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JUN-HYUNG KO
KENSUKE MIYAZAWA
and
TUAN KHAI VU

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Research Center for Price Dynamics
Institute of Economic Research, Hitotsubashi University
Naka 2-1, Kunitachi-city, Tokyo 186-8603, JAPAN
Tel/Fax: +81-42-580-9138
E-mail: sousei-sec@ier.hit-u.ac.jp
http://www.ier.hit-u.ac.jp/~ifd/

News shocks and Japanese macroeconomic fluctuations *

Jun-Hyung Ko†

University of Tokyo

Kensuke Miyazawa

Kyushu University

Tuan Khai Vu

Seikei University

April, 2012

Abstract

Are the changes in the future technology process, the so-called "news shocks," the main contributors to the macroeconomic fluctuations in Japan over the past forty years? In this paper, we take two structural vector-auto-regression (SVAR) approaches to answer this question. First, we quantitatively evaluate the relative importance of news shocks among candidate shocks, estimating a structural vector-error-correction model (SVECM). Our estimated results suggest that the contribution of the TFP news shocks is nonnegligible, which is in line with the findings of previous works. Furthermore, we disentangle the source of news shocks by adopting several kinds of restrictions and find that news shocks on investment-specific technology (IST) also have an important effect. Second, to minimize the gap between the SVAR approach and the Bayesian estimation of a dynamic stochastic general equilibrium model, we adopt an alternative approach: SVAR with sign restrictions. The SVAR with sign restrictions reconfirms the results that the news shocks are important in explaining the Japanese macroeconomic fluctuations.

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Keywords: TFP; Investment-specific Technology; News shock; VECM; Sign restriction

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†Corresponding author: Graduate School of Economics, the University of Tokyo, 7-3-1 Hongo, Bunkyo-Ku, Tokyo 113-0033 Japan. E-mail: kojunhyung@e.u-tokyo.ac.jp.

1 Introduction

Are news shocks the main source of the Japanese macroeconomic fluctuations? Previous works have presented different results. Beaudry and Portier (2005) employ a SVECM with a combination of long-run and short-run restrictions to divide the TFP shocks into surprise and news components. The news shock in their econometric model is the shock that does not have an impact effect on the current TFP but increases the future TFP several quarters after. They find that the estimated TFP news shock is a dark horse behind the Japanese macroeconomic fluctuations, and that a negative news shock occurred in the beginning at the 1990s which might have been relevant with the so-called "lost decade." Fujiwara, Hirose, and Shintani (2011) assess the importance of news shocks based on an estimation of a dynamic stochastic general equilibrium (DSGE) model using a Bayesian method. They introduced one-to-four-quarters-ahead TFP news shocks and find that the TFP news shocks are nonnegligible but minor in explaining the macroeconomic fluctuations in Japan.

The first purpose of this paper is to re-investigate whether news shocks are the major source of the Japanese macroeconomic fluctuations. As a first step, extending the two-variable SVECM in Beaudry and Portier (2005), we employ a SVECM with more variables so that TFP news shocks compete with other candidate shocks. This is to respond to the criticism that in a framework with too few shocks like that of Beaudry and Portier (2005), the role of news shocks might be overemphasized. In the benchmark case, we identify four shocks: surprise TFP shocks, IST shocks, TFP news shocks, and demand shocks. Following Beaudry and Portier (2005), we identify TFP news shocks by imposing a restriction that they do not have an impact effect, but might have long-run effects on TFP. Furthermore, we impose an additional restriction that they do not have long-run effects on IST. Our main finding is that TFP news shocks are the driving force of the Japanese economic fluctuations over the last 40 years, accounting for more than 50 percent of variances of hours worked and investment. However, the contribution to output and consumption is rather minor.

Furthermore, we disentangle the source of news shocks, which was not highlighted by previous studies. We adopt the alternative identification schemes in line with Beaudry and Lucke (2010), where the news shocks include the news on IST as well as on TFP. Comparing their results with our benchmark case, we can assess the relative importance of news shocks to TFP and IST. We find that IST news shocks are another crucial factor in explaining postwar Japanese business cycles. This feature is not observed in the U.S. data by Beaudry and Lucke (2010).

Our second purpose is to compare the results of two different approaches: SVAR and the structural estimation of a DSGE model. Fujiwara et al. (2011) find that TFP news shocks play a minor role, explaining less than 10 percent of real macro activities in Japan. A direct comparison is difficult for several reasons. First, news shocks estimated by our SVECM are somewhat different from those in Fujiwara et al. (2011). Our estimated news shocks start to increase TFP around four to 32 periods after the stock market innovation, while the news shocks in Fujiwara et al. (2011) like other previous DSGE works are built until four periods ahead. Second, the treatment of the trend is different. In our SVECM, we assume the number of stochastic trends based on the Johansen cointegration test and explicitly incorporate the common cointegrating vector, while they examine the model around the deterministic trend. Third, Fujiwara et al. (2011) investigate only news shocks on TFP, while we also examine the role of IST news. Fourth, only four types of structural shocks are identified in our four-variable SVECM, while more types of shocks are identified in their DSGE estimation.

Therefore, to narrow the gap between these two approaches, we employ an alternative approach: SVAR with sign restrictions. SVAR with sign restrictions has the following strengths. First, in contrast to the SVECM approach, the dependent variables do not have to be set in a (log) differenced form because we do not need to rely on the long-run restriction in this case. Therefore, the discrepancy originating from the trend assumptions can be resolved. Second, the actual timing of the future TFP increase can be modified. In the DSGE literature, the timing is around one to four periods ahead, while those of our estimated news shocks in SVECM are from four to 32 periods.[1] Therefore, to identify the same types of news shocks in the VAR system, we follow the same assumptions made by the DSGE literature. Third, we are able to identify only a subset of the structural shocks and thus need to impose much fewer restrictions. This enables us to estimate a larger VAR with more variables. We estimate a seven-variable VAR model in level and identify news shocks as ones that increase TFP from one to four periods ahead. The estimated results under SVAR with sign restrictions lie between the results of our SVECM and those of Fujiwara et al. (2011), showing that the news shocks explain large portions of Japanese macroeconomic fluctuations. We also find that the contribution of news shocks is larger in the U.S. economy than in the Japanese economy.

Section 2 describes the SVECM system and data. The identification procedure and benchmark results are presented in Section 3, while Section 4 discuss the source of the news shocks. Section 5 conducts the robustness check. Section 6 compares the SVAR results with sign restrictions with those in Fujiwara et al. (2011), and Section 7 concludes.

2 Set up

2.1 SVECM

In this subsection, we briefly explain our SVECM. The basic model of order p has the form

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \Phi D_t + u_t, \tag{1}$$

where $y_t = (y_{1t}, \cdots, y_{Kt})'$ is a vector of K observable endogenous variables, A_is are $(K \times K)$ coefficient matrices, D_t is a deterministic term, and $u_t = (u_{1t}, \cdots, u_{Kt})'$ is a vector of unobservable error terms. We consider the case where the variables in y_t are integrated of order one. If these variables have a common stochastic trend, there is a possibility that one of their linear combinations is I(0). When they are cointegrated, the vector error-correction representation of the process can be written as

$$\Delta y_t = \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_{p-1} \Delta y_{t-p+1} + \Phi D_t + u_t, \tag{2}$$

where $\Pi = -(I_K - A_1 - \cdots - A_p)$ and $\Gamma_i = -(A_{i+1} + \cdots + A_p)$ for $i = 1, \cdots, p-1$. Because Δy_t does not contain stochastic trends, Πy_{t-1}, which must be $I(0)$, is the only one that includes $I(1)$ variables and contains the cointegration relations. If $\text{rank}(\Pi) = r$,

[1]For example, see Schmitt-Grohé and Uribe (2009) and Khan and Tsoukalas (2009).

Π can be written as a product of $(K \times r)$ matrices α and β with rank(α) = rank$(\beta) = r$ as follows: $\Pi = \alpha\beta'$.

$$\Delta y_t = \alpha\beta' y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta y_{t-j} + \Phi D_t + u_t, \tag{3}$$

where α and β are $K \times r$ matrices of loading coefficients and co-integrating vectors, respectively, and the Γ_js, $j = 1, \cdots, p-1$, are $K \times K$ coefficient matrices. From Johansen's version of Granger's Representation Theorem, if y_t is generated by a reduced form as in equation (3), it has the following moving average representation:

$$y_t = L \sum_{i=1}^{t-1} \varepsilon_i + \sum_{i=0}^{\infty} \Xi_i^* (u_{t-i} + \Phi D_{t-i}) + y_0^*, \tag{4}$$

where y_0^* is a vector of initial variables;

$$L \equiv \beta_\perp \left[\alpha'_\perp \left(I_K - \sum_{i=1}^{p-1} \Gamma_i \right) \beta_\perp \right]^{-1} \alpha'_\perp$$

is a $K \times K$ matrix with rank $K - r$; $\alpha_\perp$ and $\beta_\perp$ denote the orthogonal complements of α and β, respectively, and the matrices Ξ_i^*, $i = 1, \cdots, \infty$, are absolutely summable. L is the matrix that represents the long-run effects of the forecast error impulse responses, whereas Ξ_i^* contains the transitory effects. In line with the literature, we assume that the covariance matrix of the vector of structural shocks, ε_t, is the identity matrix I_K. Since the covariance matrix of u_t is nonsingular, there exists a nonsingular matrix B such that $u_t = B\varepsilon_t$. Therefore, in terms of structural interpretation, L can be interpreted as the long-run effect matrix of the structural shocks ε_t, whereas B is the corresponding short-run matrix. Since the number of endogenous variables is K, we need to impose additionally $\frac{K(K-1)}{2}$ restrictions on B and L to identify K types of structural shocks. The restrictions imposed should be economically meaningful.

2.2 Choice of endogenous variables and data

In our benchmark case, we include four endogenous variables in the SVECM: TFP, an IST variable, stock prices, and an economic activity variable, and wish to identify four shocks: surprise TFP shocks, surprise IST shocks, TFP news shocks, and demand shocks. The first variable, measured TFP, is necessary to identify surprise TFP shocks and TFP news shocks. Regarding the second variable, following previous studies in the literature such as Braun and Shioji (2007), we use the inverse of the real investment price to identify IST shocks. The third variable, stock prices, is included because it is a forward-looking variable which reflects news about the future and thus is suitable to identify TFP news shocks. The fourth variable is one of the followings: hours worked, output, investment, and consumption. This variable is included for a twofold purpose: it captures demand shocks, and it allows us to analyze the effects of structural shocks, especially TFP news shocks, on the Japanese macroeconomic fluctuations.

We employ quarterly data for the period from 1960-Q1 to 2002-Q4. Data on output, consumption, investment, and hours worked are taken from Braun, Esteban-Pretel, Okada, and Sudo (2006). These variables are seasonally adjusted, in logs, and in per capita form using data for the population aged-15-and-over from *Japan's Labor Force Survey*.

TFP measures are constructed using data on output, hours worked, and capital services by Braun et al. (2006) and the capacity utilization rate in manufacturing (that is, the *operating ratio*) calculated by the *Ministry of Economy, Trade and Industry*. We assume a Cobb-Douglas production function. The capital share, 0.363, is based on Braun et al. (2006). The inverse of the real price of investment is the log-difference of the 68SNA deflator for consumption and fixed non-residential investment. As an alternative measure, we use the price index of investment goods of the *Corporate Goods Price Index* for quality-adjusted investment. The stock prices are the *Nikkei 255 Index*. This variable is deflated by the 68SNA deflator for consumption, and is in per capita form and in logs.

3 Are TFP news shocks important?

In this section, we identify and quantify the relative importance of TFP news shocks to the Japanese business cycles. Other shocks are surprise TFP shocks, IST shocks, and demand shocks. As noted in the previous section, for a four-variable SVECM, we need to impose six restrictions on the short-run and long-run matrices B and L. We follow Beaudry and Portier (2005) in identifying the unexpected and news shocks to TFP. To compare our result with the existing empirical works on Japan, we confine ourselves to the case of news on TFP. In the next section we examine the case in which news might also contain information on future IST.

3.1 Benchmark identification

In this subsection, we explain our benchmark identification scheme. The order of dependent variables is as follows: TFP, the IST variable, stock prices, and the macro activity variable. Our objective is to identify the surprise TFP shocks, IST shocks, TFP news shocks, and demand shocks. In our benchmark identification, to identify four shocks, we impose six restrictions which can be summarized in the following three assumptions, where b_{ij} and l_{ij} denote the ij-th element of B and L, respectively.

- **Assumption A1** ($b_{12} = b_{13} = b_{14} = 0$): *Only surprise TFP shocks may have contemporaneous effects on TFP.*
- **Assumption A2** ($l_{14} = l_{24} = 0$): *Demand shocks have no long-run effects on TFP and the relative price of investment.*
- **Assumption A3** ($l_{23} = 0$): *TFP news shocks do not affect the relative price of investment in the long-run.*

Assumption A1 allows us to distinguish surprise TFP shocks with other shocks. Assumption A2 is sufficient to identify demand shocks from other shocks. The demand shocks can be any shocks that do not have contemporaneous or permanent effects on the technology processes, e.g. they may include temporary changes in consumer demand, monetary shocks, government purchase shocks, and so on.

We call the third structural shock "TFP news shocks" because they may contain TFP processes. TFP news shocks are identified by postulating a zero effect on TFP on impact ($b_{13} = 0$). Note that we do not impose any restriction on the effect of news shocks on TFP in the long run. No effect on TFP in the short run can isolate news shocks from surprise TFP shocks.[2] Assumption A3 allows us to isolate IST news from TFP news shocks. Therefore, the second shock includes both the surprise and anticipated components of IST, while the third shock only includes the effect of the news on TFP.[3] In sum, assumptions A1, A2, and A3 are sufficient to identify four structural shocks. We summarize in Table 1 the restrictions imposed on the short-run matrix B and the long-run matrix L under the benchmark identification scheme:

[Table 1 is inserted here.]

3.2 Results

In our benchmark case, we consider four four-variable systems in which the first three variables are *tfp* (TFP), *pi* (the inverse of the real price of investment), *sp* (stock prices), and the fourth one is the macro activity variable x with $x \in \{h, y, i, c\}$ where h, y, i, and c are hours worked, output, investment, and consumption, respectively. We call each of these four systems the x system. We used four lags in the estimation of the four systems based on Akaike's information criteria (AIC). As for the trends, a number of theoretical papers imply that two stochastic trends representing TFP and IST progresses should be considered. However, the Johansen cointegration tests suggest only one cointegrating vector. Therefore, we assume one cointegrating vector.[4] We have four systems with four macro activities and hence, we substitute out the macro activity variable and replace it by another macro activity variable in each estimation.

In this and the subsequent sections, we show the forecast error variance decomposition (FEVD) and impulse response function (IRF) under the benchmark identification scheme. FEVDs are useful tools to show the percentage contribution of structural shocks to the forecast error variances of dependent variables. We set the business cycle horizon as 32 and 40 quarters when analyzing FEVD and IRF, respectively. IRFs of the h system under the benchmark scheme are shown in Fig. 1, where we have plotted IRFs of four variables in rows and shocks in columns.

The first column shows the IRFs of four variables to the surprise TFP shocks. In the first row, there is an initial jump of *tfp* in response to the surprise TFP shocks, and the effect remains permanently. In the second row, the effect on the real investment price is significantly positive only in the short run. The fourth row is the macro activity response to the surprise TFP shocks. The response sign of hours worked in the short run is negative.[5]

[2]We allow for the possibility that news shocks can change the relative price of investment goods on the impact period. This is because TFP news shocks can influence the relative price of investment goods in the case that the relative price of investment goods does not purely reflect IST. To overcome this problem, we also try an alternative measure in the robustness check.

[3]In the benchmark identification system, we do not restrict the long-run effect on the fourth variable because any shock can permanently affect the macro activities.

[4]Schmitt-Grohé and Uribe (2011) document that one common stochastic trend in neutral and investment-specific productivity can be a new source of business-cycle fluctuations.

[5]There is no consensus on the response of hours worked to the TFP shocks. This result is consistent with Galí (1999) and Francis and Ramey (2009).

Surprise IST shocks in the second column permanently increase the relative investment price in the second row. Estimated IST shocks seem to cause a positive response from future TFP.

IRFs to the TFP news shocks are listed in the third column. The effects of news shocks on TFP in the first row are similar to those found in Beaudry and Portier (2005, 2006) and Beaudry and Lucke (2010). Although the response of TFP fluctuates slightly in the short run, it does not increase for around three years. In the h system, this seems to convey information about TFP growth that starts 12 quarters in the future.[6] As in the previous literature, there is an immediate expansion in hours worked in response to news shocks, which peaks around four to six quarters later.

The effect of demand shocks is plotted in the fourth column. The point estimate of hours worked shows a positive response, but the results are not significant.

[Fig. 1 is inserted here.]

IRFs under the y, i, and c systems are shown in Fig. 2. The first, second, and third rows are IRFs under the y, i, and c systems, respectively. To focus on effects of the TFP news shock, we plot the measured TFP processes after the stock price innovation in the first column, and show the IRFs of macro activities to four structural shocks from the second through fifth columns.

The first column displays IRFs of tfp to the TFP news shock. The shapes are similar and consistent with those in the h system. We can observe the so-called "news-driven business cycle" in the fifth column: even though there is no initial innovation of technology in the first column, the macro activities show positive movement. The only exception is c, which is not consistent with the theory in the literature.[7] Consumption actually increases in the long run but shows a negative response in the short run. IRFs to two surprise shocks are displayed in the second and third columns. We can observe the positive responses to the surprise shocks in all cases. The effect of demand shocks is plotted in the fifth column. There are positive responses from output and consumption, which are consistent with the restriction and theory.

The timings of the actual increases of TFP are different among the systems. In the case of the y system, the actual increase of TFP is seen around 30 quarters later, while TFP starts to increase 8 and 3 quarters later in the i and c systems, respectively. The timing of news shocks has been discussed extensively in the literature. By construction, we impose minimal restrictions on our econometric model and, within the current VECM, cannot impose the actual timing with which news is conveyed. However, the news components in the DSGE literature are often assumed to be up to 4 quarters ahead. Therefore, in the latter section, we also examine the VAR with sign restriction to investigate the relationship between the DSGE results.

[Fig. 2 is inserted here.]

Fig. 3 plots the FEVDs of four macro variables in each x system for $x \in \{h, y, i, c\}$ under the benchmark identification scheme. Calculating the forecast error variances, we investigate the importance of the candidate shocks to macroeconomic activities.

[6] Beaudry and Portier (2005) use annual data, and their measured TFP starts to increase in four years.

[7] For example, see Beaudry and Portier (2005), Jaimovichi and Rebelo (2009), and Kobayashi and Nutahara (2010).

We observe the following from the table. The first and most important finding is that the TFP news shocks play the most crucial role in the h and i systems. The contribution of the TFP news shocks is dominant, accounting for more than 40 percent of hours worked and investment in all horizons. Around 20 percent of the output movement is explained by the TFP news shocks in all horizons, while the contribution to the variance of consumption is negligible.

Second, the contribution of the estimated IST shocks accounts for a large portion of all variables' variances. In the case of output and investment, large movements are explained by the IST shocks especially in the long run. The short-run variance of consumption is mostly explained by the IST shocks.

Third, surprise TFP shocks explain a considerable part of consumption movement and some fraction of output. In all horizons, the share of output variance is between 10 and 30 percent. The contribution of surprise TFP shocks to the forecast error variances of consumption become larger in the long run.

Fourth, demand shocks account for more than half of the movement of output, especially in the very short run, but they account for a very small fraction of the movement of hours and investment. Demand shocks play some role in explaining the consumption movement.

To summarize this subsection, in the benchmark system, we find that TFP news shocks and IST shocks dominate the FEVDs of almost all macro activity measures. Surprise TFP shocks account for non-negligible portions of output and consumption variances. Demand shocks are important in explaining output variance in the short run.

[Fig. 3 is inserted here.]

3.3 Historical Decomposition

In this subsection, we provide the historical decomposition results of shocks to macro activities. With these results, we can analyze the direction and magnitude of each structural shock for any given date or specific period.

The historical decomposition is presented in Fig. 4. All the data series are displayed in log-differences, excluding the effects of the initial five lags from 1960-Q1 to 1961-Q1 and the constant terms. The dashed line indicates the movements of the estimated macro activities and the contribution of each shock to the historical movement of the data is shown in the form of bar charts. One finding is that the innovations in stock prices play a substantial role in explaining the behavior of hours worked, output, and investment. Positive innovations during the bubble period and negative innovations in the early 1990s are particularly remarkable. The latter finding is consistent with that of Beaudry and Portier (2005), who also find that large negative TFP news shocks hit the Japanese economy in the early 1990s.

[Fig. 4 is inserted here]

3.4 Other identification schemes

In this subsection, we check the robustness of the benchmark results by trying other identifying restrictions. We maintain the following restrictions as in the benchmark case: $l_{23} = 0$ and $b_{13} = b_{14} = l_{14} = 0$. The restriction $l_{23} = 0$ is necessary to isolate TFP news shocks from IST, and restrictions $b_{13} = b_{14} = l_{14} = 0$ are necessary to distinguish surprise TFP shocks with other shocks. We need two more restrictions to identify four structural shocks. We choose one of them from $l_{24} = 0$ and $b_{24} = 0$, which are necessary to isolate IST shocks from others. The last restriction is chosen from the following four: $b_{12} = b_{21} = l_{12} = l_{21} = 0$. Therefore, we have a total of 8 sets of identifying restrictions multiplied by two assumptions on IST shocks.

[Table 2 is inserted here.]

Table 2 summarizes the results under 8 restriction sets. Entries correspond to the shares of the consolidated IST shocks and TFP news shocks of FEVDs at horizon 32 quarters. The fractions of consolidated IST shocks and corresponding TFP news shocks in macro activity movements are listed on the left and the right sides, respectively. Results of hours worked, output, investment, and consumption are listed in descending order. In 25 out of 32 cases, the results are almost the same as the benchmark scheme. There are almost no changes in the contributions of surprise TFP shocks and demand shocks.

4 Sources of news

In the previous section, we find that the TFP news shocks turn out to be important in explaining the Japanese business cycle. However, it might be that news shocks coming from other sources, such as IST, are also important.[8] To consider this, in this section, we introduce two alternative identification schemes following Beaudry and Lucke (2010).[9] Their benchmark identification schemes impose two kinds of restrictions. The first identification scheme imposes mostly impact restrictions. For example, the news shock is identified to be orthogonal to TFP and the relative price of investment on impact, but left unrestricted in the long run. The other identification scheme imposes fewer short-run restrictions and relies more on long-run restrictions. In both cases, no restriction is imposed on the effects of news shocks on TFP and IST in the long run. Therefore, we call the estimated news shocks in this section "consolidated news shocks" because the estimated news shocks may contain news on both future TFP and future IST. By comparing the results for consolidated news shocks in this section with those for TFP news in the previous section, we can quantify the relative importance of TFP and IST news shocks.[10]

[8] Braun and Shioji (2007) examine the role of IST in Japan. Using sign restrictions, they found that IST is as important as neutral shocks. Fisher (2006) demonstrates the importance of IST in the U.S. economy, relying on long-run restrictions in the SVAR model. One of his main assumptions is that only IST shocks affect the real investment price in the long run. Neither paper covers the role of IST news shocks. Our identification schemes generally include their identification schemes, although the variables and methods are different.

[9] They exploit a set of properties that are common to most models embodying such shocks. Following their identification schemes, we identify four shocks. There are five candidate shocks in their benchmark system. Their fifth candidate shock is monetary shock which explains around 20 percent of U.S. macroeconomic fluctuations. Therefore, we also estimated SVECM with five variables. The data for short-run nominal interest rates are the collateralized overnight average call rates of the Bank of Japan. However, its role turns out to be limited in the case of the Japanese economy and we do not include it in the benchmark case.

[10] The counterpart of this identification would be to isolate IST news shocks from TFP. This approach is hard to identify because in many cases the rank condition fails.

4.1 Beaudry-Lucke ID1 identification scheme

In this subsection, we introduce an alternative identification scheme adopted by Beaudry and Lucke (2010), replacing assumption A3 with the following impact assumption.

- **Assumption B1** ($b_{23} = b_{24} = 0$): *News shocks and demand shocks do not have an impact effect on the relative price of investment.*

Assumption B1 is one way to isolate surprise IST shocks from other shocks.[11][12] Assumptions B1, A1, and A2 are sufficient to isolate the four shocks.[13] We call this identification approach with the above assumptions the "Beaudry-Lucke ID1 identification scheme." Table 3 summarizes the impact matrix B and the long-run matrix L under this identification system.

[Table 3 is inserted here.]

4.2 Beaudry-Lucke ID2 identification scheme

Here we replace A3 with the following assumption.

- **Assumption B2** ($l_{12} = 0$): *IST shocks do not have a long-run effect on TFP.*

From Assumption B2, TFP is assumed to have an independent process from IST.[14]

Assumptions A1, A2, and B2 are sufficient to isolate four shocks. We call this identification approach with the above assumptions the "Beaudry-Lucke ID2 identification scheme." Table 4 summarizes the impact matrix B and the long-run matrix L under this system. Notice that we do not put any restriction on how the two technology shocks affect each other in the long-run.

[Table 4 is inserted here.]

In our benchmark identification case, we separate TFP shocks into surprise and anticipated parts; hence, news shocks with the stock price innovation include only news on neutral technology. However, under the Beaudry-Lucke ID1 and ID2 schemes, the third shock may contain news on both IST and TFP. Therefore, as noted above, we call the third shocks "consolidated news shocks."[15]

[11] In the IST literature, the TFP process is assumed to be independent of innovations in IST. Therefore, an additional restriction $b_{21} = 0$ purely isolates unanticipated IST shocks, but this becomes an over-identifying restriction. To guarantee orthogonality of surprise IST shocks to surprise TFP shocks, additional restriction $b_{12} = 0$ is also requested, which is already included in Assumption A1. Robustness checks are performed with alternative restrictions in the working paper version.

[12] The assumption $b_{23} = 0$ can be criticized because the second variable may not reflect the pure IST. For example, consolidated news shocks and demand shocks can change the current relative price of investment goods when adjustment costs exist in investment. Furthermore, when the price stickiness in investment and consumption sectors is different, other shocks can have a short-run effect on the real investment price. Therefore, we use an alternative measure in the sensitivity analysis.

[13] We use only $l_{14} = 0$ of Assumption A2 because of the over-identification problem. We have a similar result with the restriction, $l_{24} = 0$.

[14] To guarantee the independent processes of the two technology changes, we must impose $l_{21} = 0$. We check the robustness later.

[15] For more details on the identifications, see Beaudry and Lucke (2010).

4.3 Results under alternative identification schemes

Figs. 5 and 6 depict the IRFs under two alternative identification schemes. IRFs of the h, y, i, and c systems are shown in the first through fourth rows. To focus on the effects of the news shock, we plot two technology processes after the stock price innovation in the first and second columns, and show the IRFs of macro activities to four structural shocks in the third through sixth columns.

The first and second columns display the IRFs of the measured TFP and the inverse of the relative price of investment goods to the consolidated news shocks. The shapes of the measured TFP are similar to and consistent with those observed in the benchmark system. Furthermore, the inverse of the relative price of investment goods closely follows the paths of TFP. Therefore, we conclude that the estimated news shocks contain both types of technology.

In the fifth column, we observe a positive boom of macro activities in the short run even though there is no initial innovation of technology in the first and second columns. Again, the only exception is c. We can observe positive responses of macro activities to the surprise TFP shocks in all cases. The effect of demand shocks is plotted in the sixth column. We can observe positive responses from the macro activities.

[Figs. 5 and 6 are inserted here.]

Fig. 7 displays the FEVDs of four macro variables in each x system for $x \in \{h, y, i, c\}$ under the Beaudry-Lucke ID1 identification scheme.[16]

[Fig. 7 is inserted here.]

The most important finding is that the consolidated news shocks play the most crucial role in all systems. In all systems, the fractions explained by the third shock increase, while the contribution of the second shock decreases. The contribution of the consolidated news shocks is dominant, accounting for more than 50 percent of both hours worked and investment in all horizons. News shocks also explain a large part of the movements of output in the long run in particular, and consumption in the short run. The contributions of surprise TFP shocks and demand shocks seldom change compared to the benchmark case. Hence, we can conclude that these estimated shocks are almost the same as those in the benchmark case. Consequently, we conclude that consolidated news shocks dominate the FEVDs of almost all activity measures under the Beaudry-Lucke ID1 and ID2 schemes.

The Beaudry-Lucke identification schemes include news on both future TFP and future IST, while the benchmark scheme isolates news shocks only on future TFP. From IRFs and FEVDs, there is almost no difference in the contributions of surprise TFP shocks and demand shocks between the two identification schemes. Therefore, we conclude that the differences of IRFs and FEVDs between our benchmark and the Beaudry-Lucke identification schemes come from the definition of news shocks, and that IST news shocks as well as TFP news shocks are important factors in explaining the Japanese business cycle.[17]

[16] The result under the Beaudry-Lucke ID2 scheme is almost the same.

[17] The source of IST news shocks in Japan is another issue. We leave this issue on the future research.

4.4 Robustness of identification

We only introduce two identification schemes in the former subsection but there are other possible identifying assumptions. To impose the exogeneity of TFP, we assume $b_{13} = b_{14} = l_{14} = 0$. Furthermore, to impose the exogeneity of IST, we set $l_{24} = 0$ (Assumption A3). Alternative assumption would be the impact restriction imposing $b_{24} = 0$. Therefore we have four restrictions, and need two additional restrictions. From the standard macro models, we can impose following restrictions: $b_{12} = b_{21} = b_{23} = l_{12} = l_{21} = 0$. There are 10 pairs of restrictions among these assumptions. We have 20 sets of identifying restrictions due to the existence of two possible assumptions of IST exogeneity.

[Table 5 is inserted here.]

Table 5 summarizes the results of all possible identification schemes based on 20 kinds of restriction pairs. ID1 and ID2 schemes are also included in these groups. The upper and lower triangular parts are respectively the results under identifications combining the short-run and long-run restrictions, $b_{24} = 0$ and $l_{24} = 0$, and corresponding each row and column restrictions. Entries indicate the main shock that share the biggest fraction of macro activities, hours worked, output, investment, and consumption in a descending order.

Some restriction schemes do not work because of the rank condition, the convergence problem, or the irrelevant responses. 16 pairs work well in the h system. Among them, new shocks contribute most in 14 out of 16 cases. Positive responses of hours to surprise IST shocks are seen in 10 cases. For y, i, and c systems, 10, 11, and 13 pairs are respectively proper for identification. News shocks contribute most in explaining the variance of output and investment in all cases, and 12 out of 13 in case of consumption. Positive responses of macro activities are seen in 8, 6, and 9 cases, respectively. Therefore in most cases, we can conclude that the consolidated news shocks are the major source of macroeconomic fluctuations in Japan.[18]

5 Robustness

In this section, we perform robustness checks of two main results. We mainly perform four robustness-checks. First, we also replace the stock prices with consumption to identify news shocks. Second, we check the robustness by sub-sample period estimation. Third, we re-estimate the model with an alternative measure of IST. Fourth, we perform a historical decomposition.

5.1 Consumption instead of stock prices

Unlike other variables that exactly describe the structural shocks, news shocks can be replaced with other forward-looking variables. Following Beaudry and Lucke (2009), we

[18] We also over-impose some restrictions and check out the results. Under the assumptions A1 and A3, we set rather strict restrictions on IST shocks: they have neither impact nor long-run effect on TFP. We set the counter-part restrictions to TFP shocks so that two technology processes become independent each other. We set $b_{21} = 0$ as well as $b_{12} = 0$ for no impact effect each other in the first over-identification scheme, and then set additional restriction $l_{21} = 0$ as well as $l_{12} = 0$ for no long-run effect in the second over-identification scheme. In all cases, we find that there are almost no changes in IRs and FEVDs with additional restrictions, except some responses of IST on TFP.

use consumption as an alternative variable to identify news shocks.

Fig. 8 displays the FEVDs in y and i systems using consumption as a news shock variable.[19] Two identification schemes are shown: our benchmark scheme on the top and the Beaudry-Lucke ID1 scheme on the bottom. The contribution of the consolidated news shocks is the biggest in the Beaudry-Lucke ID1 case, while the consolidated IST shocks take up large fraction in the benchmark scheme. Under the Beaudry-Lucke ID1 scheme, the contribution of the IST shocks is negligible in all cases, while it takes up 20 to 50 percent of the variances of macro activities in most horizons under the benchmark scheme. This gap under two different identification schemes restresses the role of the IST news shocks. We can conclude that the anticipated IST shock explains a large fraction of the macro activity variances.

[Fig. 8 is inserted here.]

5.2 Subsample periods

We performed a stability test such as break-point chow test and sample-split chow test. There is a possibility of the structural shift in the middle of the 1970s. Therefore, in this subsection we re-estimate the model dividing the sample into two subsamples: pre-1975 and post-1975. We could not get the proper IRs under former subsample period so we only introduce the results of subsample period from the first quarter in 1975.

Fig. 9 shows FEVDs of macro activities and reveals that the consolidated news shocks are the major source of all macro activities in the subsample period. However, most of them are attributed to the IST news shocks in h and y systems under this subsample period. Contributions of demand shocks become larger compared to the benchmark case, but their role is still minor.

[Fig. 9 is inserted here.]

5.3 Quality adjusted measures

There are some IR results that are inconsistent with theory. For example, the signs of IRs of consumption to news shocks are negative in the short run, which is inconsistent with theory. One possible reason is that our inverse of the relative price of investment goods is not a perfect measure of IST. To address the mis-measurement issue of the relative price of investment goods, we use an alternative measure. Fisher (2006) uses quality adjusted measures of prices published in the "National income and product" of the U.S. Bureau of Economic Analysis. Bank of Japan offers the Corporate Goods Price Index (CGPI) for quality-adjusted investment. Therefore, we alternatively measure the inverse of the relative price of investment as the consumption deflator divided by the CGPI deflator for quality-adjusted investment.

Figs. 10 and 11 present IRs to each shock with alternative measure of the investment price. The results show that consumption increases in response to the TFP news shocks in both identification schemes.[20]

[19] We do not display the result under the h system because we fail to replicate the proper IRs.

[20] We do not get the proper IRs under i system under the Beaudry-Lucke identification scheme. Thus, we only show three other cases.

[Figs. 10 and 11 are inserted here]

Fig. 12 reports the corresponding FEVDs. The results under the benchmark scheme suggest that the contributions of TFP news shocks to hours worked and output are limited. However, the fractions explained by TFP news shocks become increased in the case of investment and consumption. In addition, the results under Beaudry-Lucke ID1 scheme reveal another evidence that the IST news is important.

[Fig. 12 is inserted here]

6 Sign-restriction approach

There are several differences between our SVECM and the DSGE model estimation. Most importantly, our SVECM approach imposes only minimum assumptions, while a structural estimation with a fully specified DSGE model should impose many more assumptions. Although the DSGE approach has an advantage of being straightforward to interpret shocks, it faces the risk of imposing too much structure on the model which might not necessarily capture the true structure of the actual economy. The SVAR approach (including our SVECM), on the other hand, has one problem which is that it sometimes produces impulse responses that are not consistent with theory. Therefore, to understand the limitations of both approaches, it may be desirable to compare the results produced by them. In this section, we first compare our SVECM results with the DSGE-approach results reported in Fujiwara, Hirose, and Shintani (2011), next we discuss some limitations of our SVECM above, and finally we introduce a new SVAR approach which has several advantages over the SVECM approach and also makes it more suitable to compare with the DSGE approach.

6.1 Comparison with Fujiwara, Hirose, and Shintani (2011)

Fujiwara et al. (2011) assess the relative importance of the TFP news shocks based on an estimation of a DSGE model using a Bayesian method. They build a New Keynesian DSGE model a la Christiano, Eichenbaum, and Evans (2005) and explicitly introduce TFP news shocks.[21] Table 6 reports the share of macroeconomic fluctuations explained by TFP news shocks in our SVECM and Fujiwara et al. (2011).

[Table 6 is inserted here.]

The main difference between the results is that news shocks are the main contributor in our SVECM while surprise TFP shocks are the dominant driver in their model. Why does this difference occur? There are several possible reasons. First, the estimated news shocks in our SVECM model are different from those in Fujiwara et al. (2011). Our estimated news shocks start to increase TFP around four to 32 periods after the stock market innovation, while news shocks in Fujiwara et al. (2011), like other DSGE works, are built to start to increase future TFP from one to four periods ahead. Second, the treatment of the trend may be another explanation. In our SVECM, we assume a common

[21] Sugo and Ueda (2008) perform a Bayesian estimation of the Japanese economy, introducing several kinds of candidate shocks. They conclude that investment shocks played an important role in the 1990s.

stochastic trend based on the ADF tests and the Johansen cointegration tests, while they examine the model around the deterministic trend. Third, they only introduce TFP news shocks, and do not consider other types of news shocks. The estimated TFP news shocks in our SVECM play a non-negligible role in the benchmark case. In the Beaudry-Lucke identification scheme, the contribution of the news shocks increases because the news shocks also include news on IST.

6.2 Some limitations of our SVECM

Our SVECM used above has some limitations. First, the timing of news shocks changes in each macro activity system, which makes it difficult to compare with the DSGE approach. For example, news shocks in the c system start to increase TFP three quarters after the stock market innovation, while in the y system it takes 32 quarters for news shocks to increase TFP. Second, in our SVECM it is difficult to include at the same time all the relevant variables in the VAR and we must use VAR models with only four variables and thus must substitute out a macro activity variable and replace it with another in each system. This is because in our SVECM a combination of short-run and long-run restrictions is required, and including more variables requires including more shocks and thus makes it harder to justify and set the restrictions to identify all shocks. Third, the number of shocks may influence the results as it is argued that with more shocks the contribution of TFP shocks might not as large as reported in Beaudry and Portier (2006) who employ a VAR with only two variables and two shocks. In our SVECM the number of shocks is four which is smaller than that in Fujiwara et al. (2011) who introduce many more types of shocks.

6.3 The sign restriction approach: Estimation and results

Considering the problems discussed above, here we adopt the SVAR approach with sign restrictions. As noted in Uhlig (2005), this approach allows us to identify only a subset of the structural shocks, thus it enables us to include more variables in the VAR. Below we estimate a seven-variable VAR, and we identify only two shocks, namely surprise TFP shocks and TFP news shocks, because these shocks are the major focus of our paper. The sign restriction approach also allows us to estimate the VAR in level because it does not require a long run restriction, thus we do not need to assume a common stochastic trend in the data and we can avoid the above problem regarding the difference in the treatment of trends in our paper and Fujiwara et al. (2011). As shown in the IRFs below, with the sign restriction approach we are also able to control for the timing of news. The order of the endogenous variables in the VAR is as follows: tfp, pi, sp, h, y, i, and c. We impose the following sign restrictions on the IRFs to identify surprise TFP shocks and TFP news shocks. Surprise TFP shocks are identified by the restrictions that they raise TFP and stock prices at the impact. TFP news shocks are identified by the restrictions that they have zero effect on TFP and raise stock prices and macro activities at the impact, and they raise TFP within four quarters later. Note that the first restriction distinguishes a TFP news shock with a surprise TFP shock. We do not impose any restriction on the response of the inverse of the relative price of investment goods.

Following Uhlig (2005) and Vu (2009), we start by estimating a reduced-form VAR. We include a constant term and assume two lags based on the AIC. The relationship between the residual obtained in the estimated reduced-form VAR and the structural shocks is ε_t and $u_t = B\varepsilon_t$, with $E[u_t u_t'] = \Sigma$ and $E[\varepsilon_t \varepsilon_t'] = I$. The impact matrix B can be written in the form $B = PQ$, where P is the lower triangular Cholesky factor of Σ, and Q is an orthonormal matrix with $QQ' = I$. We generate from the Wishart-Normal distributions a number of draws of the VAR coefficients and the variance-covariance matrix of the residuals. For each of these draws, we generate a number of the first two columns of the matrix Q and keep the ones (we called them valid draws) which produce IRFs to the two TFP shocks that satisfy the restrictions noted above while discard those that do not. We continue this task until we obtain 100 valid draws.[22]

Fig. 13 shows the IRFs to the TFP news shocks. The identified TFP news shocks are the same as our SVECM approach except for the timing of the increase in TFP. Although in our sign restriction scheme we leave the possibility that TFP may start to increase at two to four periods after the boom in the stock market and macro activities, it turns out in the results that estimated news shocks increase TFP only one period after the stock market boom. Among macro activities, investment shows the largest response to the news shocks. Our estimated news shocks seem to have no long-run effect on the inverse of the relative price of investment goods as shown in the second panel.

[Fig. 13 is inserted here]

Fig. 14 displays the FEVDs. We can see that the contribution of news shocks decreases compared to the four-variable SVECM. One of the reasons might be that the number of structural shocks increases. The inclusion of many candidate shocks into the model may decrease the contribution of each shock, as noted above. We also observe that the contribution of news shocks is larger as compared to Fujiwara et al. (2011), while the contribution of surprise TFP shocks becomes minor. This finding is noteworthy because we imposed few restrictions to identify surprise TFP shocks compared to the SVECM case above.

[Fig. 14 is inserted here]

6.4 The sign restriction approach: Applying to the case of the U.S.

Fujiwara et al. (2011) find that the contribution of news shocks in the U.S. economy is larger than in the Japanese economy. In this subsection we estimate the same SVAR with sign restrictions as noted above using U.S. data and compare the results with those for Japan. The data for the U.S. economy are taken from Beaudry and Lucke (2009).[23] We set the sample period to be 1960-Q1 to 2002-Q4, the same of that for the case of Japan for the purpose of comparison. The main results are shown in Figs. 15 and 16. IRFs are almost the same as those in the case of Japan. One noteworthy finding regarding FEVDs is that the contribution of news shocks in the U.S. economy increases compared to Japan's results. This finding is consistent with Fujiwara et al. (2011).

[Figs. 15 and 16 are inserted here]

[22] For more details of each estimation step, see Vu (2009).

[23] For the details of the data, see Beaudry and Lucke (2010).

7 Conclusion

What is the driving source of Japanese business cycle fluctuations? We answer this fundamental question using a SVECM approach with the combination of long-run and short-run restrictions. We assess the relative importance of possible candidate shocks with all possible identification schemes that are consistent with standard macro models.

Our main findings are as follows. First, the estimated TFP news shocks are important in explaining the variances of hours worked and investment, but play a somewhat smaller role in the cases of consumption and output. Therefore, our benchmark result lies between previous studies. Second, IST news shocks turn out to be the dark horse behind the Japanese business cycles. Therefore, the news shocks on both of future TFP and IST are capable of explaining most fluctuations in macro activities. Furthermore, the evidence also suggests that large portions of the bubble economy in the late 1980s and the stagnation in the early 1990s can be explained by news shocks. The surprise TFP shocks play some role in explaining output and consumption movement, but a negligible role in explaining hours worked and investment movement.

As an alternative approach, we estimate a SVAR model with sign restrictions. Using a SVAR model with sign restrictions, we identify more specified news shocks consistent with the previous DSGE literature. We find that news shocks explain around 10 to 30 percent of macroeconomic fluctuations under this approach. This finding lies between our SVECM and Fujiwara et al. (2011).

We also compare our results with those for the U.S. economy. The major differences between the business cycles of Japan and the U.S. are as follows. First, in the Japanese economy, we find the significant contribution of IST news shocks in the benchmark case; this was negligible in the U.S. business cycles in Beaudry and Lucke (2010). Second, the results of SVAR estimation with sign restrictions indicate that the contribution of news shocks is larger in the U.S. economy.

In the future research, more specific identifications of all structural shocks based on SVAR with sign restrictions are possible. We only identify news shocks that replicate the TFP and IST processes observed in theory. We can apply the method to identify several kinds of news shocks and investigate the relationship between macro activities. It may be also possible to explore other types of news shocks such as the announcement effect of monetary and fiscal policies.

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Table 1

Impact and long-run matrices B and L under the benchmark scheme

$B =$

	surprise TFP	*consolidated IST*	*TFP news*	*demand shock*
tfp	$*$	0	0	0
pi	$*$	$*$	$*$	$*$
sp	$*$	$*$	$*$	$*$
x	$*$	$*$	$*$	$*$

$L =$

	surprise TFP	*consolidated IST*	*TFP news*	*demand shock*
tfp	$*$	$*$	$*$	0
pi	$*$	$*$	0	0
sp	$*$	$*$	$*$	$*$
x	$*$	$*$	$*$	$*$

Note: *tfp*, *pi*, *sp*, and x respectively denote TFP, the relative price of investment goods, stock prices, and macro activity. Macro activity, x, includes h, y, i, and c, which denote hours worked, output, investment, and consumption, respectively. Dependent variables are listed in rows and structural shocks are listed in columns. Starred entries mean that the corresponding elements are not restricted. Zero entries indicate that the corresponding shocks do have no effect on the corresponding variables.

Table 2

Robustness of identifying restrictions

	$b_{12} = 0$	$b_{21} = 0$	$l_{12} = 0$	$l_{21} = 0$
$b_{24} = 0$	0.36, 0.59	0.36, 0.59	0.03, 0.59	0.36, 0.59
	0.48, 0.20	0.48, 0.20	0.42, 0.19	0.21, 0.20
	0.42, 0.41	0.47, 0.41	0.01, 0.41	0.52, 0.41
	0.11, 0.06	0.09, 0.06	0.30, 0.06	0.17, 0.06
$l_{24} = 0$	0.36, 0.59	0.36, 0.59	0.03, 0.59	0.36, 0.59
	0.44, 0.27	0.44, 0.27	0.28, 0.27	0.19, 0.27
	0.39, 0.48	0.44, 0.48	0.01, 0.48	0.49, 0.48
	0.10, 0.06	0.09, 0.06	0.29, 0.06	0.17, 0.06

Note: The upper (lower) row is the result under identifications combining the short-run (long-run) restriction $b_{24} = 0$ ($l_{24} = 0$) and corresponding each column restrcitions. The left entries below indicate the value of consolidated IST shocks at horizon 32 quarters. The right values are the corresponding TFP news shock share of variances. Their contributions for macro activities such as hours worked, output, investment, and consumption are listed in a descending order.

Table 3

Impact and long-run matrices B and L under the Beaudry-Lucke ID1 scheme

$B =$

	surprise TFP	*surprise IST*	*consolidated news*	*demand shock*
tfp	$*$	0	0	0
pi	$*$	$*$	0	0
sp	$*$	$*$	$*$	$*$
x	$*$	$*$	$*$	$*$

$L =$

	surprise TFP	*surprise IST*	*consolidated news*	*demand shock*
tfp	$*$	$*$	$*$	0
pi	$*$	$*$	$*$	$*$
sp	$*$	$*$	$*$	$*$
x	$*$	$*$	$*$	$*$

Note: The benchmark system is based on four variables: *tfp*, *pi*, *sp*, and x, respectively denote TFP, the relative price of investment goods, stock prices, and macro activity. Macro activity, x, includes h, y, i, and c, which denote hours worked, output, investment, and consumption, respectively. Dependent variables are listed in rows and structural shocks are listed in columns. Starred entries mean that the corresponding elements are not restricted. Zero entries indicate that the corresponding shocks do have no effect on the corresponding variables.

Table 4

Impact and long-run matrices B and L under the Beaudry-Lucke ID2 scheme

$B =$

	surprise TFP	*surprise IST*	*consolidated news*	*demand shock*
tfp	$*$	0	0	0
pi	$*$	$*$	$*$	$*$
sp	$*$	$*$	$*$	$*$
x	$*$	$*$	$*$	$*$

$L =$

	surprise TFP	*surprise IST*	*consolidated news*	*demand shock*
tfp	$*$	0	$*$	0
pi	$*$	$*$	$*$	0
sp	$*$	$*$	$*$	$*$
x	$*$	$*$	$*$	$*$

Note: The benchmark system is based on four variables: *tfp*, *pi*, *sp*, and x, respectively denote TFP, the relative price of investment goods, stock prices, and macro activity. Macro activity, x, includes h, y, i, and c, which denote hours worked, output, investment, and consumption, respectively. Dependent variables are listed in rows and structural shocks are listed in columns. Starred entries mean that the corresponding elements are not restricted. Zero entries indicate that the corresponding shocks do have no effect on the corresponding variables.

Table 5
Robustness of identifying restrictions

	$b_{12}=0$	$b_{21}=0$	$b_{23}=0$	$l_{12}=0$	$l_{21}=0$
$b_{12}=0$		n.i. n.i. n.i. n.i.	news (+) news (+) news (+) news (+)	news (−) news (−) news (−) news (−)	n.i. n.i. n.i. n.i.
$b_{21}=0$	n.i. n.i. n.i. n.i.		news (+) news (+) news (+) news (+)	tfp (−) n.i. news (−) news (−)	news (+) n.i. n.i. tfp (+)
$b_{23}=0$	news (+) news (+) news (+) news (+)	news (+) news (+) news (+) news (+)		news (+) news (+) news (−) news (+)	news (+) news (+) news (+) news (+)
$l_{12}=0$	news (−) news (−) news (−) news (−)	tfp (−) n.i. n.i. news (−)	news (+) news (+) news (−) news (+)		news (−) n.i. n.i. n.i.
$l_{21}=0$	n.i. n.i. n.i. n.i.	news (+) n.i. n.i. tfp (+)	news (+) news (+) news (+) news (+)	news (−) n.i. n.i. n.i.	

Note: The upper (lower) triangular part is the result under identifications combining the short-run (long-run) restriction $b_{24}=0$ ($l_{24}=0$) and corresponding each row and column restrcitions. Entries indicate the main shock that share the the biggest fraction of macro activities, hours worked, output, investment, and consumption in a descending order. The sign in each bracket indicates the direction of macro activity responses to surprise IST shocks. n.i. means not identified.

Table 6
Estimated contribution of news shocks

	h	y	i	c
SVECM				
Benchmark	0.59	0.27	0.48	0.06
Beaudry-Lucke ID1	0.90	0.52	0.60	0.14
SVECM (quality adjusted)				
Benchmark	0.07	0.03	0.69	0.23
Beaudry-Lucke ID1	0.18	0.61	n.i.	0.38
Estimated DSGE model				
Fujiwara et al. (2011)	0.02	0.07	0.01	0.05

Note: The entries below SVECM indicate the value of news shock contribution at horizon 32 quarters. The entries reported in the rows below the one entitled 'Estimated DSGE model' correspond to the share of the FEVDs of Table 4 in Fujiwara et al. (2011). n.i. means not identified.

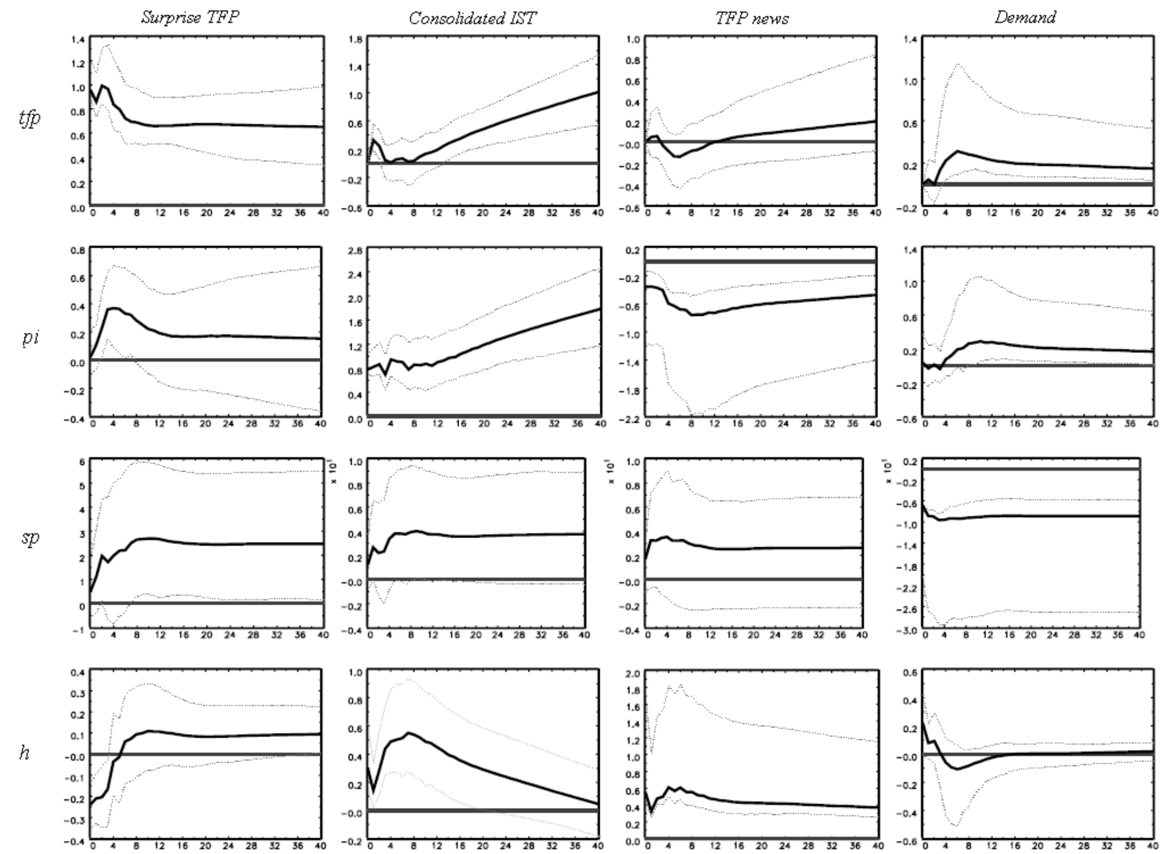

Fig. 1. IRs of the h system under the benchmark identification scheme. Impulses are given in columns, responding variables in rows. Solid lines represent estimated impulse responses to each shock, and dashed lines are two standard errors bootstrapped confidence intervals (Hall).

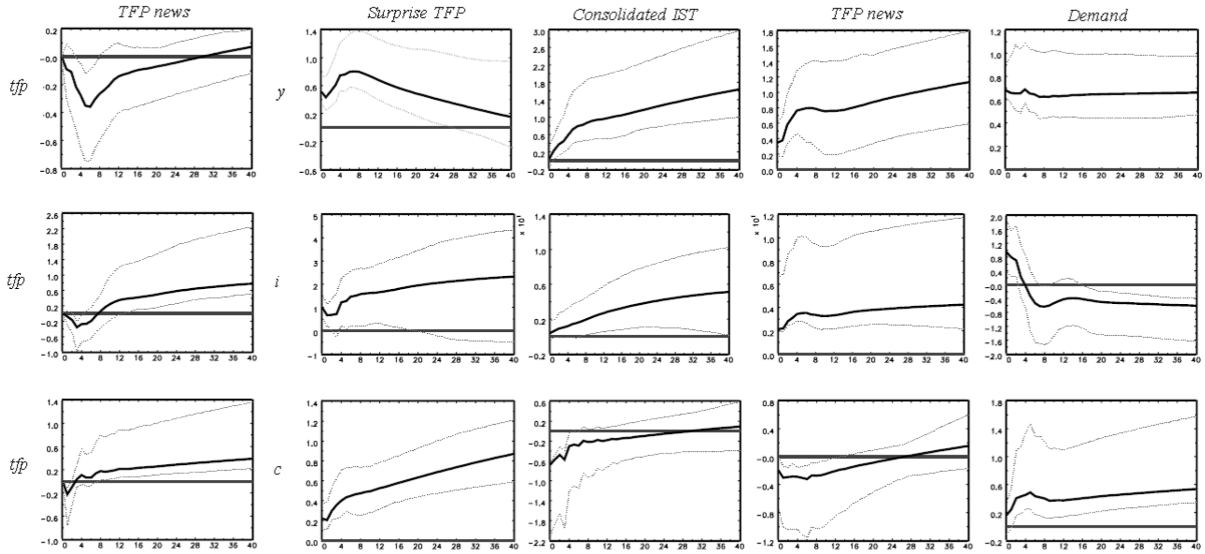

Fig. 2. IRs under y, i, and c systems under the benchmark identification scheme. Impulses are given in columns, responding variables in rows. Solid lines represent estimated impulse responses to each shock, and dashed lines are two standard errors bootstrapped confidence intervals (Hall).

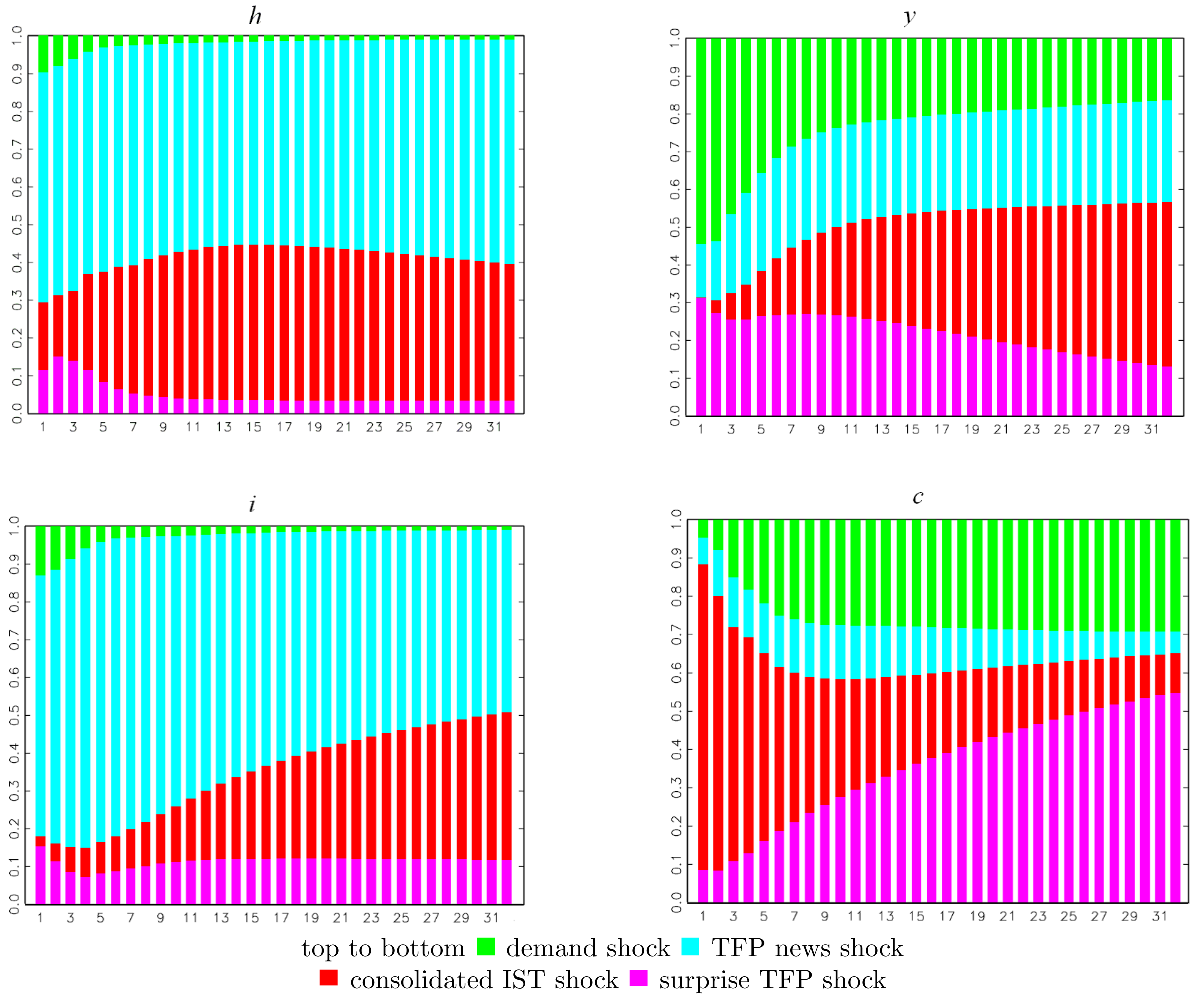

Fig. 3. *FEVD*s under the benchmark identification scheme. FEVDs of h and y (i and c) are listed from the left to the right panel in the first (second) row.

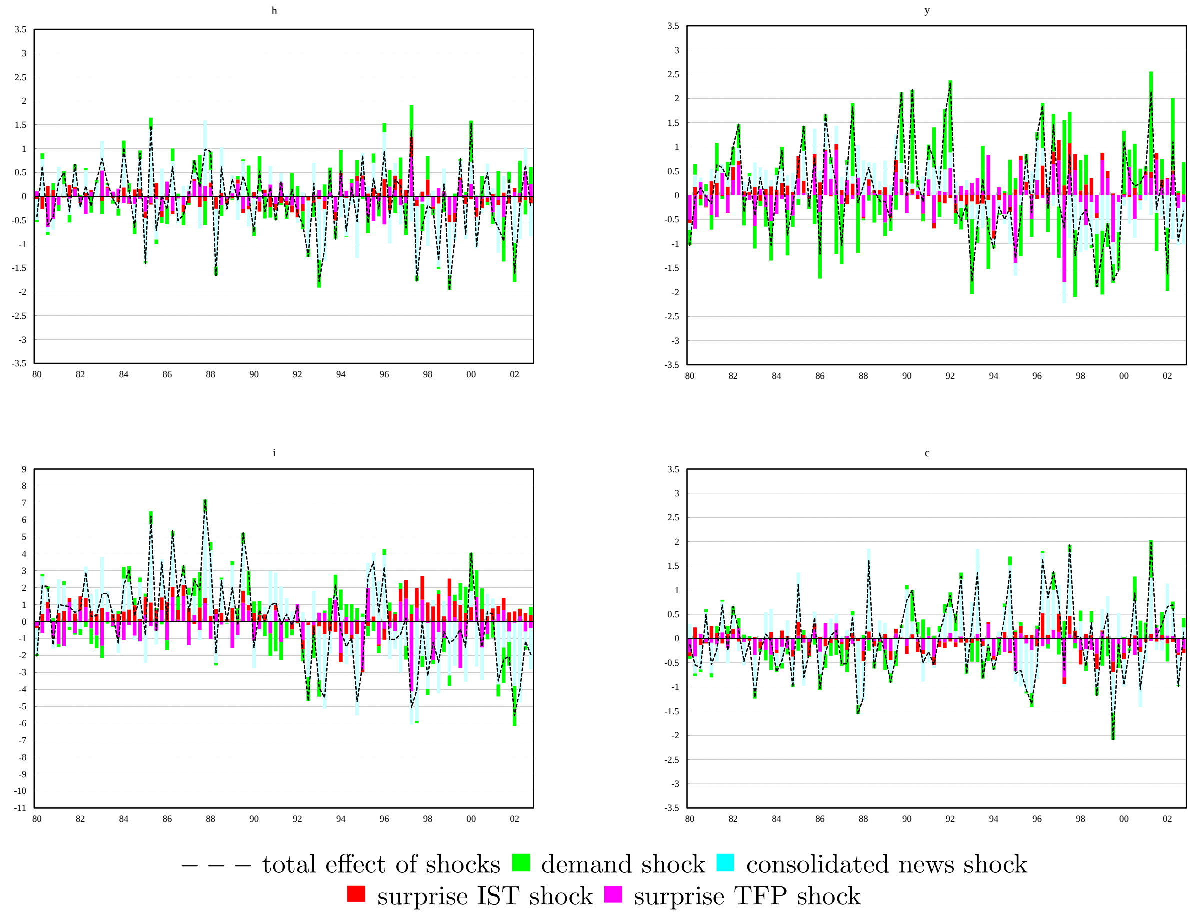

Fig. 4. Historical variance decompositions of structural shocks in 1980-2002. FEVDs of h and y are listed from the left to the right panel in the first row. FEVDs of i and c are listed from the left to the right panel in the bottom row.

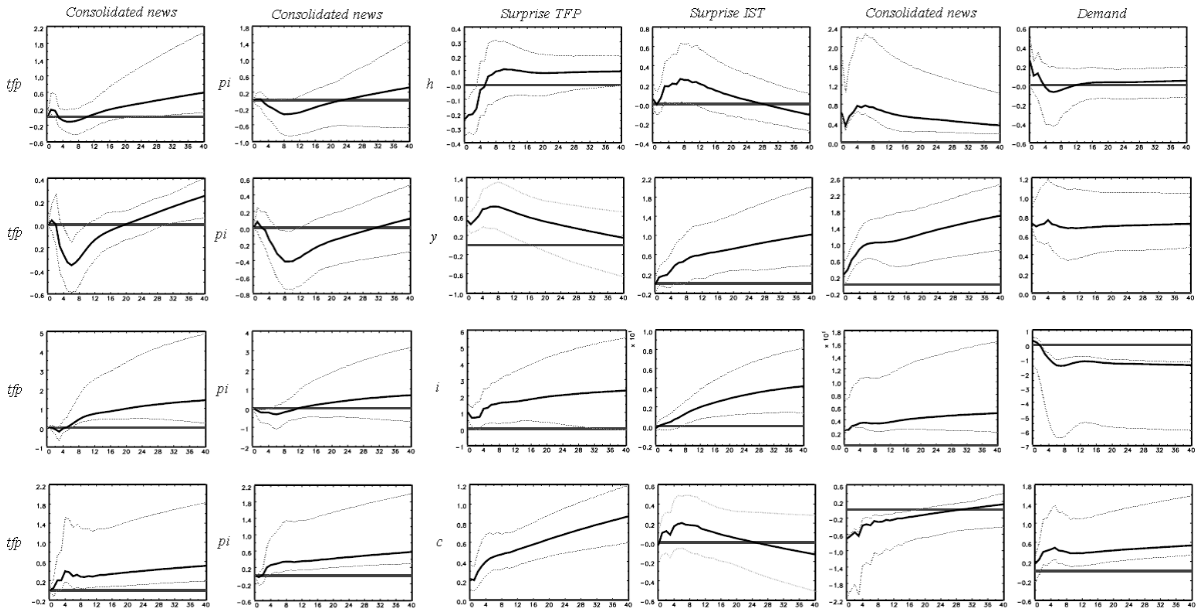

Fig. 5. IRs of the h, y, i, and c systems under the Beaudry-Lucke ID1 identification scheme. Impulses are given in columns, responding variables in rows. Solid lines represent estimated impulse responses to each shock, and dashed lines are two standard errors bootstrapped confidence intervals (Hall).

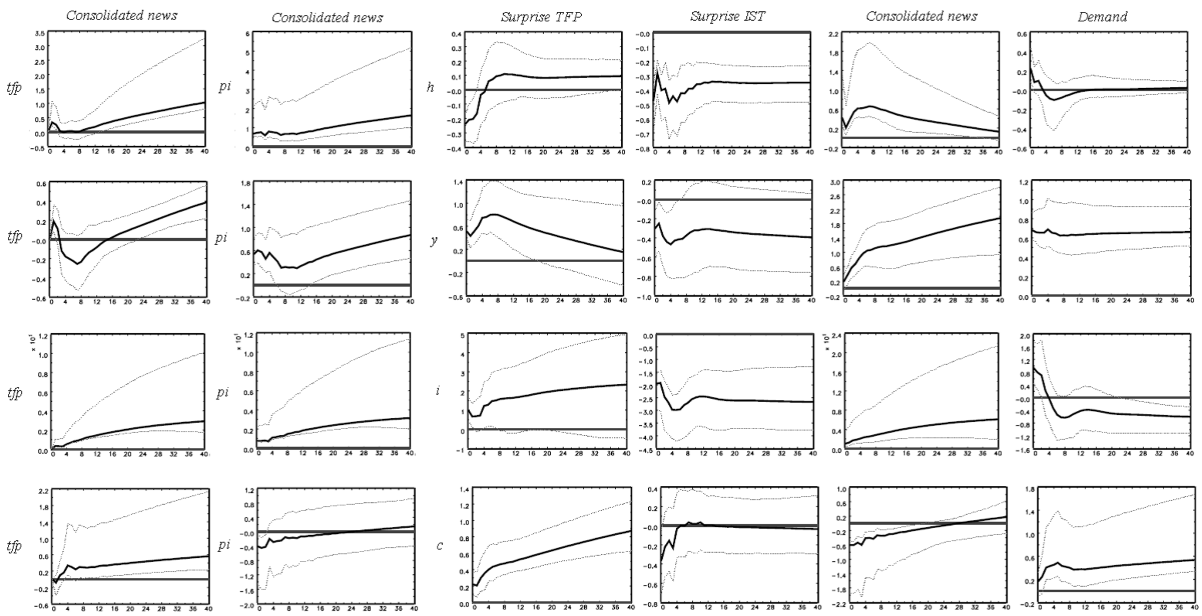

Fig. 6. IRs of the h, y, i, and c systems under the Beaudry-Lucke ID2 identification scheme. Impulses are given in columns, responding variables in rows. Solid lines represent estimated impulse responses to each shock, and dashed lines are two standard errors bootstrapped confidence intervals (Hall).

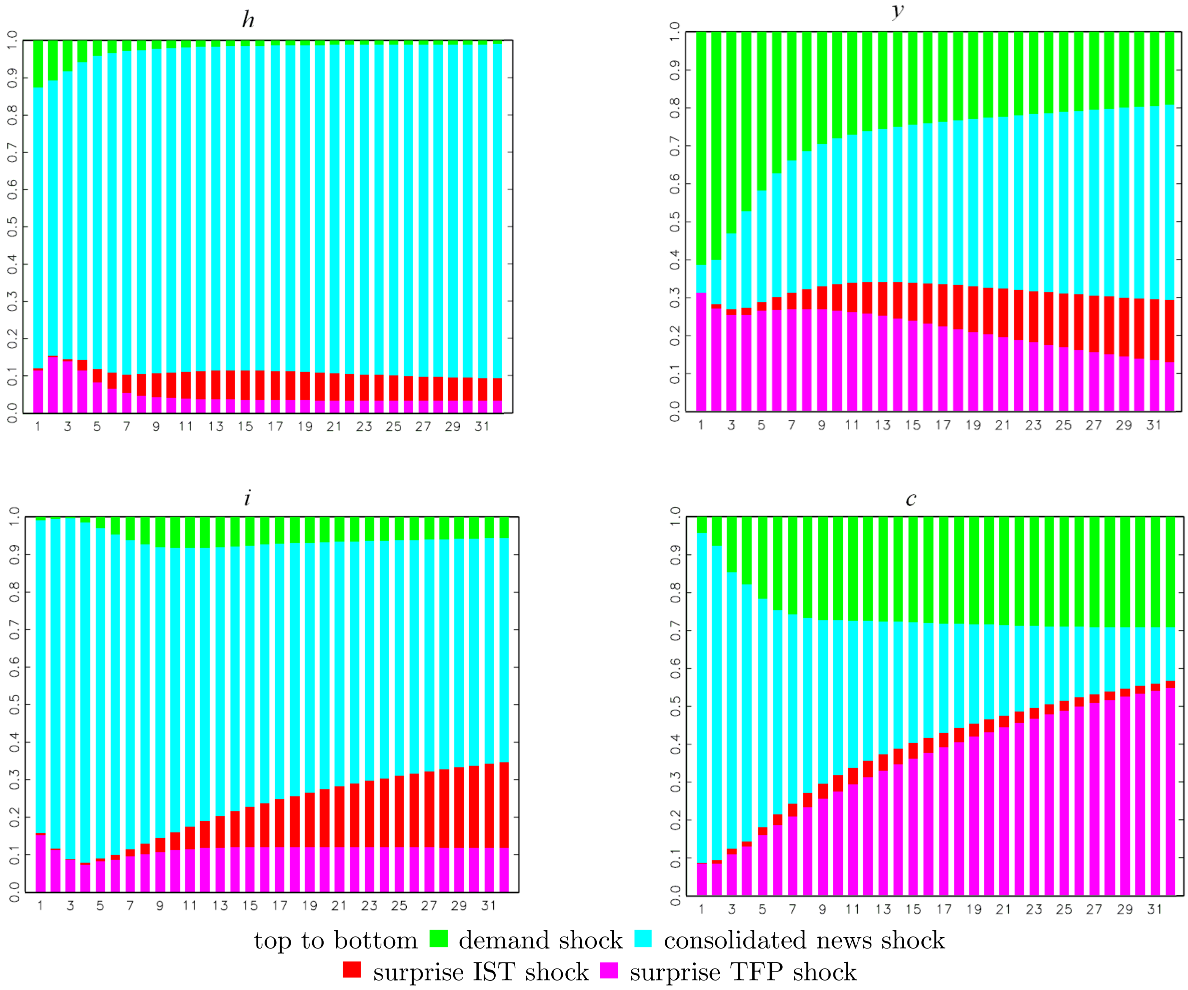

Fig. 7. *FEVDs* under the Beaudry-Lucke ID1 identification scheme. FEVDs of h and y (i and c) are listed from the left to the right panel in the first (second) row.

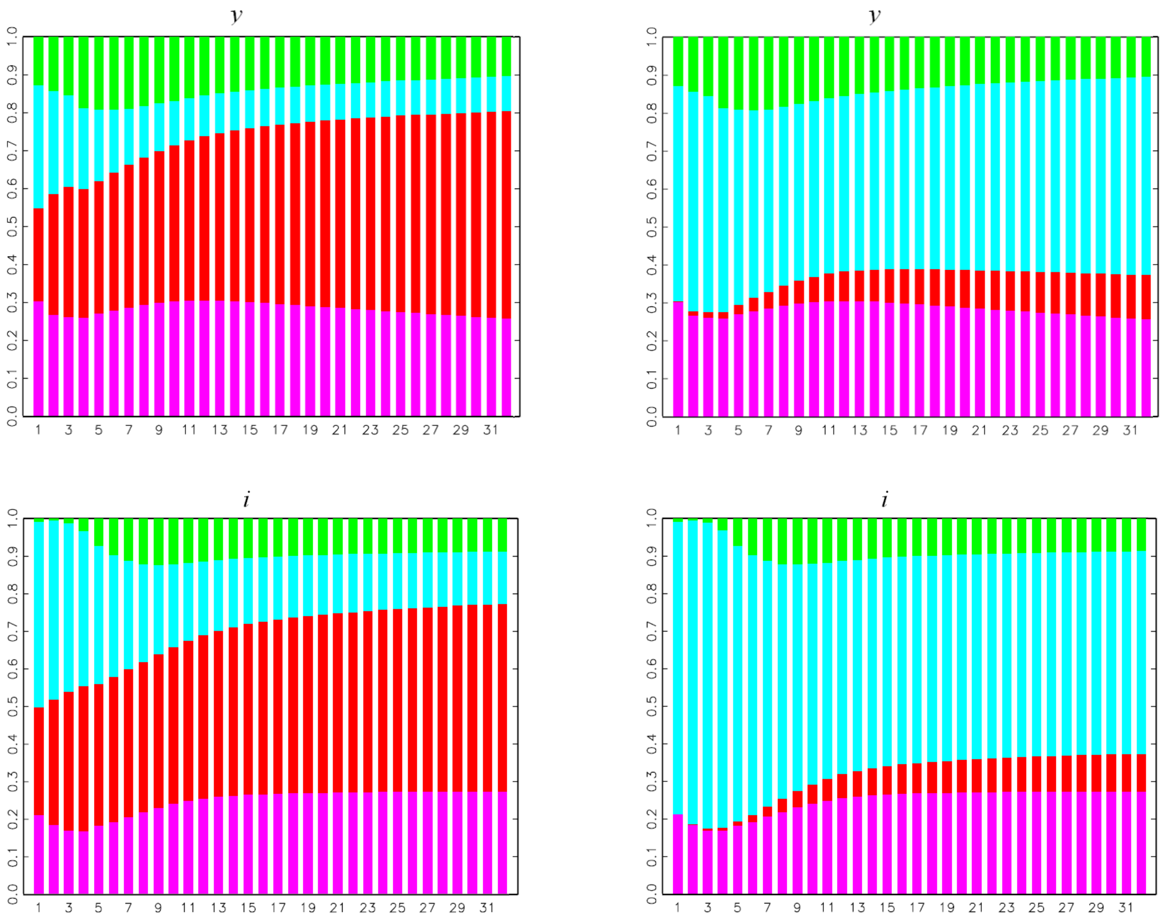

Fig. 8. *FEVDs* in the y and i systems, with consumption as a news shock variable. FEVDs of y and i under the benchmark (the Beaudry-Lucke ID1) identification scheme are listed from the left (right) column.

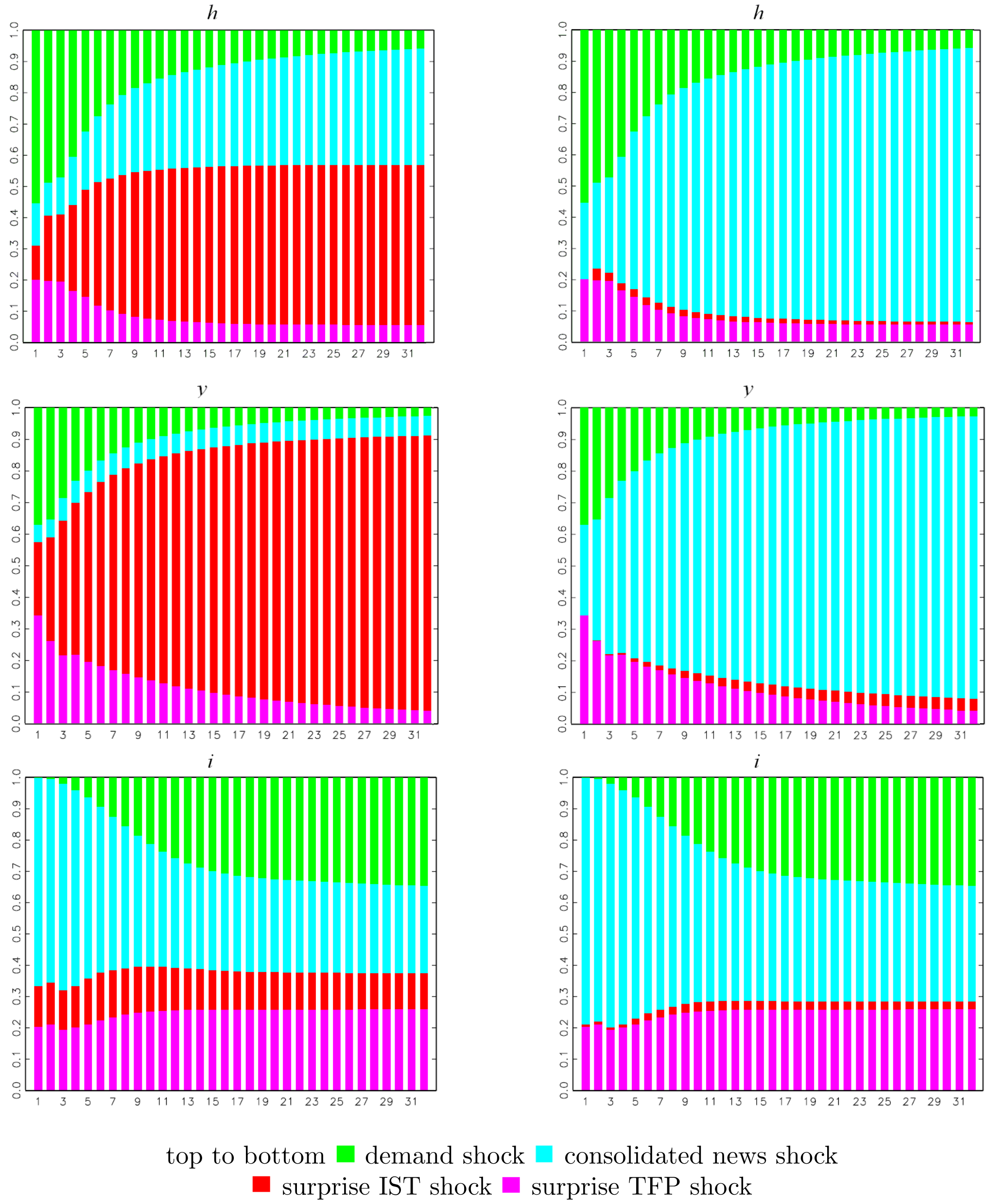

Fig. 9. *FEVD*s under subsample periods from 1975-Q1 to 2002-Q4. FEVDs of h, y, and i under the benchmark (Beaudry-Lucke ID1) identification scheme are respectively listed from the left to the right panel in the left (right) column.

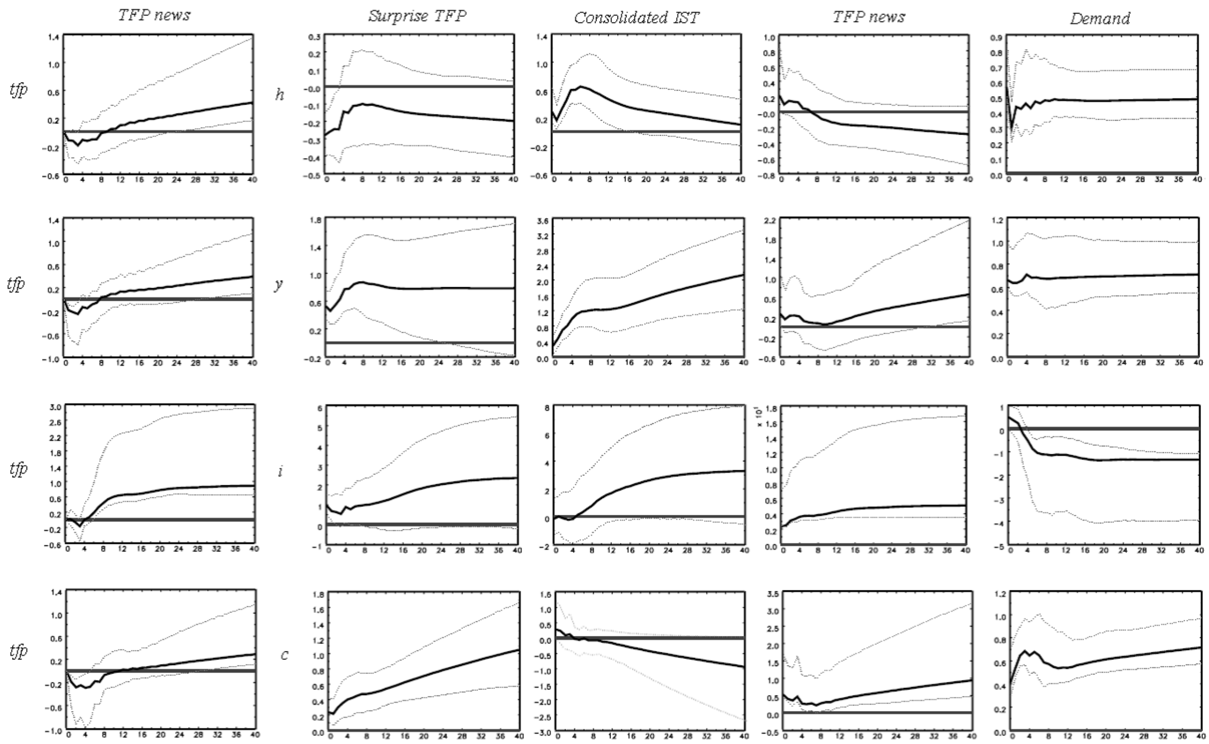

Fig. 10. IRs with quality-adjusted data under the benchmark identification scheme. Impulses are given in columns, responding variables in rows. Solid lines represent estimated impulse responses to each shock, and dashed lines are two standard errors bootstrapped confidence intervals (Hall).

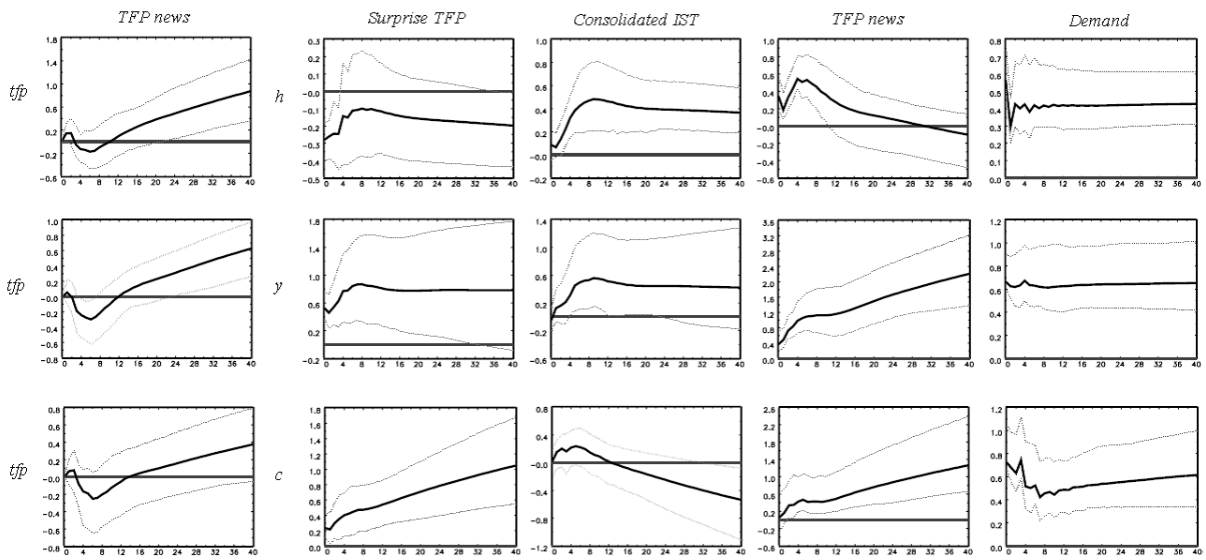

Fig. 11. IRs with quality-adjusted data under the Beaudry-Lucke ID1 identification scheme. Impulses are given in columns, responding variables in rows. Solid lines represent estimated impulse responses to each shock, and dashed lines are two standard errors bootstrapped confidence intervals (Hall).

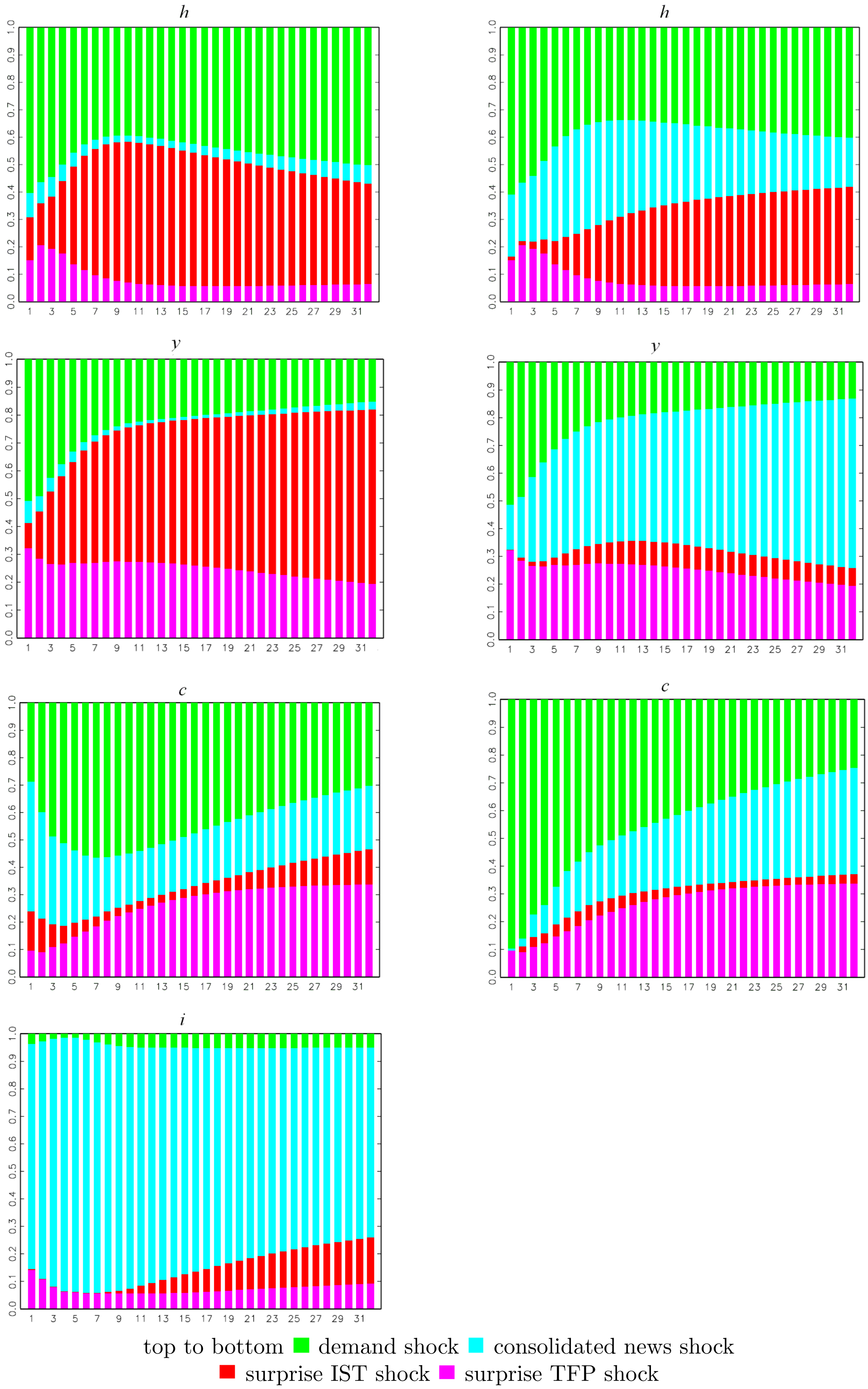

Fig. 12. *FEVD*s with quality-adjusted data under the benchmark and Beaudry-Lucke ID1 identification schemes. FEVDs under the bencmark (Beaudry-Lucke ID1) scheme are listed in the left (right) column. FEVD of i under Beaudry-Lucke ID1 scheme is not listed because of the identification failure.

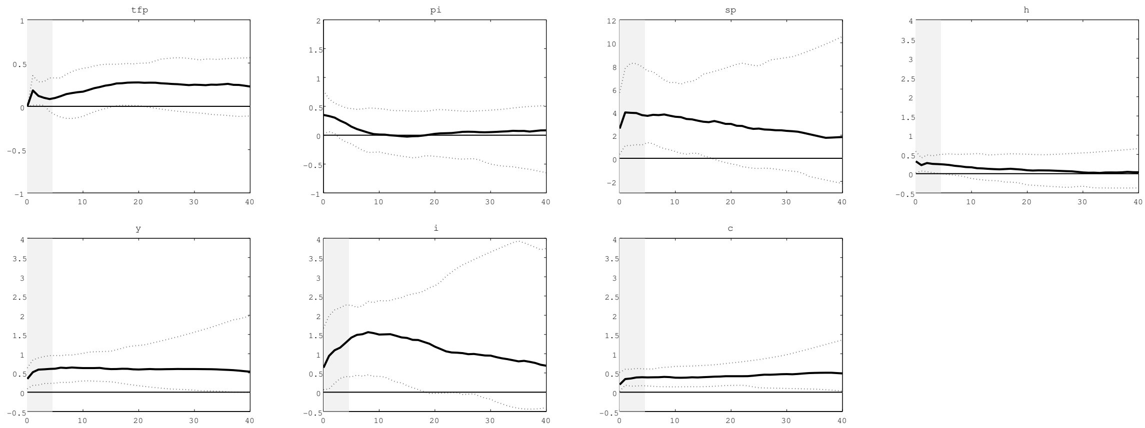

Fig. 13. IRs of seven-variable case to news shocks. The shaded areas indicate the impulses directly restricted by the identification procedure. Dotted lines indicates 5th and 95th percentiles. Thick lines are the medians of all the valid draws.

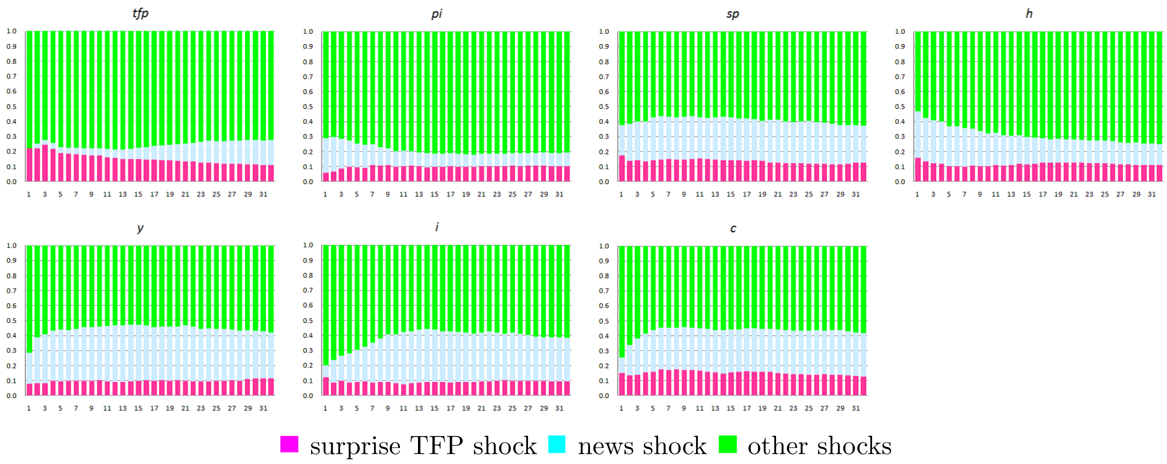

Fig. 14. FEVDs based on the VAR under sign restrictions. FEVDs of *tfp*, *pi*, *sp*, *h*, *y*, *i*, and *c* are listed in orders.

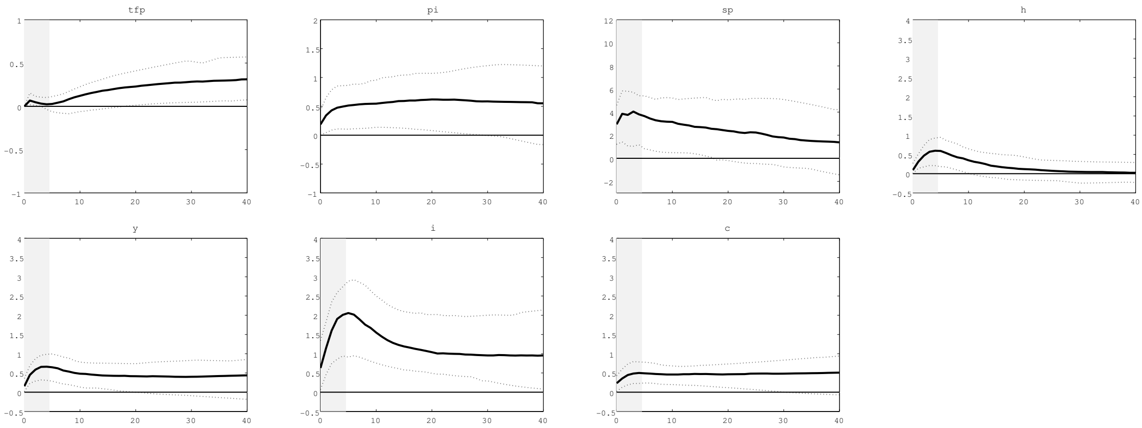

Fig. 15. IRs of seven-variable case to news shocks (U.S. case). The shaded areas indicate the impulses directly restricted by the identification procedure. Dotted lines indicates 5th and 95th percentiles. Thick lines are the medians of all the valid draws.

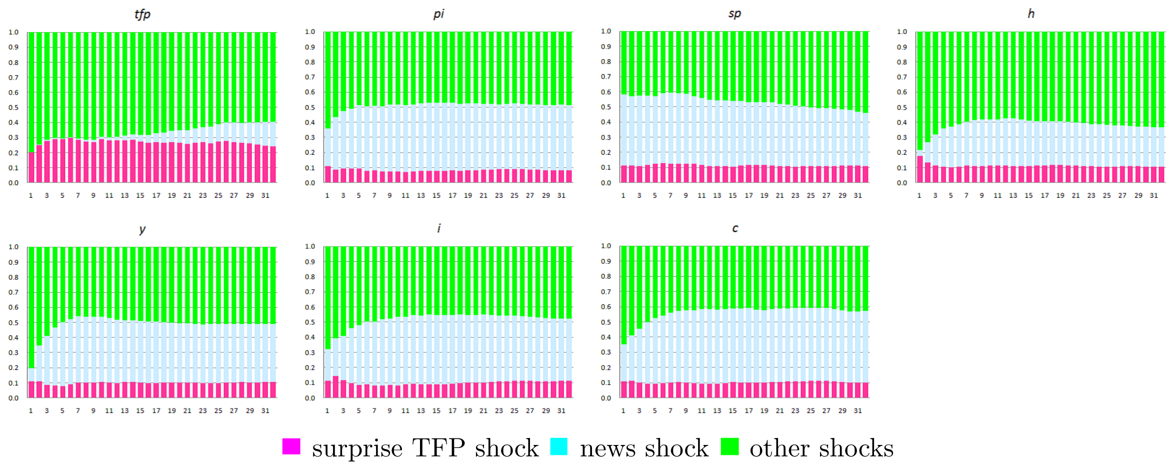

Fig. 16. FEVDs based on the VAR under sign restrictions (U.S. case). FEVDs of *tfp*, *pi*, *sp*, *h*, *y*, *i*, and *c* are listed in orders.