regime period from the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, and the ratio of loans extended under commitment to spot loans. VAR(2). Sample 1985:Q1–2007:Q2. Years from the shock on the x-axis.

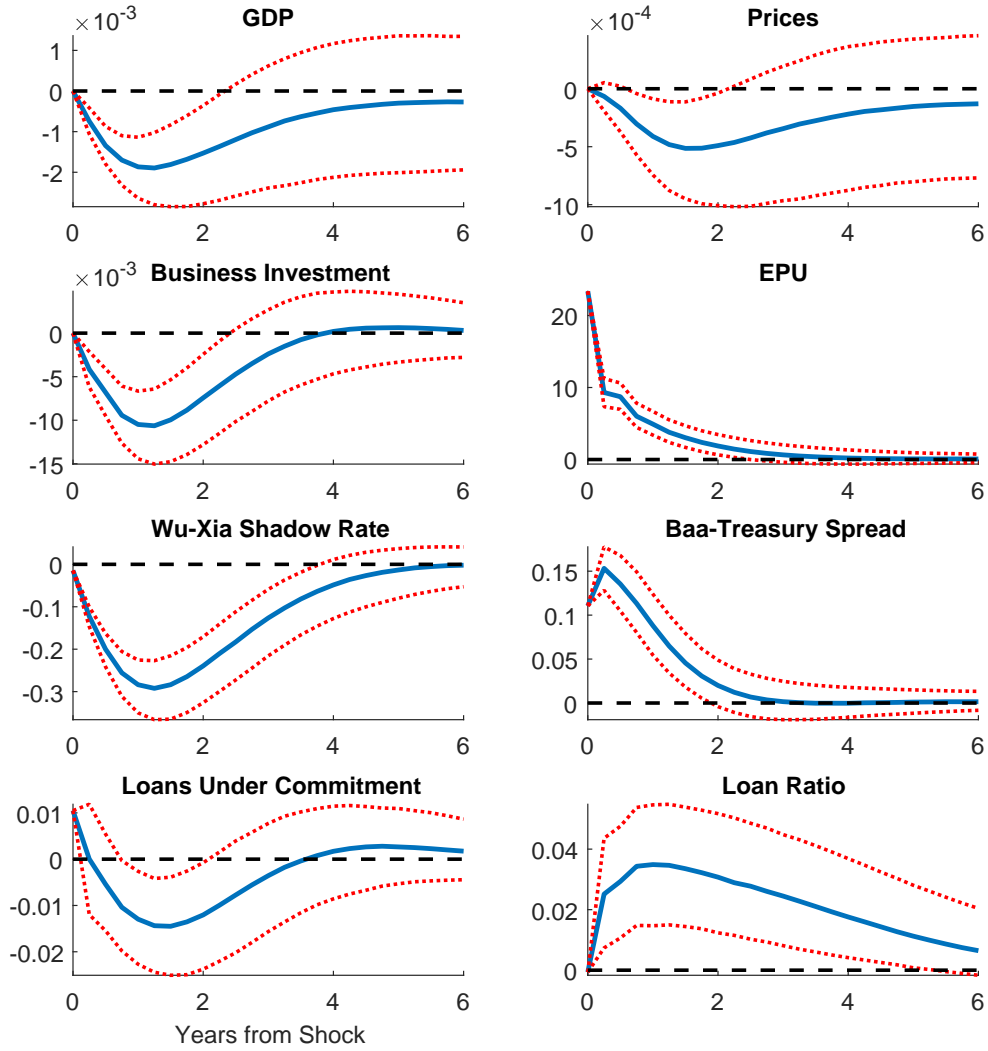


Figure A15: Adding Loans extended under Commitment to the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, the log of loans extended under commitment, and the ratio of loans extended under commitment to spot loans. VAR(2). Sample 1985:Q1–2017:Q1. Years from the shock on the x-axis.

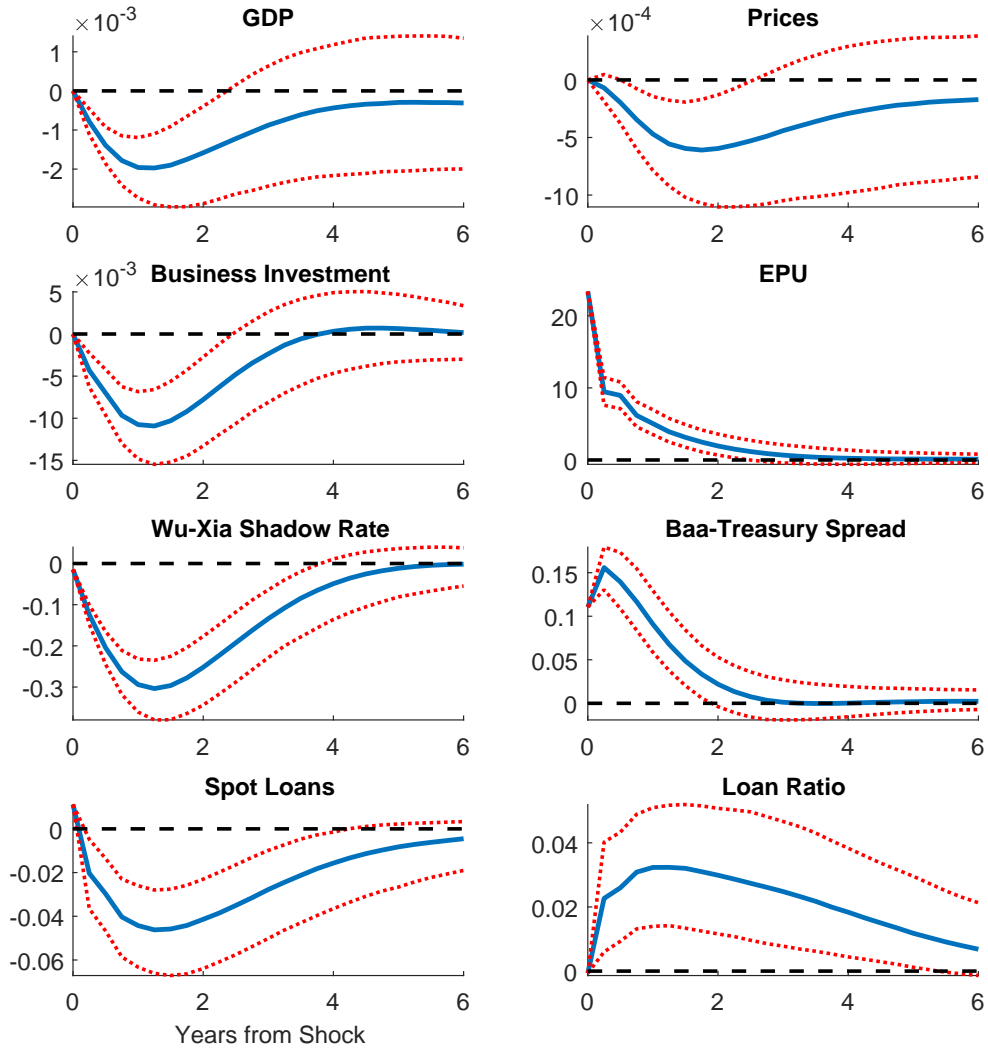


Figure A16: Adding Spot Loans to the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, the log of spot loans, and the ratio of loans extended under commitment to spot loans. VAR(2). Sample 1985:Q1–2017:Q1. Years from the shock on the x-axis.

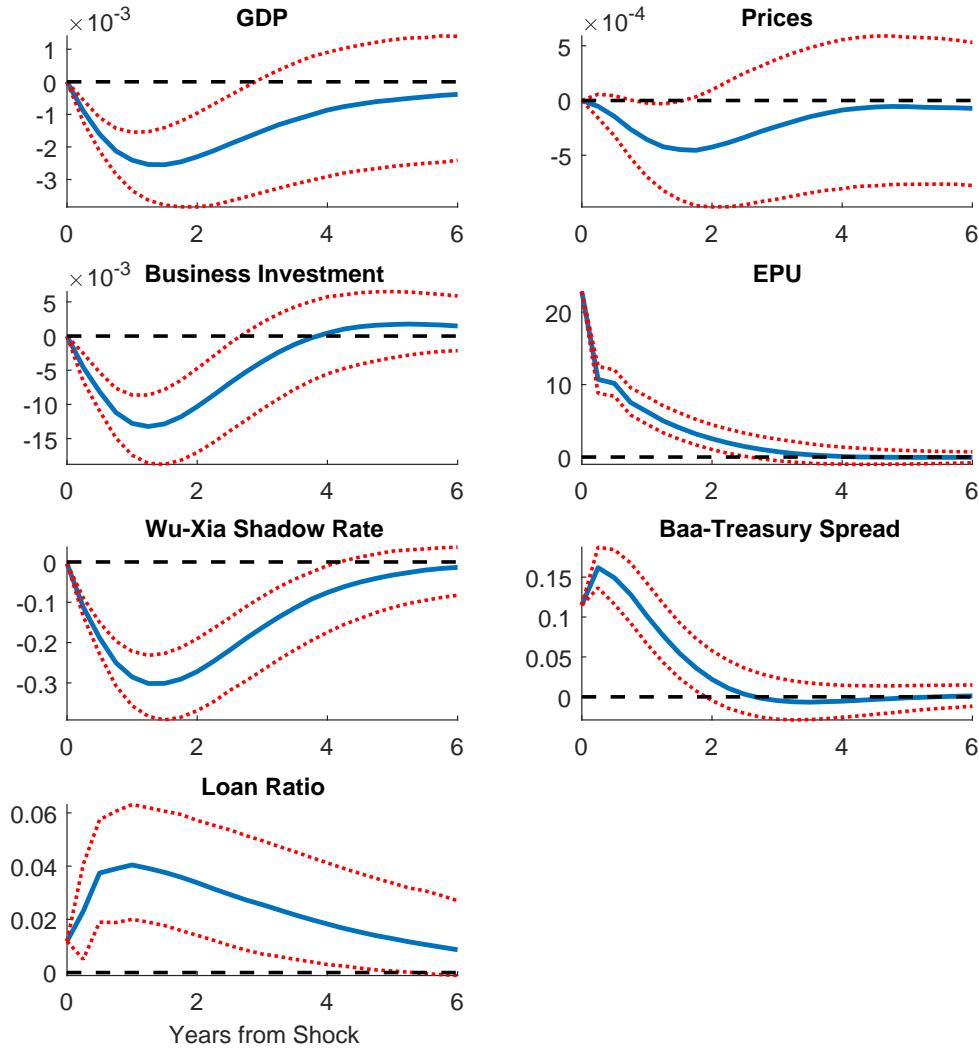


Figure A17: Baker, Bloom, and Davis (2016) Sample Period for the benchmark model. Orthogonalized responses to a one s.d. structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross private investment by domestic businesses, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, and the ratio of loans extended under commitment to spot loans. VAR(2). Sample 1985:Q1–2014:Q4. Years from the shock on the x-axis.