Economic Policy Uncertainty and the Supply of Business Loans

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Abstract

Using a Vector Autoregressive framework of analysis, we show that banks contract their supply of business credit in response to an exogenous increase in economic policy uncertainty. This contraction takes two main, distinct forms. On the one hand, banks restrict their supply of spot funds, which we document using flows of loans and term loan originations. On the other hand, banks also curtail their provision of liquidity insurance, reducing the amount of new credit lines and embedding in them a pricing structure that reduces the probability of borrowers drawing down on the lines. At the peak of the responses, we find that a one-standard-deviation increase in EPU causes a contraction in the supply of business loans between 3 and 5% on the extensive margin.

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

The literature of the last decade has shown a renewed interest in understanding the ways uncertainty affects the economy. This paper contributes to that literature by identifying a bank lending channel through which uncertainty affects the business sector. Specifically, it shows that increasing economic policy uncertainty causes a shift in the supply of business credit, restricting the provision of both spot liquidity and liquidity insurance. On the one hand, this research is motivated by the work of Baker, Bloom, and Davis (2016), who propose an Overall Economic Policy Uncertainty index (EPU henceforth) and study the effect of EPU on the real economy. One the other hand, it is also motivated by the financial literature suggesting that banks have incentives to preserve liquidity in the face of increasing uncertainty (e.g. Caballero and Krishnamurhty, 2008).

Our analysis relies on Vector Autoregressive (VAR) models and a recursive orthogonalization scheme that allows us to identify exogenous EPU shocks within the VAR framework. In order to study the effect of these shocks on the supply of spot liquidity, we first adopt the strategy originally proposed by Barraza, Civelli, and Zaniboni (2019) for the identification of supply-side effects in the response of bank lending to monetary policy shocks, which exploits the contractual differences between flows of loans disbursed under commitment and flows of spot loans obtained from the Survey of Terms of Business Lending (STBL).

Under the identifying assumption of uniform cyclical properties of business demand for funds from both types of loans, the relative responses to EPU innovations of loan flows allow us to infer changes in credit supply conditions.[1] This is so because, while banks can immediately adjust their supply of spot loans, they are contractually bound to provide liquidity on demand on open credit lines, regardless of their preference for liquidity at the time. In our analysis we find that, in response to a one-standard-deviation EPU shock, the flows of both loans extended under commitment and spot loans fall, yet the fall in the latter is about four times the size of the fall in the former, and they are accompanied by an increase in credit spreads of roughly 10 basis points. A formal test with our preferred specification of the model shows that the same one-standard-deviation increase in EPU causes a loan supply contraction of 3.2% on the extensive margin at the peak of the response one and a half year after the shock. This estimate implies an increase in EPU like the one experienced between early 2007 and late 2008 can cause a reduction in the supply of spot loans of as much as a 17%.

In a set of tests designed to validate the preceding results, we use originations of term loans in the syndicated loan market, recorded by Thomson Reuters LPC DealScan. As term loans are primarily originated for immediate use, they are closely comparable to the spot loans from STBL. DealScan, however, offers the benefit of having credit spreads directly associated to the observed loans. In these tests our attention centers on the joint responses of loan volumes and loan spreads to an EPU shock. We find that an increase in EPU leads to the concurrent fall in term loan volumes and increase in their spreads. Under the mild

[1] We focus the analysis on the sample of large domestic banks. This identifying assumption is plausibly satisfied in this sample, since large banks are mainly associated with large firms. Facing fewer financial constraints than small firms, large firms have fewer incentives to strategically manage their access to open credit lines. In Section 2.2, we discuss this assumption at length, including the related literature that substantiates it.

assumption of regularly behaved demand and supply curves – where demand is a decreasing function of spreads and supply is an increasing function of them – this is sufficient evidence to identify a loan supply contraction.

In addition to spot liquidity, banks also provide firms with liquidity insurance, primarily via credit lines, which grant firms access to liquidity on demand. In the second part of our analysis we investigate the response of banks' supply of liquidity insurance in the wake of EPU innovations. As before, we rely on the Barraza, Civelli, and Zaniboni (2019)'s approach to compare now the relative response of drawdowns on commitments reported in STBL and new credit line originations reported by DealScan. Under the identifying assumption that the demand for funds across these two different data sets is uniform over the business cycle, this test identifies shifts in the supply of liquidity insurance as banks can promptly adjust their supply of commitments to manage their off-balance-sheet credit exposures, while outstanding loans take some time to adjust (Gilchrist and Zakrajšek, 2012).[2] The results indicate that a one-standard-deviation increase in EPU causes a contraction of 4.8% in the supply of credit lines on the extensive margin about a year after the shock.

In a further set of tests we exploit the volume of new credit line originations in DealScan and their associated costs to corroborate the previous result and build a more comprehensive characterization of the response of bank lending to EPU shocks. We find two main results. First, in response to an exogenous increase in EPU, the volume of new credit lines falls and the cost of securing and maintaining those lines rises, which identifies a contraction in the supply of liquidity insurance under the mild assumption of regularly shaped demand and supply curves. Second, the pricing structure on new credit lines also adjusts. Upon the shock, credit lines carry higher costs of drawdown with respect to the costs of obtaining and maintaining the lines. As such shift in the pricing structure is associated with lower probabilities of firms ever tapping the committed funds (Berg, Saunders, and Steffen, 2016), this finding suggests yet another means by which banks can slow down future loan growth. While subtle, this is meaningful mechanism to alter loan provision, as more than four out of five dollars of business loans are extended under commitment. To the best of our knowledge, this is the first work to document this shift in the loan pricing structure in response to an EPU shock.

Altogether, our analysis depicts a rich mechanism through which banks respond to EPU innovations via business lending. On the one hand, they adjust immediately their supply of spot funds by contracting spot loans, which they can do without restrictions. On the other hand, they also adjust their supply of liquidity insurance, restricting its volume and tightening the terms of both current and future liquidity provision.

Related Literature. Our paper relates, first and foremost, to the strand of literature showing that EPU is associated with the tightening of bank credit conditions. This literature finds that higher EPU is associated with a significant tightening of overall bank lending standards (Bordo, Duca, and Koch, 2016), a reduction in the acceptance probability of new credit applications (Alessandri and Bottero, 2017), and an increase in spreads on business

[2]This assumption is based on the observation that firms borrowing under commitment from large domestic banks in STBL resemble those borrowing credit lines in the syndicated loan market. We return to this point in Section 2.3, where we discuss supporting evidence.

loans (Berger, Guedhami, Kim, and Li, 2018). Our work extends those findings by providing a new set of evidence on the causal effects of EPU on loan supply, insofar as EPU has differential effects on the volume and pricing of new business loans by commitment status.[3]

This paper also speaks to various strands of the literature that investigate the relation between uncertainty, real economy, and the financial sector. From a theoretical standpoint, our results are particularly interesting in light of the recent contributions that study the interaction between financial frictions and uncertainty in a general equilibrium framework (Bonciani and van Roye, 2015; Gilchrist, Sim, and Zakrajšek, 2014; Arellano, Bai, and Kehoe, 2016; Christiano, Motto, and Rostagno, 2014; Bianchi, Ilut, and Schneider, 2017). While relying on different designs of the underlying transmission mechanisms, all these works emphasize the amplifying effects that frictions in the financial sector can have in the propagation of uncertainty shocks to the real economy by triggering endogenous contractions in credit conditions. Our paper informs the theoretical modeling with an empirical characterization of a specific type of financial friction, hinged on the availability and use of credit lines.

From the empirical standpoint, our paper belongs with the literature using VAR models to study the effects of uncertainty on economic outcomes, such as Baker, Bloom, and Davis (2016) for economic policy uncertainty or Gilchrist, Sim, and Zakrajšek (2014) for a measure of financial uncertainty.[4] Similarly, it relates to the body of work exploring new dimensions of the transmission of uncertainty to the economy in a VAR framework. For instance, Leduc and Liu (2016) study uncertainty using the Michigan Survey of Consumers, Caggiano, Castelnuovo, and Groshenny (2014) investigate non-linear effects in the transmission, and Bachmann, Elstner, and Sims (2013) document noticeable differences across countries in this transmission. Almost invariably, the evidence from this literature ultimately suggests that heightened EPU leads to a fall in economic activity, which can translate into lower levels of employment, industrial production, and business investment. Our results provide evidence on the potential role attributable to the contraction in the supply of spot funds and liquidity insurance.[5]

The paper proceeds as follows. Section 2 presents an overview of our empirical VAR models and identification strategies. Section 3 describes the data used in the analysis. Sections 4 and 5 introduce the main findings of the paper. Section 6 discusses further insights and the main points of an extensive robustness analysis. Finally, Section 7 concludes.

[3]Other works that find that more broadly defined measures of uncertainty have detrimental effects on bank lending include Valencia (2017) and Buch, Buchholz, and Tonzer (2015) .

[4]Although in this work we use the uncertainty metric proposed by Baker, Bloom, and Davis (2016), which is primarily based on the relative prevalence of EPU-related news articles, it is worth noting that other papers have also defined policy uncertainty starting from more specific events like the unknown outcome of gubernatorial elections (Jens, 2017; Falk and Shelton, 2018).

[5]Furthermore, an extensive literature has documented, within various analytical frameworks, the contractionary effects of a broad set of uncertainty measures on economic activity (Bloom, 2009; Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek, 2016; Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2018) and, in particular, investment (Bernanke, 1983; Leahy and Whited, 1996; Bloom, Bond, and Reenen, 2007; Baum, Caglayan, and Talavera, 2008; Smietanka, Bloom, and Mizen, 2018) and employment (Schaal, 2017).

2 Empirical Methodology

2.1 VAR Framework of Analysis

The Bayesian VAR framework we use relies on 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 pth-order VAR

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

where B_i is a matrix of parameters and the VAR residuals ε_t follow a distribution $\varepsilon_t \sim \mathcal{N}(0, \Sigma_\varepsilon)$, with $\mathbb{E}(\varepsilon_t \varepsilon_t') = \Sigma_\varepsilon$ 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 the one hand, the 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 hand, the strand that uses VAR models to study the effects of uncertainty on the economy (Bachmann, Elstner, and Sims, 2013; Gilchrist, Sim, and Zakrajšek, 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

$$Y_t = \begin{bmatrix} X_t \\ epu_t \\ Z_t \end{bmatrix} \tag{2}$$

More specifically, X_t includes the log of the real gross domestic product (GDP), the log of the GDP price deflator, and the log of real gross private investment by domestic businesses; epu_t is the U.S. Baseline Overall EPU Index from Baker, Bloom, and Davis (2016), while the variables in Z_t vary to address different purposes of analysis. In the first specifications, the financial block includes the Wu-Xia shadow policy 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, alternatively considering the separate flows of loans extended under commitment and spot loans, or the ratio between them.[6] In subsequent specifications, we replace the STBL loan data with series on term loan or credit line originations from DealScan, together with their corresponding spreads. In Sections 2.2 and 2.3, we discuss in detail the purposes of these different models.

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) and assume a linear relation between the reduced-form residuals ε_t and the fundamental structural innovations of the model u_t. Thus,

[6] We 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 remained at the zero lower bound. We leave for Section A in the online Appendix a more thorough discussion of this issue.

$$\varepsilon_t = A_0 u_t \tag{3}$$

where $\mathbb{E}(u_t u_t') = V$ is diagonal, implying that the structural shocks are orthogonal, and V is normalized 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.

In the same spirit of the empirical monetary VAR analysis (Christiano, Eichenbaum, and Evans, 1999), which identifies monetary policy shocks by placing the monetary policy instrument between the real and the financial blocks of the model, our baseline identification strategy also pivots on the central position of epu_t within Y_t. The strategy boils down to assuming two main restrictions apply 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 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 Sections 4 and 5 correspond to VAR(2) models ($p = 2$), estimated with Bayesian methods that incorporate Minnesota priors (Litterman, 1979, 1986; Doan, Litterman, and Sims, 1984).[7] In Sections 4, 5, and 6 we use different specifications of Z_t, centering our attention on alternative measures of bank business lending that help us identify the transmission mechanism of economic policy uncertainty. 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 EPU by adopting a shadow rate in our baseline specifications and considering alternative sample periods and monetary policy rates in Section 6 and the online Appendix.

2.2 Identification of Shifts in the Supply of Spot Funds

Our main goal is to understand how the supply of credit responds to structural innovations in EPU, which requires an identification strategy to disentangle supply-side from demand-side effects in the changes of the observed equilibria in the business loan market. Our identification strategy comprises two main parts: one relates to the supply of spot funds, and the other to the supply of liquidity insurance. We discuss now the former and discuss in the next section the latter.

In Section 4.1, we adapt to our purposes the methodology proposed by Barraza, Civelli, and Zaniboni (2019) to study of the transmission of monetary policy shocks through bank business lending. This part of the analysis focuses on the responses of flows of loans from the STBL data set to EPU innovations. In order to uncover supply-side effects, the

[7]For this purpose, we use the econometric package developed by Dieppe, Legrand, and van Roye (2016). Dieppe, Legrand, and van Roye (2016), Canova (2007), and Kilian and Lütkepohl (2017) provide excellent overviews of the Bayesian VAR techniques used here.

approach exploits the relative differences in responses of loans disbursed under commitment and spot loans, and it relies on two key identification assumptions.

The first assumption relates to the recursive ordering imposed on the variables of the model to identify the structural EPU shocks. As previously discussed, our benchmark ordering reflects the underlying assumption that financial markets clear immediately after the observation of the macroeconomic conditions and any uncertainty in the policy stances, yet their feedback to the real sector and the policy-making process takes place with a lag. In choosing this ordering, we also follow the intuition in Gilchrist, Sim, and Zakrajšek (2014). Their VAR model uses a measure of financial uncertainty that captures common variations in volatility of daily firm stock returns, and their identification assumption is that financial uncertainty is exogenous to movements in credit spread, while responding on impact to macroeconomic fundamentals.

Although we focus on the effects of uncertainty arising from economic policy instead, we maintain the assumption that the policy-making process determining policy uncertainty is endogenous to the macroeconomic block, thereby ensuring that the effects of the real sector are accounted for when we estimate the responses of the financial block to exogenous shocks to EPU. This identification scheme, hence, allows us to distinguish between unexpected innovations in policy uncertainty and news about expected future economic conditions 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. Thus, while we deem our choice of the baseline recursive ordering plausible and appropriately grounded in the literature, we check the robustness of our results to the use of two alternative, opposite schemes, where we place EPU either first or last in the ordering structure.

EPU ordered first implies that uncertainty is the most exogenous variable in the model and it does not respond on impact to shocks to any other variable, whereas all the other variables can respond immediately to an uncertainty shock. The literature has relied on this assumption before. For instance, Leduc and Liu (2016) use this assumption in a model with a consumer uncertainty measure based on the Michigan Survey; Baker, Bloom, and Davis (2016) use it in a model with their U.S. Baseline Overall EPU Index; and Caggiano, Castelnuovo, and Groshenny (2014) employ it in a model where the VIX (volatility) Index from the Chicago Board Options Exchange is used as a proxy for uncertainty.[8] This ordering is arguably better suited for data at monthly frequency though, and it has a practical justification for survey-based consumer uncertainty measures in which the surveys run the month before new macroeconomic information is released.

In contrast, ordering uncertainty after all the other variables in the model ensures that movements due to past or contemporaneous shocks affecting the real or financial sectors are fully controlled for in estimating the uncertainty innovations. This identification is especially suitable in periods where the policy-making process promptly reacts to both economic and financial news. A case in point is the period comprising the Financial Crisis and the Great Recession, during which policy makers, including the monetary authority, reacted swiftly to news to prevent financial markets from freezing. In such cases, the EPU measure could

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

easily capture not only the effects of policy uncertainty, but also the effects of expected future credit market uncertainty, which in our model would be reflected by endogenous responses of business loans to future uncertainty in the financial sector. If this is the case, it becomes relevant to correctly account for these feedback elements in the identification of the structural EPU shock.

Once the structural EPU innovations are identified, the second key assumption of the identification strategy relates to the identification of the effect of these shocks on the supply of business loans. Following Barraza, Civelli, and Zaniboni (2019), we assume uniform cyclical properties of the business demand for funds across bank loan types.[9] The assumption allows us to exploit a key contractual difference between loans extended under commitment and spot loans reported in the STBL data set. Once a loan commitment is made, a bank is contractually bound to provide liquidity on demand on it while the agreement is in good standing, regardless of its preference for liquidity at the time. In general, this is always the case unless the borrower's conditions are such that it violates the material adverse change (MAC) clause in the contract. In contrast, a bank can freely decide whether to supply liquidity or not via new spot loans. Then, given a change in conditions that could increase a bank's preference for liquidity, the bank could immediately adjust the origination of spot loans, but it would still have to provide liquidity on demand on open credit lines. Flows of spot loans should, therefore, more closely reflect banks' preferences for liquidity over time. Once changes in credit spreads are accounted for, comparing the relative responses of loans extended under commitment and spot loans to EPU shocks allows us to make inferences regarding the willingness of banks to supply spot funds in response to exogenous changes in uncertainty.

We argue this second assumption is plausibly satisfied in our setup as we limit the analysis to loans originated by large banks, which are generally associated with large firms (Berger, Miller, Petersen, Rajan, and Stein, 2005). Large firms face fewer financial constraints than smaller firms, and they can be relatively more confident about their ability to secure funds in the future. Thus, if business opportunities warrant it, they can draw down on open credit lines or demand new spot loans as needed and maintain comparable demand for liquidity on both types of loans across the business cycle, after controlling for any change in credit spreads. 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 our identifying assumption untenable for this type of firm. Then, the exclusion of small banks from our sample becomes important. 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 firm characteristics is important in the identification of supply-side effects in the bank loan market.[10]

As this assumption is key to our conclusion of a contraction in the supply of spot

[9] This assumption builds on previous studies on the transmission mechanism of monetary policy that compare the responses of different financial aggregates to disentangle supply-side from demand-side effects in the credit markets (Kashyap, Stein, and Wilcox, 1993; Sofianos, Melnik, and Wachtel, 1990; Morgan, 1998).

[10] In Section B of the online Appendix we report an analysis for small banks. Indeed, the results presented there suggest that small firms display a different demand for funds, managing more cautiously their drawdowns on credit lines. We leave for that section a more detailed discussion of this point.

funds, we device an alternative test that helps us corroborate both results and assumptions. This test, presented in Section 4.2, examines the responses of term loan originations in the syndicated loan market, which we obtain from DealScan. In contrast to the STBL data, these loans also include well-defined costs of funds. Under the weak assumption of regularly shaped term loan demand and supply functions, with demand being a decreasing function of spreads and supply being an increasing function of them, a positive response of credit spreads combined with a negative response of loan volume provide sufficient evidence to identify a contraction in the supply of loans.

2.3 Identification of Shifts in the Supply of Liquidity Insurance

In Section 5 we explore a further dimension of the banks' response to EPU innovations, namely the provision of new liquidity insurance, which is primarily administered via credit lines. We propose and test two main hypotheses. The first hypothesis is that, in response to higher EPU, banks also curtail their supply of liquidity insurance, as their preference for liquidity increases and they become less willing to guarantee access to liquidity on demand. The hypothesis builds on the intuition advanced by Gilchrist and Zakrajšek (2012), and recently stressed by Bassett, Chosak, Driscoll, and Zakrajšek (2014), that banks can promptly adjust their supply of lines of credit as a means to reduce their off-balance-sheet credit exposure, while outstanding loans take some time to adjust.

In Section 5.1 we resort again to the Barraza, Civelli, and Zaniboni (2019)'s approach to compare the response of loans disbursed under commitment in STBL with that of new credit line originations in the syndicated loan market from DealScan. In this case, the contractual arrangements underlying both sources of data represent similar agreements to provide liquidity on demand. Then, the identification assumption of uniform demand across sources of funds fundamentally rests on the comparability of the firms drawing down on commitments from large domestic banks in STBL with those seeking credit lines in the syndicated loan market in DealScan. After controlling for changes in the cost of financing, differences in the relative pace of drawdowns and originations could be ascribed to supply factors. There are good reasons to believe that firms are comparable across data sets. Firstly, large domestic banks originate a significant portion of their business loans via syndication or participation.[11] Secondly, the syndicated loan market is dominated by large banks.[12]

As corroborating evidence, we estimate a model that includes credit line originations from DealScan together with their cost of securing and maintaining a line and the cost of drawing down on a line. This model parallels the one using syndicated term loans, with the only difference that it also includes the cost of securing and maintaining the lines – which is relevant for credit lines, but not for term loans.[13] Under the same mild assumption of regularly shaped demand and supply schedules used for term loans, a negative response

[11]The E.2 Release of April 2017 shows that loans made under participation or syndication represent 61.5% of the loans extended by large domestic banks (Board of Governors of the Federal Reserve System, 2017).

[12]Ivashina (2009) has previously made this point. Furthermore, the Global Syndicated League Tables for FY 2017 reveal that all of the top 20 bookrunners in the U.S. market, which originated 84.8% of the loans, had assets in excess of the $5.5 billion large-bank threshold used in the 2017:Q1 STBL data (Bloomberg, 2017).

[13]Funding costs for term loan and credit line originations are discussed in greater detail in Section 3.

of credit line originations combined with a positive response of the costs of securing and maintaining the lines provide sufficient evidence to identify a supply contraction.

The second hypothesis we propose is that banks further tighten their provision of credit by imposing a pricing structure on new credit lines which reduces the probability of firms tapping the committed funds, therefore slowing down loan growth. This hypothesis relies on a finding in Berg, Saunders, and Steffen (2016) showing that firms securing credit lines with a higher cost of drawdown with respect to the cost of securing and maintaining the lines are less likely to draw down the committed funds. A necessary condition for this mechanism to be discernible in our setting is a positive response of the cost of drawdown to an increase in uncertainty, which is satisfied. We then show that banks exploit this additional mechanism to tighten credit by increasing the cost of drawdown relatively more than the cost of securing and maintaining the lines, while reducing the credit line originations.

3 Data

We discuss now the four types of data used in this analysis: EPU data, flows of business loans data from the Survey of Terms of Business Lending, data on loan originations from Thomson Reuters DealScan, and standard macroeconomic data used in the VAR literature.

EPU data. Our benchmark measure of economic policy uncertainty is the *U.S. Baseline Overall EPU Index* from Baker, Bloom, and Davis (2016), simply EPU henceforth.[14] EPU is the weighted-average of four measures, with the *U.S. News-Based Policy Uncertainty Index* accounting for half the weight of EPU. The remaining three components are the *Tax Expiration Index*, the *CPI Forecast Disagreement Measure*, and the *Federal/State/Local Purchases Disagreement Measure*, which are all equally-weighted.

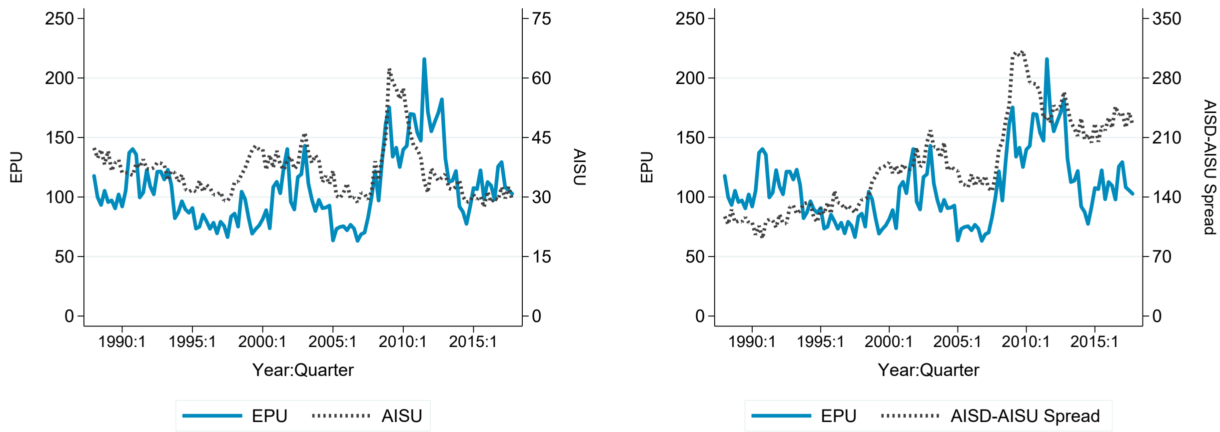
While we refer the reader to Baker, Bloom, and Davis (2016) for a thorough discussion on the methodological aspects behind the construction of these measures, it is worth noting here that the EPU index is normalized by construction and stationary in levels, although fairly persistent.[15] Arguably, a significant degree of persistence in which innovations exert their effects on EPU for multiple periods can be seen as broadly consistent with the assumptions made in the benchmark identification ordering of our analysis.

STBL data. Our data on flows of bank loans to businesses come from the Survey of Terms of Business Lending. Between 1977 and 2017 the Board of Governors of the Federal Reserve System ran this quarterly survey among roughly 350 banks. The survey responses are reweighted and aggregated to represent the population of banks and the Board publishes the main results through the E.2 Release.[16] We are particularly interested in the series of business loans disbursed by domestic banks via two different types of contractual agreements,

[14]In some robustness exercises, we also use variations of the EPU index meant to capture only monetary policy uncertainty or fiscal policy uncertainty.

[15]An AR(1) model adequately fits the EPU process at quarterly frequency. The estimated auto-regressive coefficient is .64 (with p-value of .00).

[16]The most recent portion of the historical data is publicly available through the Board's website. In this work, nonetheless, we also use the earlier portion kindly made available to us by the Board upon request.



(a) EPU and the Cost of Liquidity Insurance (b) EPU and the Relative Cost of Liquidity

Figure 1: EPU and Spreads on New Credit Lines from DealScan. Panel (a): EPU index Vs. All-In Spread Undrawn (AISU) from new credit lines on DealScan. Panel (b): EPU index Vs. the spread between All-In Spread Drawn (AISD) and All-In Spread Undrawn (AISU).

namely loans disbursed under commitment and spot loans.[17] 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 an excellent source of information about *flows* of bank credit to businesses. 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 2.2, we focus our analysis on lending by large domestic banks, which broadly dominate the business loan market and drive the aggregate dynamics.[18] 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.

DealScan data. 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, where large banks originate a significant portion of their business loans. In this market, banks finance portions of loans originated to mid-size and large borrowers, which allows them to efficiently diversify their lending portfolios. The loans originated in this market typically correspond to one of two main types of loans: term loans or revolvers, a contractual form commitment.[19] The data series we use relate to facilities originated in U.S. dollars, to non-financial U.S. firms, and syndicated in the U.S. market between 1988 and 2017.

We first study term loan originations and their associated costs of liquidity. A term

[17]Throughout the paper, we use the term business loans to refer to commercial and industrial loans.

[18]To 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).

[19]See Sufi (2007) for a more comprehensive description of this market. And see Strahan (2010) for an excellent discussion of the workings and key economic rationales in this market.

loan gives the borrower a short availability period to borrow up to a maximum amount agreed on the deal. Generally, after drawdown, the loan is due for repayment either following an amortizing schedule or as a bullet payment at maturity, when repayment in full is due. Term loans are primarily priced adding spread and fees on top of a base market rate. The most frequently used base rate is LIBOR, and this is the case for the All-In-Spread-Drawn (AISD) reported by DealScan (see Berg, Saunders, and Steffen, 2016). AISD is a good measure of the cost of spot liquidity after accounting for the cost of interbank lending. Moreover, given that term loans are originated for prompt disbursement and use, they are closely comparable to the flow of spot loans from the STBL data set.

We then study the origination of revolvers. Revolvers are lines of credit whereby banks offer businesses liquidity on demand. 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. Banks charge for this service a commitment fee proportional to the unused amount on the line, or less frequently a fixed annual facility fee. These fees are referred to as the All-In-Spread-Undrawn (AISU) in DealScan. And as with term loans, banks also charge clients for the actual use of the funds, and this cost is reflected in the AISD of the credit line.

In a credit line, AISU and AISD are costs associated with two distinctly different services. On the one hand, AISU represents the cost of an insurance granting access to liquidity on demand, which might or might not materialize – in other words, the price of an option to access liquidity on demand. On the other hand, AISD represents the actual cost of tapping the committed funds, and can be thought of as the exercise price on that option. The relation between EPU, AISD, and AISU is of particular interest in our analysis, as it can shed light on different aspects of the credit market conditions. A plot of EPU and the AISU on new credit lines, shown in Panel (a) of Figure 1, suggests that the cost of securing and maintaining a credit line moves along with EPU. Moreover, a plot of EPU and the spread between AISD and AISU on new credit lines, displayed on Panel (b) of the same figure, also illustrates that this spread widens as policy uncertainty increases. Thus, the combined evidence in Figure 1 suggests not only that the cost of liquidity insurance increases with EPU, but also that the relative cost of outright liquidity increases with respect to the cost of the liquidity insurance as EPU heightens.

Macroeconomic data. The main source of our macroeconomic data is the Federal Reserve Bank of St. Louis's FRED database. 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. Additionally, we also use three shadow rates that proxy for the effective monetary policy stance during the period in which the Federal Funds rate reached the zero lower bound. These measures come from Wu and Xia (2016), Krippner (2013, 2015) and Lombardi and Zhu (2018), and were respectively obtained from the Federal Reserve Bank of Atlanta, the Reserve Bank of New Zealand and the authors.[20] All dollar-denominated series are expressed in real terms and series are seasonally adjusted following standard practices in the literature.[21]

[20] We thank Marco Lombardi for kindly providing these data.

[21] That is, all series are seasonally adjusted, except for the interest rates, spreads, and the EPU indexes.

4 Shifts in the Supply of Spot Funds

In the first part of our empirical analysis we exploit a key contractual difference between commitments and spot loans, namely that banks can immediately alter their supply of spot loans while they are contractually bound to provide liquidity on demand on pre-existing commitments, in order to identify a supply-side effect in the transmission mechanism of EPU shocks to the business loan market. Section 2.2 discusses the identification strategy used in this exercise.

4.1 Evidence from the Flow of Funds in STBL

Flows of Loans Extended under Commitment and Spot Loans. The first model of the analysis includes the flow of loans disbursed under commitment and the flow of spot loans taken separately. Figure 2 reports the response functions of all the variables in the model to a one-standard-deviation innovation to the EPU index, which roughly corresponds to an increase in the uncertainty index of 22 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. The solid lines correspond to the median response of a variable to the shock, whereas the dashed lines represent the 14/86th percentile bands of the posterior distribution of the responses.[22] The estimation sample is 1985:Q1-2017:Q1 and the x-axis represents years from the shock.

The variables included in this first model are the log of the real GDP, the log of the GDP deflator, the log of real gross business investment, the EPU index, the Wu-Xia shadow rate, the credit spread, and the log of real business loans extended by large domestic banks under commitment or as spot loans. This ordering of variables defines the baseline identification scheme of the structural innovations as well. Observing variables at the same point in time within the quarter is important for an accurate application of the contemporaneous restrictions imposed by the Cholesky scheme. As explained in Section 3, STBL variables are observed during the second month of a quarter. For this reason, and given our focus on the response of lending to EPU innovations, we align the observation of other variables in the model to the timing of the STBL data. Hence, we use the observation corresponding to the second month within each quarter for the EPU index, the shadow rate, and the credit spread.[23]

Figure 2 provides the first evidence of a supply contraction on spot funds. Loans extended under commitment exhibit a mildly negative, but not significant, response from the second quarter on, with a fall close to 1% at its trough. The timing of this response is comparable to that of business investment, which lends support to the conjecture that loans extended under commitment plausibly reflect the changing financial needs firms face in the wake of an EPU shock. In contrast, the EPU shock foreshadows a much larger and

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

[23] The macro variables are necessarily measured over the quarter instead, and are observed at the end of the period only. In the baseline identification scheme, however, they are assumed to respond to the EPU shock with one lag, which in part mitigates any concerns about the observation timing issue.

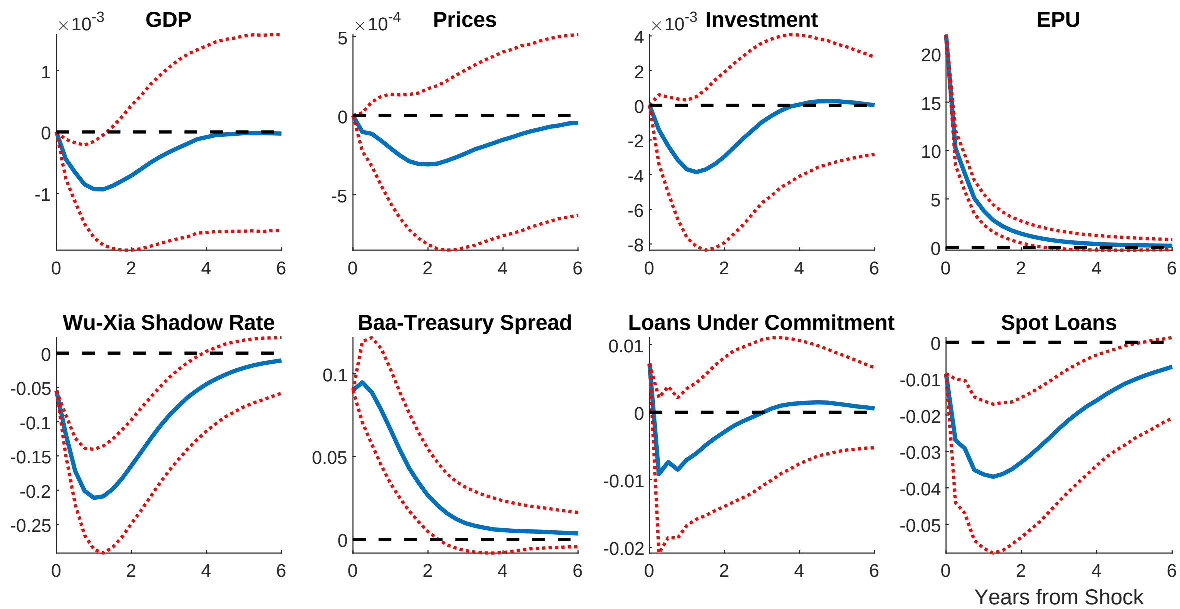


Figure 2: EPU and the Response of Loans Extended under Commitment and Spot Loans Extended by Large Banks from STBL, 1985:Q1-2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real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

significantly negative response of spot loans, which fall by almost 4% at the trough, five to six quarters from the shock. Thus, the magnitude of the fall in spot loans, which banks can adjust immediately, is about four times as large as that of loans extended under commitment, which banks are contractually bound to serve upon demand.[24]

The credit spread, on the other hand, rises sharply in response to the EPU innovation. This increase is economically and statistically significant. At the peak of the response, two quarters from the shock, the credit spread rises about 10 basis points. It takes three to four years for the response to fade out. The effect we find is in line with the impulse response function reported by Gilchrist, Sim, and Zakrajšek (2014) for a measure of financial uncertainty, and it is interpreted as an implicit outcome of a supply side contraction in 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 below.

The responses of the other variables of the model are in line with what has been typically found in the VAR literature on the effects of uncertainty on macroeconomic outcomes. Noticeably, GDP, business investment, and the policy rate fall as well. The effects

[24]For completeness, in Figure A4 in the online Appendix, we also report a model where total loan flows are aggregated. The response of total loans is negative, persistent, and significant, and with a maximum fall of roughly 2% after one year.

are smaller in order of magnitude than those observed for the loan series, but the responses are similarly inversely hump-shaped and relatively persistent. Output displays a decline in the first year and a half, dropping about one tenth of a percentage point at its trough. It then gradually recovers in about four years after the impulse. This result is consistent with previous findings documenting falls in the level of activity, such as the fall in industrial production in Baker, Bloom, and Davis (2016).

Business investment also experiences a contraction, falling close to half a percentage point six to seven quarters after the EPU shock. This decline is sizable when compared to that of GDP and underscores the sensitivity of corporate investment to EPU. This fall is also in line with what both the theoretical and the empirical literature has documented regarding the effects of uncertainty on corporate investment (e.g. 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). Moreover, as our main interest lies in studying the response of loan supply to EPU shocks, this response makes evident that controlling for corporate investment in our model plays an important role, as falling investment could naturally result in weaker demand for funds, and this is an element to control for.

Ratio of Loans Extended under Commitment to Spot Loans. We now test more formally the hypothesis that EPU shocks foreshadow a contraction in the supply of business loans by studying the response of the ratio of loans extended under commitment to spot loans, reported in Figure 3. We emphasize that, in the face of increasing uncertainty, banks have incentives to accumulate liquidity (Caballero and Krishnamurhty, 2008), and that restricting lending offers a means to do so. Still, as they are contractually bound to serve pre-existing commitments. We expect this ratio to have a positive response to an exogenous increase in EPU, implying that firms cannot secure new spot loans at the same pace they can draw down funds from their credit lines. As discussed in Section 2.2, this identification strategy relies on the assumption that loan demand has uniform cyclical properties across the two types of contracts, after controlling for any change in credit spreads.

The literature has dedicated significant attention to the role financial frictions play in the transmission of uncertainty shocks to the real economy, especially to business investment. For instance, in the theoretical models of Christiano, Motto, and Rostagno (2014) and Arellano, Bai, and Kehoe (2016) financial frictions interact with uncertainty shocks determining credit supply restrictions, ultimately amplifying the impact that uncertainty has on the economy, beyond the "wait and see" effect usually observed at firm level. Finding evidence in support of this channel is certainly of economic interest.

The response of the loan ratio to an EPU innovation in Figure 3 is positive from impact onward. It is hump-shaped, persistent, with a peak of 3.2% between the fifth and sixth quarters, and statistically significant up to six years from the shock. Comparing these results to those for the separate loan series, we can conclude that the loan ratio response is driven by the fall in spot loans. This evidence, combined with the spike in credit spreads, strongly points to a contraction in the supply of liquid funds.[25]

[25] The responses of the other variables in the model are not affected. We report them in Figure A5 of the online Appendix. All results presented here are robust to an extensive set of checks discussed in Section 6.2.

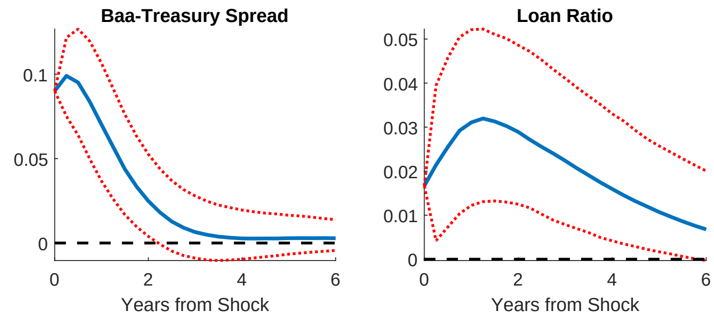


Figure 3: EPU and the Response of the Ratio of Loans Extended under Commitment to Spot Loans Extended by Large Banks from STBL, 1985:Q1-2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the 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 log of the ratio of real loans extended under commitment to real spot loans extended by large domestic banks. VAR(2). Years from the shock on the x-axis.

4.2 Evidence from Term Loan Originations in DealScan

Additional evidence of a loan supply contraction in response to an EPU shock, and indirectly in support of our main identification strategy, is provided by using syndicated term loan originations from DealScan. These data allow us to estimate a new model where the volume of new term loans and their corresponding AISD replace the flows of loans from the STBL and the credit spread. We illustrate the responses of the term loans and AISD spread in Figure 4, while Figure A6 in the online Appendix presents the full set of impulse response functions for this model.[26]

Identification in this exercise only requires the mild assumption of regularly shaped demand and supply functions. If an overall supply contraction dominates the spot loan market equilibrium after a shock that heightens EPU, the fall in spot loans will be accompanied by an increase in the price firms pay to obtain these new loans. Figure 4 illustrates precisely this result. Spot loans fall by roughly 4%, an amount similar to that of the baseline STBL specifications (compare to Figure 2), with a sharp decline in the short-run after the shock, reaching a trough about a year from the shock, and slowly recovering in the longer run. The response of the AISD, at the same time, is positive on impact and continues with a dynamic that mirrors the response of loan volumes. The model is also robust to using the flows of spot loans from STBL in lieu of the volume of term loan originations from DealScan, which is expected as term loans recorded in DealScan are generally meant for prompt disbursement and should thus compare well to the flow of spot loans reported in the STBL.

The combined responses of the extensive and intensive margins identify a loan supply contraction. This strategy goes beyond extant findings, where inference is based on the

[26]The advantage of using the DealScan data is that we can construct series of both loan volumes and their exactly matching spreads. Notice that, as the DealScan series are constructed as quarterly summations and averages from the individual facilities, we must now align the observation of the other variables in the model to this timing of the aggregation. Consequently, we use quarterly averages for the EPU index and the shadow rate as well.

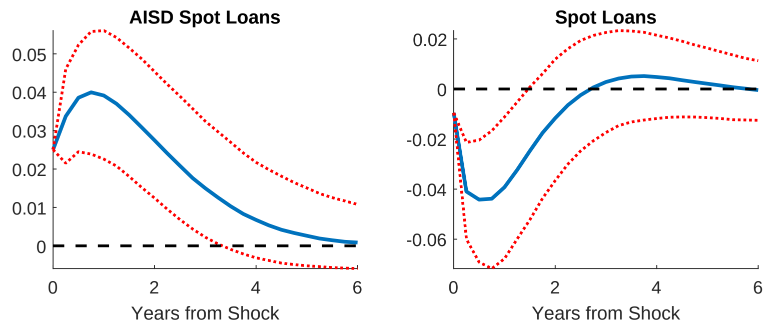


Figure 4: EPU and the Response of the All-In Spread Drawn on New Term Loans and the Volume of Term Loan Originations from DealScan, 1988:Q1–2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross business investment, the baseline overall EPU index, the Wu-Xia shadow rate, the AISD on new term loans, and the log of real term loan originations from DealScan. VAR(2). Years from the shock on the x-axis.

behavior of a single margin in reduced-form settings. For instance, our results provide more conclusive evidence to support the claim in Berger, Guedhami, Kim, and Li (2018) that banks hoard liquidity when faced with higher EPU, which they base primarily on the results from regressing loan spreads on lagged EPU and a set of controls.

5 Shifts in the the Supply of Liquidity Insurance

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; Strahan, 2010). In relation to the business sector, this function is fundamentally implemented via commitments, which offer firms a form of liquidity insurance. In this section, we rely on the identification strategies laid out in Section 2.3 to show that banks constrain their supply of liquidity insurance in response to an exogenous increase in EPU.

5.1 Drawdowns on Commitments vs. Credit Line Originations

We start by combining the information from STBL with that from DealScan to device a test that compares the pace at which firms draw down on credit lines from large banks (STBL) with the pace at which large banks are willing to originate new credit lines (DealScan).[27] This test is in the spirit of the one presented in Section 4.1. However, it compares loan volumes reflecting the same type of contract, yet from two different data sets. As discussed in Section 2.3, the plausibility of the identification assumption of uniform demand across sources of liquidity in this case is supported by the similarity of the firms borrowing funds under commitment from large domestic banks, which originate over 60% of their business loans under syndication, and the firms seeking credit lines in the syndicated loan market, which is dominated by large banks.

[27]We thank an anonymous referee for suggesting this insightful idea.

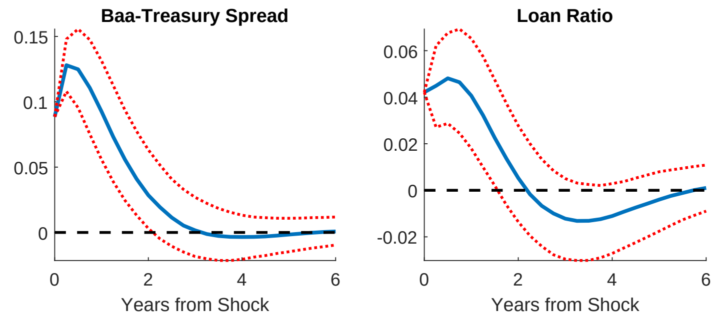


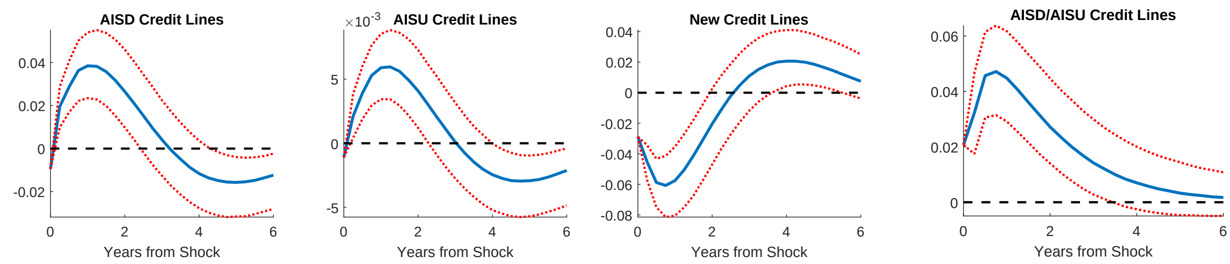
Figure 5: EPU and the Response of the Ratio of Loans Extended under Commitment from STBL to New Credit Line Originations from DealScan, 1988:Q1-2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, 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 log of the ratio of real loans extended under commitment by large domestic banks (STBL) to real new credit line originations (DealScan). VAR(2). Years from the shock on the x-axis.

Figure 5 presents the response to a one-standard-deviation EPU shock of the ratio of loans disbursed under commitment (STBL) to new credit line originations (DealScan), while Figure A7 in the online Appendix presents the full set of responses. The model replicates the baseline specification of Figure 3, but the new loan ratio replaces the previous one used in Section 4.1. The loan ratio response is positive and significant on impact, showing a peak of 4.8% a couple of quarters after the shock, and fading off after two years. The response is shorter-lived than that of the loan ratio presented in Figure 3. This is to be expected because, as banks restrict the origination of new credit lines starting immediately on impact, firms have increasingly fewer credit lines open over time to draw down funds from. The credit spread also rises to peak half a year after the shock, and this effect only dissipates after three years. Overall, this result conveys the same conclusion that EPU shocks cause a contraction in the supply of business credit, this time through credit lines. At the same time, it also offers indirect evidence in support of the identification strategy used in Section 4.1.[28]

5.2 Evidence from Credit Line Originations in DealScan

We now rely entirely on data on origination of credit lines recorded in DealScan and the identification strategies laid out in Section 2.3 to make two main points. First, we provide further support to the preceding result that banks contract their supply of liquidity insurance in response to an exogenous increase in EPU. We show in fact that banks raise the cost of originating and maintaining new credit lines, while reducing the amount of funds they commit through them. Second, we show that the new credit lines carry steeper costs to actually access liquidity on demand with respect to the cost of securing and maintaining the lines. By means of this pricing strategy, banks reduce the probability of drawdown on commitments, ultimately slowing down loan growth and further contracting loan supply.

[28]In an alternative specification, we use the AISD and AISU in lieu of the 10-year Baa-Treasury credit spread. The results we obtain are very similar to the ones presented here.



(a) AISD and AISU Separately (b) AISD/AISU Ratio

Figure 6: EPU and the Response of the All-In Spread Drawn, All-In Spread Undrawn, and Volume of New Credit Line Originations from DealScan, 1988:Q1–2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. Panel (a) model: log of real GDP, log of the GDP deflator, log of real gross business investment, baseline overall EPU index, Wu-Xia shadow rate, AISD and AISU on new credit lines, and the log of real new credit line originations. Panel (b) model: AISD and AISU on new credit lines are replaced with the AISD to AISU ratio. VAR(2). Years from the shock on the x-axis.

This is a subtle yet meaningful finding, provided that loans extended under commitment account for over 80% of the flows of business loans.

From an option theory standpoint, this latter mechanism is equivalent to writing liquidity options carrying steeper strike prices with respect to the option price. Ceteris paribus, higher strike prices should translate into lower probabilities of the option ever being *in the money*, thus reducing the probability of exercise – i.e. drawdown in our case. This notion is rooted in the intuition developed in previous work that sees credit lines as options, including Thakor, Hong, and Greenbaum (1981), Shockley and Thakor (1997), and Berg, Saunders, and Steffen (2016).[29] Yet more specifically, this insight builds on the finding in Berg, Saunders, and Steffen (2016) showing that borrowers paying higher costs to draw down on their credit lines with respect to the costs of securing and maintaining those lines are significantly less likely to draw down the committed funds.

As we have discussed, the AISU on new credit lines recorded in DealScan closely corresponds to the notion of the cost of purchasing an option of liquidity on demand, while the AISD can be thought of as the exercise price on the option – which is exercised when the locked-in AISD is below the market spread on comparable credits. We hence estimate a model that includes in its financial block the originations of new credit lines together with the associated AISD and AISU. This model is molded on that reported in Figure 4, with the difference that credit lines are priced using two relevant spreads, instead of just one.

The responses of the three key variables of this model are reported in Panel (a) of Figure 6 – see Figure A8 in the online Appendix for the full set of impulse responses. The positive response of AISU along with the negative response of new credit line volumes provide a clear sign of a predominant contraction in the supply of liquidity insurance, under the weak assumption of regularly sloped demand and supply curves. The contraction is immediate

[29] Shockley and Thakor (1997) point out that a commitment can be thought of as 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 the option to draw down on the line whenever the total committed rate is below the market spot rate on a comparable loan.

and peaks between four and six quarters after the shock, with the origination of credit lines falling up to 6%. The effect is also long lasting, taking roughly three years to fade out, and it is accompanied by an increase of AISD as well.

This evidence leads us to consider a second model focused on the relative levels of the pricing components in the credit lines, where the ratio AISD/AISU replaces the two separate spreads. Panel (b) of Figure 6 illustrates the result – see Figure A9 in the online Appendix for the full set of responses. The AISD/AISU ratio displays a positive response on impact and rises quickly to peak about a year after the shock, indicating a *relative* increase in the cost of accessing liquidity with respect to the cost of obtaining the liquidity option. As this pricing structure is associated with lower probabilities of drawdown (Berg, Saunders, and Steffen, 2016), the results indicate that following the EPU shock banks further curtail credit growth by issuing new credit lines bearing a pricing structure that reduces the probability of borrowers tapping the committed funds.

6 Quantitative Assessments and Robustness Checks

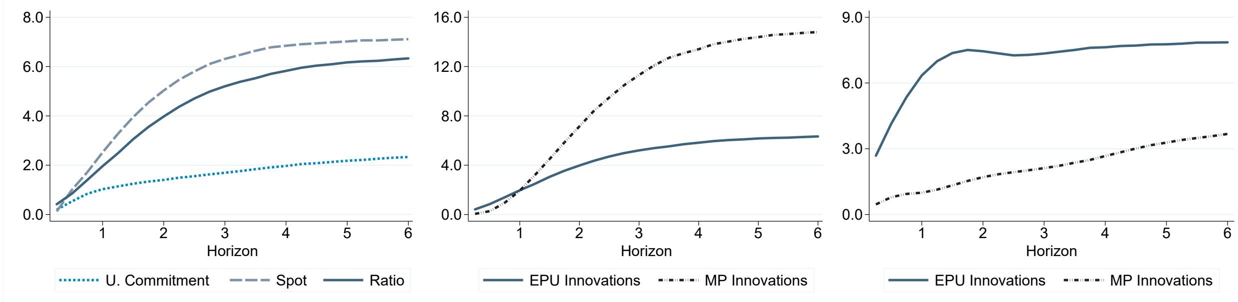
6.1 Quantitative Assessments

Quantitatively, the response of the loan ratio presented in Figure 3 suggests a spot loan supply contraction of roughly 14-15 basis points at peak for each unit increase of EPU. This corresponds, for instance, to a fall in loan supply of 3.2% in response to a typical one-standard-deviation EPU shock, or about 17% for a shock of 120 points – a size comparable to the increase EPU experienced between early 2007 and late 2008.

The relevance of EPU innovations in explaining variations in the loan variables can be assessed with an analysis of the forecast error variance decomposition (FEVD) of these variables. Panel (a) of Figure 7 illustrates the contribution of EPU shocks to the FEVD of loans extended under commitment, spot loans, and the loan ratio from the two models reported in Figures 2 and 3. Since banks can adjust immediately their supply of spot loans but face frictions in adjusting their supply of liquidity on demand, we would expect spot loans to be more responsive to EPU innovations than loans extended under commitment. In fact EPU shocks explain 7.1% of the six-year forecast error variance of spot loans, but only 2.3% of that of loans extended under commitment.[30] As a result, 6.3% of the forecast error variance of the loan ratio can be attributed to EPU innovations.

We put these results in perspective by comparing them to the effects of monetary policy shocks on the loan variables. Although we do not specifically identify the other structural shocks of the model, the recursive ordering adopted in the empirical analysis provides a model in which all shocks are formally fully identified. Monetary shocks, in particular, are identified with the standard argument in the literature that the real block of the model responds with a lag to the policy innovations, while the financial variables are allowed to respond on impact. Relying on this identification scheme, we find that, while the magnitude of the effects of monetary shocks is larger than that of EPU shocks, the two shocks are still fairly comparable. For instance, the peak response of the STBL loan ratio

[30] A comparable pattern is found for the case of liquidity insurance, where credit line originations substitute spot loans.



(a) STBL (b) STBL Ratio (c) STBL/DealScan Ratio

Figure 7: Panel (a): Contribution of the EPU innovations to the FEVD of STBL Loans Extended under Commitment, Spot Loans, and their Ratio. Panel (b): Contribution of the EPU and Monetary Policy innovations to the FEVD of the Ratio of STBL Loans Extended under Commitment to Spot Loans. Panel (c) Contribution of the EPU and Monetary Policy innovations to the FEVD of the Ratio of STBL Loans Extended under Commitment to DealScan New Credit Line Originations. FEVD(%) on the y-axis. Horizon in years on the x-axis.

to a one-standard-deviation monetary impulse is, in absolute terms, about one time and a half the response to the EPU shock. Additionally, Panel (b) of Figure 7 shows that the contributions of monetary and EPU shocks to the FEVD of the STBL loan ratio are very close in the short run and that the share of the monetary component becomes about twice as large as that of EPU over the medium-to-long run.

The supply of liquidity insurance, in contrast, seems more sensitive to EPU shocks than the supply of spot loans. The peak response of 4.8% of the loans extended under commitment to new credit lines ratio in Figure 5, implies that a 120-point increase in EPU would result in a contraction in the supply of liquidity insurance of 27%. Furthermore, the provision of liquidity insurance also seems more sensitive to uncertainty than monetary policy innovations. The FEVD in Panel (c) of Figure 7 shows that the contribution of the EPU shock to the dynamics of this ratio is 7.9% over a six-year horizon, compared to the 3.7% contribution of the monetary shock. All considered, the overarching message from the analysis of both loan ratios is that EPU innovations are significant determinants of the business lending dynamics.

Finally, we quantify the portion of the GDP response to EPU shocks that can be attributed to the business lending channel. To this end, we compare the estimated GDP response to an EPU shock with a *counterfactual* response where the spillover effect of the EPU shock through the loan ratio is shut down. The counterfactual response is constructed by setting to zero the coefficient $a_{7,4}$ of the estimated structural impact multiplier matrix A_0, which corresponds to the effect of the EPU shock on the loan ratio. We conduct this exercise for the two models presented in Figures 3 and 5. We find that the total GDP loss following an EPU shock, computed as the integral of the estimated GPD response over a six-year horizon, would be roughly 7% smaller without the contraction in the supply of spot loans in Figure 3. Similarly, the total GDP loss would be roughly 11% smaller without the contraction in supply of liquidity insurance in Figure 5.

6.2 Robustness Checks

Figures A1 and A2 in Section A of the online Appendix present an extensive set of robustness checks for the models discussed in Figures 3 and 5, respectively. All the robustness exercises we conduct validate the main conclusion of the paper that EPU shocks cause a contraction in the supply of business lending, both through spot loans and credit lines. We briefly discuss four main sets of robustness checks here.

First, in addition to standard checks for the VAR lag order, we find that the main results are robust to the use of measures of monetary policy stance alternative to the Wu-Xia shadow rate, such as the Federal Funds Rate, the Krippner shadow rate (Krippner, 2013, 2015), or the Lombardi-Zhu shadow rate (Lombardi and Zhu, 2018).

Second, when relying on a recursive structural identification scheme, it becomes relevant to assess the sensitivity of the results to alternative orderings of the variables in the model. Hence, we change the position of EPU by alternatively placing it first and last in the identification ordering of the VAR. These two alternative approaches replicate those previously adopted in the literature by Baker, Bloom, and Davis (2016) and Gilchrist, Sim, and Zakrajšek (2014), respectively. In a model with EPU ordered first, uncertainty is the most exogenous variable in the system, and both the real economy and the financial markets adjust immediately to an uncertainty shock. In a model with EPU ordered last, any other contemporaneous shock is controlled for in the construction of the EPU innovation. As can be observed in Figures A1 and A2, the modifications in the causal ordering do not meaningfully affect our results.

Third, we check whether our results hold to the exclusion of the post-2007 period from the estimation sample, a period characterized by persistently high EPU and a documented contraction in the supply of credit (Ivashina and Scharfstein, 2010; Cornett, McNutt, Strahan, and Tehranian, 2011; Santos, 2011; Gilchrist and Zakrajšek, 2012; Adrian, Colla, and Shin, 2013; Chodorow-Reich, 2014). While the response of the loans extended under commitment to spot loans ratio is slightly milder when we exclude this period, the responses of both loan ratios fully preserve their main shape and statistical significance.

Lastly, we check for the robustness of the results to the use of different definitions of EPU index, specifically using the Monetary Policy Uncertainty (MPU) and Fiscal Policy Uncertainty (FPU) sub-indexes. The responses of both loan ratios broadly retain the same characteristics as in the benchmark results, with a short delay of the response of the loans extended under commitment to spot loans ratio for the MPU shock and a smaller significance of the response of the loans extended under commitment to new credit line originations ratio for the FPU shock.

7 Conclusion

In this work, we investigate the effect of economic policy uncertainty on bank business lending. Our results show that an exogenous increase in EPU causes a contraction in the supply of business lending, which takes two main, distinct forms.

The first form entails a straight reduction in the availability of spot funds. We show this result in two different ways. First, we document a sharp fall in the flow of spot loans with respect to loans extended under commitment in response to EPU shocks, all while credit spreads rise. Second, we also find that the origination of new term loans in the syndicated loan market falls, while loan spreads increase.

The second form of credit contraction relates to the provision of liquidity insurance, a key function of the banking system. This effect entails banks tightening their supply of liquidity insurance in response to heightening EPU, which they do in two ways. First, they curtail the origination of new credit lines with respect to loans extended under commitment. Second, they embed in the new credit lines a pricing structure that reduces the probability of borrowers drawing down the committed funds. This subtle mechanism that can further restrain loan growth over time.

Our findings highlight the role banks play in the transmission of EPU shocks to the rest of the economy via the supply of loans to the business sector. Our estimates find that the supply contraction on the extensive margin of business lending in response to a one-standard-deviation increase in EPU is around 3 and 5% for spot loans and liquidity insurance, respectively. The effects of uncertainty on business lending are comparable to those of monetary policy shocks, and the business credit channel of the transmission of uncertainty to the economy accounts for roughly a tenth of the loss in real activity over a six-year horizon.

These findings are particularly relevant in light of the theoretical literature showing that financial frictions amplify the contractionary effects on the economy resulting from heightened uncertainty. Our results convey a simple, yet clearly relevant policy implication: predictability in policy-making can prove a powerful policy in itself.

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Economic Policy Uncertainty and the Supply of Business Loans

by S. Barraza and A. Civelli

Additional Material for Online Appendix

In this appendix, we present additional material to accompany the results in the main text of the paper "Economic Policy Uncertainty and the Supply of Business Loans." We include a more detailed discussion on the robustness checks introduced in Section 6 and the full set of impulse-response functions for all the results of the paper.

A Robustness Checks

In the discussion hereinafter, we focus for sake of simplicity on the robustness checks presented in Figure A1 for the model introduced in Figure 3 relying on the ratio of loans extended under commitment to spot loans. A similar discussion could also be extended to the model presented in Figure 5 using the ratio of loans extended under commitment to new credit line originations, whose results are presented in Figure A2. The overall message that emerges from this extensive exercise is that our finding of a tightening in the supply of business lending on the extensive margin resulting from an EPU shock is very robust.

VAR Order Selection. The choice of lag order two in the benchmark model was guided by the standard criteria of comparing the posterior odds of models. To this end, we considered lag orders between one and four. In the first robustness check of the benchmark loan ratio model, we use a lag order of four instead. This lag order is frequently used in the monetary policy literature for analyses based on quarterly data. Figure A1a shows that the response of the loan ratio under this alternative specification is consistent with the response in the benchmark model. We find similar results in unreported tests using lag order one or three.

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. We check the robustness of the results to the 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 scheme we adopt, this is achieved by placing EPU first in the vector of endogenous variables. The response for this case is reported in Figure A1b, and it shows that 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 Zakrajšek (2014), for instance. This ordering choice could be more suitable 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. Figure A1c shows that, while the magnitude of the loan ratio response for this model is slightly reduced, 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 three 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 financial crisis, when the Federal Reserve resorted to large-scale asset purchases and forward guidance to further ease the monetary conditions as the federal funds rate reached the zero lower bound.[1] As a first check, Figure A1d 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 zero 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 Krippner shadow rate (Krippner, 2013, 2015) replaces the Wu-Xia rate. While conceptually similar, these two measures of the shadow rate bear differences in the modeling and estimation procedures, which could have an impact on the identification of the EPU shock as well.[2] This new response of the loan ratio, displayed in Figure A1e, is very similar to the benchmark one as well. Lastly, we use the shadow rate proposed by Lombardi and Zhu (2018), which builds on a broad set of variables associated with both conventional and unconventional monetary policy measures. The response of the loan ratio, presented in Figure A1f, is once again unaltered. Overall, we conclude that our results are robust to alternative measures of the monetary policy stance.

Financial Crisis. The sample we use in our benchmark model includes the Financial Crisis, a period that not only entails persistently high levels of EPU, but also a documented acute contraction in the supply of credit (see, for instance, Ivashina and Scharfstein, 2010; Cornett, McNutt, Strahan, and Tehranian, 2011; Santos, 2011; Gilchrist and Zakrajšek, 2012; Adrian, Colla, and Shin, 2013; Chodorow-Reich, 2014). It is then pertinent to assess whether the result of a supply-side contraction from the benchmark model is driven by this period of unusually high levels of uncertainty and pronounced contraction in the supply of loans, and whether the benchmark result would hold should we exclude this recent extreme

[1]See Bernanke (2012) for a description of these policies.

[2]Both 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. The two methods yield different shadow rates, as can be seen in Figure A15.

event. Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016) raise a similar point in regard to their baseline results based on the 1973:M1–2015:M3 period, and they address it by replicating their analysis using only the pre-crisis period. We follow the same approach and re-estimate our baseline models using data through 2007:Q2.

Figure A1g 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 and significant, with a peak roughly two years after the shock. This peak is delayed by about one year with respect to the benchmark response, indicating a slower adjustment process of loan supply in the pre-crisis period. Although the magnitude of the response is somewhat milder, this is partially explained by the smaller standard-deviation of the EPU shocks in the pre-crisis period. Once this is accounted for, the measured supply contraction corresponds to about 9-10 basis points at peak per unit increase of EPU – that is, one third smaller than the benchmark result.

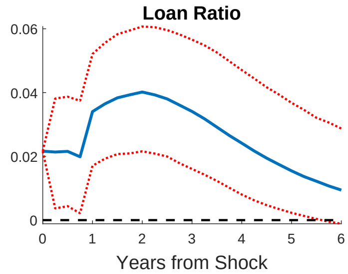
The specific characteristics of the data in the post-crisis period and limitations in our modeling approach prevent us from formally testing the significance of this mild difference. Although we recognize that uncovering the causes of any potential difference exceeds the purpose of this work, we consider studying whether changes in the economic and regulatory environment have affected the transmission of EPU shocks through business lending post-crisis an interesting open issue. This is particularly relevant in light of the regulation emanating from the Dodd-Frank Act and the recent experiences of government liquidity support programs in periods of economic distress (Fleming, 2012).

Monetary and Fiscal Policy Uncertainty. Using solely news data, Baker, Bloom, and Davis (2016) also build sub-indexes that gauge different dimensions of policy uncertainty. Two such sub-indexes of interest here are the Monetary Policy Uncertainty index (MPU) and the Fiscal Policy Uncertainty index (FPU).[3]

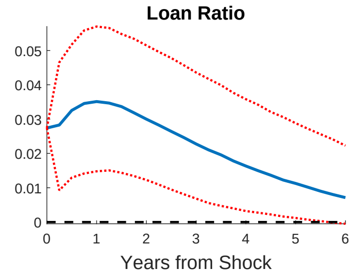
Given the direct link of monetary policy with the cost of bank funding, we would expect heightened MPU to discourage banks from lending. Figure A1h shows evidence in this sense. Upon an MPU shock, the response of the loan ratio is positive from the third quarter on, becoming significant after the first year since the shock and with a peak around two and a half years. This result is consistent with recent findings in Husted, Rogers, and Sun (Forthcoming) as well.

Increasing FPU could also discourage banks from lending. For instance, higher FPU could hinder output, which would result in deteriorating business conditions and creditworthiness, making it sensible for banks to restrict loan supply. Figure A1i presents evidence consistent with this outcome. Again, the loan ratio presents a hump-shaped response that peaks around the second year and remains significantly different from zero for most of the horizon.

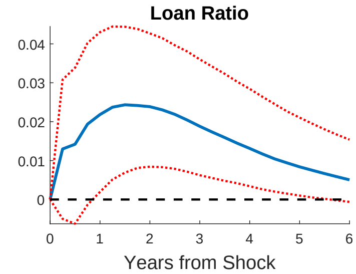
[3] We refer the reader to Appendix B of Baker, Bloom, and Davis (2016) for further details on the constructions of these measures.



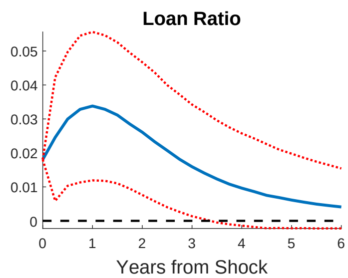
(a) VAR(4)



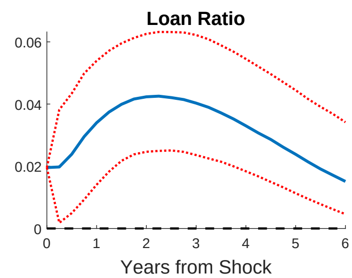
(b) EPU first in the identification ordering



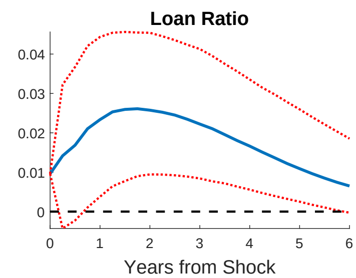
(c) EPU last in the identification ordering



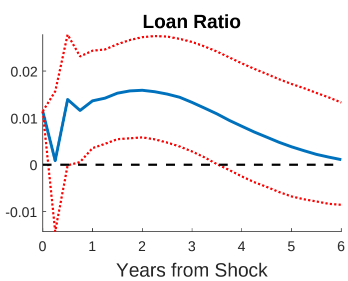
(d) Federal Funds Rate



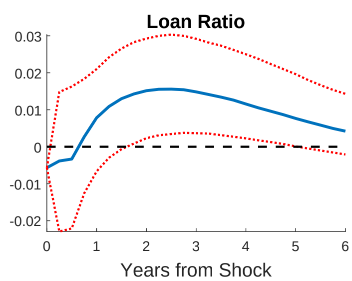
(e) Krippner



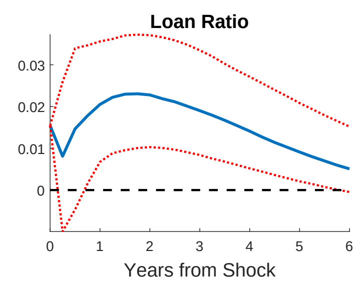
(f) Lombardi-Zhu



(g) Pre-Crisis

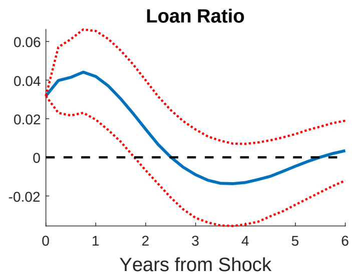


(h) MPU

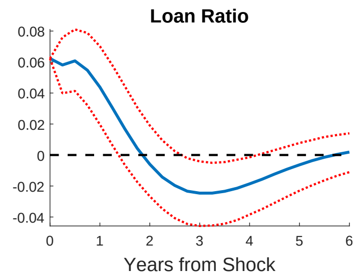


(i) FPU

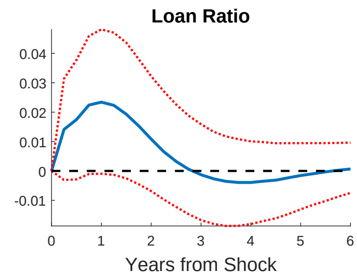
Figure A1: Robustness Checks: Response of the Ratio of Loans Extended under Commitment to Spot Loans Extended by Large Banks. Sample period is 1985:Q1–2017:Q1, except in Panel (g), where the sample ends in 2007:Q2. Response to a one-standard-deviation structural innovation in EPU, except in Panels (h) and (i) where the shocks correspond to MPU and FPU, respectively. The benchmark model is modified in each robustness exercise as described in the panels. Years from the shock on the x-axis.



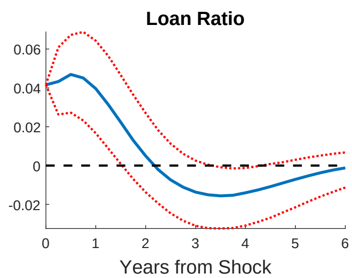
(a) VAR(4)



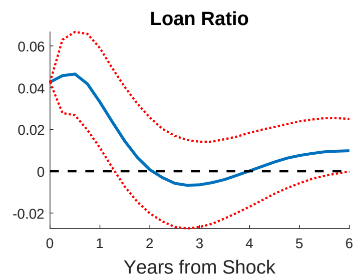
(b) EPU first in the identification ordering



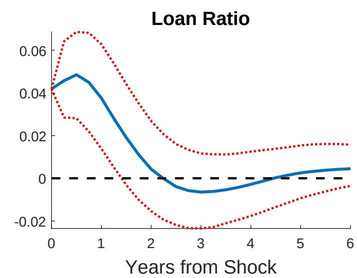
(c) EPU last in the identification ordering



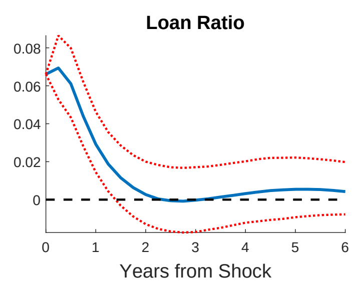
(d) Federal Funds Rate



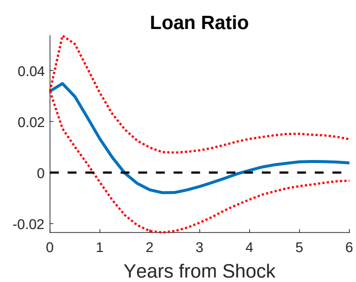
(e) Krippner



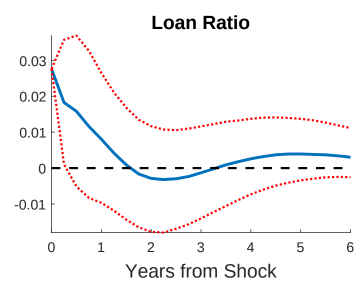
(f) Lombardi-Zhu



(g) Pre-Crisis



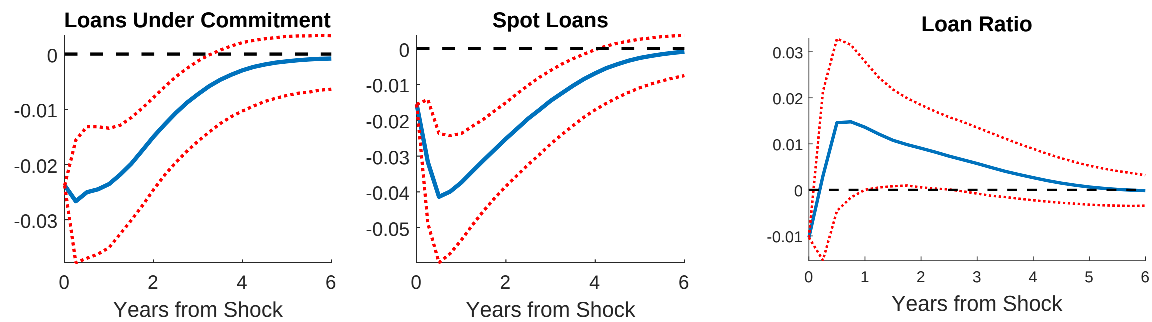
(h) MPU



(i) FPU

Figure A2: Robustness Checks: Response of the Ratio of Loans Extended under Commitment by Large Domestic Banks, from STBL, to New Credit Line Originations, from DealScan. Sample period is 1988:Q1–2017:Q1, except in Panel (g), where the sample ends in 2007:Q2. Response to a one-standard-deviation structural innovation in EPU, except in Panels (h) and (i) where the shocks correspond to MPU and FPU, respectively. The benchmark model is modified in each robustness exercise as described in the panels. Years from the shock on the x-axis.

B The Role of Bank Size



(a) Small Banks - Loans Separately

(b) Small Banks - Loan Ratio

Figure A3: EPU and the Response of Loans Extended by *Small* Banks, 1985:Q1–2017:Q1. Orthogonalized responses to a one-standard-deviation 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 either (a) the log of real amount of loans extended under commitment and the log of real amount of spot loans or (b) the log of the ratio of real loans extended under commitment to real spot loans extended by small domestic banks. VAR(2). Years from the shock on the x-axis.

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. 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 this, more credit constrained. This naturally creates incentives for small firms to strategically manage their use of available liquidity. Thus, in the face of increasing uncertainty, they could have incentives to slow down drawdowns and preserve access to open credit lines. This behavior would differ from that of larger, less constrained firms, with access to alternative sources of financing.

Figure A3 replicates the main results of Figures 2 and 3 using data on small bank loans.[4] In the analysis of large banks-large firms we have seen that, while the response of loans extended under commitment is relatively mild, the response of spot loans builds up to become three to four times the size of the former. In clear contrast, in the analysis of small banks-small firms we also observe in Panel (a) of Figure A3 a sharp decline in loans extended under commitment in the short- and medium-run, which is comparable in size to the fall of spot loans during most of the horizon. These individual responses lead to a much smaller and largely non-significant response of the loan ratio in Panel (b) of Figure A3.

[4]The full set of impulse response functions for these two models can be respectively found in Figures A12 and A13 of the online Appendix.

The immediate fall in loans extended under commitment among small banks seems to suggest that small firms do manage their access to liquidity more cautiously than larger firms would in response to heightening EPU, slowing down their drawdowns on credit lines so as to preserve the liquidity insurance they offer. It is mainly for this reason that we deem appropriate to consider large and small banks separately in our baseline analysis. Still, it should be mentioned that an analysis of loans extended by large and small banks combined yields very similar results to those from the analysis of large banks alone. This is hardly surprising, as large banks originate most of the aggregate business loans, driving the aggregate dynamics. For completeness, we report the impulse response functions of this model in Figure A14 of the Appendix.

C Full Sets of Responses for Models in the Main Text

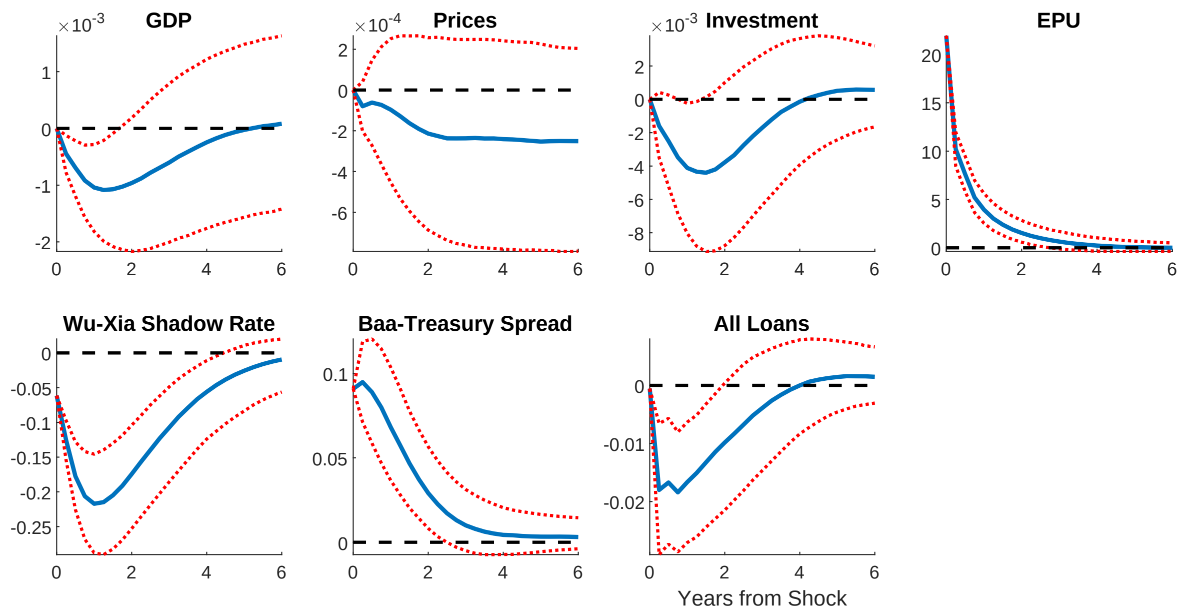


Figure A4: EPU and the Response of Total Business Loans Extended by Large Banks from STBL, 1985:Q1-2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross business investment, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, and the log of real business loans extended by large domestic banks. VAR(2). Years from the shock on the x-axis.

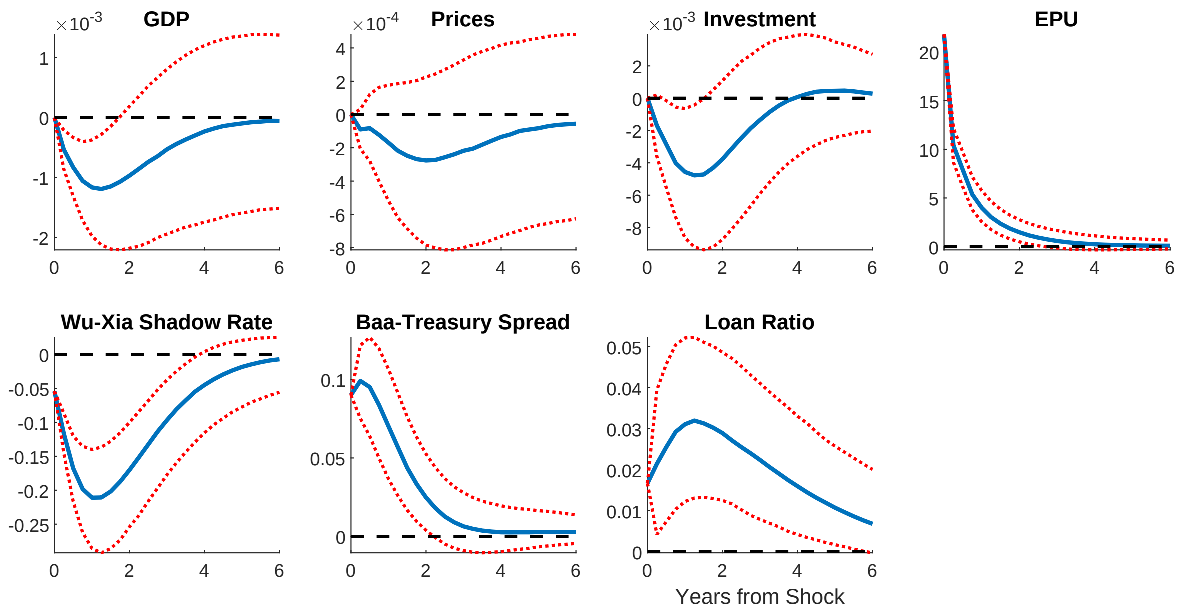


Figure A5: EPU and the Response of the Ratio of Loans Extended under Commitment to Spot Loans Extended by Large Banks from STBL, 1985:Q1-2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the 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 log of the ratio of real loans extended under commitment to real spot loans extended by large domestic banks. VAR(2). Years from the shock on the x-axis.

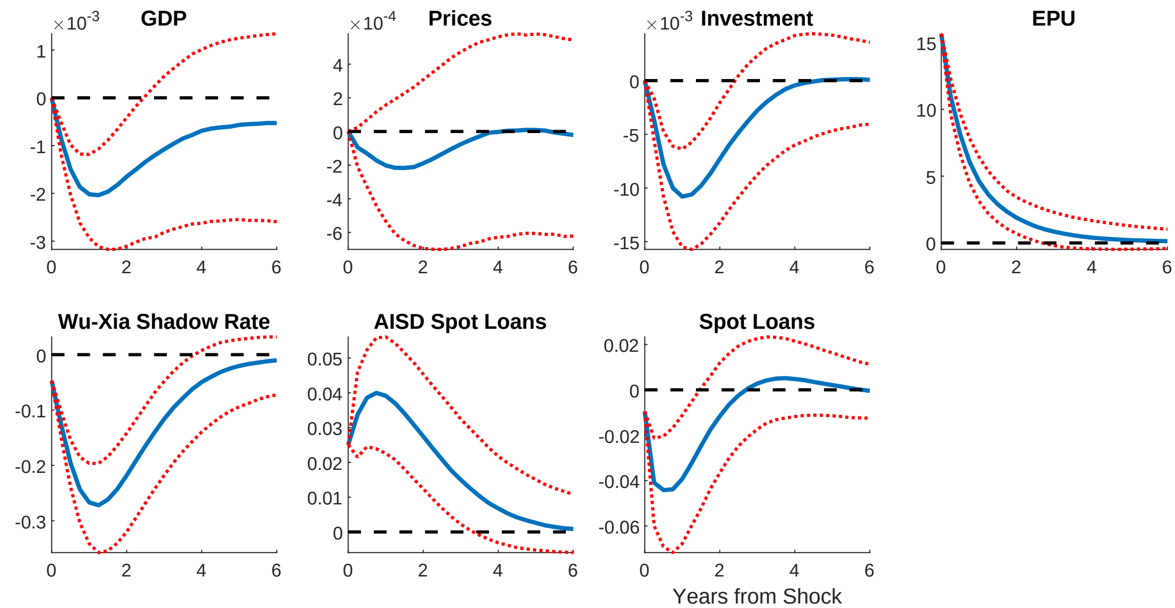


Figure A6: EPU and the Response of the All-In Spread Drawn on New Term Loans and the Volume of Term Loan Originations from DealScan, 1988:Q1–2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross business investment, the baseline overall EPU index, the Wu-Xia shadow rate, the AISD on new term loans, and the log of real term loan originations from DealScan. VAR(2). Years from the shock on the x-axis.

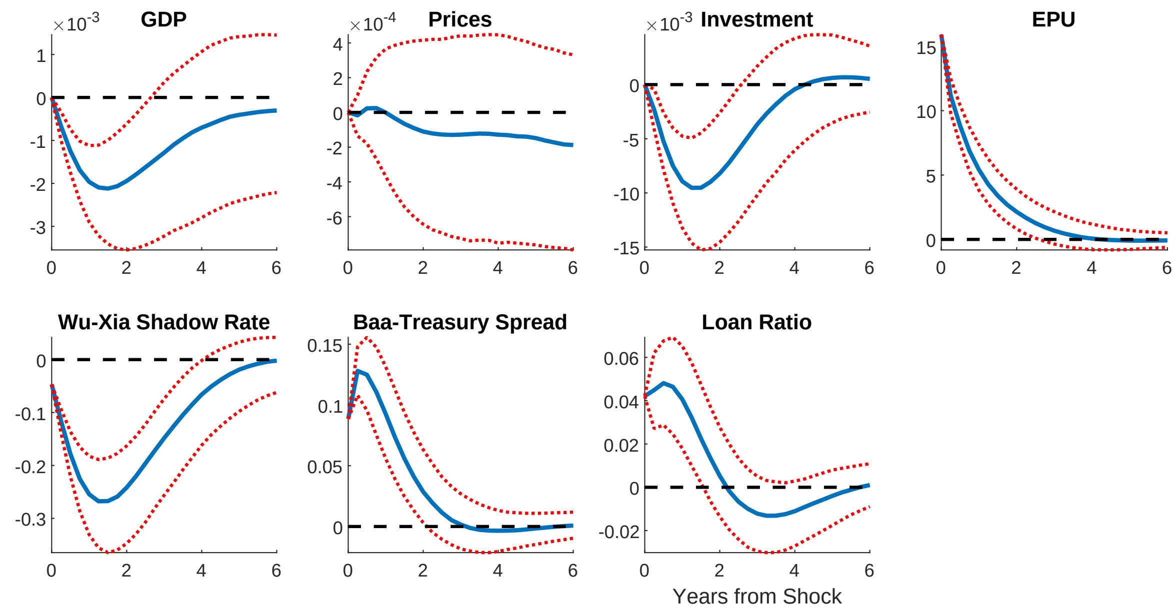


Figure A7: EPU and the Response of the Ratio of Loans Extended under Commitment from STBL to New Credit Line Originations from DealScan, 1988:Q1-2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, 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 log of the ratio of real loans extended under commitment by large domestic banks (STBL) to real new credit line originations (DealScan). VAR(2). Years from the shock on the x-axis.

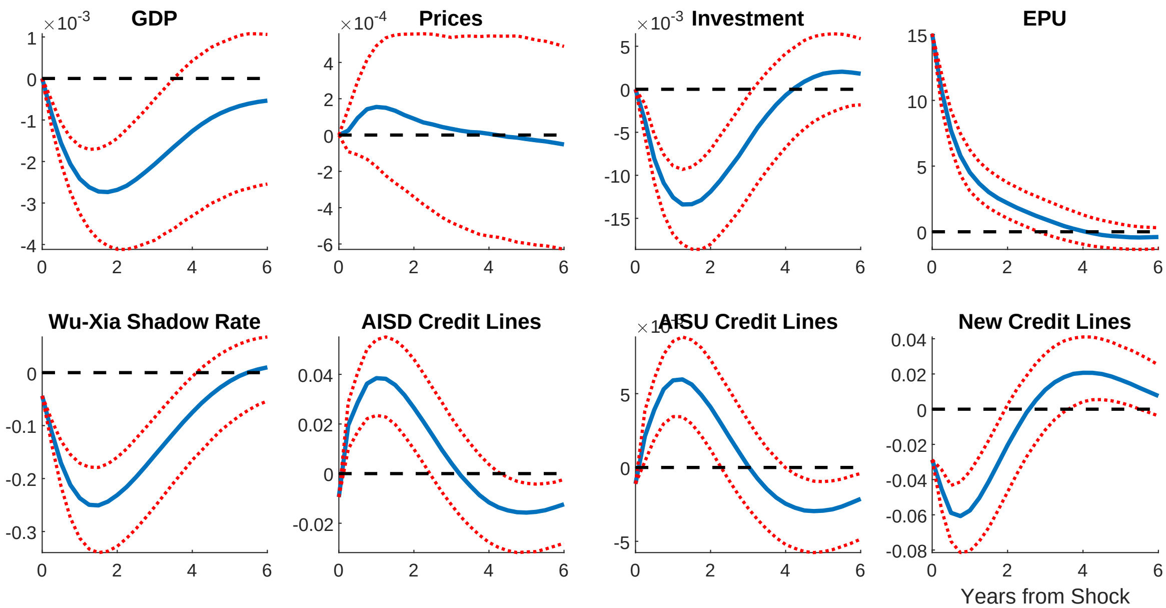


Figure A8: EPU and the Response of the All-In Spread Drawn, All-In Spread Undrawn, and Volume of New Credit Line Originations from DealScan, 1988:Q1–2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross business investment, the baseline overall EPU index, the Wu-Xia shadow rate, the AISD and AISU on new credit lines, and the log of real new credit line originations from DealScan. VAR(2). Years from the shock on the x-axis.

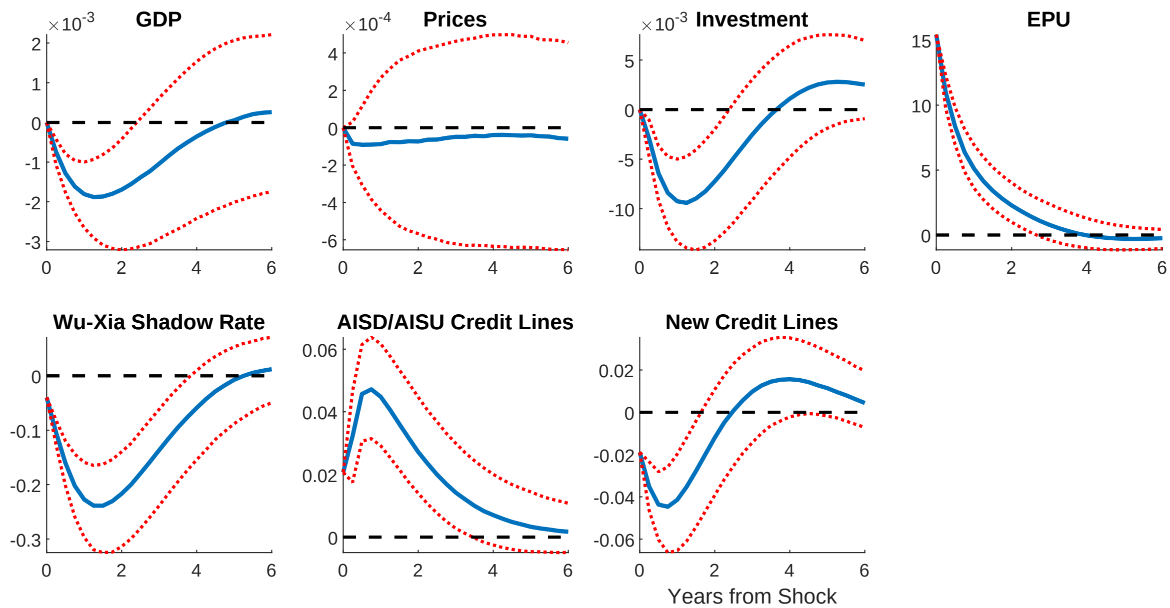


Figure A9: EPU and the Response of the AISD/AISU Ratio on New Credit Lines and the Volume of New Credit Line Originations from DealScan, 1988:Q1-2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross business investment, the baseline overall EPU index, the Wu-Xia shadow rate, the ratio of All-In Spread Drawn (AISD) to All-In Spread Undrawn (AISU) on new credit lines, and the log of real new credit line originations from DealScan. VAR(2). Years from the shock on the x-axis.

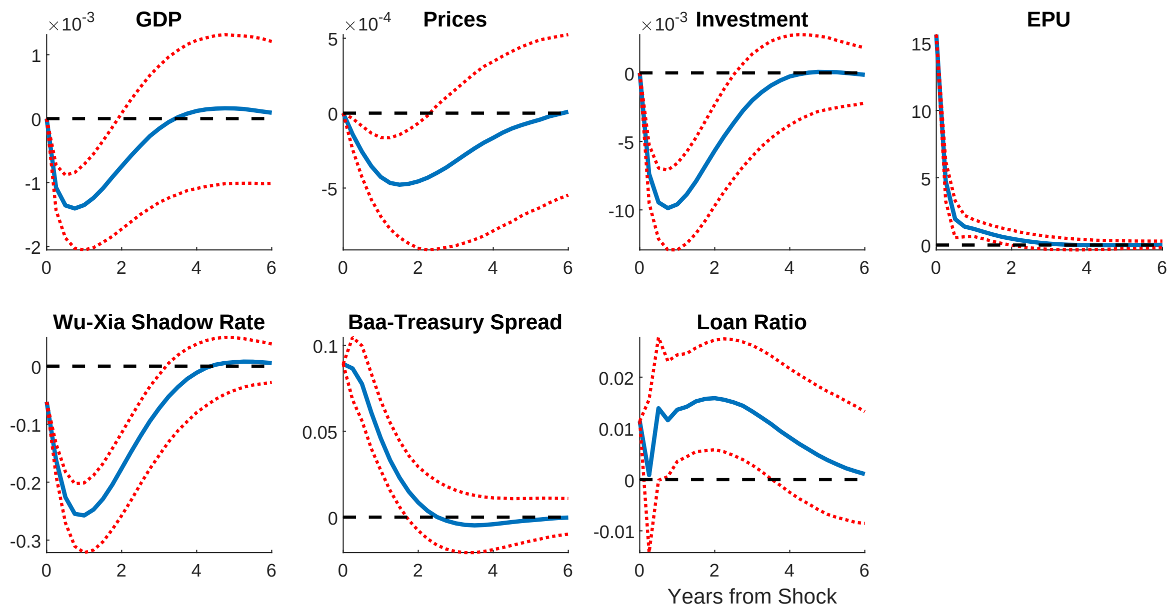


Figure A10: EPU and the Response of the Ratio of Loans Extended under Commitment to Spot Loans Extended by Large Banks from STBL, *Pre-Financial Crisis, 1985:Q1–2007:Q2*. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log 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 log of the ratio of real loans extended under commitment to real spot loans extended by large domestic banks. VAR(2). Years from the shock on the x-axis.

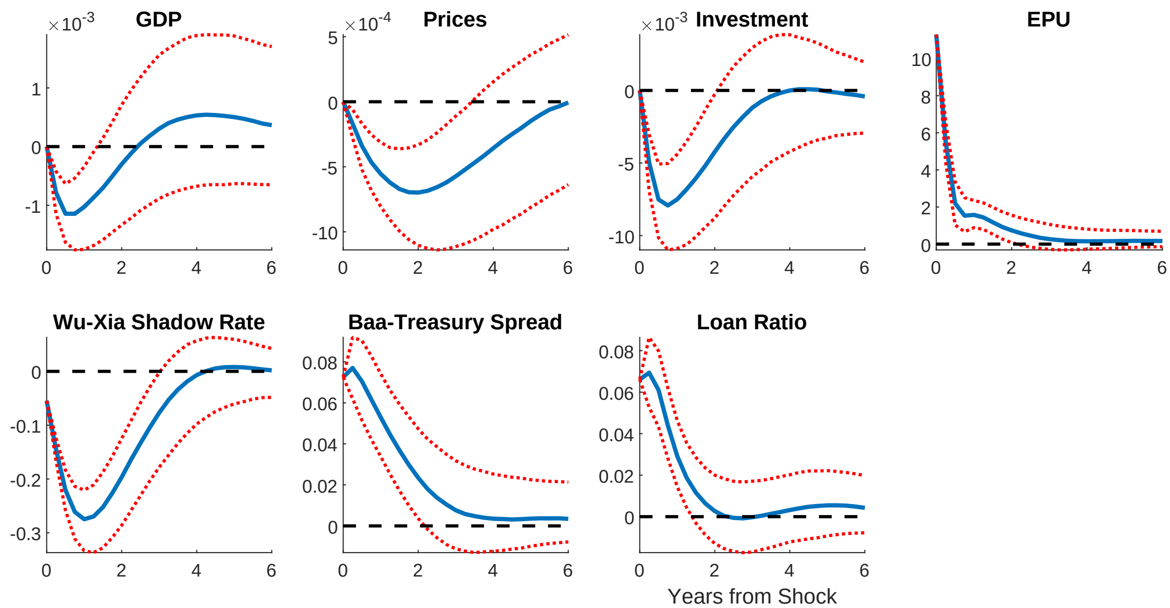


Figure A11: EPU and the Response of the Ratio of Loans Extended under Commitment by Large Banks from STBL to New Credit Line Originations from DealScan, *Pre-Financial Crisis, 1988:Q1–2007:Q2*. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log 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 log of the ratio of real loans extended under commitment (STBL) to real new credit line originations (DealScan). VAR(2). Years from the shock on the x-axis.

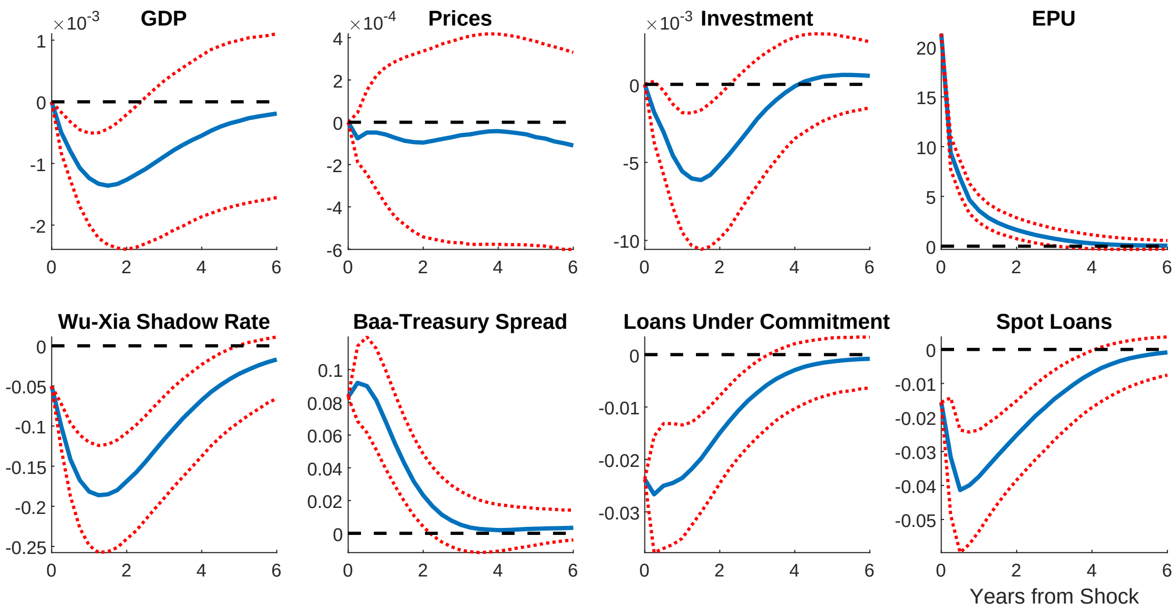


Figure A12: EPU and the Response of Loans Extended under Commitment and Spot Loans Extended by *Small* Banks, 1985:Q1-2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross business investment, the baseline overall EPU index, the Wu-Xia shadow rate, the 10-year Baa-Treasury credit spread, and the log of real loans extended under commitment and log of real spot loans extended by small banks. VAR(2). Years from the shock on the x-axis.

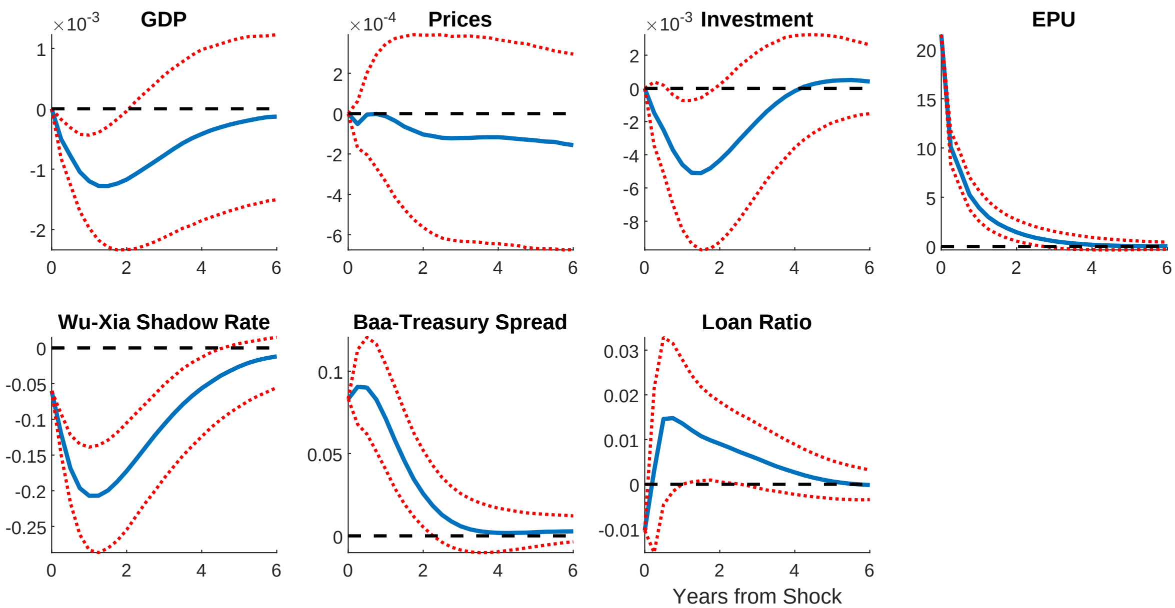


Figure A13: EPU and the Response of the Ratio of Loans Extended under Commitment to Spot Loans Extended by *Small* Banks from STBL, 1985:Q1–2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, 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 log of the ratio of real loans extended under commitment to real spot loans extended by small domestic banks. VAR(2). Years from the shock on the x-axis.

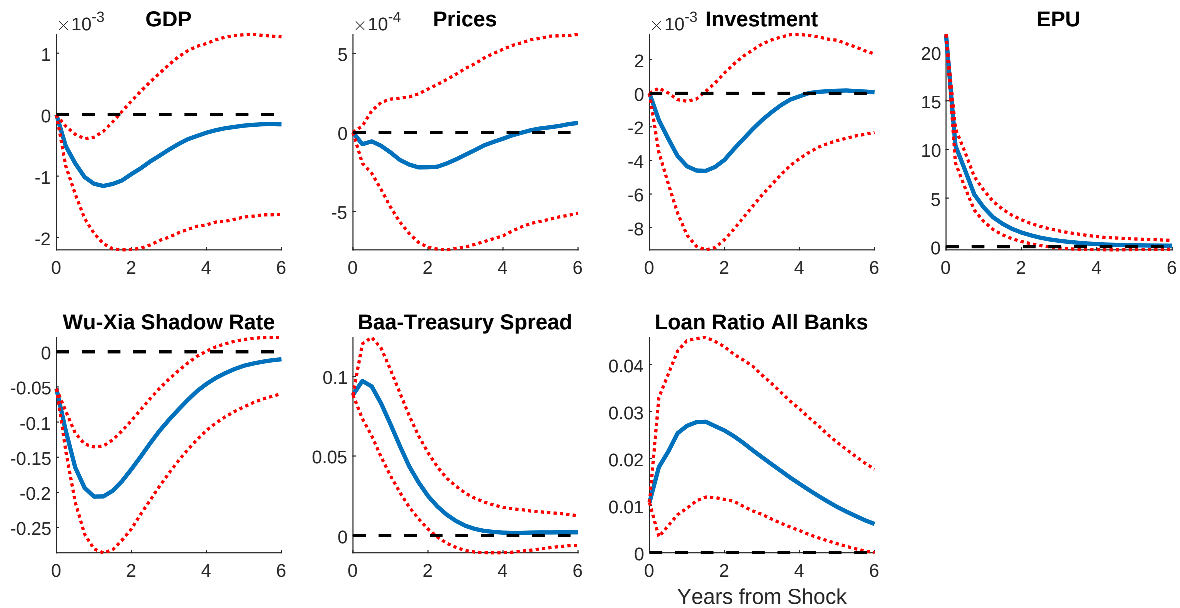


Figure A14: EPU and the Response of the Ratio of Loans Extended under Commitment to Spot Loans Extended by *All* Banks from STBL, 1985:Q1–2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the 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 log of the ratio of real loans extended under commitment to real spot loans extended by all domestic banks. VAR(2). Years from the shock on the x-axis.

D Additional Figures: Monetary Policy Stance

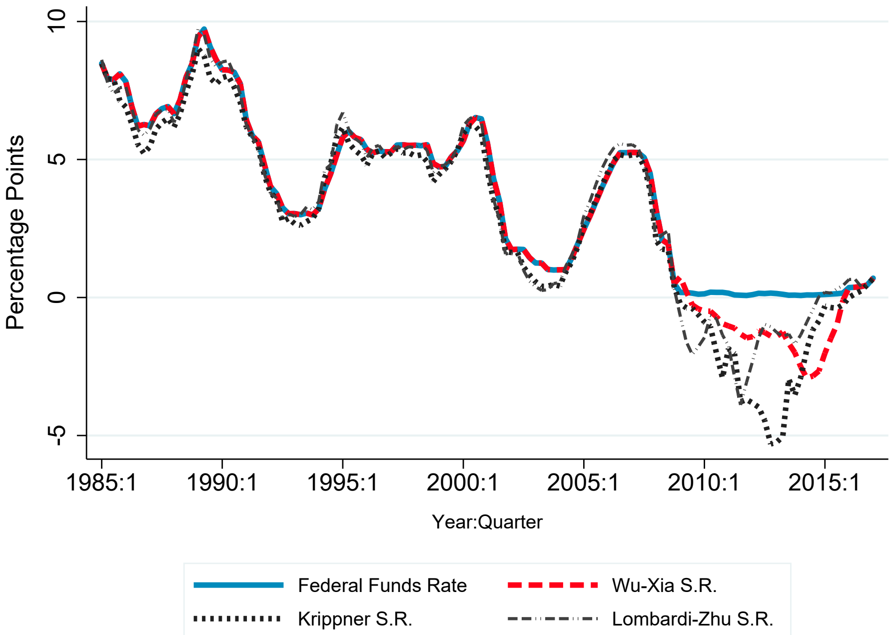


Figure A15: Monetary Policy Rates: Federal Funds Rate, Wu-Xia Shadow Rate, Krippner Shadow Rate, Lombardi-Zhu Shadow Rate.

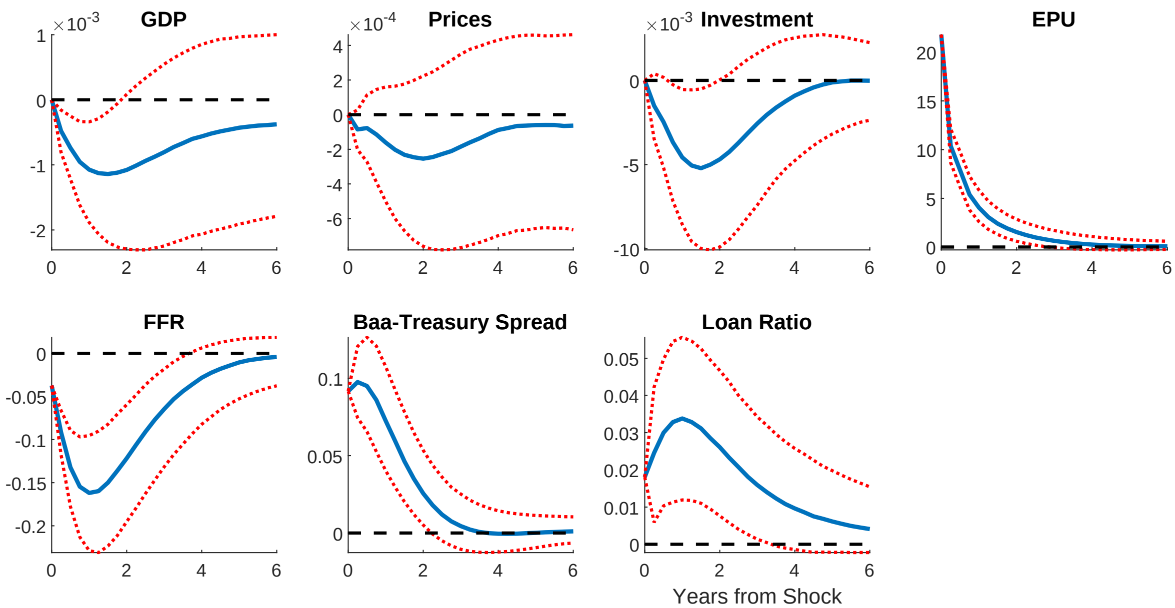


Figure A16: EPU and the Response of the Ratio of Loans Extended under Commitment to Spot Loans Extended by Large Banks from STBL, where *Federal Funds Rate* replaces the Wu-Xia Shadow Rate, 1985:Q1–2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model includes the log of real GDP, the log of the GDP deflator, the log of real gross business investment, the baseline overall EPU index, the Federal Funds rate, the 10-year Baa-Treasury credit spread, and the log of the ratio of real loans extended under commitment to real spot loans extended by large domestic banks. VAR(2). Years from the shock on the x-axis.

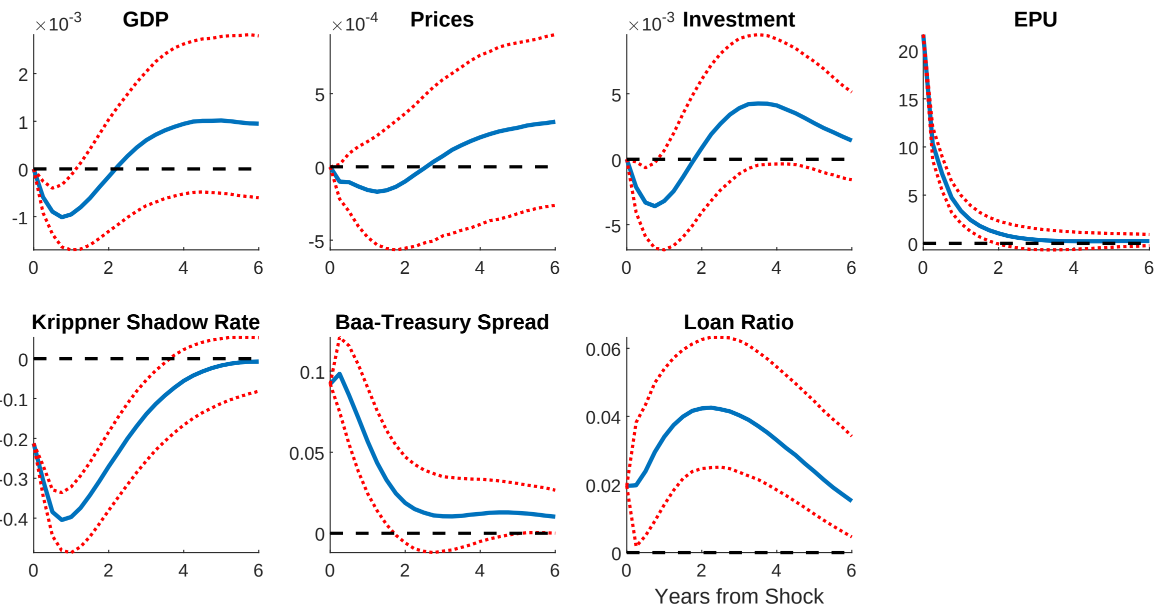


Figure A17: EPU and the Response of the Ratio of Loans Extended under Commitment to Spot Loans Extended by Large Banks from STBL, where the *Krippner Shadow Rate* replaces the Wu-Xia Shadow Rate, 1985:Q1–2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The model 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 Krippner shadow rate, the 10-year Baa-Treasury credit spread, and the log of the ratio of real loans extended under commitment to real spot loans extended by large domestic banks. VAR(2). Years from the shock on the x-axis.

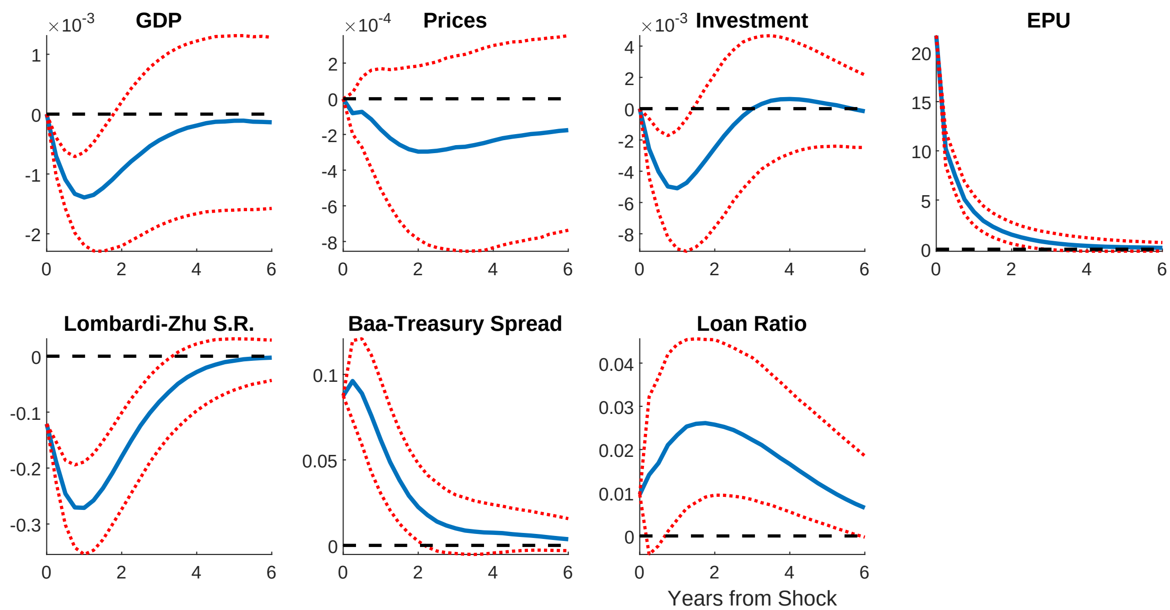


Figure A18: EPU and the Response of the Ratio of Loans Extended under Commitment to Spot Loans Extended by Large Banks from STBL, where the *Lombardi-Zhu Shadow Rate* replaces the Wu-Xia Shadow Rate, 1985:Q1–2017:Q1. Orthogonalized responses to a one-standard-deviation structural innovation of EPU. The 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 Lombardi-Zhu shadow rate, the 10-year Baa-Treasury credit spread, and the log of the ratio of real loans extended under commitment to real spot loans extended by large domestic banks. VAR(2). Years from the shock on the x-axis.