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The Effect of a Financial Block on the Identification of Confidence Shocks in a Structural VAR Model

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Abstract

This paper studies the propagation and properties of a confidence shock in a structural vector autoregression (VAR) model with and without financial variables. The addition of a financial block does not considerably change the propagation and the contribution to the forecast error variance by the confidence shock. Nevertheless, for specific historical episodes, the inclusion of a financial block plays a role. In several recessions, the VAR with the financial block assigns a smaller role to confidence shocks for the fall in GDP. This suggests that the confidence shock may not be properly identified in a structural VAR when financial variables are omitted. Further, I identify a financial channel by which the confidence shock affects economic activity.

JEL class: C32, E32, E44

Keywords: Confidence shocks, structural VARs, financial channel.

1 Introduction

In the empirical literature, confidence shocks are seen as an important driver of business cycles, especially in the short run (see, e.g., Barsky and Sims, 2012; Beaudry, Nam, and Wang, 2011; Fève and Guay, 2018).[1] These shocks, which are unrelated to changes in technology, shift expectational variables about economic activity and have the flavor of mood swings or animal spirits.[2] Typically, papers that study confidence shocks using structural vector autoregression (VAR) models do not contain financial variables. This lack of a financial block is potentially problematic, because the confidence shock may be misidentified. The shock might be misidentified since financial variables are inherently forward-looking and are likely to reveal useful information about expectations of future economic activity. Further, confidence can also react strongly to financial market conditions, and vice versa, as was observed, for example, during the 2007–2008 financial crisis. If confidence reacts to financial markets conditions, this reaction may erroneously be picked up as a confidence shock when the model specification does not control for a financial block. Including a financial block is also interesting because this addition enables the identification of a financial transmission channel of the confidence shock. Myohl and Stucki (2018) show in a DSGE model that financial frictions affect the propagation of confidence shocks both on impact and in the medium run.

In this paper, I identify a confidence shock in a structural VAR, using US data. I investigate the effect of adding a financial block on the properties of the identified confidence shock. The VAR without the financial block contains total factor productivity (TFP), consumption, GDP, hours worked and two expectational variables: the forecast of GDP and consumer confidence.[3] I begin the analysis by identifying two shocks that explain movements in TFP. First, a surprise technology shock is identified as the only shock that drives TFP contemporaneously. Second, a news shock about future TFP is identified as in Barsky and Sims (2011). Next, the identification of the confidence shock follows Levchenko and Pandalai-Nayar (2015). More precisely, the confidence shock is identified as the shock orthogonal to the two technology shocks that maximizes the contribution to the residual forecast error variance (FEV) of the forecast of GDP and consumer confidence in the short run. The confidence shock thus explains movements in these expectational variables once movements in TFP have been controlled for. In contrast to Levchenko and Pandalai-Nayar (2015), who only use the forecast of GDP or the consumer confidence index, this specification features both series. While the consumer confidence series can be riddled with errors, the series will still add valuable information in order to improve the identification of the confidence shock.

In a second step, I add to the VAR a financial block that contains variables that are directly related to the financial market and financial conditions. In particular, I augment the vector of variables with the Chicago Fed's National Financial Conditions Index (NFCI), the stock market, credit, and investment. To ensure that the confidence shock does not pick up a

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[1]Some theoretical papers that study the role of confidence or sentiment shocks on fluctuations of macroeconomic aggregates are, for example, Angeletos and La'O (2013), Angeletos, Collard, and Dellas (2018), Huo and Takayama (2015), and Benhabib, Wang, and Wen (2015).

[2]Here I refer to the interpretation of Keynes (1936), that human behavior can be driven by spontaneous instincts and emotions.

[3]The choice of variables closely follows Barsky and Sims (2011) and Levchenko and Pandalai-Nayar (2015).

financial shock, I identify a financial shock in the augmented VAR specification. Conditional on the two technology shocks, I identify the financial shock as the shock that maximizes the contribution to the short-run residual FEV of the NFCI. Therefore, in the augmented VAR, the confidence shock is identified conditional on the two technology shocks and the financial shock. The two VAR specifications allow comparing if and how the properties of the confidence shock change with the addition of a financial block.

The confidence shock's overall role for business cycle fluctuations does not considerably change by adding the financial block. Both, the impulse response functions (IRFs) and the FEV decomposition are quite similar. In both VAR specifications, the confidence shock leads to a positive co-movement across macroeconomic aggregates and explains a considerable share of the FEV in the short run. However, for some specific business cycle episodes, the pattern of the identified confidence shocks and their role for economic activity differ considerably when the financial block is added. I illustrate this observation with the following experiment. I perform several historical counterfactuals where the confidence shock is shut off. This exercise tells us how, say, GDP would have evolved in the absence of confidence shocks, and how much of the fall in GDP can be attributed to the confidence shock. I find that in several recessions, the VAR with the financial block assigns a much smaller role to confidence shocks for the fall in GDP. This suggests that the confidence shock is misidentified when the financial block is not included in the VAR but the misidentification issue is only problematic for some specific episodes.

The inclusion of a financial block allows the identification of a financial transmission channel of confidence shocks, connecting the paper to a theoretical literature that studies a financial transmission channel of confidence shocks (see, e.g., Angeletos, Lorenzoni, and Pavan, 2010; Goldstein, Ozdenoren, and Yuan, 2013; Benhabib, Liu, and Wang, 2016). In the augmented VAR, following a positive confidence shock, financial conditions are tighter than average after a couple of quarters. To identify the transmission channel, I use the technique by Bachmann and Sims (2012) and neutralize the effect of financial conditions on the propagation of confidence shocks. I find that if financial conditions were unchanged following a positive confidence shock, then economic activity would be higher in the medium run. This observation is consistent with Myohl and Stucki (2018) who find that following a positive confidence shock, financial conditions have a negative impact on economic activity in the medium run.

Finally, this paper also connects to the literature that considers financial shocks as a source of macroeconomic fluctuations (see, e.g., Christiano, Motto, and Rostagno, 2014; Meeks, 2012; Gilchrist and Zakrajšek, 2012; Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek, 2016). As noted by Benati and Kyriacou (2017), financial shocks such as credit shocks or uncertainty shocks display similar features as a confidence shock. Hence, an identified financial shock may be polluted by a confidence shock and vice versa. This concern can be addressed by changing the identification ordering of the financial shock and the confidence shock and by comparing the identified impulses of each shock between the two orderings. More precisely, I identify the confidence shock ordered third, conditional on the two technology shocks. The financial shock is then identified ordered fourth, conditional on the two technology shocks and the confidence shock.[4] The identified impulses of the confidence

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[4]The identification strategy is recursive. By ordered third, I mean the shock is identified conditional on

shock are very similar and are highly correlated. The same is true for the impulses of the financial shock. This result suggests that the structural VAR with the financial block can disentangle the financial shock and the confidence shock relatively well.

The remainder of the paper is organized as follows. Section 2 describes the data and the identification of shocks. Section 3 presents the results. Section 4 performs robustness checks with regard to the recent financial crisis and considers an alternative to the NFCI series. Section 5 concludes.

2   Empirical strategy

This section describes the data and the identification strategy of the structural shocks.

2.1   Data and specification of the reduced-form VAR

The first block of the VAR consists of total factor productivity, consumption of services and nondurables, GDP, hours worked, the forecast of the next quarter's GDP and a consumer confidence index. The data for TFP is the utilization-adjusted series of Fernald (2014) which is based on the methodology of Basu, Fernald, and Kimball (2006). Real GDP, real consumption of services, and real consumption of non-durables are taken from the Bureau of Economic Analysis (BEA). Because there is no chain-weighted series for the sum of consumption of non-durables and services, I use the Tornqvist approximation to construct this series.[5] The data for hours worked are aggregate hours worked in the non-farm business sector from the Bureau of Labor Statistics (BLS). To construct the GDP forecast series, I use the mean forecast of growth rates of the Survey of Professional Forecasters of the Philadelphia Fed. The survey provides level forecasts, but because of changing base years the forecasts are not comparable in levels. I, therefore, construct the implied GDP forecast level series by multiplying the real GDP series with the mean forecast of the growth rate. These series are the same as used in Barsky and Sims (2011) and Levchenko and Pandalai-Nayar (2015). For the confidence measure, I use the Conference Board Consumer Confidence Index. The index measures consumers' current and future perceptions (in six months time) about employment and business conditions.[6] Consumption, GDP, and hours worked are transformed into per capita series by dividing them by the civilian non-institutional population of the BLS.[7] Finally, all series except the confidence index are logarithmized.

In the second block of the VAR, I add variables that are sensitive to financial conditions and markets. As a measure of financial conditions, I use the NFCI which summarizes financial conditions in money markets, debt and equity markets, and the traditional and the "shadow" banking systems. The index is constructed to have an average of zero. Positive values imply that financial conditions are tighter than average and negative values indicate

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two previously identified shocks. Ordered fourth means the shock is identified conditional on three previously identified shocks. The identification strategy is described in more detail in the next section.

[5]For issues with adding chain-weighted components, see Whelan (2000).

[6]I also evaluate robustness with respect to other data series. Replacing the forecast with the (current quarter's) forecast error leads to the same results qualitatively. The results are also robust to replacing the mean of the forecast growth series with the median. Replacing the conference series with other commonly used series from the Surveys of Consumers of the University of Michigan does not change the picture either.

[7]I apply the HP-filter on the population series to smooth out apparent changes in the construction of this series.

that conditions are looser than average. The index is updated weekly and I take the average of each quarter. Further, I include three additional variables, the S&P 500 Index, credit to nonfinancial corporations, and investment. The data for the S&P 500 is obtained from Robert Shiller's website.[8] I take the average of the monthly data and divide it by the GDP deflator from the BEA. The series for credit is from the Board of Governors of the Federal Reserve System, namely "Nonfinancial Corporate Business; Credit Market Instruments; Liability" and is also deflated by the GDP deflator. Real investment is obtained from the BEA. The series for investment, credit, and the S&P500 are also calculated per capita and logarithmized.

I estimate the VAR with quarterly data from 1971Q1 to 2007Q4. The starting date is dictated by the availability of the NFCI. The observation period stops at the end of 2007 to exclude the financial crisis (see 4.1 for a discussion). Following Barsky and Sims (2011) and Levchenko and Pandalai-Nayar (2015), the VAR is estimated in (log) levels because parameter estimates are consistent in the presence of co-integration. In contrast, vector correction error models may be misspecified if the co-integration is of unknown form (this follows the recommendation of Hamilton, 1994). I choose two lags, as selected by the final prediction error criterium.[9]

2.2 Identification of the structural shocks

The identification of the shocks follows the maximum forecast error variance approach of Uhlig (2003) and Barsky and Sims (2011). Shocks are identified by maximizing their contribution to the forecast error variance (FEV) of a target variable between 0 and H periods. Let the reduced-form VAR(p) model be

$$Y_t = B_0 + B_1 Y_{t-1} + \ldots + B_p Y_{t-p} + u_t, \ E_t[u_t u_t'] = \Sigma,$$

where Y_t is a vector of k observable series at time t, u_t is the vector of the reduced-form innovations and Σ is the covariance matrix of the innovations. The moving-average representation is then given by $Y_t = C(L)u_t$, where $C(L) \equiv [B(1)]^{-1}B_0 + [B(L)]^{-1}$, $B(L) \equiv I - B_1 L - \ldots - B_p L^p$ and $C(L) \equiv I + C_1 L + C_2 L^2 + \ldots$.

We assume there exists a linear mapping between the innovations u_t and structural shocks ε_t, i.e.

$$u_t = A_0 \varepsilon_t.$$

Assuming the structural shocks have unit variance, the matrix A_0 must then satisfy $A_0 A_0' = \Sigma$. This condition is for example satisfied by the Cholesky decomposition A_0^* of Σ. The space of possible impact matrices is then given by $A_0 = A_0^* D$ where D is any orthonormal matrix, i.e. $DD' = I$.

Maximizing the share of the forecast error variance. The approach of Uhlig (2003) and Barsky and Sims (2011) boils down to the following exercise. Given a candidate

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[8]www.econ.yale.edu/∼shiller/data.htm
[9]The Schwarz and the Hannan-Quinn information criteria indicate one lag which is rather short, while the Akaike information criterium always selects the maximum lag length. Another option would be to choose four lags, as is also common in the literature. The propagation of the confidence shock is qualitatively similar with regard to these lag lengths.

matrix A_0^*—e.g. the Cholesky decomposition of Σ—we look for a column vector d of an orthonormal matrix D such that the impact vector A_0^*d maximizes the share of the FEV. In other words, we look for the linear combination of innovations $u_{i,t}$ that maximizes the share of the FEV of the target variable over a certain horizon. Once found, A_0^*d is then the impact vector associated with the identified structural shock that contributes the most to the FEV.[10]

The h-step ahead forecast error of variable i is defined as

$$y_{i,t+h} - E_{t-1}[y_{i,t+h}] = e_i' \sum_{l=0}^{h} C_l A_0^* D \varepsilon_{t+h-l},$$

where e_i is a unit vector with one in the i-th position and zeroes elsewhere. The share of the FEV of variable i due to shock j at horizon h is then

$$\Omega_{i,j}(h) = \frac{e_i'(\sum_{l=0}^{h} C_l A_0^* D e_j e_j' D' A_0'^* C_l')e_i}{e_i'(\sum_{l=0}^{h} C_l A_0^* A_0'^* C_l')e_i}.$$

The e_i's select the FEV of variable i. The e_j's select the column j of D, identifying the shock j that maximizes the share of the FEV. Let $De_j = d_j$. The expression above can be rewritten as

$$\Omega_{i,j}(h) = \frac{e_i'(\sum_{l=0}^{h} C_l A_0^* d_j d_j' A_0'^* C_l')e_i}{e_i'(\sum_{l=0}^{h} C_l \Sigma C_l')e_i}.$$

The vector d_j that maximizes the share of the FEV of variable i between 0 and H periods is then the solution d_j^* to the following problem:

$$d_j^* = \arg\max_{d_j} \sum_{h=0}^{H} \Omega_{i,j}(h) = \arg\max_{d_j} \sum_{h=0}^{H} \frac{e_i'(\sum_{l=0}^{h} C_l A_0^* d_j d_j' A_0'^* C_l')e_i}{e_i'(\sum_{l=0}^{h} C_l \Sigma C_l')e_i}. \tag{1}$$

The numerator of the fraction in (1) can be rewritten in the following way:[11]

$$
\begin{aligned}
e_i'(\sum_{l=0}^{h} C_l A_0^* d_j d_j' A_0'^* C_l')e_i &= \sum_{l=0}^{h} \text{trace}[(e_i e_i')(C_l A_0^* d_j)(d_j' A_0'^* C_l')] \\
&= \sum_{l=0}^{h} \text{trace}[(d_j' A_0'^* C_l')(e_i e_i')(C_l A_0^* d_j)] \\
&= d_j'(\sum_{l=0}^{h} A_0'^* C_l' e_i e_i' C_l A_0^*) d_j.
\end{aligned}
$$

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[10]In Uhlig (2003), the structural shock is identified as the shock that explains as much as possible of the FEV. In Barsky and Sims (2011) and Levchenko and Pandalai-Nayar (2015), the structural shocks are identified as the shocks that maximize the contribution to the FEV, or, in other words, the share of the FEV. I follow the latter approach.

[11]First, note that the e_i's pick the ith element of the matrix inside the sum. The same can be achieved by taking the trace after applying the selector matrix $e_i e_i'$ which leaves all elements on the diagonal but i equal to zero. The second equality follows because permutations of a matrix product leave the trace unchanged. Finally, the third equality follows because the object inside of the trace is a scalar and, because of linearity, the d_j's can be taken outside of the sum operator.

Applying this result to equation (1), we can rewrite:

$$d_j^* = \arg\max_{d_j} \; d_j' S d_j, \tag{2}$$

where

$$S = \sum_{h=0}^{H} \frac{\sum_{l=0}^{h} A_0'^* C_l' e_i e_i' C_l A_0^*}{e_i' (\sum_{l=0}^{h} C_l \Sigma C_l') e_i}.$$

Note that the object S entirely consists of objects derived from the reduced-form VAR. With the restriction that d_j is a unit vector, the Lagrangian of this problem is

$$\mathcal{L} = d_j' S d_j - \lambda(d_j' d_j - 1)$$

and the first order condition is[12]

$$S d_j = \lambda d_j.$$

That is, d_j^* is an eigenvector of S with eigenvalue λ. Multiplying both sides with d_j' yields

$$d_j' S d_j = \lambda,$$

which is just the expression to be maximized in (2). It follows that d_j^* is the eigenvector of S associated with the largest eigenvalue. To solve the problem, it is therefore sufficient to calculate the eigenvector decomposition of S and extract the eigenvector associated with the largest eigenvalue. This returns the impact vector $A_0^* d_j^*$ of the identified shock.

Maximizing the share of the forecast error variance of two variables. The problem from (1) can be adapted to identify a shock that maximizes the share of the FEV of two variables. The problem becomes

$$\max_{d} \mu d' S_1 d + (1 - \mu) d' S_2 d \;\; \text{s.t. } d'd = 1,$$

where S_i is the matrix that sums the shares of the FEV of variable $i, i = 1, 2$, and μ is the relative weight between the two shares of the FEV. The Lagrangian reads

$$\mathcal{L} = \mu d' S_1 d + (1 - \mu) d' S_2 d - \lambda(d'd - 1)$$

and the first order condition is

$$\mu S_1 d + (1 - \mu) S_2 d = \lambda d$$
$$\Leftrightarrow [\mu S_1 + (1 - \mu) S_2] d = \lambda d.$$

It follows that the vector d is an eigenvector of the weighted sum of S_1 and S_2. Multiplying both sides with d' again implies that d is the eigenvector associated with the largest eigenvalue.

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[12]Because S is symmetric: $\frac{\partial d' S d}{\partial d} = 2 S d.$

In the following, I describe the recursive identification and its implementation. It is recursive in the sense that each shock is identified conditional on the previously identified shock(s).

Surprise technology shock and news shock. Following Barsky and Sims (2011), the assumption is that technology is driven by two shocks. More precisely, it is driven by a surprise technology shock, that drives TFP contemporaneously and a news shock that drives TFP in the future. For example, the process $tfp_t = tfp_{t-1} + \varepsilon_t^{surprise} + \varepsilon_{t-j}^{news}$ with $j > 0$ would satisfy this assumption.

The surprise technology shock is identified as the only one driving TFP contemporaneously. With TFP ordered first in the VAR, the surprise technology shock is then identified as the first column of the Cholesky decomposition and is simply the reduced form innovation in TFP, $u_{1,t}$.[13]

Next, the news shock is identified as the shock that maximizes the share of the residual FEV of TFP between 0 and 40 quarters and is orthogonal to the identified surprise technology shock.[14] The shock is identified by maximizing its contribution to the *residual* FEV, because a part of the FEV is explained by the already identified surprise technology shock.

We solve the problem

$$\max_{\bar{d}_2} \bar{d}_2' S \bar{d}_2 \quad \text{s.t.} \quad \bar{d}_2' \bar{d}_2 = 1, \ \bar{d}_2(1) = 0,$$

where the subindex 2 signifies that (without loss of generality) $\bar{d}_2$ is the second column vector of the matrix $\bar{D}$. The first constraint ensures that $\bar{d}_2$ has unit length as $\bar{D}$ needs to be orthonormal. The second constraint ensures that the news shock is orthogonal to the surprise technology shock and does not drive TFP on impact. Given the zero entry in $\bar{d}_2(1)$, this problem is equivalent to taking the eigenvalue decomposition (see above) of the lower $(N-1) \times (N-1)$ submatrix of S. Ordering the eigenvectors by their eigenvalues—from the highest to the lowest—gives an orthonormal basis that fills out the lower $(N-1) \times (N-1)$ block of the matrix $\bar{D}$. The first column of $\bar{D}$ is the unit vector e_1 such that the first column of the Cholesky matrix A_0^* and thus the identification of the surprise technology shock is unchanged. The matrix $\bar{D}$ is then orthonormal and the new candidate impact matrix for the subsequent identification of the financial shock is $\bar{A}_0 = A_0^* \bar{D}$. The first and the second column of $\bar{A}_0$ are the impact vectors of the surprise technology shock and the news shock, respectively.

Financial shock. The financial shock is identified as the shock that maximizes the share of the residual FEV of the financial condition index between zero and four quarters and is orthogonal to the surprise technology shock and the news shock.[15] This financial shock captures fluctuations in financial conditions that are unrelated to innovations in technology.

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[13]Given that the surprise technology shock is the only one driving TFP on impact, with $A_0 \varepsilon_t = u_t$, it follows that $u_{1,t} = A_0(1,1)\varepsilon_{1,t}$, as $A_0(1,n) = 0, n > 1$. The impact vector is then determined uniquely. Because it must be that $A_0 A_0' = \Sigma$, it follows $\sigma_{1,1} = A_0(1,1)^2, \sigma_{1,2} = A_0(1,1)A_0(1,2)$ etc. The first column of A_0 is the impact vector of the surprise technology shock and determined uniquely.

[14]The choice $H = 40$ follows Barsky and Sims (2011) and Levchenko and Pandalai-Nayar (2015).

[15]Choosing a different horizon, say $H = 2, 6$ or 8, leads to results that are qualitatively and quantitatively very similar.

Therefore, $\bar{A}_0 = A_0^* \bar{D}$ is the new candidate impact matrix and we look for a vector $\tilde{d}_3$ of an orthonormal matrix $\tilde{D}$. Setting $\tilde{d}_1 = e_1$ and $\tilde{d}_2 = e_2$ ensures that the previously identified technology and news shocks are held fixed. The restrictions that the first two columns of $\tilde{D}$ are the first two unit vectors and that $\tilde{D}$ is orthonormal implies that the first two entries of the remaining column vectors are zero. The column vector corresponding to the impact vector of the financial shock is thus the solution to the following problem:

$$\max_{\tilde{d}_3} \tilde{d}_3' S \tilde{d}_3 \quad \text{s.t.} \ \tilde{d}_3' \tilde{d}_3 = 1, \ \tilde{d}_3(1) = \tilde{d}_3(2) = 0.$$

Given the restriction that the first two entries are zero, solving this problem is again equivalent to taking the eigenvector decomposition of the $(N-2) \times (N-2)$ lower submatrix of S and finding the eigenvector associated with the largest eigenvalue. Again, the remainder of $\tilde{D}$ can be filled with the remaining eigenvectors. The new candidate impact matrix for the identification of the confidence shock is thus $\tilde{A}_0 = \bar{A}_0 \tilde{D}$.

Confidence shock. The confidence shock is identified as the shock that maximizes the share of the residual FEV of the forecast of GDP and the confidence index between zero and two quarters conditional on the two technology shock and the financial shock.[16] That is, the shock explains fluctuations in the forecast of GDP and confidence that are unrelated to movements in TFP or innovations on the financial market. Movements in the forecast of GDP and consumer confidence that are related to information about TFP and shocks on the financial market should be accounted for by the previous three shocks.

Mechanically, the identification of the confidence shock works in the same manner as for the news shock and the financial shock. However, we now look for a vector d that maximizes the contribution to the FEV of two variables. Therefore, we have two S-matrices, S_{gdpf} for the forecast of GDP and S_{conf} for the confidence index. In order to hold the three previously identified impact vectors constant, the new candidate matrix that enters S_{gdpf} and S_{conf} is $\tilde{A}_0$ and the first three columns of the new orthonormal matrix $\hat{D}$ are the first three unit vectors. The problem is then

$$\max_{\hat{d}_4} \hat{d}_4' [\mu S_{gpdf} + (1-\mu) S_{conf}] \hat{d}_4 \quad \text{s.t.} \ \hat{d}_4' \hat{d}_4 = 1, \ \hat{d}_4(1) = \hat{d}_4(2) = \hat{d}_4(3) = 0.$$

With the restriction that the first three entries of $\hat{d}_4$ are zero, the problem can be solved by taking the eigenvalue decomposition of the lower $(N-3) \times (N-3)$ submatrix of the weighted sum of S_{gdpf} and S_{conf}. We again look for the eigenvector associated with the largest eigenvalue, place it in the fourth column and fill out the remainder with the remaining eigenvectors. Finally, the impact matrix with the identified shocks is then $\hat{A}_0 = \tilde{A}_0 \hat{D} = A_0^* \bar{D} \tilde{D} \hat{D}$. By construction, $\hat{A}_0$ satisfies the condition that $\hat{A}_0 \hat{A}_0' = \Sigma$. The first four columns of $\hat{A}_0$ are then, in this order, the impact vectors of the surprise technology shock, the news shock, the financial shock and the confidence shock.

In the baseline specification, I choose $\mu = 0.5$, that is, the confidence shock maximizes the share of the FEV of the two variables equally.[17]

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[16]In the baseline specification I choose $H = 2$, following Levchenko and Pandalai-Nayar (2015). Choosing a longer horizon, say, four or eight quarters does not change the results qualitatively.

[17]The value of μ does not influence the propagation mechanism of the confidence shock qualitatively but

3 Results

This section presents the results. In 3.1, I compare the properties of the confidence shock across the two VAR specifications and show that while the IRFs and the contribution to the FEV are largely similar, the pattern of shocks can differ in specific episodes. Section 3.2 exemplifies this result by looking at counterfactuals during recessions which assess the contribution of confidence shocks to the fall in GDP. In 3.3, I isolate the effect of financial conditions on the propagation of confidence shocks. Finally in 3.4, I show that the specification with the financial block can disentangle financial shocks and confidence shocks relatively well.

3.1 Comparison of the two structural VAR specifications

In order to assess the impact of augmenting the VAR with the financial block, I first discuss the propagation of the identified shocks in the smaller VAR specification with TFP, consumption, GDP, hours worked, the forecast of GDP and the consumer confidence index only. Since this specification does not include any financial variables, I do not identify a financial shock. The identified confidence shock is ordered third, conditional on the surprise technology shock and the news shock. Therefore, the identified confidence shocks can only be compared up to a certain degree across the two structural VAR specifications. In particular, I only compare the qualitative shape of the propagation and not the amplitude.

3.1.1 VAR without the financial block

Figure 1 shows the IRFs to a confidence shock for the first, small, specification. TFP decreases initially, however, the response is zero after one year. This is consistent with the identification restriction that the confidence shock does not move current or future TFP. The shock leads to a positive co-movement of consumption, GDP and hours worked. The responses revert to zero after 10 quarters and turn slightly negative thereafter. This pattern reflects a rather short-lived transitory effect of the confidence shock. These responses are similar to Levchenko and Pandalai-Nayar (2015) except that in their specification it takes longer for the response to return to zero. The main reason for this difference seems to be that they include the financial crisis in their sample (see 4.1). Table 1(a) presents the contribution by the confidence shock to the FEV. The confidence shock explains the majority of the FEV of GDP, hours worked and consumer confidence up to a horizon of one year. The confidence shock still explains 51 percent of the FEV of consumer confidence and 44 percent of the FEV of hours worked at the five-year horizon. For consumption, the shock explains 17 percent of the FEV on impact.

Figures 9 and 10 in the Appendix depict the responses of the variables to the surprise technology and news shocks. The response of TFP to its own innovation is transitory. Consumption, GDP and the forecast of GDP increase on impact and then revert back, whereas the response of hours worked is negative. Consumer confidence is positive on impact and reverts back and is negative 15 quarters after impact. In response to the news shocks, TFP increases and has a peak response around 15 quarters after impact. Consumption

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affects (by construction) the contribution to the FEV between the forecast of GDP and consumer confidence.

Figure 1: Confidence shock; small VAR.
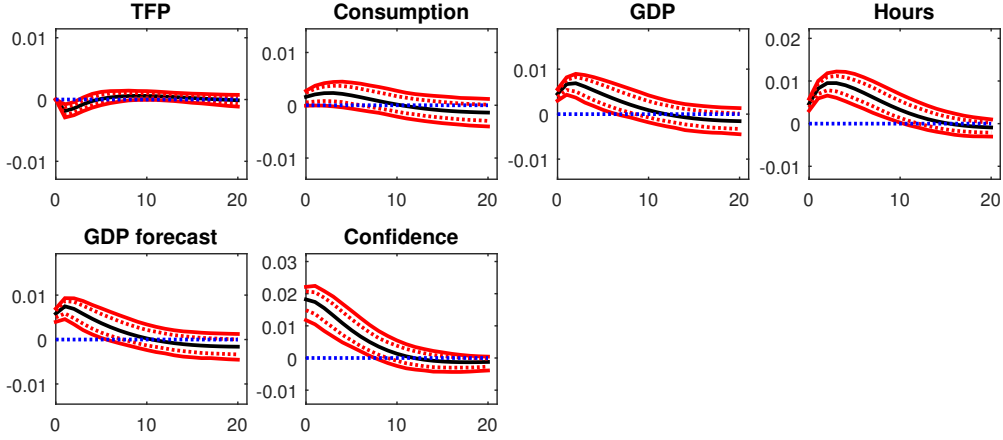
Table 1: FEV contribution of the confidence shock

| | (a) w/o financial block | | | | | (b) w/ financial block | | | | |
	impact	2Q	1Y	2Y	5Y	impact	2Q	1Y	2Y	5Y
TFP	0	0.04	0.03	0.02	0.01	0	0.02	0.01	0.01	0.01
Consumption	0.17	0.16	0.14	0.09	0.05	0.18	0.18	0.16	0.11	0.05
GDP	0.53	0.66	0.55	0.37	0.19	0.43	0.50	0.35	0.22	0.11
Hours	0.68	0.80	0.77	0.66	0.44	0.53	0.59	0.49	0.35	0.22
GDP Forecast	0.65	0.64	0.51	0.34	0.19	0.53	0.47	0.33	0.20	0.10
Confidence	0.66	0.65	0.61	0.56	0.51	0.74	0.60	0.50	0.38	0.32
Financial Conditions	-	-	-	-	-	0.01	0.01	0.01	0.05	0.05
S&P 500	-	-	-	-	-	0.02	0.01	0.01	0.01	0.01
Credit	-	-	-	-	-	0.05	0.15	0.23	0.25	0.13
Investment	-	-	-	-	-	0.16	0.44	0.33	0.20	0.17

is higher on impact and initially rises before it reverts back to zero, as does consumer confidence. GDP and hours worked rise slowly, and the response of hours worked is negative on impact.

3.1.2 VAR with the financial block

Here I add the financial block to the VAR and study the propagation of the confidence shock of the augmented VAR. Given the tight connection between confidence and the financial sector (c.f. Myohl and Stucki, 2018), one would expect the financial block to have an impact on the propagation mechanism. Indeed, many coefficients on the lags of the financial block are significantly different from zero. Moreover, the series of the financial block Granger cause the series of the smaller VAR specification and, in particular, the confidence index

Figure 2: Confidence shock; augmented VAR
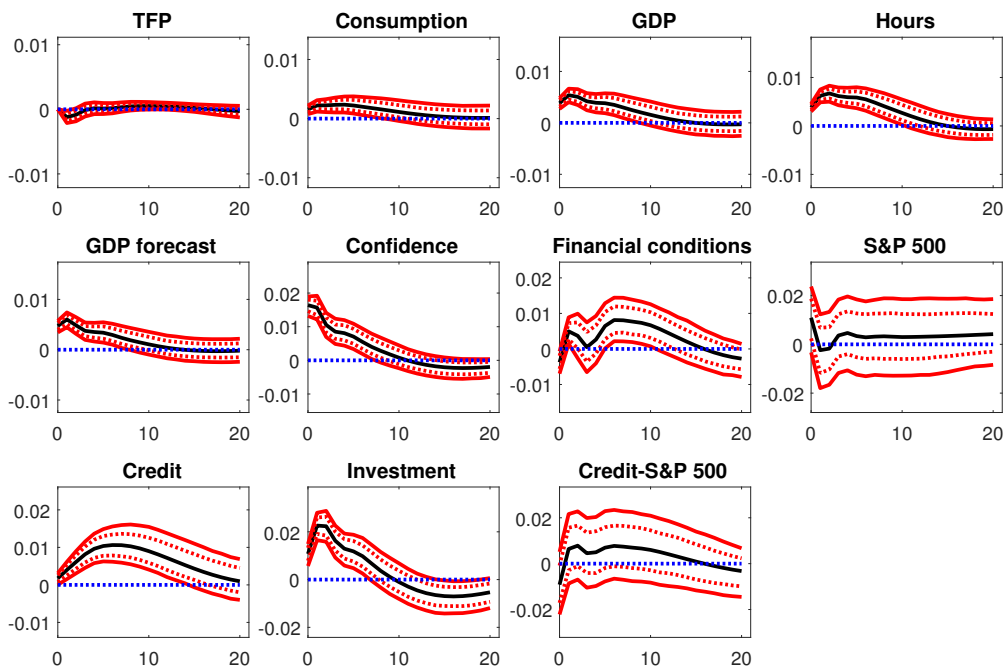
Note: Confidence bands are obtained with 2000 bootstrap replications and cover 68% and 90%. Bias-correction of the IRFs and computation of the confidence bands has been implemented as in Kilian (1998).

series.[18]

However, Figure 2 shows that the responses to a confidence shock are largely similar to those described in Figure 1.[19] The response of TFP is again zero, suggesting that the identified shock is orthogonal to movements in current or future TFP. Also, the shock leads to the same co-movement in consumption, GDP and hours. One observable difference is that at the horizon of twenty quarters, the 68% confidence bands now includes zero for consumption, GDP and hours worked. The response of consumer confidence is also comparable between the two specifications. Initial optimism falls below zero after 15 quarters, just as in the previous specification without the financial block. To sum up, there is no considerable difference in the IRFs between the two specifications.

Nevertheless, the financial condition index is clearly impacted by the identified confidence shock. Financial conditions are significantly looser than average on impact but are tighter than average between five and up until ten quarters after impact. Thus, the confidence shock leads to a significant and prolonged tightening in financial conditions after five quarters. The confidence shock also leads to an expansion in credit and investment on impact, which are therefore co-moving with consumption, GDP and hours. In contrast, the stock market index does not increase. The response of investment shows a hump shape and becomes significantly negative after 15 quarters, possibly as a result of the tight financial conditions.

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[18]I conduct a Wald test following Lütkepohl (1993). The Null hypothesis that the financial block is not Granger-causal for the first block can be rejected with a p-value of 0.00.

[19]Of course, these two specifications could simply be observationally equivalent in terms of the observed IRFs.

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As a measure of leverage in the economy, I also graph the response of credit over the stock market. The median response of leverage is positive after a couple quarters, but the response is not significant. The result of the response of investment falling below zero is consistent with Myohl and Stucki (2018). In Myohl and Stucki (2018), entrepreneurs overleverage their net worth following a confidence shock. The overleveraging eventually leads to a depressed net worth and subsequently to a fall in investment below its long-run trend.

The contribution to the FEV of the confidence shock gives a similar picture as without the financial block (see Table 1). Overall, the numbers are the same or a little lower. The lower numbers can partly be explained because the confidence shock is now identified conditional on the financial shock. However, the confidence shock still accounts for a sizable contribution to the FEV. The confidence shock explains up to 50 percent of the FEV in GDP and more than half of the variation in hours worked on impact and at the two-quarter horizon. It also explains 18 percent of the FEV in consumption at the same horizon. On impact, the confidence shock now explains more of the FEV of the confidence index compared to the VAR without the financial block. The contribution to the FEV of TFP and the financial condition index is almost zero, indicating that the identified confidence shock is not polluted by a shock driving TFP or financial conditions. The confidence shocks also explain very little of the FEV of the stock market, which is primarily explained by the news shock and the financial shock. Further, the confidence shock explains a sizable portion of the FEV of credit and investment. For example, at a horizon of two quarters, the confidence shock explains 44 percent of the FEV of investment and more than the financial shock at most horizons (see Tables 1(b) and 2(a) in the Appendix).

Figure 11 in the Appendix depicts the IRFs to the financial shock. TFP slightly increases and then decreases but is zero in the medium run. Financial conditions are significantly looser than average but tighten over time. After five quarters, financial conditions are tighter than average and the peak response is ten quarters after impact. Consumption increases on impact and over time, while the responses of GDP, hours worked, and consumer confidence are zero on impact and increase over time. Overall, the financial shock also leads to a positive co-movement. In particular, credit has a similar response as GDP and hours. Interestingly, the response of investment is significantly negative on impact but turns quickly positive and begins to revert back to zero once financial conditions are tighter than average. The stock market increases significantly and the response is still positive after 20 quarters. With a relatively weaker response in the expansion of credit, leverage, measured as credit over the stock market is significantly lower.

Figures 12 and 13 in the Appendix show the responses to the surprise technology shock and the news shock. The propagation of the surprise technology is similar to the VAR without the financial block. Investment increases on impact and financial conditions are tighter than average after five quarters. The response of credit is negative and the response of the stock market is zero and negative after 20 quarters. The news shock also leads to a similar response of all variables. Financial conditions are looser than average after three quarters and then revert back to the average. The response of the stock market to the news shock is positive, and credit and investment also increase with a peak response after seven quarters.

Overall, the IRFs and the FEV decomposition of the augmented VAR with a financial

Figure 3: Scatter plot of identified confidence shocks
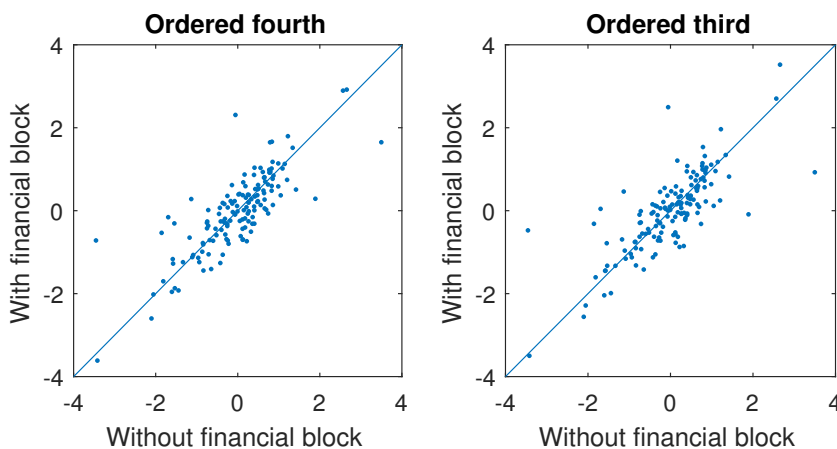
Note: Scatter plot of identified impulses of the small VAR against the augmented VAR. Left: specification where the confidence shock is ordered fourth (baseline). Right: specification where the confidence shock is ordered third. The blue line is the 45°- line.

sector do not change much from the VAR without the financial sector. And this is true not only for the confidence shock but also for the surprise technology shock and the news shock.

However, the identified impulses can have a different magnitude across the two specifications. In Figure 3, I compare the identified confidence shocks with and without the financial block when the shock is identified fourth (left panel) and when it is identified third (right panel). The impulses are scattered relatively close around the 45°-line: The correlations are 0.81 and 0.77, respectively.[20] While at times the identified impulses are very similar, they can differ substantially. This suggests that there are episodes where the inclusion of the financial block is potentially important. I explore this idea with the help of counterfactuals in the next subsection.

3.2 Historical counterfactuals

In this section, I discuss historical counterfactuals of US recessions since 1971, shutting off one identified shock at a time. The counterfactuals begin at the start of the recession and simulate how GDP evolves in the absence of, say, the confidence shock. This exercise tells us how much this shock contributed to the fall of GDP during the recession. I first show in 3.2.1 that when I control for the financial sector and financial shock, the counterfactual may assign a smaller role to confidence shocks. I then discuss the contribution of financial and confidence shocks during the same recessions in 3.2.2.

3.2.1 Does the financial block matter?

Figure 4 shows the evolution of actual GDP (dashed blue), the counterfactual evolution of GDP in the absence of confidence shocks in the VAR without the financial block (red), and

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[20]The right panel in Figure 3 serves as a robustness check to ensure that the difference is not due to the fact that, in the augmented VAR, the confidence shock is identified conditional on an additional shock—the financial shock.

Figure 4: Contribution of confidence shock; small and augmented VAR
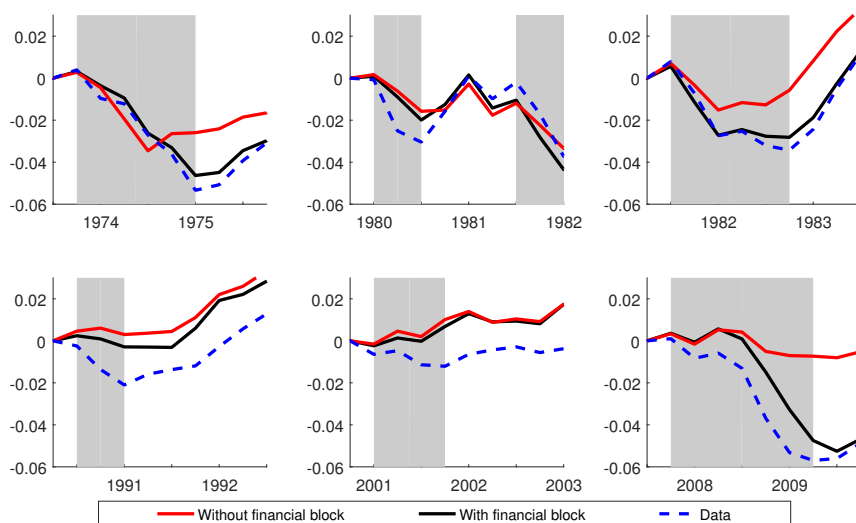
Note: The graphs display the percentage deviation to the quarter before the business cycle peak. Confidence shocks are set to zero from this date onwards.

in the VAR with the financial block (black). Each panel depicts one recession as identified by the NBER's Business Cycle Dating Committee. The grey-shaded area indicates the time between the business cycle peaks and troughs identified by the committee. The series are normalized to equal zero in the quarter before the peak, which is the last quarter where the three series coincide. The graphs thus depict the percentage deviations from this date.[21]

If the two counterfactual series differ substantially from each other, this implies that the two VAR specifications assign a different role to the confidence shock for the evolution of GDP. For example, during the Volcker recession (top right panel), the VAR with the financial block assigns a small role to the confidence shock, as the counterfactual practically coincides with the actual evolution of GDP. In contrast, in the VAR without the financial sector, the fall of GDP is two percentage points lower, hence assigning a significant role to the confidence shock. Similarly, during the Great Recession (bottom right panel), the VAR with the financial block indicates that in the absence of confidence shocks, the trough of GDP is almost as deep.[22] In the VAR without the financial block, however, counterfactual GDP falls about one percent only, assigning a large share of the drop in GDP to confidence shocks. On the other hand, after the dot-com bubble in 2001, a comparable role is assigned to the confidence shock across the two VAR specifications.

This comparison suggests that while the identified confidence shocks do not differ in terms of IRFs and FEV decompositions, in some episodes, historical counterfactuals assign a different role to the contribution of confidence shocks to movements in GDP. That is, for some specific business cycle episodes, the confidence shock is misidentified when the VAR lacks the financial block since the identified confidence shocks play a different role for

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[21]I start the counterfactual in the quarter before the start of the recession; starting the counterfactual one period before or later does not substantially change the counterfactuals.

[22]I extend the sample to 2015Q3 and reestimate the VAR for the counterfactual during the financial crisis.

Figure 5: Contribution of confidence shock and financial shock; augmented VAR
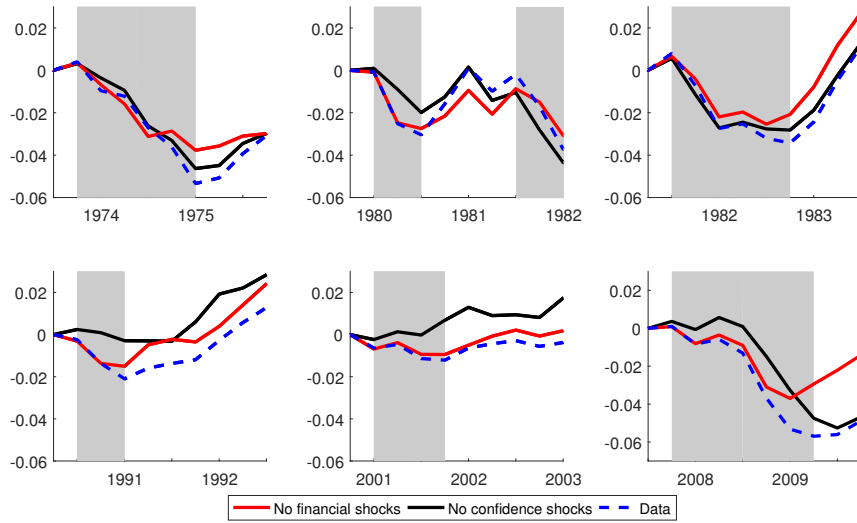
Note: The graphs display the percentage deviation to the quarter before the business cycle peak. Shocks are set to zero from this date onwards.

economic activity.

3.2.2 Historical contribution of confidence shocks and financial shocks

In Figure 5, I consider the augmented VAR and analyze the contribution of financial (red) and confidence shocks (black) during the US recessions. For the 1973–74 recession (first panel), both financial and confidence shocks play a rather small role. In both counterfactuals, the recession ends at the same time and the fall in GDP is 1.6 percentage points lower without financial shocks. In 1980 (second panel), in the absence of confidence shocks, GDP falls by two percent instead of three percent, while the financial shocks do not contribute to the fall in GDP. The counterfactuals during the Volcker recession (third panel) show that without financial shocks, the fall in GDP is around 1 percentage point lower and the economy escapes the recession sooner. The contribution assigned to confidence shocks is even smaller, which is in line with the idea that primarily a monetary policy shock contributed to the recession. For the early 1990s recession (fourth panel), the counterfactual series indicate that without confidence shocks, the fall in GDP is much milder without confidence shocks. GDP barely falls, and the bulk of the recession can be attributed to confidence shocks. A similar picture is observed in the 2001 recession (fifth panel). Without confidence shocks, GDP actually grows after the burst of the dot-com bubble, while financial shocks do not contribute to the fall in GDP. Finally, the sixth panel depicts the Great Recession. The counterfactual series without confidence shock shows that at the beginning of the recession, confidence shocks contribute to the fall in GDP. Two quarters into the recession, GDP is even higher in the absence of confidence shocks. Nevertheless, the fall of GDP is only delayed. The trough is barely higher and delayed by one quarter in the absence of confidence shocks. On the other hand, the financial shock substantially contributes to the fall in GDP. The trough is 3.7

percent below the peak instead of the realized drop of 5.7 percent. In addition, the recovery starts sooner in the absence of financial shocks.

Overall, these counterfactuals are in line with common perceptions about the nature of shocks that caused these recessions. For completeness, Figure 27 in the Appendix displays the counterfactuals where the surprise technology shock and the news shock is shut off.

3.3   Isolating the financial channel

Augmenting the VAR with the financial condition index allows assessing the indirect effect of financial conditions on the propagation of confidence shocks. Variables not only react directly to a confidence shock but also indirectly to (the lags of all) the other variables' responses. I isolate the effect of financial conditions by using the approach of Bachmann and Sims (2012), and Fève, Garcia, and Sahuc (2018) and "shut off" the indirect effect of the financial condition index. More precisely, I feed into the model a series of hypothetical financial shocks that zero out the response of the financial conditions index. Stated differently, at each horizon, I calculate the size of a financial shock that drives the financial condition index back to zero. This exercise answers the following question: How would the economy react to a confidence shock if at the same time the economy is hit concurrently with a series of financial shocks that offset the reaction of the financial condition index to a confidence shock? The comparison between this hypothetical response and the original response allows assessing whether financial conditions matter for the transmission of confidence shocks.

Figure 6 graphs this hypothetical response, together with the IRFs to the confidence shock. The IRFs start to diverge from the original IRFs after around five quarters. The only exception is for TFP, suggesting, that the financial channel does not affect the level of technology. The results indicate that the tighter financial conditions after five quarters have a negative effect and the expansion would be longer lasting if financial conditions were not tightening. More credit would be handed out and investment would not fall below zero. Overall, it takes longer for all responses to return to zero. The identification of the financial channel shows that financial conditions have an impact on the propagation of confidence shocks.

Remark. Of course the other variables also react to the sequence of hypothetical financial shocks, which keeps this a structural exercise. However the size of the shocks are rather small—the mean of the absolute value of the shocks is 0.047 compared to a shock of size one for the confidence shock. As an additional exercise, I perform the following, non-structural, exercise: Instead of feeding hypothetical financial shock into the system, I assume there is an additional shock that drives the financial condition index back to zero and does not affect any of the other variables.[23] These IRFs are quite similar, especially for GDP, hours worked, confidence, and investment (see Figure 14 in the Appendix).

3.4   Disentangling confidence and financial shocks

Figures 2 and 11 in the Appendix show that the IRFs and thus the propagation of the financial and the confidence shock differ substantially. While both lead to a positive comovement

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[23]Mathematically this is equivalent to simply deleting the row and column with the financial condition index in the structural VAR and then computing the IRFs with this shrunk VAR. This gives the same outcome as when I simply fix the financial condition index at zero for all lags.

Figure 6: Isolating the financial channel
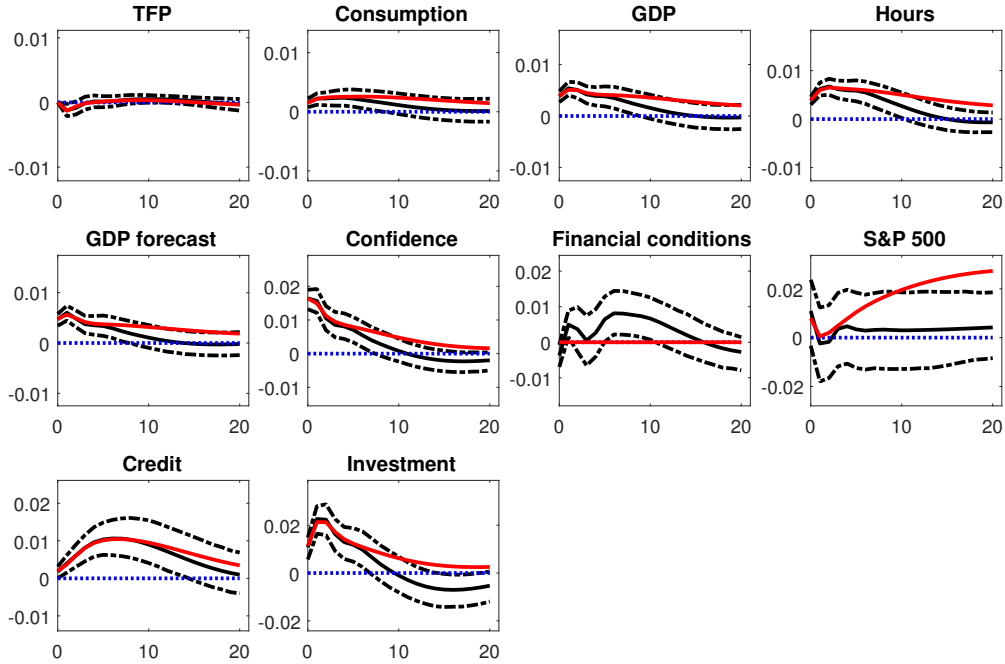
Note: Red: IRFs to the confidence shock where, in addition, concurrent hypothetical financial shocks offset the response of the NFCI to the confidence shock. Black: Original IRFs to a confidence shock with 90% Bootstrap confidence bands.

in consumption, GDP, hours worked, and consumer confidence (and to a lesser degree also in credit and investment), the impact responses differ. The variables are positive on impact following a confidence shock. In contrast, the IRFs to the financial shocks are zero on impact and rise over time. The response of the stock market also differs: It is positive following a financial shock but zero in response to the confidence shock.

However, since the shocks are identified recursively, the possibility remains that the financial shock is polluted by the confidence shock. I, therefore, change the recursive identification ordering to see whether my identification scheme would identify a different financial shock if it is identified conditional on the two technology shocks and the confidence shock. After identifying the confidence shock ordered third, I also identify the financial shock in the same manner as before but conditional on the confidence shock, and thus ordered fourth. Figure 7 compares the identified structural financial shocks (left panel) and the confidence shocks (right panel). The x-axis indicates the size of the identified impulses when the shock is ordered third and the y-axis indicates their size when the shock is ordered fourth. Clearly, the identified shocks are scattered closely around the 45°line—the correlation is 0.98 for both panels. Therefore, the identification scheme identifies a comparable financial shock when it is identified conditional on the confidence shock. The IRFs and the FEV decompositions are also quite similar.[24]

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[24]See Figures 15 and 16, and Tables 2 and 3 in the Appendix. The contributions to the FEV by the confidence shock are somewhat higher for most horizons and variables if the confidence shock is identified third, compared to when it is ordered fourth. The same is true for the financial shock.

Figure 7: Disentangling
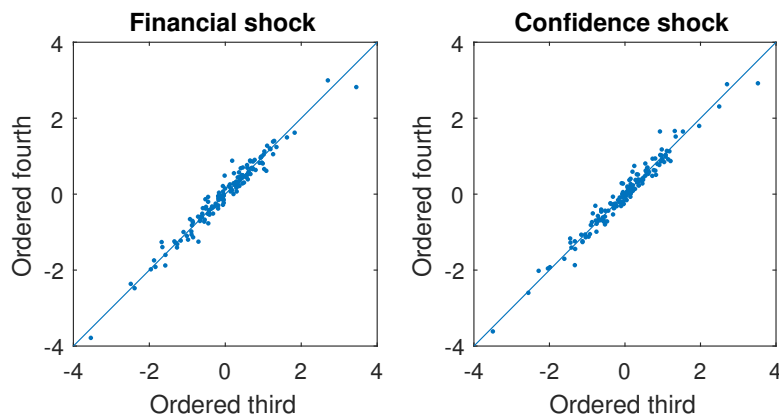
Note: Scatter plot of identified shocks, ordered third vs. ordered fourth. Blue line is the 45°-line.

This exercise of changing the identification ordering suggests that the specification with the financial block can disentangle the confidence shock and the financial shock relatively well. Whether the confidence shock is identified conditional on the financial shock or not has no considerable impact.

4 Robustness

This section discusses robustness with regard to the inclusion of the financial crisis and the replacement of the NFCI with a credit spread index.

4.1 Including the financial crisis

I estimate the same VAR, from 1971Q1–2015Q3 and thus include the financial crisis. Figures 17–20 in the Appendix show that the IRFs are not significantly different except for the IRFs to the financial shock. In the sample that includes the financial crisis, the responses of consumption and GDP are still significantly positive after 20 quarters in response to the financial shock. Similarly, it takes longer for the responses of investment and credit to go back to zero. This suggests that when the financial shock is identified in the sample with the financial crisis, it identifies a shock that has a more permanent effect.[25]

The inclusion of the financial crisis allows looking at the shock pattern between the two VAR specifications during this episode. As seen by the counterfactual in Figure 4, the financial block can play a role for the identified shocks and their effect on economic activity. The left panel of Figure 8 displays the pattern of confidence shocks in the VAR without the financial block (left panel) after 2001. The right panel displays the pattern of confidence and financial shocks in the VAR with the financial block. In 2008Q3–Q4, the VAR without a financial sector identifies large negative confidence shocks, whereas large negative financial

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[25]I also estimated a VAR with the sample 1983Q1–2007Q4 to exclude times when financial conditions were very tight and volatile during the 1970s. The propagation of the confidence shock is quite similar compared to the baseline sample.

Figure 8: Including the financial crisis
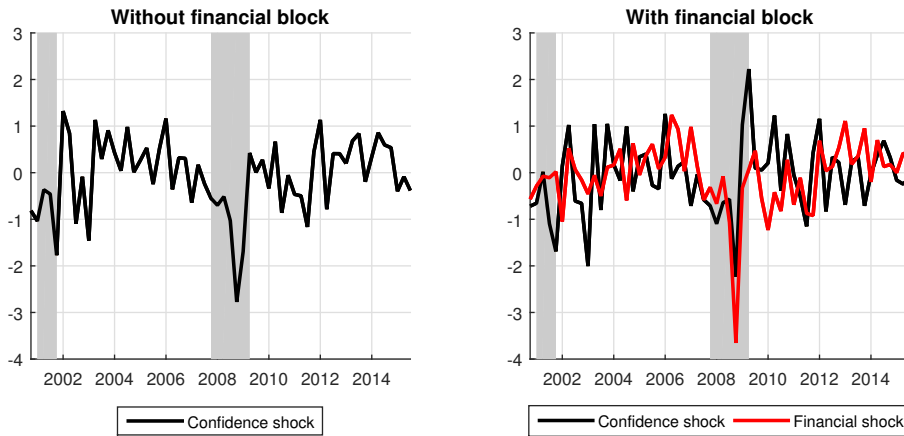
Note: Structural shocks after 2000. Left: VAR without the financial block. Right: VAR with the financial block.

shocks are identified in the VAR with the financial sector and shock. Therefore, in the VAR without the financial block, the identified confidence shock appears polluted by a shock to financial conditions in this episode.

4.2 Replacing the NFCI with a credit spread

Another financial variable that is often used to identify a financial shock is a credit spread. I run the same VAR with the credit spread index of Gilchrist and Zakrajšek (2012) in place of the financial condition index. The credit spread index is constructed of interest rates of corporate bonds on the secondary market over the interest rates of synthetic risk-free securities that feature the same duration as their corporate counterparts. Gilchrist and Zakrajšek (2012) show that their credit spread index has considerable predictive power for economic activity. Replacing the NFCI with the credit spread index does not change the propagation of the confidence shock.[26] Similarly, the propagation of the other shocks are comparable (see Figures 21-24 in the Appendix). However, the recursive identification ordering of the financial and the confidence shock matters as the identified shocks deviate quite a bit, depending on whether the shocks are identified ordered third or ordered fourth (see Figure 25 in the Appendix). The correlation between the identified shocks is only 0.89, for both the confidence shock and the financial shock. This suggests that with the credit spread index in place of the NFCI, the identified financial shock is partially polluted by the confidence shock and the disentangling between financial and confidence shocks is more difficult. Indeed, the financial shock explains up to 40 percent—up from 20 percent in the baseline VAR—of the FEV of the confidence index at the one-year horizon, more than the identified confidence shock (see Table 5 in the Appendix).

Finally, the historical counterfactuals are largely similar. One noticeable difference is that the specification with the credit spread index assigns a much larger role to the financial shock for the Great Recession. In fact, without financial shocks, GDP barely falls (see Figure

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[26]The sample starts in 1973Q1, the first date for which this series is available.

5 Conclusion

This paper investigates how the addition of a financial block to a structural VAR changes the properties of the identified confidence shock. Looking at the propagation of the shock and the contribution of the shock to business cycles in terms of the FEV contribution, there is little difference. However, for specific episodes, controlling for a financial block is important. Especially during episodes where financial markets are in turmoil, such as financial crises, the confidence shock can be misidentified if the VAR specification does not feature a financial block. For example, during the Great Recession, the specification that lacks a financial block falsely identifies a confidence shock as a main driver. This observation, and the identification of the financial channel confirm the commonly held perception that confidence is sensitive to financial conditions and vice versa.

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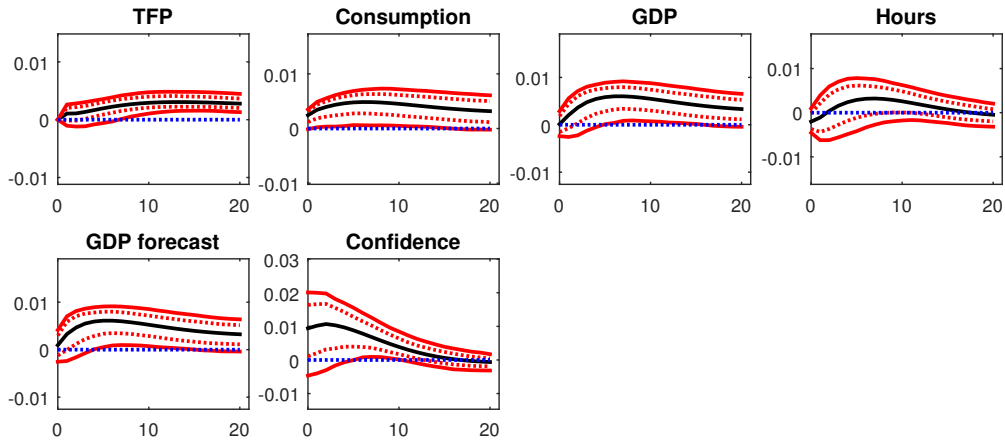
A   Appendix

A.1   Additional figures

Figure 9: Surprise technology shock; small VAR
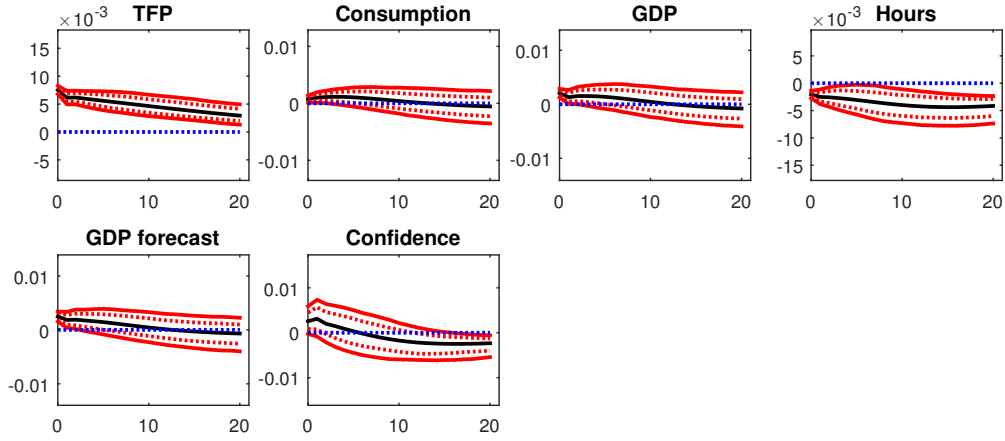
Note: Confidence bands are obtained with 2000 bootstrap replications and cover 68% and 90%. Bias-correction of the IRFs and computation of the confidence bands has been implemented as in Kilian (1998).
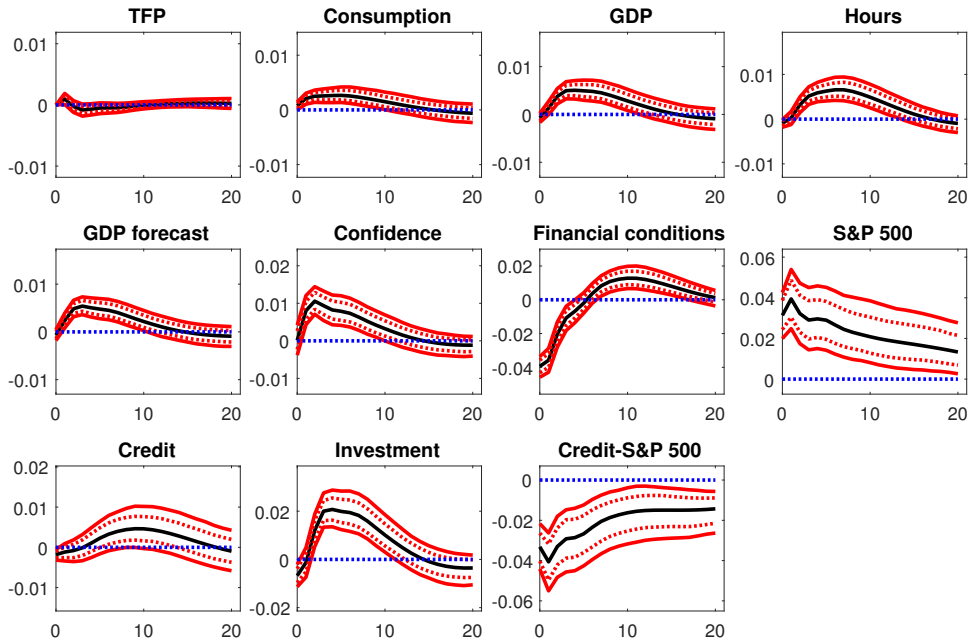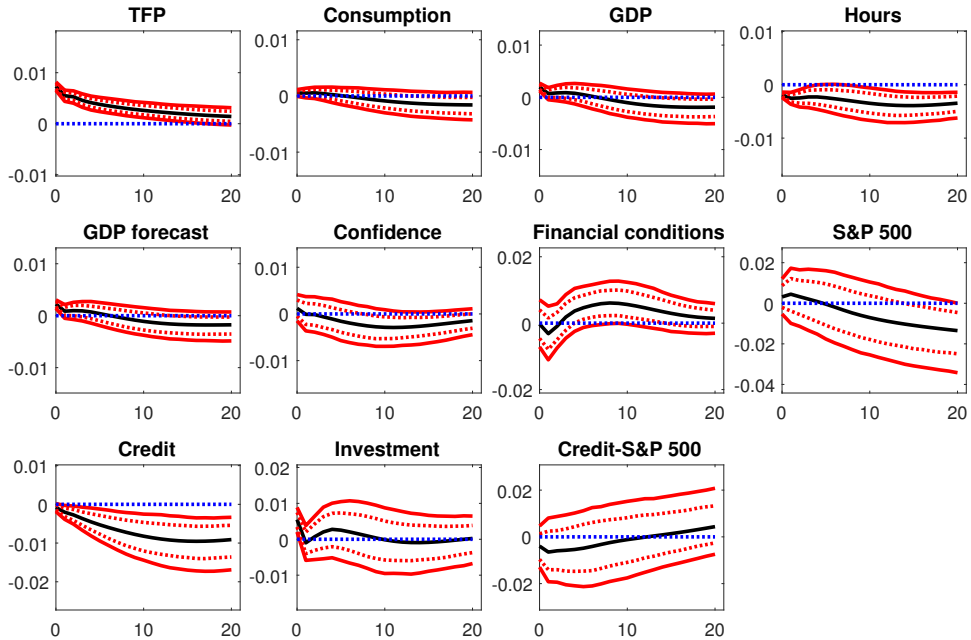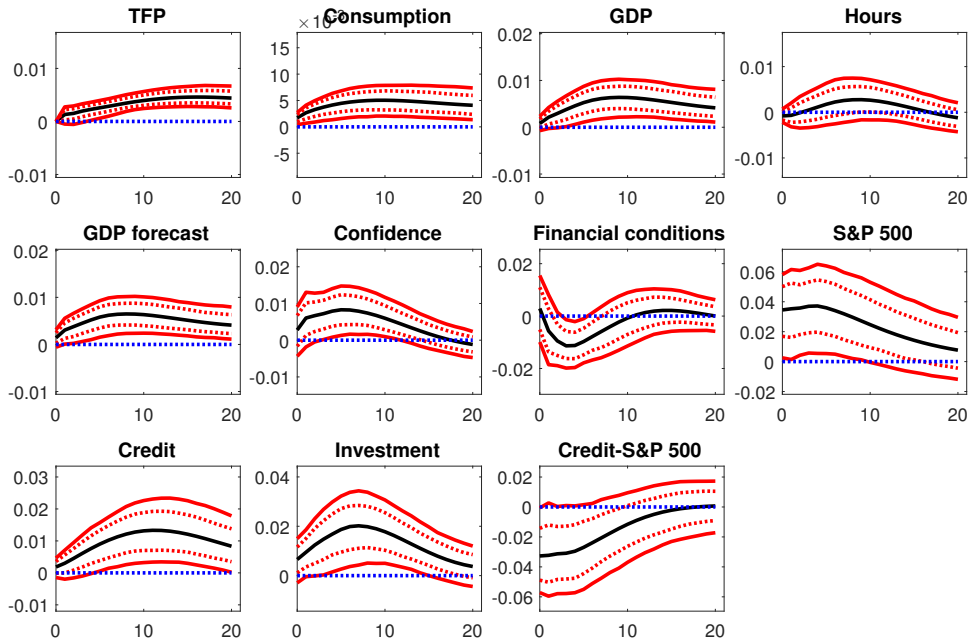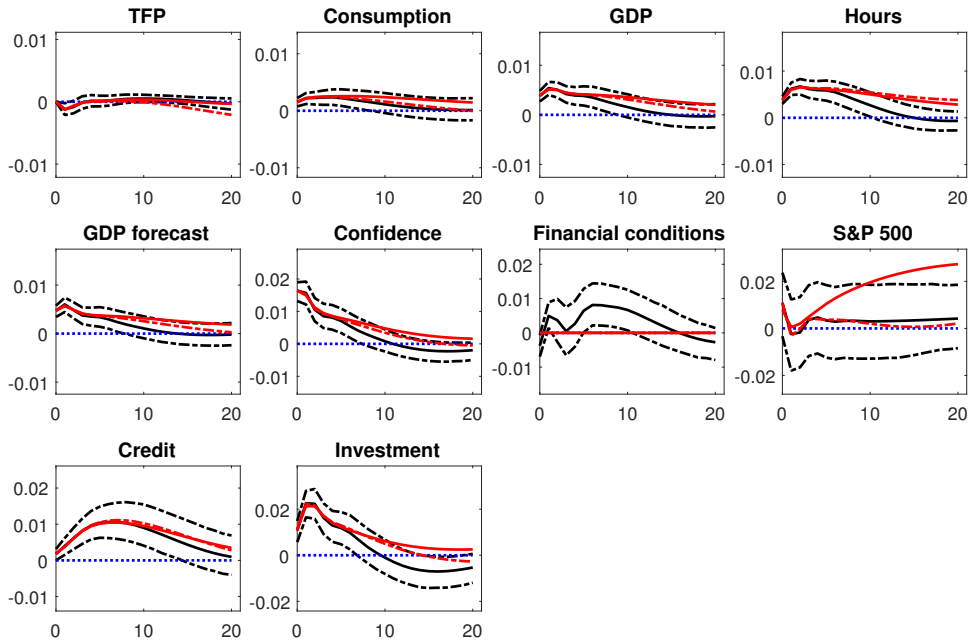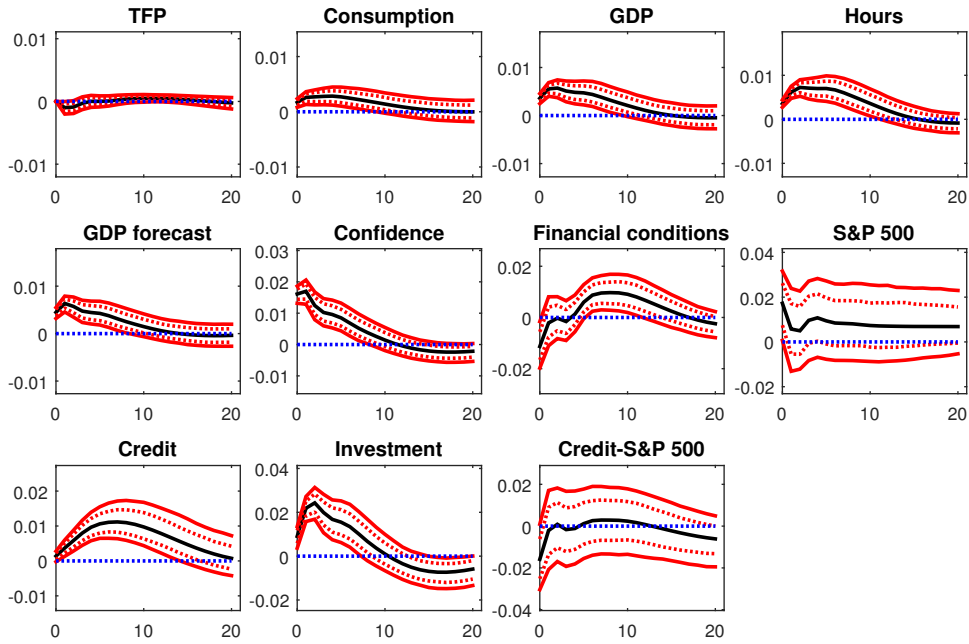
Figure 10: News shock; small VAR

Note: Confidence bands are obtained with 2000 bootstrap replications and cover 68% and 90%. Bias-correction of the IRFs and computation of the confidence bands has been implemented as in Kilian (1998).

Figure 11: Financial shock; augmented VAR

Note: Confidence bands are obtained with 2000 bootstrap replications and cover 68% and 90%. Bias-correction of the IRFs and computation of the confidence bands has been implemented as in Kilian (1998).

Figure 12: Surprise technology shock; augmented VAR

Note: Confidence bands are obtained with 2000 bootstrap replications and cover 68% and 90%. Bias-correction of the IRFs and computation of the confidence bands has been implemented as in Kilian (1998).

Figure 13: News shock; augmented VAR

Note: Confidence bands are obtained with 2000 bootstrap replications and cover 68% and 90%. Bias-correction of the IRFs and computation of the confidence bands has been implemented as in Kilian (1998).

## Figure 14: Isolating the financial channel; alternative

Note: Red: IRFs to the confidence shock where financial shocks offset the response of the NFCI to a confidence shock. Red dashed: IRF of the reduced VAR with the NFCI is fixed to zero. Black: Original IRFs to a confidence shock with 90% Bootstrap confidence bands.

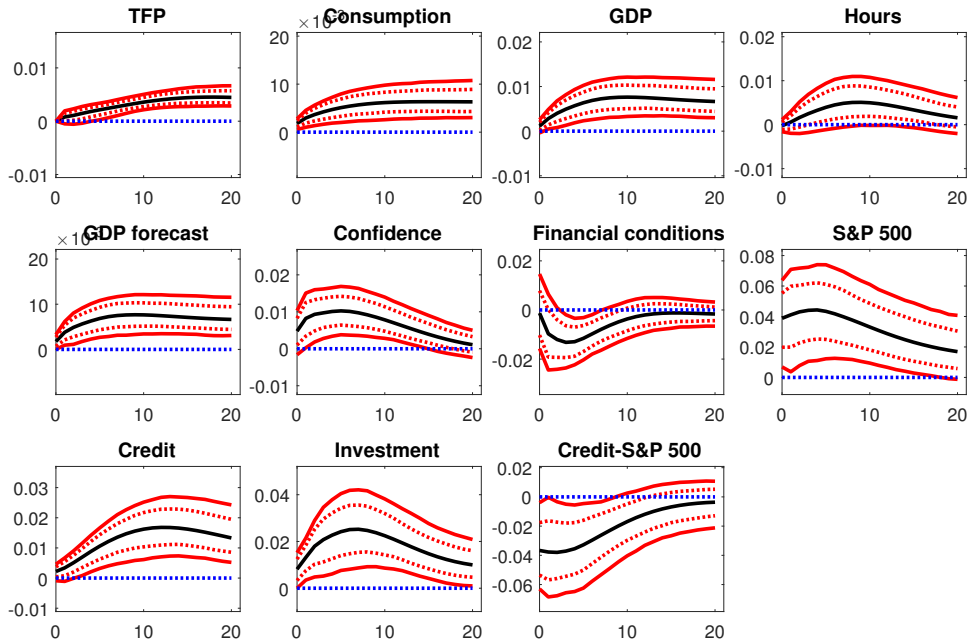Figure 15: Confidence shock, ordered third

Note: Confidence bands are obtained with 2000 bootstrap replications and cover 68% and 90%. Bias-correction of the IRFs and computation of the confidence bands has been implemented as in Kilian (1998).

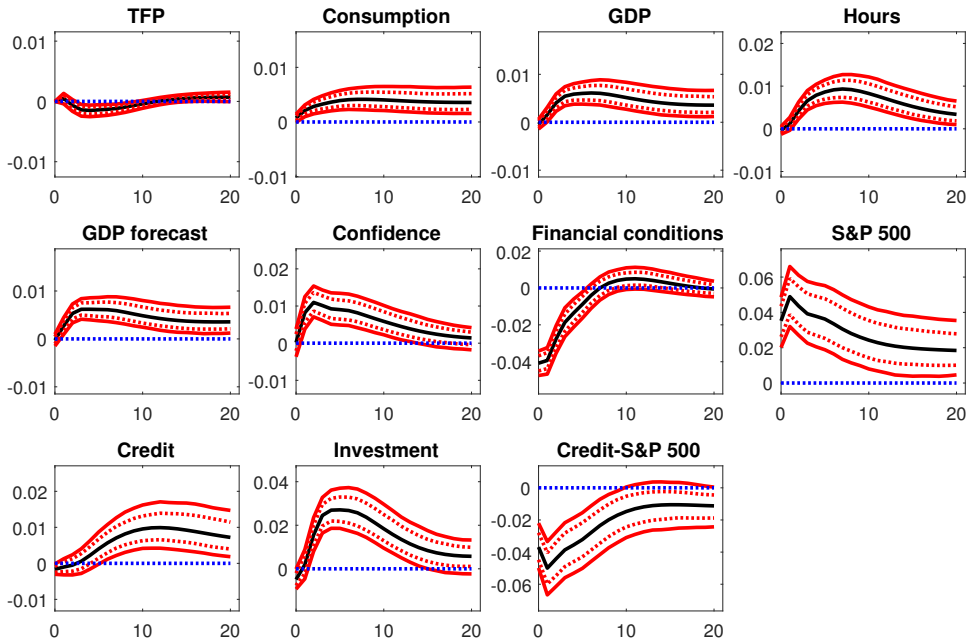Figure 16: Financial shock, ordered fourth
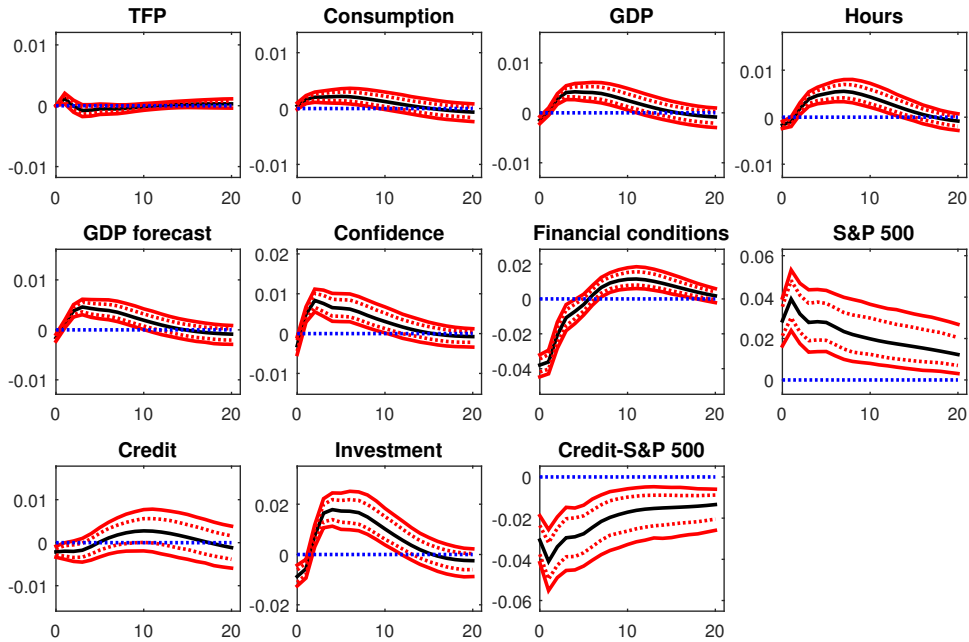
Note: Confidence bands are obtained with 2000 bootstrap replications and cover 68% and 90%. Bias-correction of the IRFs and computation of the confidence bands has been implemented as in Kilian (1998).

Figure 17: Surprise technology shock, 1971Q1-2015Q3.
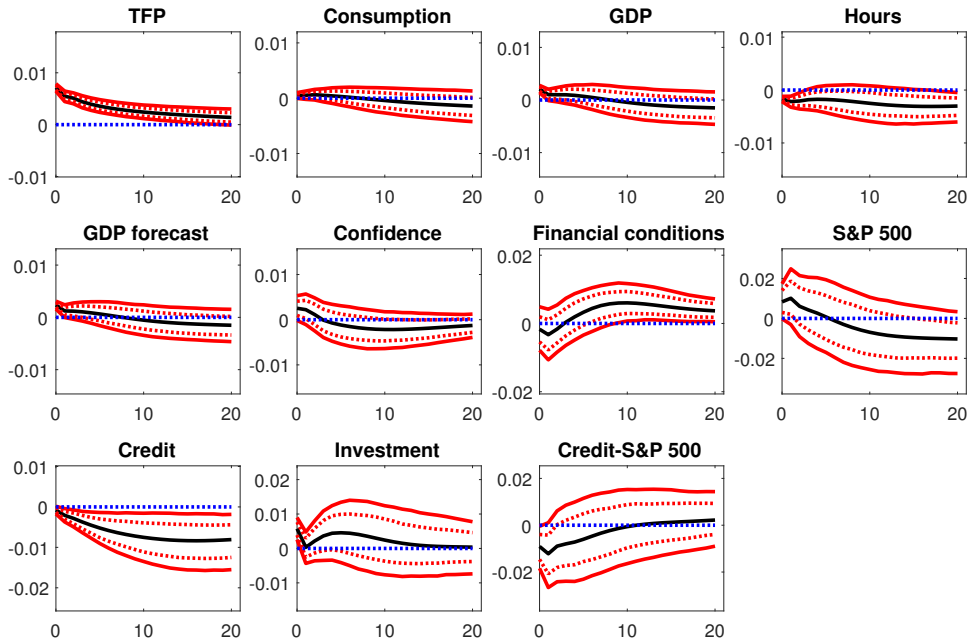
Figure 18: News shock, 1971Q1-2015Q3.

Figure 19: Financial shock, 1971Q1-2015Q3.

Note: Confidence bands are obtained with 2000 bootstrap replications and cover 68% and 90%. Bias-correction of the IRFs and computation of the confidence bands has been implemented as in Kilian (1998).

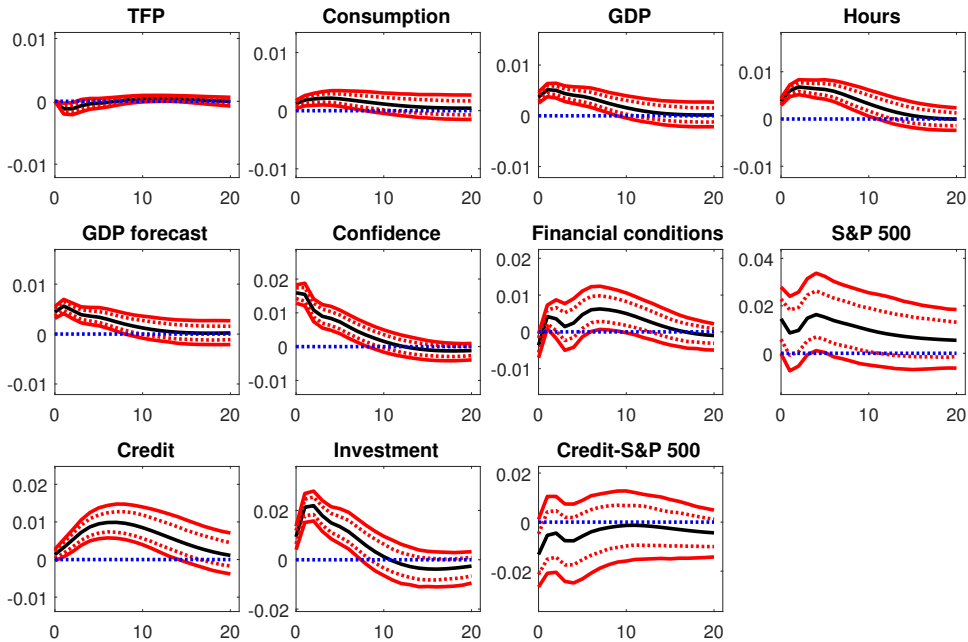Figure 20: Confidence shock, 1971Q1-2015Q3.

Note: Confidence bands are obtained with 2000 bootstrap replications and cover 68% and 90%. Bias-correction of the IRFs and computation of the confidence bands has been implemented as in Kilian (1998).

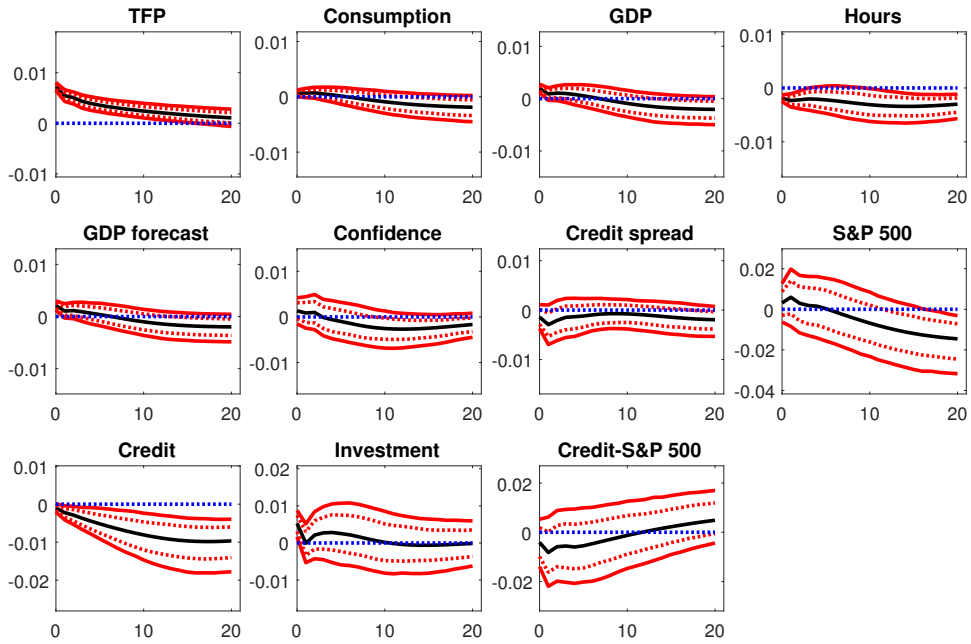Figure 21: Surprise technology shock, GZ credit spread index

Note: Confidence bands are obtained with 2000 bootstrap replications and cover 68% and 90%. Bias-correction of the IRFs and computation of the confidence bands has been implemented as in Kilian (1998).

Figure 22: News shock, GZ credit spread index

Note: Confidence bands are obtained with 2000 bootstrap replications and cover 68% and 90%. Bias-correction of the IRFs and computation of the confidence bands has been implemented as in Kilian (1998).

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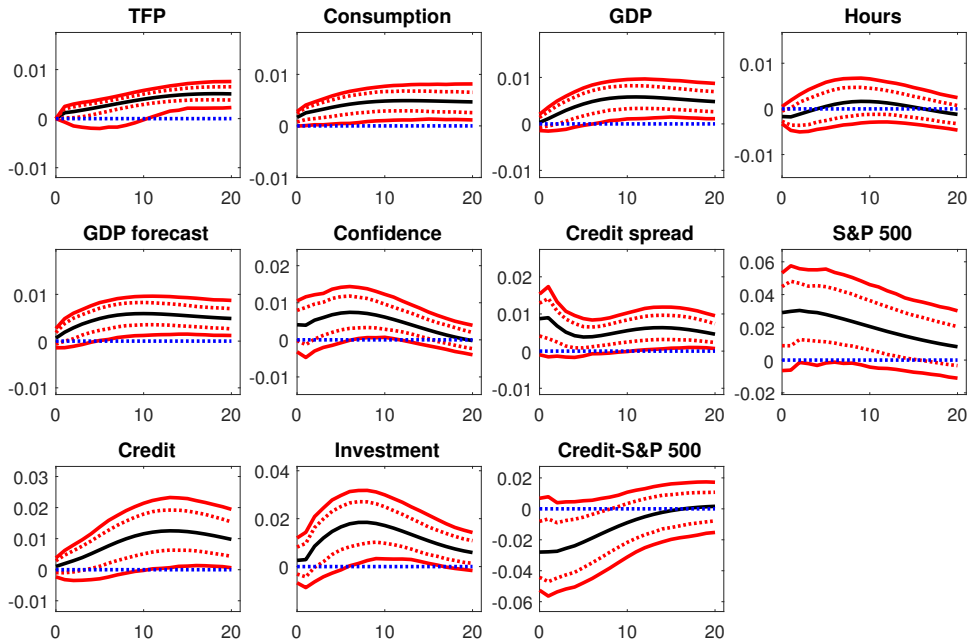## Figure 23: Financial shock, GZ credit spread index

Note: Confidence bands are obtained with 2000 bootstrap replications and cover 68% and 90%. Bias-correction of the IRFs and computation of the confidence bands has been implemented as in Kilian (1998).
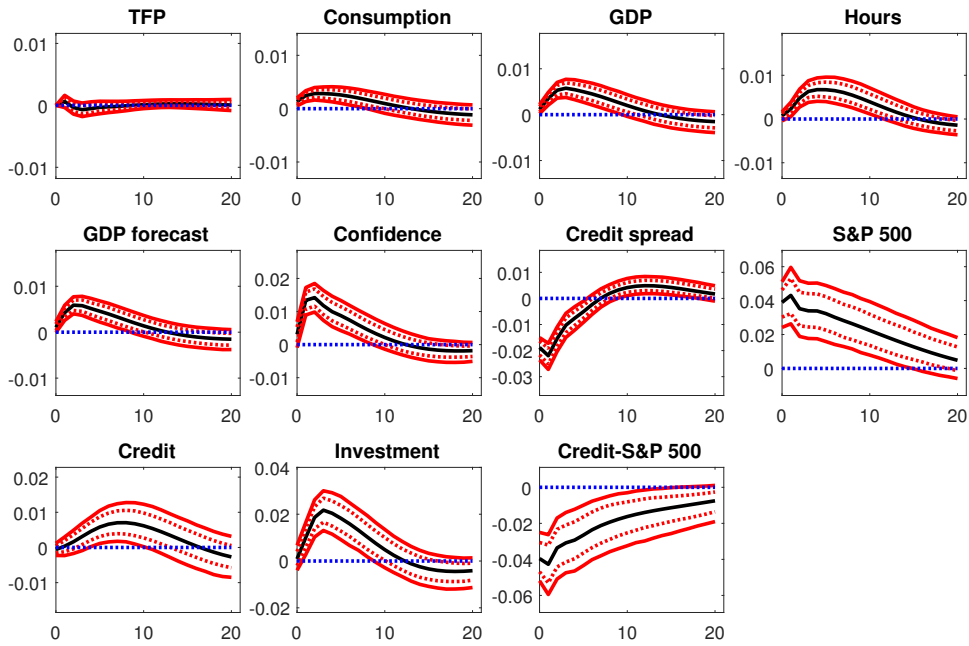
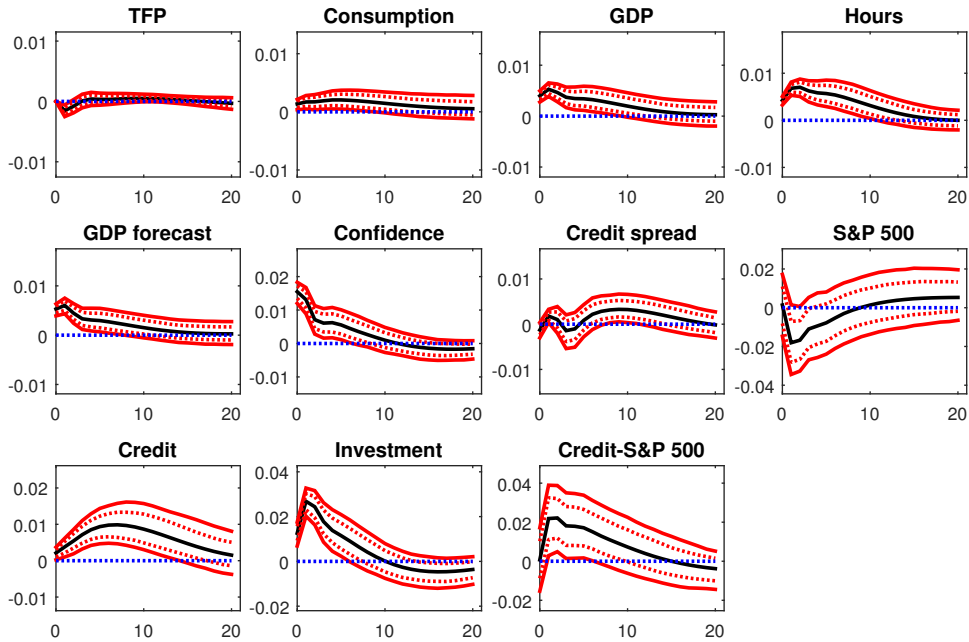## Figure 24: Confidence shock, GZ credit spread index

Note: Confidence bands are obtained with 2000 bootstrap replications and cover 68% and 90%. Bias-correction of the IRFs and computation of the confidence bands has been implemented as in Kilian (1998).

Figure 25: Disentangling: GZ spread index
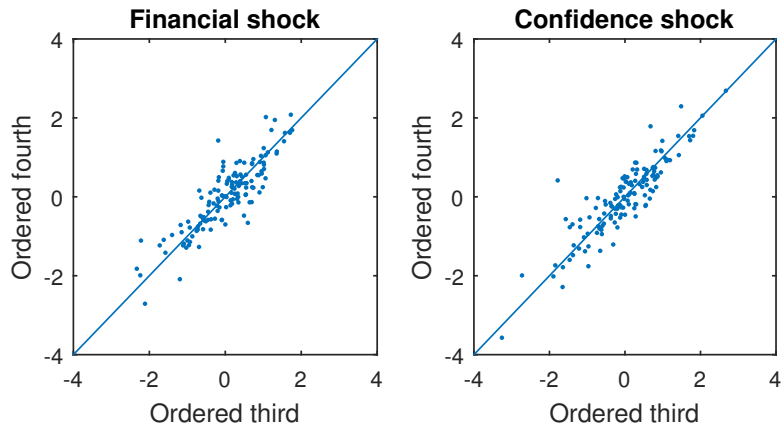
Note: Scatter plot of identified shocks. The NFCI is replaced with the GZ credit spread index.

Figure 26: Contribution of confidence shock and financial shock; GZ spread index
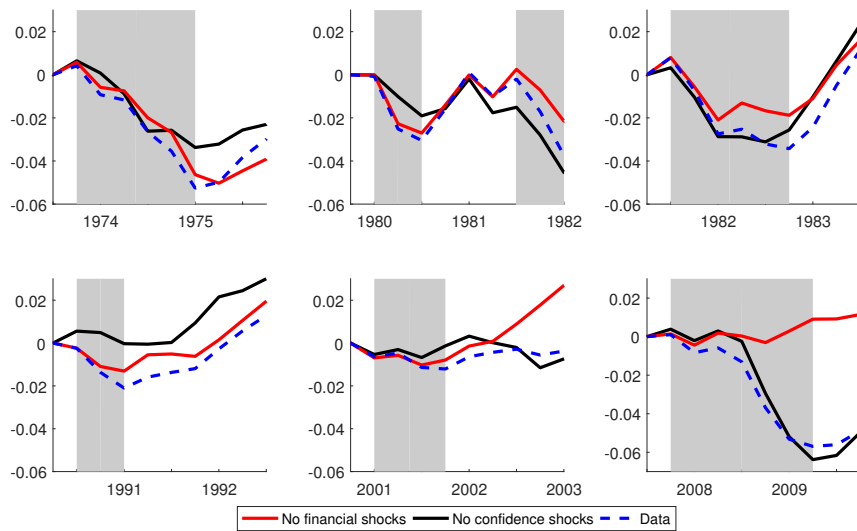
Note: The graphs display the percentage deviation to the quarter before the business cycle peak. Shocks are set to zero from this date onwards.

Figure 27: Contribution of all shocks

Note: The graphs display the percentage deviation to the quarter before the business cycle peak. Shocks are set to zero from this date onwards.

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A.2 Additional tables

Table 2: FEV contribution of the financial shock

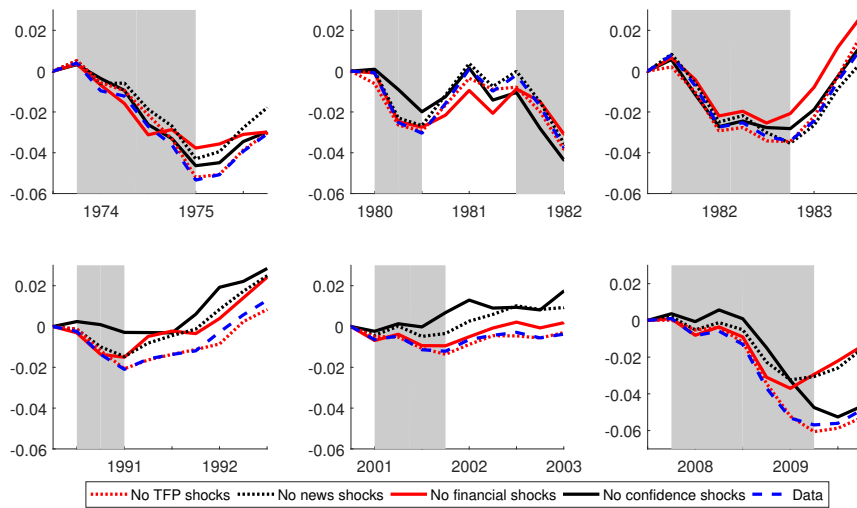|	(a) ordered third					(b) ordered fourth				
	impact	2Q	1Y	2Y	5Y	impact	2Q	1Y	2Y	5Y
TFP	0	0.01	0.01	0.01	0.01	0	0.01	0.01	0.01	0.01
Consumption	0.05	0.17	0.17	0.14	0.06	0.02	0.10	0.11	0.09	0.04
GDP	0.02	0.12	0.23	0.23	0.13	0.06	0.07	0.15	0.16	0.09
Hours	0.03	0.07	0.21	0.30	0.24	0.10	0.04	0.12	0.20	0.17
GDP forecast	0.01	0.17	0.25	0.12	0.14	0.06	0.10	0.17	0.16	0.09
Confidence	0.00	0.17	0.22	0.23	0.20	0.03	0.10	0.13	0.15	0.13
Financial Conditions	0.95	0.86	0.73	0.57	0.51	0.88	0.84	0.72	0.55	0.47
S&P 500	0.20	0.24	0.23	0.21	0.19	0.17	0.23	0.21	0.20	0.18
Credit	0.05	0.01	0.01	0.02	0.02	0.08	0.03	0.02	0.01	0.01
Investment	0.06	0.08	0.21	0.26	0.21	0.11	0.06	0.16	0.20	0.17

Note: Numbers indicate the share of the forecast error variance explained by the shock.

Table 3: FEV contribution of the confidence shock, ordered third and fourth

	(a) ordered third					(b) ordered fourth				
	impact	2Q	1Y	2Y	5Y	impact	2Q	1Y	2Y	5Y
TFP	0	0.01	0.01	0.01	0.01	0	0.02	0.01	0.01	0.01
Consumption	0.22	0.25	0.23	0.16	0.07	0.18	0.18	0.16	0.11	0.05
GDP	0.38	0.55	0.44	0.30	0.15	0.43	0.50	0.35	0.22	0.11
Hours	0.46	0.62	0.57	0.46	0.30	0.53	0.59	0.49	0.35	0.22
GDP Forecast	0.48	0.53	0.41	0.27	0.14	0.53	0.47	0.33	0.20	0.10
Confidence	0.71	0.67	0.59	0.47	0.40	0.74	0.60	0.50	0.38	0.32
Financial Conditions	0.08	0.04	0.03	0.07	0.09	0.01	0.01	0.01	0.05	0.05
S&P 500	0.06	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01
Credit	0.03	0.13	0.22	0.26	0.14	0.05	0.15	0.23	0.25	0.13
Investment	0.11	0.45	0.38	0.26	0.21	0.16	0.44	0.33	0.20	0.17

Note: Numbers indicate the share of the forecast error variance explained by the shock.

Table 4: FEV contribution of the surprise technology shock and the news shock

	(a)Surprise technology shock					(b) News shock				
	impact	2Q	1Y	2Y	5Y	impact	2Q	1Y	2Y	5Y
TFP	1	0.89	0.84	0.73	0.44	0	0.03	0.07	0.18	0.50
Consumption	0.02	0.01	0.01	0.00	0.03	0.22	0.31	0.36	0.42	0.45
GDP	0.12	0.04	0.02	0.01	0.03	0.02	0.10	0.17	0.29	0.38
Hours	0.13	0.10	0.08	0.07	0.16	0.02	0.01	0.01	0.03	0.04
GDP forecast	0.12	0.04	0.02	0.01	0.03	0.05	0.15	0.22	0.33	0.40
Confidence	0.00	0.00	0.00	0.01	0.03	0.02	0.08	0.13	0.20	0.22
Financial Conditions	0.00	0.00	0.01	0.02	0.04	0.01	0.03	0.08	0.09	0.07
S&P 500	0.00	0.00	0.00	0.00	0.02	0.24	0.25	0.28	0.29	0.24
Credit	0.01	0.03	0.05	0.08	0.15	0.06	0.09	0.14	0.22	0.28
Investment	0.04	0.01	0.01	0.01	0.00	0.06	0.11	0.17	0.25	0.30

Note: Numbers indicate the share of the forecast error variance explained by the shock.

Table 5: FEV decomposition with the GZ spread

	(a) Financial shock					(b) Confidence shock				
	impact	2Q	1Y	2Y	5Y	impact	2Q	1Y	2Y	5Y
TFP	0	0.00	0.01	0.01	0.00	0	0.02	0.02	0.01	0.01
Consumption	0.13	0.24	0.23	0.16	0.06	0.14	0.12	0.11	0.1	0.05
GDP	0.04	0.28	0.36	0.29	0.14	0.44	0.43	0.31	0.21	0.11
Hours	0.02	0.15	0.27	0.31	0.24	0.57	0.58	0.45	0.34	0.24
GDP forecast	0.02	0.29	0.34	0.27	0.13	0.61	0.45	0.32	0.21	0.10
Confidence	0.03	0.36	0.4	0.35	0.29	0.67	0.42	0.34	0.26	0.22
Credit spread index	0.79	0.80	0.76	0.67	0.50	0.00	0.00	0.01	0.02	0.03
S&P 500	0.31	0.32	0.33	0.32	0.26	0.00	0.04	0.04	0.03	0.02
Credit	0.01	0.01	0.04	0.08	0.04	0.07	0.12	0.18	0.21	0.11
Investment	0.00	0.15	0.26	0.25	0.19	0.21	0.49	0.38	0.25	0.19

Note: Numbers indicate the share of the forecast error variance explained by the shock. Compared to the baseline specification, the NFCI is replaced with the spread of Gilchrist and Zakrajšek (2012).