Sentiments in SVARs

Patrick Fève* Alain Guay

November 1, 2017

Abstract

This paper investigates the contribution of sentiments shocks to US fluctuations in a Structural VAR setup with restrictions at various frequencies. Sentiments shocks are identified as shocks orthogonal to fundamentals that account for most of the variance of confidence. We obtain that, contrary to news shocks on total factor productivity, sentiments shocks explain little of quantities and prices. Sentiments shocks mostly appear as an idiosyncratic component of confidence. These results are robust to various perturbations.

Following the last crisis, a particular attention has been paid to the driving role of sentiments, as they may account for a bulk of aggregate fluctuations. The existing literature offers many explanations: multiple equilibria and sunspot fluctuations, changes in expectations resulting from news and noise on economic fundamentals and modifications in market sentiments without any change in economic outcomes (see e.g. Benhabib, *et al.*, 2015, Beaudry and Portier, 2014, Lorenzoni, 2009, Angeletos and La'o, 2013, and Angeletos *et al.*, 2016).

No consensus seems to emerge about the contribution of sentiments shock to aggregate fluctuations. Structural Vector Autoregressions (SVARs) yield mixed results about the effects of news shocks on Total Factor Productivity (TFP) (see e.g. Beaudry and Portier, 2006, Barsky and Sims, 2011 and Forni *et al.*, 2014). Dynamic Stochastic General Equilibrium (DSGE) models deliver conflicting quantitative evidences about the sentiments shocks (see e.g. Barsky and Sims,

*Corresponding author: Patrick Fève, Toulouse School of Economics, University of Toulouse–Capitole, manufacture des Tabacs, bât. F, 21 allée de Brienne, 31000 Toulouse, France. emails: patrick.feve@tse-fr.eu and guay.alain@uqam.ca. We would like to thank M. Ravn (Editor) and two anonymous referees for useful comments on the paper. We also thank P. Andrade, P. Beaudry, F. Canova, F. Collard, M. Dupaigne, J. La'o, T. Lee, M. Pientrunti, F. Portier, G. Primiceri and D. Stevanovic for valuable suggestions, and participants in several conferences and seminars for helpful remarks. We thank L. Savoie-Chabot for excellent research assistance.

2012, Blanchard *et al.*, 2013 and Angeletos *et al.*, 2016). The heterogeneity of the quantitative findings partly results from the use of different structural models (the parametric structure of the DSGE model deeply impacts the reduced form) and restrictions (in SVARs) imposed for identification. The aim of this paper is to propose a weakly restrictive identification scheme of the sentiments shocks in a SVAR setup.

Using a Structural Vector Error Correction Model (SVECM) that exploits long–run relations among two non-stationary (unit–root) variables (TFP, GDP), the sentiments shock is identified as a shock *i)* orthogonal to fundamentals (for example expected and unexpected or surprise TFP shocks) *ii)* with no long–run effect on TFP and other real quantities and *iii)* that accounts for most of the variance of various measures of confidence. Restrictions *i)* and *ii)* are standard in the SVAR literature, as they just exploit long–run restrictions (Blanchard and Quah, 1989) and the exogeneity of a proper measure of TFP. The novelty here concerns the restriction *iii)*. The sentiments shock is identified as a transitory shock that best explains future movements in the measure of confidence up to a certain horizon. Notice that this procedure does not impose any restrictions on the contribution of the two permanent shocks to confidence. Our identification scheme is in accordance with Angeletos *et al.* (2016), who obtain that the estimated confidence from various estimated DGSE models is highly correlated with the University of Michigan Index of Consumer Sentiment. We assess the reliability of our identification procedure using simulation experiments from a DSGE model and we obtain that our approach yields good estimates of the impulse response functions under challenging configurations (news shocks on TFP with delay, noisy news).

We next apply our SVAR setup to the US economy for the sample period 1960:1–2016:4. We obtain that, while contributing for a large part of confidence in the short–run, the sentiments shock explains little of output and inflation. To the contrary, the news shock on TFP accounts for most of the variance of GDP (except in the short–run) and inflation, and it equally explains (with the sentiments shock) the volatility of confidence. The two other shocks (unexpected shock on TFP and the demand shock) explains a sizeable part of GDP and inflation. Sentiments shocks thus mostly appear as an idiosyncratic component of confidence. Of course, our findings rely on the identification of a single sentiment shock that can potentially mix different shocks some of which could be important business cycle drivers.[1] We show that our results are robust to many

[1]Benati and Kyriacou (2017) show that a partial identification of sentiments shocks tends to confound this

perturbations: alternative identification strategy, factors, data measurement, zero restriction and maximisation horizon. Our findings are in line with Beaudry and Portier (2006) and Barsky and Sims (2012).

Our paper adds to the SVARs literature about the role of sentiments in various dimensions. First, Matsusaka and Sbordone (1995) have been the first (to our knowledge) to consider the role played by confidence in SVARs. However, they only use a partial identification of shocks. Second, contrary to previous contributions that use SVARs in level (Barsky and Sims, 2011, Barsky *et al.*, 2015, and Forni *et al.*, 2016), we exploit the weak restriction that the output is cointegrated with TFP in a VECM to consistently identify both permanent and transitory shocks.[2] This allows us to investigate the contribution of two potential permanent shocks often considered in previous studies: an unexpected and news TFP shocks.[3] Third, we adapt the identification strategy proposed by Uhlig (2003) in a VECM to identify the transitory sentiments shock.[4] As we want to remain agnostic about the proper way to identify shifts in expectations, the flexibility of our approach allows to identify different setups of confidence/sentiments. Forni *et al.* (2016) propose to use dynamic rotations in SVARs to disentangle news from noise on TFP expectations. Their identification scheme is specially designed for the noisy news setup. The identification strategy implemented here is less specialised because other representations of sentiments have been proposed in the literature. For instance, in Angeletos and La'o (2013) and Angeletos, *et al.* (2016), information distortions appear under the form of an additional exogenous state variable for which our identification scheme is valid.

The paper is organised as follows. In the first section, we present the SVAR setup and our identification strategy. In section 2, we assess the reliability of our procedure. Section 3 reports the main empirical results. Section 4 is devoted to the robustness analysis. A last section concludes.[5]

shock with other fundamentals. Our approach is less subject to this critic as it identifies simultaneously four structural shocks.

[2]By using a VECM, we avoid a key criticism of Phillips (1998) that unrestricted VARs with unit roots or roots near unity give inconsistent estimates of impulse responses and forecast error variance decompositions at long horizons.

[3]See for instance, Barsky *et al* (2015), Barsky and Sims (2011), (2012), Beaudry and Lucke (2010), Beaudry and Portier (2006, 2014), Forni *et al.* (2014), Schmitt-Grohé and Uribe (2012).

[4]This identification strategy has been already used to identify news shocks on TFP (Barsky and Sims, 2011) or on defense spending (Ben Zeew and Pappa, 2017).

[5]An on–line appendix provides details about the implementation of our identification procedure, the DSGE model, results from simulation experiments and various robustness exercises.

1 Identification from SVARs

1.1 *The Setup*

Our empirical strategy relies on a SVECM with restrictions at various frequencies. Let $\mathbf{y}_t$ be a vector that includes four time series variables

$$\mathbf{y}_t = (\text{TFP}_t, \text{Quantities}_t, \text{Inflation}_t, \text{Confidence}_t)' .$$

The variable TFP_t is a measure of Total Factor Productivity. This variable is used here for the separate identification of surprise and news shocks on TFP. The variable labeled Quantities_t will refer to real non–stationary variables (*i.e.* GDP, consumption, investment). The variable Inflation_t is introduced for identification of transitory shocks. Finally, Confidence_t is a measure of confidence in the private sector (households and business sector). This variable is central in our quantitative analysis. It allows to identify the sentiments shock, but we also use it to evaluate the contribution of various structural shocks to confidence. This set of variables is assumed to follow a VECM of the form

$$\Delta \mathbf{y}_t = \alpha\beta' \mathbf{y}_{t-1} + \mathbf{\Gamma}_1 \Delta \mathbf{y}_{t-1} + \ldots + \mathbf{\Gamma}_p \Delta \mathbf{y}_{t-p} + \mathbf{u}_t \quad , \tag{1}$$

where Δ is the first difference operator and p denotes the number of selected lags on $\Delta \mathbf{y}_t$. α and β are $K \times r$ (where $K = 4$) matrices of loading parameters and cointegrating vectors, respectively. The $(K \times K)$ matrices $\mathbf{\Gamma}_j$ $(j = 1, \ldots, p)$ are referred to short–run parameters. The deterministic part is omitted to simplify the presentation without altering the results below. Finally, the error term $\mathbf{u}_t$ is assumed to be a zero–mean weak white noise with unconditional time invariant covariance matrix, $E(\mathbf{u}_t \mathbf{u}_t') = \mathbf{\Sigma}$. From (1), the Moving-Average representation is uncovered, namely $\Delta y_t = \mathbf{C}(L)\mathbf{u}_t$, with $\mathbf{C}(L) = \sum_{i=0}^{\infty} \mathbf{C}_i L^i$ and $\mathbf{C}_0 = \mathbf{I}_K$.

The reduced form error terms in $\mathbf{u}_t$ are a combination of structural shocks ε_t. A common normalisation identification assumption is that the structural innovations ε_t have zero–mean and identity covariance matrix. In addition, they are linearly related to $\mathbf{u}_t$ such that

$$\mathbf{u}_t = \mathbf{A}_0 \varepsilon_t \quad , \tag{2}$$

where $\mathbf{A}_0$ is $K \times K$ matrix. From the above normalisation, it follows that $\mathbf{\Sigma} = \mathbf{A}_0\mathbf{A}_0'$. Without additional restrictions, $\mathbf{A}_0$ is not uniquely identified and we must impose additional restrictions. Following Lütkepohl (2007), the multivariate Beveridge-Nelson Moving–Average representation of the VECM (1) can be obtained by applying the Granger's representation theorem, namely

$$\mathbf{y}_t = \mathbf{C}(1)\sum_{i=1}^{t}\mathbf{u}_i + \sum_{i=0}^{\infty}\mathbf{C}_i^*\mathbf{u}_{t-i} + \mathbf{y}_0^* \quad , \tag{3}$$

where $\mathbf{y}_0^*$ contains the initial values and $\mathbf{C}_i^*$ are absolutely summable. The $(K \times K)$ matrix $\mathbf{C}(1)$ allows to uncover the long-run effect of structural shocks: $\mathbf{C}(1) = \beta_\perp \left[\alpha_\perp' \left(\mathbf{I}_K - \sum_{i=1}^{p}\mathbf{\Gamma}_i\right)\beta_\perp\right]^{-1}\alpha_\perp'$, where $\alpha_\perp$ and $\beta_\perp$ denote the orthogonal complements of α and β. The rank of the long-run matrix $\mathbf{C}(1)$ is $K-r$, where r is the cointegrating rank. Thus, there exists $K-r$ common trends in the terminology of Stock and Watson (1988). Using (2) and (3), the long–run effects of the structural shocks is then given by $\mathbf{A}(1) = \mathbf{C}(1)\mathbf{A}_0$. Because the matrix $\mathbf{A}_0$ is of full rank, the rank of $\mathbf{A}(1)$ is $K-r$ and there can be at most r zero columns in the matrix of the long-run effects of the structural shocks. It means that at most r structural shocks can have transitory effects and at least $K-r$ structural shocks can have permanent effects. Consequently, the rank of $\mathbf{C}(1)\mathbf{A}_0$ yields at most $r(K-r)$ independent restrictions. The knowledge of the cointegrating rank r gives the maximum number of independent restrictions that can be imposed on the long-run effects of the structural shocks (see Lütkepohl, 2007). However, the number of transitory shocks can be smaller that r requiring that the remaining structural permanent shocks are linearly dependent in order to respect the rank condition for $C(1)A_0$. For the local identification of the structural shocks, we must impose $K(K-1)/2$ restrictions on $\mathbf{A}_0$ and $\mathbf{C}(1)\mathbf{A}_0$. With $K=4$, six restrictions (at least) are needed to identify the four structural shocks.

1.2 *Identification*

The aim of the identification strategy is to retrieve two potential permanent structural shocks, labeled as a pure surprise TFP shock (or unexpected TFP shock) and a news TFP shock (a shock that does not materialise today but that can follow a slow diffusion process), and two transitory shocks, one of them being the sentiments shock. Let us review now the different identifying restrictions.

Identification I (two long–run restrictions): *the two stationary shocks (including sentiments) have no long–run effect on TFP and quantities.*

This restriction, together with the cointegration between TFP and quantities, allows to identify separately the two permanent and transitory shocks. The resulting structure of the matrix $A(1)$ imposes that it exists one common long-run trend in the vector of variables y_t, the share of the variance of TFP and real quantities explained by the two permanent shocks are the same (the first and second lines are perfectly co–linear) and the two stationary shocks have no long–run effect on TFP and quantities. This is compatible with a rank of the long–run matrix $A(1)$ equal to one, *i.e.* one common trend. These two shocks have a proportional effect on the first two variables and the two other shocks are transitory. This means that the number of zeros in the matrix $A(1)$ and the rank of $A(1)$ result in two identifying restrictions only.

Identification II (one short–run restriction): *the news TFP shock has no short–run effect on the level of TFP.*

This short–run restriction follows the empirical strategy first proposed by Beaudry and Portier (2006). This assumption is now common in the SVAR literature to disentangle a pure surprise TFP shock from a news shock (see Beaudry and Portier, 2005, 2006, Barsky and Sims, 2011, Beaudry and Lucke, 2010). A news shock accounts for expectations of future productivity changes and it is orthogonal to a surprise TFP shock. Namely, a news shock has zero impact effect on the level of TFP but could explain the main bulk of TFP in the medium and the long–run.

Identification III (two short–run restrictions): *the two stationary shocks (including sentiments) have no short–run effect on the level of TFP.*

The restrictions imply that the measure of TFP is unaffected on impact by the two stationary shocks. The sentiments shock represents shifts in expectations about business cycles without changes in the fundamentals of the economy. The zero impact effect of the sentiments shock is a weak version of the fact that this shock is assumed to be disconnected from changes in economic fundamentals and, in particular, changes in aggregate productivity. This identification also imposes that the remaining stationary shock has no contemporaneous impact on TFP. If the TFP is properly measured (see Fernald, 2014 and Sims, 2016), we can expect almost no effect of stationary shocks on TFP. These restrictions combined with identification II allow to identify the structural technology shock to be the unpredictable residual component of TFP.

Identification IV (one medium–short–run restriction): *among transitory shocks, the sentiments shock maximises its contribution to the variance decomposition of confidence series up to a certain horizon.*

The sentiments shock is identified as the shock that best explains the future movements in the measure of confidence, conditional on the identification of the supply shocks (the two permanent shocks in our setup). In other words, identification IV imposes that the sentiments shock is the shock that represents the largest share of the confidence's variance (up to a certain horizon) among the two transitory shocks conditional on identification I and identification II of the TFP and news shocks.

2 Assessing the SVAR Model

2.1 *The Simulation Setup*

In order to assess the reliability of our procedure, we generate artificial data from a DSGE model. The model used is similar to Ireland (2003) extended to the case of sentiments. All the model's details are reported in the on–line appendix. The model features capital accumulation, adjustment costs on capital, monopolistic competition and nominal price rigidities under the form of a quadratic adjustment costs function. The economy is composed of a representative household, a representative finished goods-producing firm, a continuum of intermediate goods-producing firms and a central bank. The model is feeded by a permanent TFP shock, with both an unexpected and expected (with four lags) components.[6] The model also includes persistent shocks to the monetary policy. Following Barsky and Sims (2012), we assume that confidence follows a persistent stochastic process and it can be correlated with shocks of the economy (news, noise and demand shocks). We investigate three situations: *i)* a case in which sentiments shocks are idiosyncratic to confidence and have no aggregate effects, *ii)* a situation in which agents receive a noisy signal about future improvement in TFP ("noisy news") and sentiments (noise) may

[6]The model is parametrised such that output displays a positive response (except on impact for which the response is almost zero) to news shocks on TFP before the news is materialised. As robustness check, we also investigated other situations for which the DSGE model displays a negative response of output before the materialisation of the news shock. None of our quantitative findings are modified.

have sizeable effects on economic activity and *iii)* a case where the stationary demand (monetary policy) shocks is the main driver of confidence, thus violating our identification assumption IV. The SVAR model includes the TFP, output, inflation and confidence. To compute artificial time–series, we draw 1000 independent random realisations of the TFP shocks (unexpected and expected), the monetary policy shock, and depending on the experiment on the idiosyncratic or the noise shock. The sample size is equal to 250 quarters, as in actual data.[7] The number of lags in VECM models is set to 3 and we apply the identification procedure described in Section 1. Figures report the 90% confidence interval (the grey area) together with the true impulse responses.[8]

2.2 *Simulation Results*

In our first experiment, only the news and the idiosyncratic shocks can affect confidence and sentiments shocks have no effect on economic activity. To save space, we only report the responses to a news shock, as it appears central in our quantitative results (see the Figure 1). All the other responses are reported in the on–line appendix. The SVAR model reproduces well the true responses of TFP, output, inflation and confidence. The true responses are within the 90% confidence interval of the estimated ones. Notice that when we inspect the non-fundamentalness of the DSGE model with four lags in the news shock (Fernandez-Villaverde *et al.*, 2007), we obtain that one eigenvalue that exceeds largely unity, meaning the VAR setup is potentially unable to recover the structural shocks. As pointed out by Sims (2012) and Beaudry *et al.* (2105), the problem of non-fundamentalness is a quantitative issue, because we can always obtain SVARs that are not invertible but they continue to deliver reliable results. This good performances are also confirmed by the comparison of forecast error variance decompositions and the high correlation between the true and estimated structural shocks. For example, the DSGE model is calibrated such that the news and the idiosyncratic shocks equally explain the variance of confidence. In the SVAR model, the variance explained by news shocks is equal to 53% in the short run.

We now examine another situation when agents receive a noisy signal about future improve-

[7] In order to reduce the influence of initial conditions, the simulated sample includes 250 initial points which are subsequently discarded before the estimation of the VECM.

[8] To avoid singularity problems in the case of a noisy signal about expected TFP, we add a small measurement error in the sentiments/confidence equation. See Table 1 in the on–line appendix.

ments in TFP. In such a case, the agents cannot identify separately the news and the noise before the materialisation of the shock. In this version of the DSGE model, the noise shock on TFP can affect aggregate variables independently from any changes in fundamental shocks. As pointed out by Blanchard *et al.* (2013), this setup is really challenging for SVARs as without the use of strong theoretical restrictions (estimating for example a DSGE model with information problems), it seems impossible to properly identify shocks. We acknowledge that our identification procedure may suffer from the existence of "noisy news" but we want to quantitatively evaluate if it is a serious problem in our setup.[9] By varying the variance of noise (with respect to the variance of news), we can increase or decrease the information problem. In practise, we set the same variance for the news and the noise shocks. It follows that the news and the noise equally explain confidence. With our parametrisation, the contribution of the noise after one year is equal to 10%, 35% and 50%, for output, inflation and confidence, respectively. Contrary to the previous experiment, the sentiments shock (the noise shock) now affect economic fluctuations. The responses to a news shock are reported in the Figure 2. All the other responses are included in the on–line appendix. The SVAR models tends to underestimate the true response of the TFP to a news shock, but the estimated responses for output, inflation and confidence are close to the true ones. The responses to the other shocks are also pretty well estimated.

A natural additional investigation is about the reliability of the procedure when our identification assumption (see Identification IV in the previous section) is not satisfied. We parameterise the measurement equation for confidence such that news, demand and sentiments shocks equally explain the variance of confidence. The dynamic responses are reported in the on–line appendix. The estimated responses to the unexpected and news shocks on TFP are close to the true ones. This is not surprising because these two shocks are separately identified (from demand and sentiments shocks) using long–run restrictions. The main differences concern the estimated effects of the sentiments and demand shocks. The procedure tends to confound (in the very short–run) these two shocks. For example, the estimated response of output and inflation to a sentiments shock is positive, as in the case of a demand shock. The inspection of the correlation between the true and estimated structural shock reveals a positive link between the estimated sentiments shock with the true demand (monetary policy) shock, revealing the confusion creating by the

[9] Note that we can not apply the procedure described in Fernandez-Villaverde *et al.* (2007), because the noise creates a singularity problem into the measurement equation. In their notations, the matrix D is non-invertible.

identification procedure. Finally, the estimated response of confidence to demand shock (as imposed by the identification procedure) is close to zero. This finding is not problematic for our findings from actual data. They just indicate that if demand shocks contribute a lot to confidence, the econometrician tends to attribute too much weight on sentiments shock. If she obtains very small effect of sentiments shocks on prices and quantities, this just reveals that she would not confound this shock with a demand shock.

3 Empirical Results

3.1 *US Data*

Our identification of the news shocks requires the observation of the TFP_t variable, which we will decompose into an unexpected (or surprise) component and a news shock. This implies that the empirical measure of productivity properly reflects the unobserved variations in inputs. Fernald (2014) proposed a quarterly frequency measure with adjustments for variations in factor utilisation–labour effort and the workweek of capital. We use the more recent vintage of the adjusted TFP, as it is less predictable from other aggregate shocks than previous vintages (see Sims, 2016). According to specification (1), the growth rate of TFP_t is then included in our VECM. The variable Quantities_t is the log of real GDP (GDPC96) divided by population 16 and over (CNP16OV). The growth rate of GDP is thus included in the VECM. The rate of inflation is obtained from the Consumer Price Index for all urban consumers all items (CPIAUCSL). In DSGE models with nominal rigidities, inflation is a jump variable reflecting expected marginal costs. So, we believe that this variable contains a sizeable amount of forward–looking component. In addition, this allows us to disentangle two stationary shocks. Finally, a "proxy" measure of the variable Confidence_t is obtained from the Michigan Survey data. Following Barsky and Sims (2012), the survey that we first use is the responses to the question: "Turning to economic conditions in the country as a whole, do you expect that over the next five years we will have mostly good times, or periods of widespread unemployment and depression, or what?". The variable is then obtained as the difference between the percentage giving a favourable answer and the percentage giving a negative answer, plus one hundred. This variable (E5Y) is taken in log. We have also investigated other measures of quantities, prices and confidence. Results are reported either in Section 4 or in the on–line appendix.[10] The sample period runs from 1960:1 to 2016:4. Our VECM is consistent with unit root (level versus first difference) and cointegration tests for non–stationary variables.

3.2 *Dynamic Responses in the Benchmark Case*

The VECM is estimated with three lags, according to standard statistical criteria. Our results are modestly affected by other lag selection. The sentiments shock is identified as the main driver (among stationary shocks) of consumer confidence from impact to 10 years. Other choices for the horizon does not change so much our results.[11] The estimated impulse response functions (IRFs) are reported in Figure 3. The shaded areas represent the 90% confidence bands obtained from bootstraps with 2000 replications.

Let us first consider the dynamic responses of the four variables after a surprise TFP shock. The adjusted TFP jumps immediately and then slowly decreases to its long–run level. At the same time, GDP increases and the rate of inflation too after some delay. Our findings are similar to Barsky *et al.* (2015) who obtain a positive and significant response of inflation during eight quarters. This surprising result is difficult to reconcile with sticky price models, because a mean reverting TFP shock will decrease the marginal cost for several period. This is also inconsistent with Basu *et al.* (2006) who show that inflation persistently decreases after a TFP shock. This results may originate from a measurement error problem in TFP because the latter can be contaminated by demand and/or sentiment shocks (see Barsky *et al.*, 2015, for a discussion). We partially address this issue in section D.4 of the on-line appendix, by relaxing the zero restriction on impact and we obtain the same findings. Finally, the consumer confidence increases on impact, but afterward the dynamic response is persistently negative (not precisely estimated).

The dynamic responses after a news shock on TFP differ sharply (see the right top panel of Figure 3). First, the adjusted TFP does not react on impact (by construction), stays around zero during two years and then increases very gradually. TFP reaches its new long–run value

[10] For real quantities, we consider real per-capita consumption (non durables and services) and real per-capita investment (durables and private fixed investment) in replacement of GDP. We also investigated the effect of another measure of inflation, using the CPI all items less food and energy (CPILFESL). See the on–line appendix. As in Barsky and Sims (2012), we consider other measures of confidence: a second measure of confidence is obtained from a similar question for a shorter horizon of twelve months (E12M) and a third measure is an index of consumer sentiments (ICS) partly constructed from E5Y and E12M. We will also consider CEO confidence survey condition. See Section 4.

[11] See section D.5 in the on-line appendix.

after more than ten years. This shape of the response highlights a slow diffusion process of a technology improvement (see Portier, 2015). We obtain a significantly positive response of output on impact followed by a rapid increase. This finding is consistent with the news-driven business cycles (see Beaudry and Portier, 2014), as output reacts immediately to an expected component in TFP. An important additional result is about the response of inflation to a "good" news shock. The rate of inflation drops immediately and gradually goes back to its steady state. This finding is in line with Barsky and Sims (2011) and Barsky *et al.* (2015) who obtain that news shock on TFP looks like a standard supply shocks. This results appears robust in all our experiments and perturbations of the benchmark case. The DSGE literature has not paid so much attention to this dynamic response of inflation, with the noticeable exceptions of Barsky and Sims (2011), Jinnai (2013) and Barsky *et al.* (2015). In this latter paper, they show that real wage rigidity will help to reduce marginal cost and then inflation can drop after a news shock. Even more striking is the large and persistent response of consumer confidence to the news shock. This result is in contrast with the surprise TFP shock that has limited effects on consumer confidence. The response is significantly different from zero for all the selected periods (10 years) after the shock. Our finding is in line with Barsky *et al.* (2015) from a different SVAR setup, but we obtain a more persistent response of confidence.

We concentrate now our analysis on the effects of the sentiments shock. The dynamic responses after a sentiments shock are reported in the right bottom panel of Figure 3. Our findings give little support to the the sentiment shock (given our identification scheme).[12] First, GDP slightly decreases on impact and then displays a positive hump with a peak after two years. However, the effect on GDP is rather limited if we compare the estimated response to those obtained after a news shock. Moreover, the dynamic response is not precisely estimated. Second, the rate of inflation increases a little after the sentiments shock, but again all the estimated responses are not significantly different from zero. So neither quantities nor prices are significantly affected by the sentiments shock. Third, the response of consumer confidence is large and persistently positive. The response of confidence to a sentiments shock (except in the short–run) appears similar to the one obtained after a news shocks. Together with the weak response of confidence

[12]We do not detail the response of TFP to a sentiment shock. Except on impact (by construction, zero), the TFP reacts positively to a sentiment shock, but the response is not significantly different from zero. As for the response to an unexpected TFP shock, this may reveals a measurement error problem, so the zero restriction is not valid. We relax this restriction in section D.2 of the on-line appendix (for the demand shock, as it displays the same pattern for TFP). Our results are not altered.

to the surprise TFP, this suggests that news and sentiments shocks are almost the sole drivers of consumer confidence.

Figure 3 also reports the dynamic responses of the remaining stationary shock, that we interpret as a demand shock. This shock has little effects on TFP (by construction zero on impact) and the dynamic responses are almost not different from zero for all the periods after the shock. So, our impact restriction does not seem to distort the shape of the response.[13] The response of output displays a hump–shaped pattern and is persistently positive. At the same time, the rate of inflation increases significantly during the same time span. So, this shock is highly pro–cyclical. We retrieve the persistent effects of stationary (demand) shocks already highlighted by the SVARs literature. In what follows, we will then label this shock as a *demand shock*. This shock has a small positive impact on consumer confidence followed by a negative effect for 10 quarters.

3.3 *Contribution to the Business Cycle*

Figure 4 reports the variance decomposition for the four variables. First, the measure of adjusted TFP is almost totally explained by the surprise TFP shock in the short–run. By construction, the three other shocks have no effect on impact. As the number of periods after the shock increases, the share of the variance of TFP explained by the surprise TFP shock decreases and the share explained by the news shock gradually increases. Notice that the contribution of the two stationary shocks is very small. Second, the surprise TFP shock and the labeled demand shock explained almost 60% of the variance of GDP in the short–run (on impact and after one period). The news shock appears progressively as the main driver of output fluctuations, since its share exceeds 50% after two years and is around 90% after ten years. These findings are similar to those of Beaudry and Portier (2006, 2014). The sentiments shock has a negligible effect on GDP for all horizons. Third, the demand (50%) and the news shocks (40%) are the two main drivers of inflation. Barsky *et al.* (2015) obtain a similar result for the contribution of the news shock to inflation. The effect of surprise TFP shock is very small in the short–run and the sentiments shock has again a limited effect (less than 5%). Fourth, Figure 4 illustrates our identification strategy. Among the two transitory shocks, sentiments shock explains the bulk of the consumer

[13] As previously mentioned, we have investigated this issue and relaxed the zero restriction on impact for this shock.

confidence. Only two shocks accounts for the volatility of consumer confidence. In the short–run, the sentiments shock is the main driver (around 70%), followed by the news shock (around 30%). For longer horizons, the ranking is inverted, since the news shock accounts for more than 60% of the variance of consumer confidence after ten years, whereas the share of the sentiments shock falls to 35%. This finding is in line to what obtained Barsky and Sims (2011) and Barsky *et al.* (2015) in a SVAR setup. Importantly, our results confirm those of Barsky and Sims (2012) who obtained a similar conclusion from estimating a New Keynesian structural model. To sum up, the sentiments shock explains a tiny portion of aggregate fluctuations (quantities and prices) and this shock does not appears as the dominant shock of consumer confidence in the medium-run. Although the sentiments shock we identified could potentially mix shocks, some of which could be important business cycle drivers, this identified shock seems more of an idiosyncratic component of the consumer confidence.

4 Robustness

Here, we present three robustness exercises.[14]

4.1 *Another Identification Strategy*

According to the previous results, the news shock appears as the key driver of aggregate fluctuations and it is thus legitimate to assess the robustness of our result to alternative identification strategies of this shock. Following Barsky and Sims (2011), we depart from our long–run restrictions and estimate a VAR in levels. We use the same variables as in our benchmark setup, *i.e.* the model includes TFP, GDP, inflation and consumer confidence. We still impose that only the unexpected TFP shock can have an effect on current TFP. Among the three other shocks without an effect on current TFP, the news shock is identified as the shock that yields the largest contribution to the TFP for a given horizon. We maintain our approach to identify the

[14]Other robustness exercises have been also performed. We investigate the role of conditioning variables, *i.e.* we replace real per capita GDP by consumption and investment. In addition, we assess the sensitivity of our findings to price measurement (CPI all items less food and energy). We have also relaxed the assumption that demand shocks cannot have an effect (on impact) on TFP (see Ben Zeev and Pappa, 2015, for a quantitative assessment). The demand shock has now an immediate effect on TFP but none of our previous results are affected. In addition, we have investigated the robustness of the results to other sample selection. When we consider a shorter sample (1960–2006), *i.e.* excluding the recent crisis, we obtain the same findings. Finally, we check the sensitivity of our results the maximisation horizon. See the on–line appendix.

sentiments shock. A direct comparison of Figure 5 (top panel) with Figure 4 makes clear that the identification strategy of news shocks does not modify our previous findings. The variance decomposition shows very similar results as before. The sentiments shock explains almost zero of the variance of TFP and GDP and a very small portion of inflation. This shock contributes a lot to the variance of the consumer confidence in the short–run, but ten periods after the shock, the share of the news shock on TFP is above 60%.

4.2 *A Quantitative Assessment of Non-Fundamentalness*

The presence of news shock raises additional problems related to non–fundamentalness. This problem occurs because actual variables used by the econometrician might not contain enough information to properly uncover structural shocks. To address this issue, we adapt the simple procedure developed by Forni and Gambetti (2014) to our setup. We proceed in the following four steps: *i)* we estimate the VECM and apply our approach to identify the structural shocks; *ii)* we regress the identified news shock on lagged values of different factors. If the test statistic does not reject the null hypothesis of orthogonality, then we stop. If not, we go to the following steps: *iii)* we include the relevant factors into our VECM and we identify the structural shocks; *iv)* we compare the estimated responses to news shock to those obtained without the relevant factors in the VECM.[15] Two remarks are worth noting. First, in step *iii)* of the procedure, we maintain identifications I-IV and we adapt these restrictions to the case of additional stationary variables. Second, we do not separately identify the remaining stationary shocks. Identification can be obtained only if we impose additional restrictions among these shocks. This is not problematic for our purpose because we still can identify the news and sentiments shocks and we mainly concentrate our analysis on these shocks. For the variance decomposition exercise, the composite shock must be interpreted as a combination of stationary shocks with no long–run effect on TFP and quantities and these shocks explain the smallest part of the forecast error of confidence up to a certain horizon.

We use 8 factors constructed by Michael W. McCracken at monthly frequency from 168 macro series.[16] The monthly data are then converted in a quarterly frequency by selecting the

[15]We have also investigated the case where variables enter in levels in the VAR model, and then applying the Barsky and Sims (2011) identification strategy. None of our results are altered. See Figure **??** in the on–line appendix.

[16]See `https://research.stlouisfed.org/econ/mccracken/fred-databases/` and McCracken and Ng

last month of the quarter. In *step ii)*, the Wald and Lagrange multiplier statistics are large and their p-value are almost zero. So the null hypothesis of orthogonality is rejected. At the same time, the coefficient of determination of this regression is not that large ($R^2 = 0.30$). We also investigate which factor contributes the more to this rejection. Inspecting each factor separately, we obtain that only one factor yields a p-value for the test of orthogonality under 10% level. This also confirmed by the Wald statistic when we test for the significance of each factors when they are all included into the regression. Despite the rejection of orthogonality with the unique factor, the coefficient of determination of this regression is rather small ($R^2 = 0.13$). This R^2 measures the share of the variance of news shocks explained by this most important factor.[17] Anticipating on the next results, this suggests that nonfundamentalness indeed an issue present in the data (the orthogonality is rejected), but its effect can remain quantitatively small (the coefficient of determination is small). We now proceed with the third step and then include this factor in the VECM. We re–apply the orthogonality test by regressing the identified news shock in the five–variable model on a constant and four lags of the remaining factors. Now, the test statistics (Wald and Lagrange multiplier) do not reject the null hypothesis at conventional level. So, in this Factor Augmented VECM the contribution of these factors to news shock is very small. Finally, we compare the estimated responses of TFP, output and consumer confidence to unexpected TFP, news on TFP and sentiments shocks. Results are reported in section C.1 of the on–line appendix. The comparison with Figures 3 makes clear that the estimated responses are similar. Let us first concentrate on the news shock. Again, TFP increases gradually after a news shock, reflecting the slow diffusion of a technology improvement. GDP immediately jumps and the medium–run responses are identical in the benchmark VECM and the Factor Augmented VECM. An additional robust feature is the persistent decrease of inflation after a positive news shock. Finally, as in the benchmark case, the news shock has a positive and long-lasting effect on consumer confidence. Now consider the sentiments shock. This shock has still a small effect on quantities and prices and only strongly affects consumer confidence. These findings are confirmed by the variance decomposition exercise (see the bottom panel in Figure 5), to be compared to Figure 4. The presence of a factor in the VECM does not alter our previous findings and all our conclusions are maintained.

(2016).

[17]See Beaudry *et al.* (2015) about the use of the R^2 diagnosis for judging the severity of non-fundamentalness on the estimation of news shocks.

4.3 *Confidence Variables*

Since the confidence variable is central in our analysis, it is legitimate to assess the sensitivity of our results to other measures. We replace our measure of consumer confidence E5Y by the a second measure of confidence obtained from a similar question for a shorter horizon of twelve months (E12M) and an index of consumer sentiments (ICS). The top right panel of Figure 6 reports the results with E12M and the bottom left with ICS. Compared to the benchmark case (for direct comparison, the benchmark case is included into the Figure 6 at the top left position), the pictures are almost the same.[18] The contribution of the sentiments shocks to GDP is almost zero. The sole minor difference concerns the contribution of the sentiments shock to inflation that becomes a bit larger in the short–run (between 5% and 10%, depending wether ICS or E12M is included). We also consider a measure of confidence related to the business sector. We use CEO Confidence-survey conditions in six months as a proxy for sentiments. The results are reported in the bottom right panel of Figure 6. As it is clear from this figure, benchmark results are maintained. The main driver of GDP is still the news TFP shock and the sentiments shock contributes very little to quantities and prices. This shock only explains the volatility of business sector confidence.

5 Conclusion

The main driving forces of the business cycle are still the subject of much debate and controversy. We found that a SVAR model incorporating a measure of confidence together with aggregate variables predicts that sentiments shock explains little of output and inflation, but the news shock on TFP accounts for most of the variance of quantities and confidence. In addition, the transitory shock (labeled as a demand shock) represents a sizeable part of fluctuations in the short–run. These findings are robust to alternative identification strategy, non–fundamentalness and data measurement. Our results from a flexible SVAR model show that the news story of the business cycles, as advocated by Beaudry and Portier (2006, 2014) remains a very plausible source of aggregate fluctuations. As in Barsky and Sims (2012), the sentiments shock, identified as the main contributor of confidence at business cycle frequencies seems to play a minor role.

[18]The result is not surprising given the high level of correlations between these three measures of consumer confidence in our sample (greater than 0.9).

However, it is worth noting that our identification of a single sentiment shock does not prevent that unidentified shocks hitting it could be important sources of the aggregate fluctuations.

Toulouse School of Economics and University of Toulouse I-Capitole
Université du Québec à Montréal, CIRPÉE and CIREQ

References

Angeletos, M., F. Collard and H. Dellas (2016) 'Quantifying confidence', previous version *NBER Working Paper* 20807, National Bureau of Economic Research, Inc.

Angeletos, M. and J. La'o (2013) 'Sentiments', *Econometrica*, 81(2), 739–779.

Barsky, R., S. Basu, and K. Lee (2015) 'Whither news shocks?', *NBER Macroeconomics Annual 2014*, ed. by J. Parker, and M. Woodford, 29(1), 225–264. University of Chicago Press.

Barsky, R. and E. Sims (2011) 'News shocks and business cycles', *Journal of Monetary Economics*, 58(3), 273–289.

Barsky, R. and E. Sims (2012) 'Information, animal spirits, and the meaning of innovations in consumer confidence', *American Economic Review*, 102(4), 1343–1377.

Basu, S., J. Fernald and M. Kimball (2006) 'Are technology improvements contractionary?', *American Economic Review*, 96(5), 1418–1448.

Beaudry P., P. Fève, A. Guay and F. Portier (2015) 'When is nonfundamentalness in vars a real problem? An application to news shocks', *NBER Working Papers* 21466, National Bureau of Economic Research, Inc.

Beaudry, P. and B. Lucke (2010) 'Letting different views about business cycles compete', in *NBER Macroeconomics Annual 2009*, ed. by D. Acemoglu, K. Rogoff and M. Woodford, 24, 413–455, National Bureau of Economic Research, Inc.

Beaudry, P. and F. Portier (2005) 'The news view of economic fluctuations: evidence from aggregate japanese data and sectoral us data', *Journal of the Japanese and International Economics*, 19(4), 635–652.

Beaudry, P. and F. Portier (2006) 'Stock prices, news, and economic fluctuations', *American Economic Review*, 96(4), 1293–1307.

Beaudry, P. and F. Portier (2014) 'News driven business cycles: insights and challenges', *Journal of Economic Literature*, 52(4), 993–1074.

Benati, L. and L. Kyriacou (2017) 'Does sentiment matter?', *mimeo* University of Bern.

Benhabib, J., P. Wang and Y. Wen (2015) 'Sentiments and aggregate demand fluctuations', *Econometrica*, 83(2), 549–585.

Ben Zeev, N. and E. Pappa (2015) 'Multipliers of unexpected increases in defense spending: an empirical investigation', *Journal of Economic Dynamics and Control*, 57, 205–226.

Ben Zeev, N. and E. Pappa (2017) 'Chronicle of a war foretold: the macroeconomic effects of anticipated defence spending shocks', *Economic Journal*, 127(603), 1568–1597.

Blanchard, O. J., J.-P. L'Huillier, and G. Lorenzoni (2013) 'News, noise, and fluctuations: an empirical exploration', *American Economic Review*, 103(7), 3045–70.

Blanchard, O. J., and D. Quah (1989) 'The dynamic effects of aggregate demand and supply disturbances', *American Economic Review*, 79(4), 655–673.

Fernald, J. (2014) 'A quarterly, utilization-adjusted series on total factor productivity', Federal Reserve Bank of San Francisco, Working Paper Series 2012-19.

Fernandez-Villerde, J, J. Rubio-Ramirez, T. Sargent, and M. Watson. (2007) 'ABCs (and Ds) of understaning vars', *American Economic Review*, 97(3), 1021–1026.

Forni, M., and L. Gambetti (2014) 'Sufficient information in structural vars', *Journal of Monetary Economics*, 66(C), 124–136

Forni, M., L. Gambetti, M. Lippi, and L. Sala (2016) 'Noisy news in business cycles', forthcoming *American Economic Journal: Macroeconomics*.

Forni, M., L. Gambetti, and L. Sala (2014) 'No news in business cycles', *The Economic Journal*, 124(581), 1168–1191.

Ireland, P. (2003) 'Endogenous money or sticky prices?', *Journal of Monetary Economics*, 50(8), 1623–1648.

Jinnai, R. (2013) 'News shock and inflation', *Economics Letters*, 119(2), 176–179.

Lorenzoni, G. (2009) 'A theory of demand shocks', *American Economic Review*, 99(5), 2050–84.

Lütkepohl, H. (2007) *New Introduction to Multiple Time Series Analysis*, Springer.

Matsusaka, J. and A. Sbordone (1995) 'Consumer confidence and economic fluctuations', *Economic Inquiry*, 33(2), 296–318.

McCracken, M. and S. Ng (2016) 'FRED-MD: a monthly database for macroeconomic research', *Journal of Business & Economic Statistic*, 34(4), 574–589.

Phillips, P. C. (1998) 'Impulse response and forecast error variance asymptotics in nonstationary vars', *Journal of Econometrics*, 83(1-2), 21–56.

Portier, F. (2015) 'A comment on whither news shocks? by Barsky, Basu & Lee', *NBER Macroeconomics Annual 2014*, ed. by J. Parker, and M. Woodford, 29(1). University of Chicago Press.

Schmitt-Grohé, S., and M. Uribe (2012) 'What's news in business cycles', *Econometrica*, 80(6), 2733–2764.

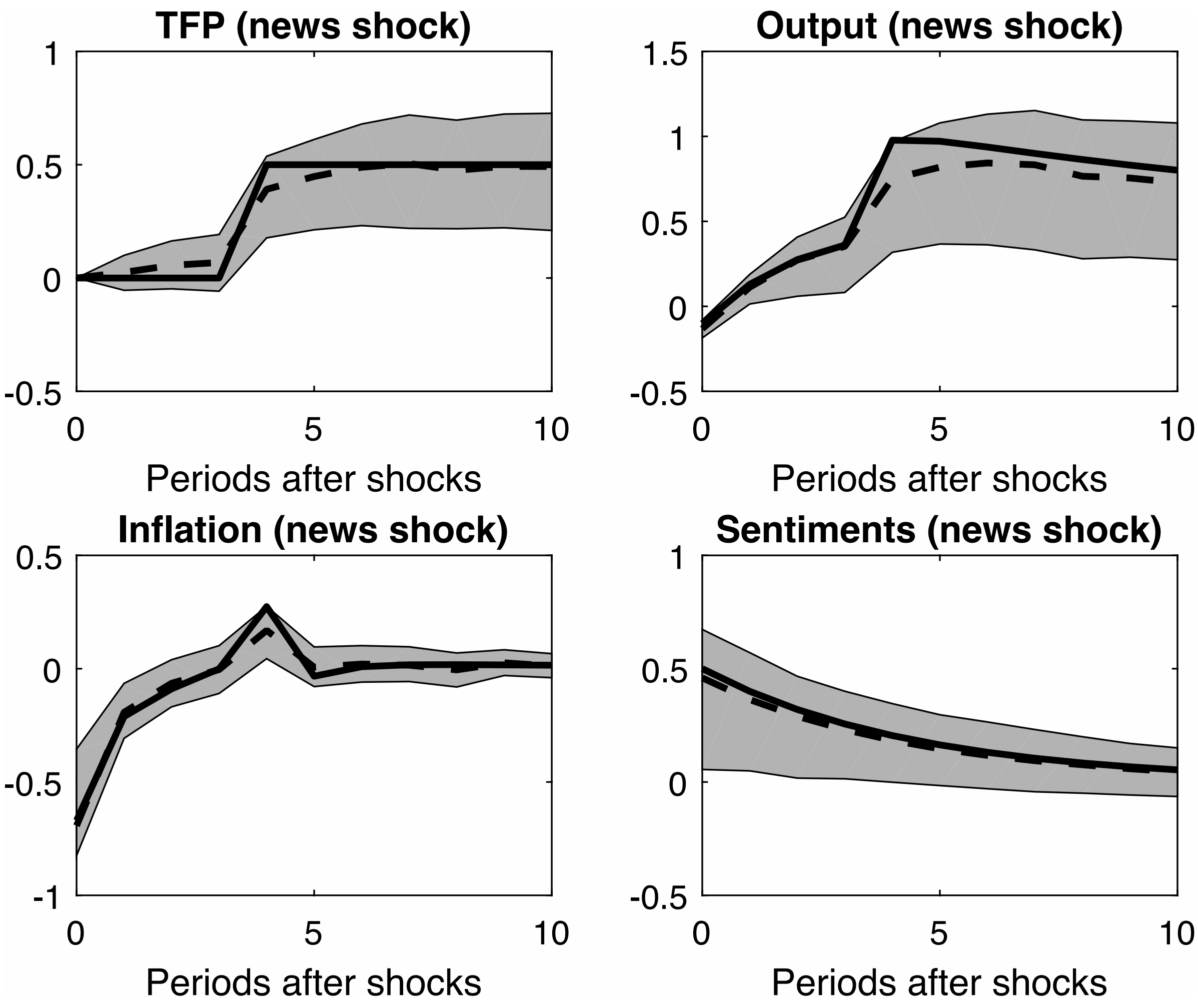
Sims, E. R. (2012) 'News, non–invertibility, and structural vars', *Advances in Econometrics*, 28, 81–136.

Sims, E. R. (2016) 'Differences in quarterly utilization-adjusted tfp by vintage, with an application to news shocks', *NBER Working Papers* 21466, National Bureau of Economic Research, Inc.

Stock, J. and M. Watson (1988) 'Testing for common trends', *Journal of the American Statistical Association*, 83(404), 1097–1107.

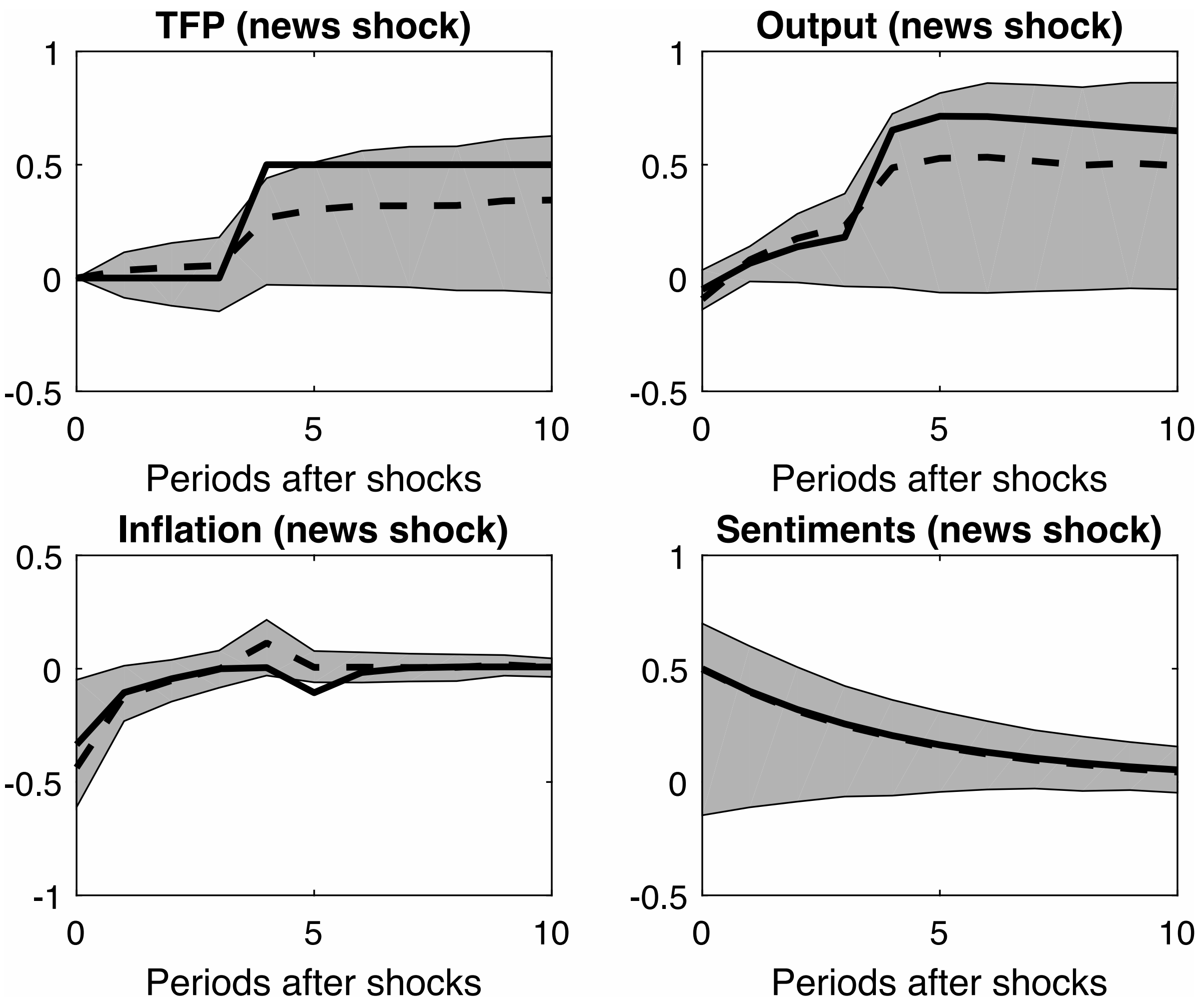
Uhlig, H. (2003) 'What drives gnp?', Unpublished manuscript.

Figure 1: *Responses to a News Shock on TFP (Idiosyncratic Shock on Confidence)*



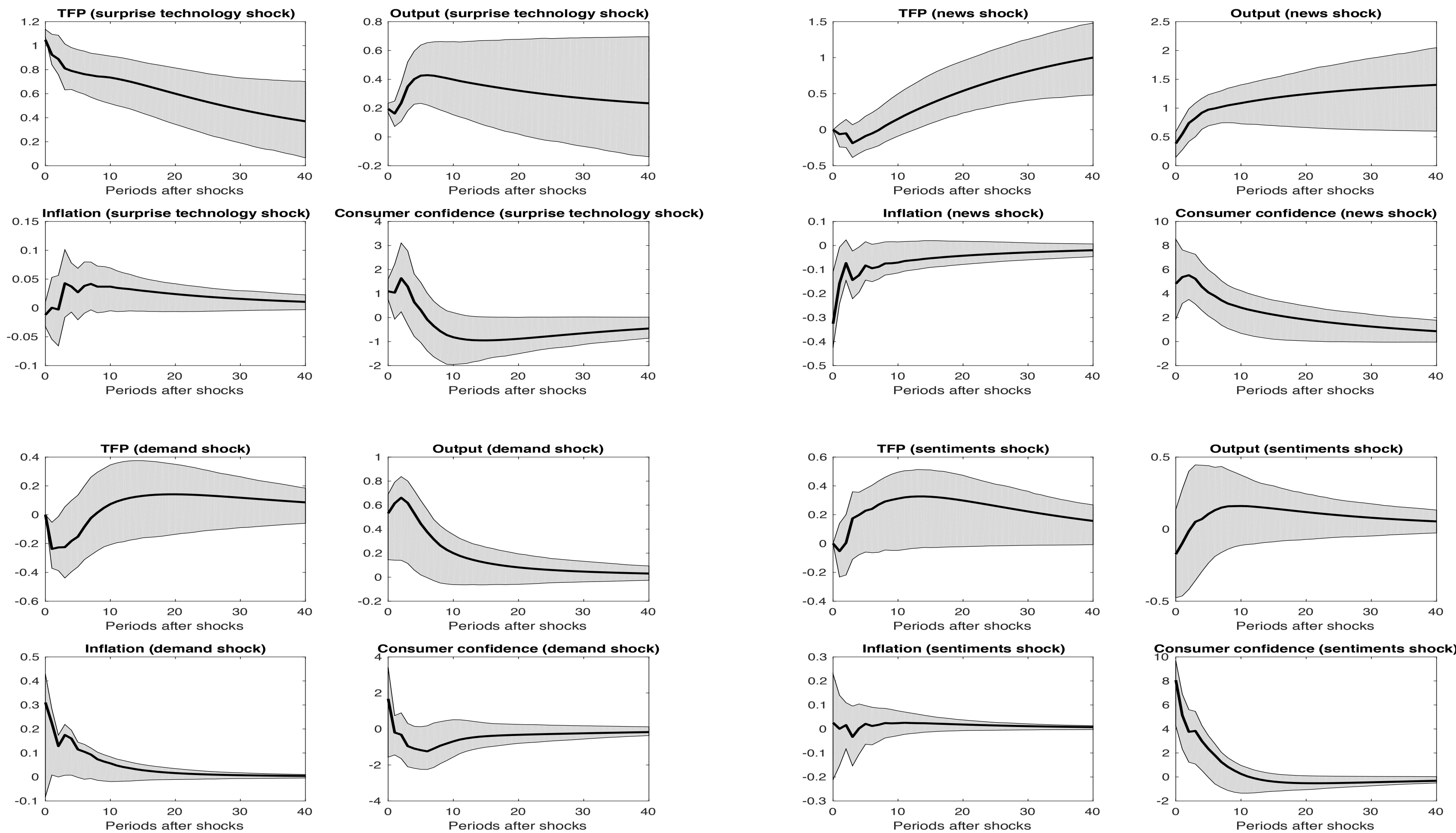
Note: Solid line: true responses. Dotted line: estimated responses. The VECM includes the growth rate of TFP, the growth rate of real per capita GDP, the rate of inflation and our measure of sentiments. The sample size is equal to 250. Three lags are included in the VECM. The selected horizon for IRFs is 11. 90% percent confidence interval (grey area) obtained from 1000 replications.

Figure 2: *Responses to a News Shock on TFP (Noisy News in Confidence)*



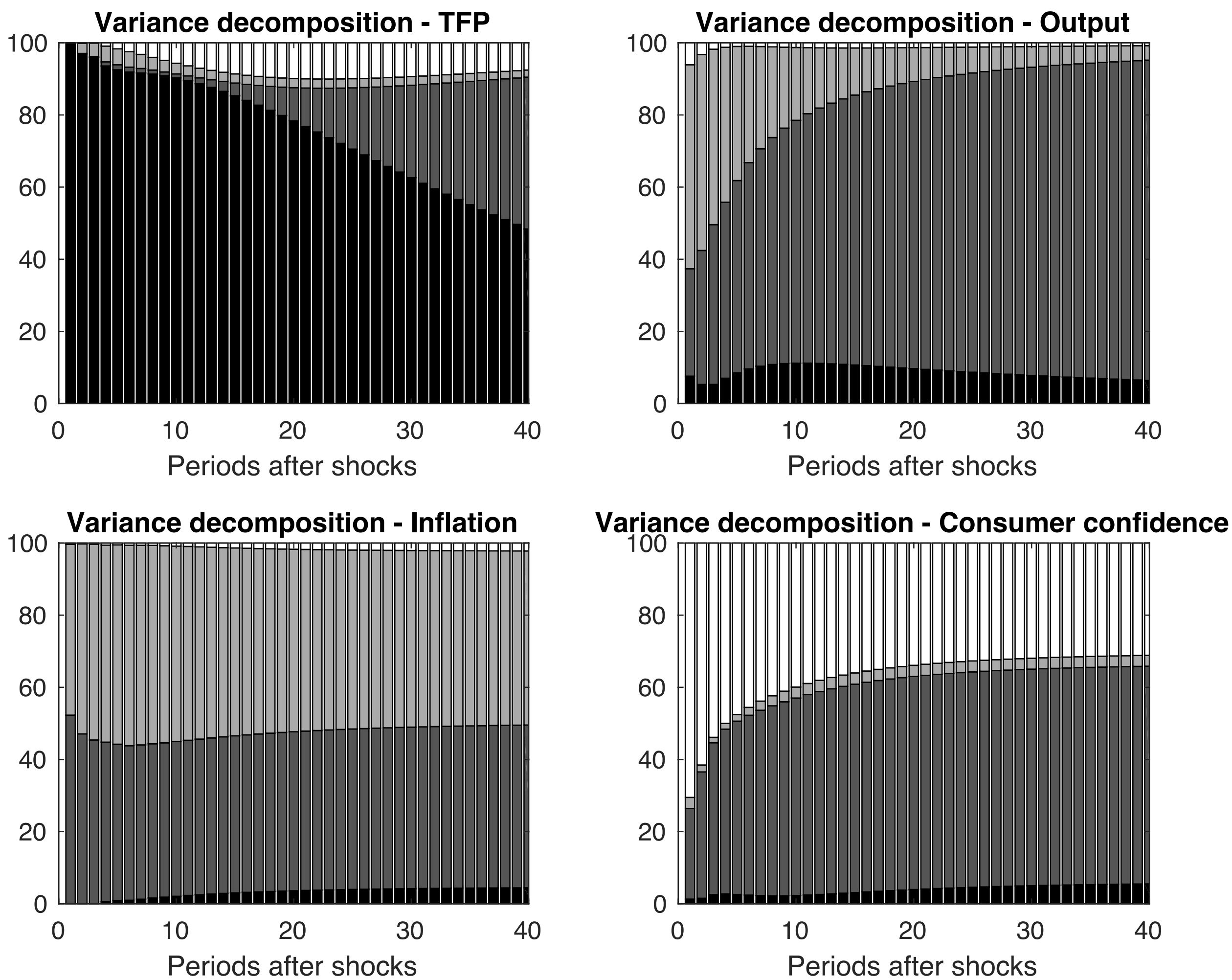
Note: Solid line: true responses. Dotted line: estimated responses. The VECM includes the growth rate of TFP, the growth rate of real per capita GDP, the rate of inflation and our measure of sentiments. The sample size is equal to 250. Three lags are included in the VECM. The selected horizon for IRFs is 11. 90% percent confidence interval (grey area) obtained from 1000 replications.

Figure 3: *Impulse Response Functions (SVECM & GDP)*



Note: The VECM includes the growth rate of adjusted TFP, the growth rate of real per capita GDP, the rate of inflation (CPI all) and the measure E5Y of consumer confidence. The sample period is 1960:1-2016:4. Three lags are included in the VECM. The selected horizon for IRFs is 40. 90% percent confidence interval obtained from a standard bootstrap technique with 2000 replications.

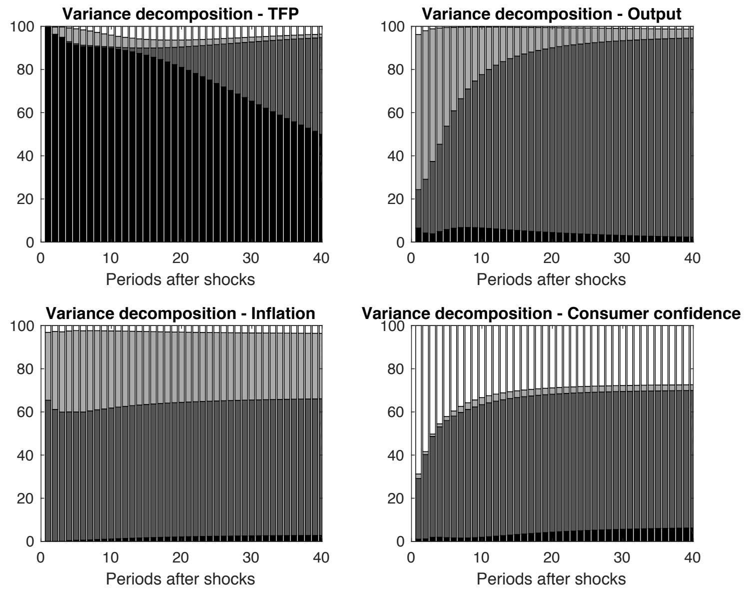
Figure 4: *Variance Decomposition (SVECM & GDP)*



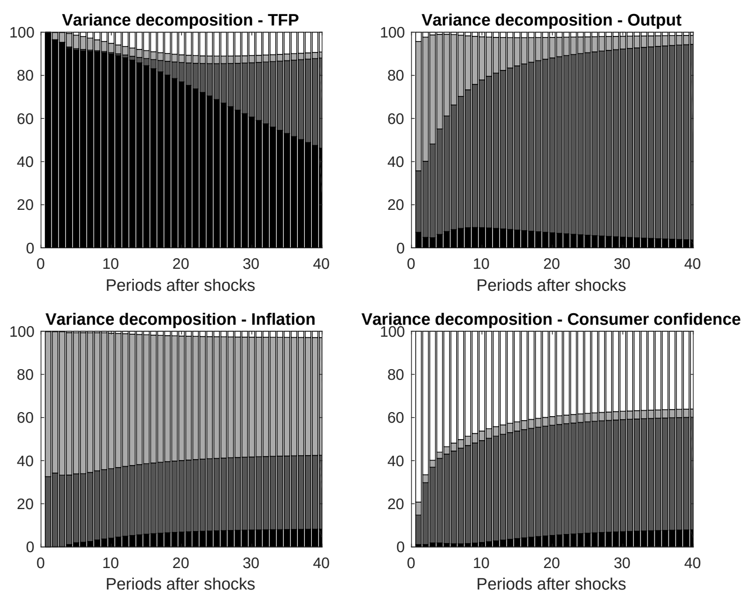
Note: The VECM includes the growth rate of adjusted TFP, the growth rate of real per capita GDP, the rate of inflation (CPI all) and the measure E5Y of consumer confidence. The sample period is 1960:1-2016:4. Three lags are included in the VECM. The selected horizon for IRFs is 40. The white area corresponds to the share of variance explained by the sentiments shock, the light grey area to the demand shock, the dark grey area to the news shock on TFP and the dark area to the surprise shock on TFP.

Figure 5: *Robustness (Variance Decomposition)*

Barsky–Sims Identification



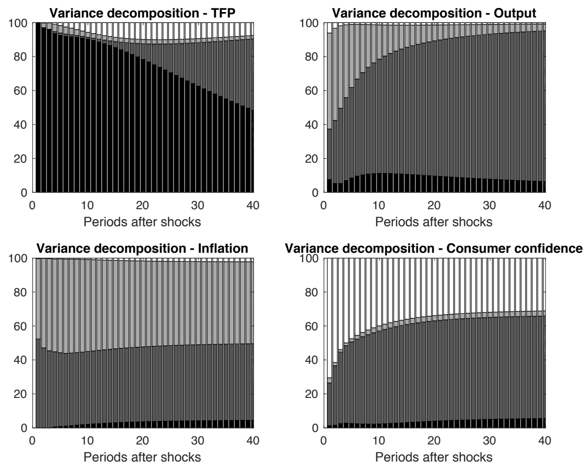
Factor Augmented VECM



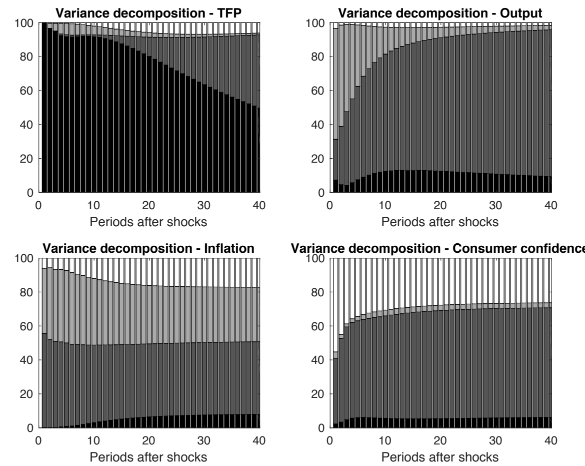
Note: The VECM includes the growth rate of adjusted TFP, the growth rate of real per capita GDP, the rate of inflation (CPI all) and the measure E5Y of consumer confidence. In the case of the factor augmented VECM, one factor is added to the model. The sample period is 1960:1-2016:4. Three lags are included in the VECM. The selected horizon for IRFs is 40. The white area corresponds to the share of variance explained by the sentiments shock, the light grey area to the demand shock, the dark grey area to the news shock on TFP and the dark area to the surprise shock on TFP.

Figure 6: *Confidence Measurement (Variance Decomposition)*

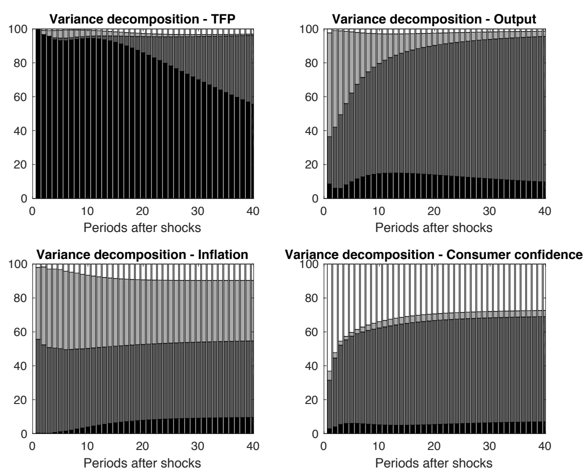
SVECM with E5Y



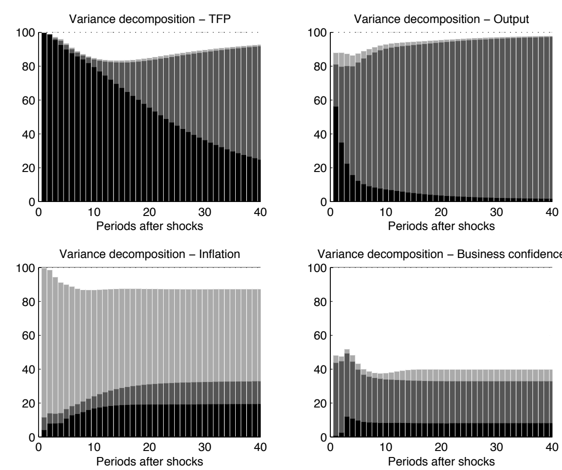
SVECM with E12M



SVECM with ICS



SVECM with Business Confidence



Note: The VECM includes the growth rate of adjusted TFP, the growth rate of real per capita GDP, the rate of inflation (CPI all) and different measures of (consumer or CEO) confidence. The sample period is 1960:1-2016:4. Three lags are included in the VECM. The selected horizon for IRFs is 40. The white area corresponds to the share of variance explained by the sentiments shock, the light grey area to the demand shock, the dark grey area to the news shock on TFP and the dark area to the surprise shock on TFP.