Letting Different Views about Business Cycles Compete

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I. Introduction

The rise of real business cycle (RBC) models in the 1980s initiated much controversy about the main driving forces of macroeconomic fluctuations. Some 25 years later, economists have still not reached a consensus on this issue. Shocks to disembodied technology had been singled out by the RBC literature as a central element in business cycle fluctuations. In contrast, a large literature based on new Keynesian models tends to emphasize instead the importance of monetary and other nontechnology shocks in fluctuations. For example, an influential paper by Galí (1999) has suggested that surprise technology shocks may not be an important contributor to business cycle fluctuations. More recently, Fisher (2006) reframed the debate by distinguishing between shocks to disembodied and those to embodied technology. While he found the former to be unimportant indeed, he claimed that shocks to investment-specific technology (IST) are the major source of hours variance. Simultaneously, Beaudry and Portier (2006) suggested expectational shocks reflecting news about future technological developments (referred to as news shocks) as an important force behind macroeconomic fluctuations.

In this paper, we aim to assess the relative importance of several candidate explanations of macroeconomic fluctuations by adopting a framework that allows them to compete. Following, among others, Galí (1999) and Fisher (2003, 2006), we use a structural vector autoregressive (SVAR) approach to explore this issue. We depart slightly from these authors by explicitly allowing for cointegration. Within this framework, we explore several alternative identification schemes that allow us to isolate five shocks commonly discussed in the literature. These are as follows: surprise changes to disembodied and to embodied technology, news shocks, monetary policy shocks, and preference shocks.
Our benchmark identification scheme imposes only a few long-run restrictions since at least three of the shocks we consider (two surprise technology shocks and the news shocks) may well cause permanent effects. The first identification scheme we propose therefore relies mostly on impact restrictions. For example, the news shock is identified to be orthogonal to measures of total factor productivity (TFP) and the relative price of investment on impact but unrestricted in the long run. However, to illustrate the robustness of our results, we also work with an alternative identification scheme that imposes fewer short-run restrictions and relies more on long-run restrictions.

Our baseline vector error correction model (VECM) framework is composed of five variables: measured TFP, the relative price of investment goods, an index of stock prices, hours worked, and the federal funds rate. In accordance with much of the literature, we choose hours of work as our primary measure of aggregate economic activity. We also document the robustness of our results by considering alternative measures of economic activity such as consumption, investment, and output. Following Fisher (2006), we use the relative price of investment to help identify IST shocks. Since standard deflators from the National Income and Product Accounts (NIPA) have been criticized for insufficient quality adjustment, for example, by Gordon (1989), we also work with a measure of the real price of investment based on the work of Cummins and Violante (2002) and adjust investment, output, TFP, and capital stock data accordingly. We do not find that the issue of quality adjustment matters much.

Our main findings are as follows. Our two main identification schemes give very similar results. In both cases we find that neither type of surprise technology shock explains more than a small share of activity variance. The dominant force appears to be the news shock, which precedes growth in measured TFP by about 2 years. Monetary shocks, preference shocks, and in some cases surprise TFP shocks play more minor roles but are not negligible. IST shocks, on the other hand, appear to play a negligible role in fluctuations, provided the analysis allows for the possibility of news shocks reflected in stock prices. These results are shown to be robust across various modifications of the underlying dependent variables and the identifying assumptions.

The paper is organized as follows: Section II presents our structural VECM framework and discusses the identifying assumptions for our two basic identification schemes. Section III describes the database, and Section IV contains the analysis of the benchmark system under both identification strategies. In Section V we modify the system to allow for
improved investment good quality adjustment. Further robustness checks are in Section VI. Here we also explore why our results differ from previous studies. Section VII concludes.

II. Framework of the Analysis

Our objective is to identify and quantify the relative importance of five shocks that we consider as important contenders for explaining business cycle fluctuations. These shocks are as follows: surprise shocks to TFP, surprise shocks to IST, news about future technology, preference shocks, and monetary shocks. To achieve this goal, we will work mainly with a five-variable structural vector error correction model (SVECM). Specifically, we consider an environment where a $K$-dimensional vector of observable variables $y_t$ is integrated of order one and can be represented as a vector autoregressive (VAR) process of order $p < \infty$. Allowing for $r > 0$ cointegrating vectors, the error-correction representation of the process is given by

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

where $\alpha$ and $\beta$ are $K \times r$ matrices of loading coefficients and cointegrating vectors, respectively; the $\Gamma_j$, $j = 1, \ldots, p - 1$, are $K \times K$ coefficient matrices; and $u_t$ are the reduced-form error terms. These can be thought to be linear combinations of the structural shocks, $\varepsilon_t$, we are interested in. As is common in the literature, we assume that the covariance matrix of $\varepsilon_t$ is the identity matrix $I_K$. Since the covariance matrix of $u_t$ is nonsingular, there exists a nonsingular matrix $B$ such that $u_t = B \varepsilon_t$. This matrix is not unique, and suitable assumptions must be imposed on its coefficients to identify it. The structural model, a $B$-model in the sense of Lütkepohl (2005), is then obtained from (1) by applying the Granger representation theorem:

$$y_t = L \sum_{\tau=1}^{t-1} \varepsilon_\tau + B \varepsilon_t + \sum_{\tau=1}^{\infty} \Xi_\tau B \varepsilon_{t-\tau} + y^0,$$

where $y^0$ is a vector of initial conditions, $L = \beta_\perp \left( \alpha_\perp' \left( I_K - \sum_{i=1}^{p-1} \Gamma_i \right) \beta_\perp \right)^{-1} \times \alpha_\perp' B$ is a $K \times K$ matrix with rank $K-r$, $\alpha_\perp$, $\beta_\perp$ denote orthogonal complements of $\alpha$, $\beta$, respectively, and the matrices $\Xi_\tau$, $j = 1, \ldots, \infty$, are absolutely summable; that is, $\lim_{\tau \to \infty} \Xi_\tau = 0$. Hence, in terms of structural interpretation, $L$ is the long-run multiplier matrix of the structural
shocks \( \epsilon_t \) and \( B \) is the corresponding short-run impact matrix. We have to propose and justify (at least) \( K(K - 1)/2 \) restrictions on \( B = (b_{ij}) \) and \( L = (l_{ij}) \) to identify the structural shocks. Thus for \( K = 5 \), we need at minimum 10 restrictions to identify the five structural shocks of interest.\(^1\)

Many structural models can be approximated by the type of moving average representation given in (2), for example, most linearized stochastic dynamic general equilibrium models. To set ideas, it is useful to imagine the underlying data-generating process as potentially being derived from a representative agent model where there is a final good sector and an investment good sector, and where technology in each sector is stochastic. Moreover, the representative agent in this model economy is allowed to be subject to stochastic changes in preferences. The idea of technological news in such a setting can be captured by assuming that the representative household learns about productivity innovations before they are effectively implemented in the economy (news shocks can be interpreted as diffusion lags in technology). In a Web appendix (http://www.wiso.uni-hamburg.de/beaudry-lucke), we present an extended RBC model that incorporates all these characteristics. The illustrative model we present in that appendix is also an example of a model that satisfies the type of identification assumptions we will pursue here to recover structural shocks.

Many papers, including, for example, a paper by Chari, Kehoe, and McGrattan (2008), question the plausibility of structural VAR methodology being used to identify structural shocks. For this reason, in our Web appendix we use artificial data generated from the structural model to explore whether the identification strategies we use in this paper are likely to allow identification. When the model is calibrated to deliver a variance decomposition similar to that observed in U.S. data, we find that the methodology works well.

A priori, it is not obvious that our five shocks of interest can be identified; that is, it is not obvious that there exists a vector \( y \) with corresponding \( B \) and \( L \) matrices that exhibit 10 theoretically plausible restrictions. However, as we will show, by choosing the vector \( y \) carefully, the desired identification can be achieved quite easily by exploiting a set of properties that are common to most contemporary models embodying such shocks. In fact, we will advance two main identification schemes to isolate the shocks of interest. While these two identification schemes share some common restrictions, they will also differ considerably. Since in many models both of these schemes should achieve the same identification, it is of interest to know whether their empirical
implementation renders similar results. If the identification schemes do lead to similar results, it will offer support to the claim that we have isolated the shocks of interest. In fact, in the robustness section we will study a broad variety of identification schemes related to the two basic settings and show that our findings are very robust across these schemes.

The five observable variables on which we will base our primary analysis are as follows: measured TFP, the inverse of the relative price of investment goods, a stock market index, a measure of economic activity (such as hours worked, investment, consumption, or output), and finally the rate of interest on federal funds. Details on the construction of the variables are discussed in the next section. Intuitively, the reasons we choose these variables are that (i) measured TFP should help identify innovations to disembodied technology; (ii) the value of the stock market should help isolate news about future technological developments; (iii) the federal funds rate should help identify monetary policy shocks; (iv) we need a measure of economic activity since it is our main focus; and finally, (v) since the relative price of investment goods is modeled by most researchers as an indicator of investment-specific technological change, it therefore is likely to be helpful in identifying investment-specific technological shocks.2

Since in most of the business cycle literature TFP is considered a driving force, we will exploit this property to help identify shocks. In particular, we will begin by assuming the following properties for the relationship between TFP and the structural shocks.

Assumption A1. Only TFP shocks may have contemporaneous effects on TFP.

Assumption A2. Preference shocks and monetary shocks have no long-run effects on TFP.

Without loss of generality, if we let the order of dependent variables in the vector $y_t$ be TFP, inverse of relative investment price, stock price index, activity, and federal funds rate, and let the order of the structural $e_t$ shocks be TFP shock, IST shock, news shock, preference shock, and monetary shock, then assumptions A1 and A2 imply the identifying restrictions $b_{12} = b_{13} = b_{14} = b_{15} = 0$ and $l_{14} = l_{15} = 0$, respectively.

Assumptions A1 and A2 follow directly from common assumptions regarding TFP as a driving force of economic fluctuations. In particular, it is quite natural to assume that the TFP process is independent of preference shocks and monetary shocks both in the short and long run. In addition, in the literature on IST, the process for TFP is generally modeled as independent of innovations in investment-specific technological
change. With respect to news about future technological change, by
definition, these shocks have no impact effects on TFP (following Beaudry
and Portier [2006]) or IST but are allowed to predict long-run movements
in TFP. Since measured TFP may be contaminated by changes in the price
of capital, we will later explore the effect of dropping the restrictions
\[ b_{12} = 0. \]

The second identification restriction we will impose in this section is
that monetary shocks affect economic activity only with delay, as stated
under assumption A3. This assumption has been widely used in the lit-
erature aimed at identifying the effects of monetary disturbances (cf.,
e.g., Bagliano and Favero 1998). Since we want to be consistent with this
literature, we maintain this assumption. Assumption A3 yields the iden-
tifying restriction \[ b_{45} = 0. \]

**Assumption A3.** Monetary shocks do not have a contemporaneous
effect on economic activity.

Assumptions A1, A2, and A3 provide seven restrictions. To identify
the five shocks of interest we therefore need at least three additional re-
strictions. We will begin by suggesting two sets of additional restrictions.
In both cases, these restrictions will exploit properties of the relative price
of investment. Our first approach is to examine impact restrictions im-
plied by the literature that incorporates investment-specific technologi-
cal change into macro models. In most of this literature, the final good
can be transformed to investment goods using a linear technology,
and it is shocks to this linear technology that are referred to as IST shocks.
The market implementation of this technology implies that the relative
price of investment goods in terms of consumption goods reflects the IST.
Since the process for investment specific technological change is modeled
as a process driven by one shock, it follows that monetary shocks, pref-
erence shocks, and news shocks should have no contemporaneous effects
on the relative price of investment goods. This feature is captured by
assumption B1.

**Assumption B1.** News shocks, preferences shocks, and mone-
tary shocks have no contemporaneous effects on the relative price of
investment.

Assumption B1 implies the restrictions \[ b_{23} = b_{24} = b_{25} = 0. \] The combi-
nation of assumptions A1, A2, A3, and B1 provides sufficient theoretical
restrictions for isolating the five shocks of interest. As we shall later show,
adding the restriction \[ b_{21} = 0 \] to this system—which becomes an over-
identifying restriction—is not rejected by the data and does not alter re-
sults. We will refer to the identifying scheme embodying assumptions
A1, A2, A3, and B1 as ID1. The restrictions associated with ID1 are
summarized below, where the set of restrictions on matrices $B$ and $L$ is shown explicitly:

$$
B = \begin{pmatrix}
* & 0 & 0 & 0 & 0 \\
* & * & 0 & 0 & 0 \\
* & * & * & * & * \\
* & * & * & 0 \\
* & * & * & * & * \\
\end{pmatrix}, \\
L = \begin{pmatrix}
* & * & * & 0 & 0 \\
* & * & * & * & * \\
* & * & * & * & * \\
* & * & * & * & * \\
* & * & * & * & * \\
\end{pmatrix}.
$$

(3)

Here, starred entries denote unrestricted elements of $B$ and $L$. Note that under ID1 the news shock is identified by postulating zero effects on both types of technology on impact but allowing for unrestricted long-run effects. Thus, under this identification scheme news can be news about both TFP and IST innovations. Similarly, under ID1, the notion of a preference shock can be given a far more general interpretation than the term may suggest. For example, our identification strategy is compatible with the preference shocks representing any kind of temporary nonmonetary demand shocks (e.g., increases in government spending or foreign demand) or with changes in market structure (e.g., transitory changes in markups). It is also compatible with nontechnology expectational shocks (e.g., socially inefficient market rushes in the sense of Beaudry, Collard, and Portier [2006] or even sunspot shocks and bubbles). Thus, while we label this shock a “preference” shock, the rather weak identifying assumptions for this shock allow it to stand in for any nonmonetary shock that is orthogonal to technology on impact and has no long-run effect on TFP. One of the attractive features of ID1 is that it mainly relies on impact restrictions and therefore is less likely subject to the criticism presented in Chari et al. (2008) regarding the use of long-run restrictions.

Most models that incorporate IST assume that the relative price of investment reacts only to investment-specific technological shocks. Our identification scheme ID1 imposes considerably weaker restrictions; for example, the relative price of investment can react to any shock with a lag. Nevertheless, ID1 might be criticized for ruling out that news, preference, or money shocks change the relative price of investment on impact. For example, if it is the case that there are adjustment costs associated with investment, then the relative price of investment may vary in the short run with any shock that increases investment. If this is the case, assumption B1 would not be valid. For this reason, it appears desirable to search for an alternative identification scheme that is not subject to this criticism.

An alternative means to identify the shocks of interest is to drop assumption B1 and instead focus on long-run restrictions that models impose on
the relative price of investment. This approach is very similar to that pro-
posed in Fisher (2006). In most of the literature incorporating investment-
specific technological change, investment-specific shocks are the sole
driver of the long-run behavior of the relative price of investment goods.
This property will also hold in models where there are adjustment costs
to investment and therefore the previous criticism does not apply. Hence
it is natural, at a minimum, to assume that monetary shocks and pref-
erence shocks do not affect the relative price of investment in the long
run.

Assumption C1 expresses this property. In addition, we could impose
that news and TFP shocks do not affect the long-run behavior of the
relative price of investment, since this would be consistent with the idea
that only IST shocks drive the long-run behavior of the relative price of
investment. However, instead of imposing these additional restrictions,
we will examine whether such properties are supported by the data. In
particular, we want to allow news shocks to potentially contain informa-
tion about future changes in the relative price of investment since there is
no a priori reason to eliminate such a possibility. As for TFP shocks, we
will show that the additional restriction in which TFP shocks do not
affect the relative price of investment in the long run is easily accepted
by the data.

**Assumption C1.** Preference shocks and monetary shocks have no
long-run effects on the relative price of investment.

Assumption C1 implies the identification restrictions \( l_{24} = l_{25} = 0 \). If we
combine assumptions A1, A2, and C1, this is insufficient to identify the
five shocks of interest since there is nothing that differentiates a news
shock from an investment-specific shock. Another common long-run
property that characterizes investment specific shocks in most models
is that such shocks do not determine the long-run behavior of TFP. This
property is expressed in assumption C2.

**Assumption C2.** IST shocks do not have a long-run effect on TFP.

Assumption C2 implies \( l_{12} = 0 \). As we already noted in the parallel case
of the \( B \)-matrix, we might also have used the analogous restriction \( l_{21} = 0 \)
(TFP shocks do not have a long-run effect on IST). We keep this in mind
as an overidentifying restriction to be tested in the robustness section
below.

Our second identification scheme, which we will refer to as ID2, will be
comprised of assumptions A1, A2, A3, C1, and C2. Note that this identi-
fication scheme (which we will refer to as ID2) does not place any restric-
tion on the short-run behavior of the relative price of investment and
therefore is not subject to our previous criticism.
Summing up, the just identifying restrictions for ID2 are as follows:

\[
B = \begin{pmatrix}
* & 0 & 0 & 0 & 0 \\
* & * & * & * & * \\
* & * & * & * & * \\
* & * & * & * & * \\
* & * & * & 0 & * \\
\end{pmatrix}, \quad L = \begin{pmatrix}
* & 0 & 0 & 0 \\
* & * & * & 0 \\
* & * & * & * \\
* & * & * & * \\
* & * & * & * \\
\end{pmatrix}. \tag{4}
\]

III. Data

We will estimate our SVECM model using quarterly data from different sources. For the economic activity variables, we use seasonally adjusted data for gross domestic product, \( y \), personal consumption expenditures, \( c \), and gross private nonresidential investment, \( i \), from the National Income and Product Accounts (NIPA) of the Bureau of Economic Analysis (BEA), table 1.1.5. These variables are expressed in real terms using standard NIPA deflators taken from the same source (table 1.1.9). Hours of the nonfarm business sectors, \( h \), are drawn from the U.S. Basic Economics Database. All variables are in logs and \( y, c, i \), and \( h \) are in per capita form using civilian noninstitutional population, ages 16 and over. TFP data, \( \text{tfp} \), are constructed using data on capital services for the private nonfarm business sector published by the Bureau of Labor Statistics (BLS). We multiply capital services by the capacity utilization rate in manufacturing drawn from the Federal Reserve Statistical Release G.17. For TFP construction, hours and real GDP series are also for the nonfarm business sector, the latter taken from NIPA table 1.3.5. The capital share is set at 0.31, the mean over the sample compiled by the BLS.

To check robustness, we also construct a set of quality-adjusted (QA) variables. To this end, we use QA deflators for total investment and equipment as used in Fisher (2003, 2006). The one drawback of the QA data is that they are available only on a shorter time span. To construct a QA capital stock we use the perpetual inventory method with fixed nonresidential investment deflated by the QA deflator for total investment. This deflator results in lower estimates of real investment prior to 2000 because all capital goods are measured in constant year 2000 quality. The resulting real investment series is denoted \( iq \). The capital stock starting value is taken from the private nonresidential fixed assets series published by the BEA (table 4.1). Depreciation is set at 0.025 per quarter. We measure the real GDP series \( yq \) in consumption units (deflator for nondurables and services), also in the construction of QA total factor productivity, \( \text{tfpq} \).
The inverse of the real price of fixed nonresidential investment, $pi$, is the log-difference of the NIPA deflator for consumption and the respective NIPA investment price index. An alternative measure, denoted $pieq$, uses the deflator for nondurables and services consumption and for QA equipment investment instead.\(^3\) Real per capita stock prices, $sp$, are derived as the log-difference between the Standard and Poors 500 Index (SP500), the population series, and the NIPA consumption deflator. In the case of QA variables we use the deflator for nondurables and services and denote this series $spq$. The short-run nominal interest rate, $int$, is the H15 effective rate on federal funds.

Capital services and capital stock are available only at annual frequency. They are converted to quarterly data assuming constant growth rates within each year. Stock prices and the federal funds rate were retrieved at monthly frequency from Global Insight; the quarterly values are the monthly averages. The sample size is 1955.1–2007.2 for NIPA variables and 1955.1–2000.4 for all variables that rely on the QA deflators.

### IV. The Benchmark System

Our first set of results is based on the five-variable system consisting of $tfp$, $pi$, $sp$, an activity measure, and $int$. The only deterministic series in the VAR is a constant. If the activity is $x$, we call this the NIPA$_x$ system. Using Akaike’s information criterion (AIC) to determine the appropriate lag length, six lags are recommended for NIPA$_h$ and NIPA$_c$, three lags for NIPA$_i$, and nine lags for NIPA$_y$. However, as figure 1 shows, six lags seem to be a reasonable specification for all these systems. For the sake of maximum comparability we therefore estimate all systems with six lags (i.e., five lags in differences).

Turning to cointegration properties, one might expect from theory that the NIPA systems are driven by two stochastic trends representing disembodied and investment-specific technical progress. Johansen tests for cointegration (using six lags in levels) generally give support for this conjecture, finding evidence of either two or three cointegrating vectors. As three cointegrating vectors are consistent with our prior of having two stochastic trends in the system, we will assume three cointegrating vectors in the benchmark system and consider the possibility of only two cointegrating vectors when we study robustness.

We proceed by estimating a VECM for the NIPA$_h$ system, which will be our benchmark. We impose three cointegrating vectors and five lags in differences. Note that we do not assume that all variables in this system
have a unit root. The stationarity properties of hours, in particular, has been the subject of much debate (see Christiano, Eichenbaum, and Vigfusson 2004). These authors show that the maintained assumption on whether or not hours have a unit root implies vastly different conclusions for its response to technological innovations if VARs in differences are used. In a VECM framework, by contrast, we do not need to impose any assumptions on the stationarity properties of hours, for if hours were in fact stationary, one of the cointegrating vectors would give nonzero weight only to the hours variable, so that the level of hours affects the first differences of the other variables in the VECM via the error correction term. Of course, if hours were trend stationary, the cointegrating combination should allow for a linear trend, but the hours series we use does not seem to have a discernible trend (see fig. 2).

A. Identification ID1

We begin by estimating a structural decomposition of the VECM using identification scheme ID1. The variables are ordered as $\text{tfp, pi, sp, h, int}$. We compute impulse responses (IR) and forecast error variance decompositions (FEVD).

The FEVDs (see fig. 3), show the contributions of the identified structural shocks to the forecast error variances of each dependent variable.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig1.png}
\caption{AICs for lags 1–10, NIPA system with activity $h, i, y, c$}
\end{figure}
over a business cycle horizon of 32 quarters. In discussing the results, we will refer to the shocks as the surprise TFP, surprise IST, news, preference, and monetary shocks.

The most interesting findings from the FEVDs are the following: First, surprise TFP and IST shocks contribute almost nothing to the variance of hours at all horizons. The single most important contributor to hours variance is the news shock, in our interpretation the anticipation of future technological possibilities. Only in the very short run (the first three quarters) does the preference shock dominate the variance of hours. The monetary shock explains a sizable share (about 20%) of the variance of hours after 2 years, while most of the rest (roughly 70%) is due to the news shock.

Second, stock prices are mainly driven by the news shock, accounting for roughly 80% of the variance at all horizons. Much of the remaining variance seems to be due to preference shocks. Again, it is remarkable that “fundamentals” as represented by surprise TFP and IST shocks seem to be quite unimportant for stock prices. This would be consistent with the view that most technological innovations are known before they are implemented on a scale large enough to have a significant impact on the economy. In fact, the FEVDs show that news shocks contribute up to 30% of the variance of tfp at business cycle horizons, and this share increases further as time goes by; for instance, it is 60% after 15 years. Since this finding is, as we will show, very robust across different modifications
Fig. 3. FEVDs of the NIPA_h system, identification ID1. All FEVDs in this paper are available as colored graphs in the electronic NBER working paper version of this paper, Beaudry and Lucke (2009).
of our benchmark system, it seems appropriate to infer that the major component of what we label a news shock reflects information about future disembodied technology.

Third, we have a negative result for our measure of IST. The relative investment price itself seems quite disconnected from other shocks. News shocks, in particular, which might also contain information about future IST, do not play a major role in its variance, at least not to the extent they do for disembodied technical progress. We will return to this issue after having discussed the impulse responses, to which we now turn (see fig. 4).

Impulse responses in figure 4 display the responses of each dependent variable row-wise with the columns representing the shocks. Responses are given for the first 32 quarters.

As can be seen in the fifth column, monetary policy shocks are found to have effects on hours similar to those documented elsewhere in the literature, with the effect setting in gradually, peaking after about 2 years and then phasing off back to zero.

Preference shocks (fourth column) feature positive responses of hours and interest rates for at least the first year along with a prolonged negative response of stock prices. There is a small short-run negative impact on measured TFP and an apparently long-run positive response of the IST-variable. We do not emphasize the latter, however, since this effect is quantitatively negligible (see the FEVD of $p_i$), and—as our further analysis will show—it is one of the few features that is not robust with respect to using QA variables.

News shocks (third column) have effects very similar to those found in Beaudry and Portier (2006), although their analysis focused mainly on a bivariate system and never included information on the relative price of investment. The news shock seems to convey information about TFP growth that starts 8–10 quarters in the future. This shock nevertheless causes an immediate expansion in hours lasting for about 10 quarters. These news shocks also appear to be associated with an increase in nominal interest rates, although this estimate is mostly not significant. Moreover, news shocks seem to have a marginally significant positive effect on IST within the first 4 years or so. Note that the effect of news on hours is transitory, in line with the standard assumption of hours being a stationary series. However, as we will see below, news shocks cause permanent effects on output, investment, and consumption, which strongly suggests that the identified news is predominantly technological.

Surprise shocks to TFP cause a somewhat unconventional short-run response for TFP itself, which may indicate the presence of measurement
Fig. 4. Impulse responses of NIPA_h: identification ID1. Impulses are given in columns, responding variables in rows. Solid lines are estimated impulse responses; dashed lines are two standard errors bootstrapped confidence intervals (Hall).
error in the form of a rapidly mean-reverting transitory component on top of the stochastic trend. However, the most important finding in this column seems to be that TFP shocks have no significant effects on hours at all. Moreover, we find that the negative initial response of hours to positive technology shocks emphasized by Galí (1999) is insignificant, and even the point estimate is almost zero for the first quarters. For the three types of technology shocks (TFP, IST, and news shocks) considered in this exercise, only the news shock causes a significant response of hours and this response is unambiguously positive.

Although minor in total stock price variance, IST shocks seem to cause a positive response of stock prices. (The point estimate is positive for all business cycle frequencies and significantly so after 3 years.) This could be in line with higher profitability of existing firms or with successfully developing equipment producers that make it into the SP500 after a number of years.

Note that the largest responses of $tfp$ are due to surprise TFP shocks in the short run and to news shocks in the long run. Further, $tfp$ seems to initially decrease slightly in response to news, preference, and monetary shocks. This probably indicates that these shocks require some factor usage in order to adjust to these shocks, for example, reorganization that is not captured by measured output. The marginally significant positive response of $tfp$ to IST shocks in the long run is probably due to incomplete quality adjustment in the capital stock series.

B. Identification ID2

As noted previously, our identification scheme ID1 may be criticized for its short-run restrictions on the relative price of investment. For this reason, we now turn to reporting results based on using identification scheme ID2. Recall that the rational of ID2 is that, under a long-run perspective, the real price of investment is likely to be a good measure of IST. It is less clear whether this is also true for the short run, which is why ID1 may be questioned as an appropriate identification strategy.

The results of the structural decomposition obtained under ID2, where a selection is given in figures 5 and 6, are found to be very close to those we obtained under identification ID1. In fact, a simple correlation analysis confirms that the two identification schemes yield more or less the same type of shocks: Computing the correlation matrices of the shocks retrieved from ID1 with those retrieved from ID2, we find that all diagonal elements are higher than 0.8 and the off-diagonal elements are—with few exceptions—small in absolute value (see table 1).
Thus, it is not too surprising that the IRs and FEVDs of ID2 are quite similar to those of ID1. In particular, the news shock always explains most of the variance of hours, followed by the preference shock. By contrast, both IST and TFP shocks are negligible for hours variance.

Fisher (2003, 2006) expresses output and productivity in consumption units. We checked if our results hinge on using the GDP deflator in the computation of TFP and real stock prices. Redefining these variables with either the Consumer Price Index or a price index for the consumption of nondurables and services (also for $pi$) has almost no effect on the variance decomposition of hours, under both ID1 and ID2. The only major change is a smaller news shock share in TFP and a larger news shock share in $pi$.

V. Quality-Adjusted Systems

An apparent difficulty in interpretation of our first set of results is the permanently negative response of nominal interest rates to IST shocks. This response (prevalent under both ID1 and ID2) is related to the sizable share of federal funds rate variance attributable to IST shocks at long horizons (see fig. 3). Both results are hard to explain and could be due to $pi$ being an imperfect measure of IST. A possible remedy is the use of variables with improved investment quality adjustment. Moreover, it may be the case that our finding that IST shocks play little role in hours fluctuations is due to mismeasurement of the relative price of investment.

To address these issues, consistency requires some changes in the variables in order to create a QA system. In particular, the use of a QA

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**Fig. 5.** FEVDs for NIPA$_h$, identification ID2
Fig. 6. Impulse responses for NIPA_h, identification ID2
deflator for investment implies different quantities for investment, output, and the capital stock. Hence we use the series $iq, yq$ (in the construction of TFP), and $tfpq$ as described above. We measure the inverse of the relative price of investment as the ratio of the NIPA deflator for consumption of nondurables and services divided by the QA deflator for equipment investment $pieq$, since Fisher (2003) argues that the equipment price series might capture IST somewhat better than the relative price of total investment. To ensure comparability, we retain the settings of three cointegrating vectors and five lags in differences in the VECM. We begin with identification ID1.

A. Identification ID1

Results for the FEVD associated with the QA system are presented in figure 7. Somewhat surprisingly, we find that adjusting for quality in the construction of the investment price little changes the results. We still have the central finding that TFP shocks and IST shocks do not explain much of hours or stock price variance. Instead, the news shock is by far the most important contributor to hours variance, and it also explains up to 30% of $tfpq$ variance at the low business cycle frequencies (increasing further at longer horizons). The importance of the preference shock, while reduced in hours, has increased substantially in the variance of stock prices. The role of the monetary shock is similar to its role in the NIPA system. Note that now the IST shock explains less of the long-run variance of nominal interest rates.

Turning to the impulse responses of the QA system (see fig. 8), we confirm that the change from NIPA to QA variables does not matter much. The monetary policy impulse of hours is virtually unchanged, as is the significant long-run response of TFP to news shocks. We have a strong positive response of hours to anticipated technological innovations (news) and only a minor, though now significant, negative response to

<table>
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<th>.00</th>
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Fig. 7. FEVDs of the QA_h system, identification ID1
Fig. 8. Impulse responses of QA_h, identification ID1. Impulses are given in columns, responding variables in rows. Solid lines are estimated impulse responses; dashed lines are two standard errors bootstrapped confidence intervals (Hall).
surprise TFP shocks. Unlike in the NIPA_h system, news shocks cause a small positive response in the investment price variable over the first 4 years or so, but this effect, which may be due to using a variable that better captures IST, is small in terms of the variance of the relative price of investment.

There are minor changes in the responses to preference shocks (see col. 4 of fig. 8). The short-run response of hours to the preference shock is less pronounced. The preference shock still has a tiny positive long-run impact on the relative price of investment (denoted \( \pi_{eq} \)), but it becomes significant only after the 32 quarters depicted in figure 8. Similarly, the negative effect on stock prices is transitory, but it takes more than 32 quarters to return to the initial level—the long-run effect is actually positive. Thus, while there are quantitative changes, the interpretation of the preference shock given for the NIPA_h system continues to hold.

B. Identification ID2

Turning to identification ID2, we obtain more or less the same results (see the selection shown in figs. 9 and 10). Under both schemes, the counter-intuitive significant long-run response of the nominal interest rate to IST shocks has vanished, but in its place we observe (with opposite sign) a marginally significant long-run response to TFP shocks (not shown for ID2, but similar to the response in fig. 8). The news shock remains by far the most important shock for hours, with the monetary shock a distant second.

We correlate the structural residuals obtained from NIPA_h under ID1 with the structural residuals from QA_h under ID2. As the QA_h sample

![Fig. 9. FEVDs for QA_h, identification ID2](image)
Fig. 10. Impulse responses for QA_b, identification ID2
is shorter, we only use the NIPA\_h residuals up to 2000.4. Thus, we correlate residuals obtained from different samples, estimated with different variables and decomposed under different identifying assumptions. The results (see table 2) show that most diagonal elements of the correlation matrix are still in the range of 0.8 or higher. The one exception is the correlation between the identified IST shocks, which is 0.6. Thus, the bottom line from our analysis with QA variables seems to be that the usage of QA variables might have a notable impact on the identification of IST shocks—but not on much more. In particular, the finding that IST shocks appear unimportant for economic fluctuations remains unchallenged.

Summing up, the differences between NIPA\_h and QA\_h seem relatively small, and even with (possibly) improved variables there is very little evidence that IST shocks drive a substantial fraction of macroeconomic fluctuations. The most notable qualitative change in the QA system seems to be a more plausible long-run response of the nominal interest rate to IST shocks. But as we will show below, this property can be enforced on the NIPA\_h system without any essential changes elsewhere. Thus, while we continue to use QA variables in some of the robustness checks below, we prefer to work with NIPA variables, as these exploit more information in terms of the time span of the available sample.

VI. Robustness

A. Other Activities

We now study the robustness of our results by looking at other measures of activity in both the NIPA and the QA systems, focusing on identification ID1. (We still use QA variables here to make sure that results do not differ when activity is measured by variables that are themselves quality

<table>
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<td>Correlation Matrix for NIPA_h Shocks Identified by ID1 and QA_h Shocks Identified by ID2</td>
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<td>NIPA_h Shocks Identified by ID1</td>
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adjusted.) Hence, we substitute out the hours series and replace it by investment \((i \text{ or } iq)\), output \((y \text{ or } yq)\), or consumption \((c)\). We use the same identification (ID1) throughout. The FEVDs of these exercises are given in figure 11 (activities only). As in the case of hours, we see that IST shocks do not matter much—and they matter even less in QA systems than in NIPA systems. Surprise TFP shocks rarely account for more than 10% of the variance, the exception being the variance of output where the TFP shock sometimes reaches 20%–30%. The preference shock seems generally more important in NIPA systems than in QA systems and is basically a short-run phenomenon. The importance of the money shock is also mostly smaller in QA systems than in NIPA systems, and consumption seems to be the activity most receptive to monetary policy. The one shock that clearly dominates the FEVDs of all activity measures is the news shock with rarely less than 50% of the variance.

Selected impulse responses are given in figure 12, where the six rows represent, from top to bottom, the systems NIPA\(_i\), NIPA\(_y\), NIPA\(_c\), QA\(_i\), QA\(_y\), and QA\(_c\). TFP seems to respond to TFP shocks with much the same kind of transitory dynamics in all systems, and news shocks generally have a positive long-run effect on TFP in line with Beaudry and Portier (2006). For investment, output, and consumption, both TFP shocks and news shocks have permanent effects, unlike the responses for hours in either the NIPA or QA system. These permanent effects strongly suggest that news shocks are essentially technological. Recall that the identification would, in principle, also be compatible with nontechnological news or sunspot shocks, but, given the estimated impulse responses, such an interpretation seems hard to support.

The preference shock on activity is generally more pronounced in the NIPA systems than in the QA systems. Its effect on activity is clearly transitory. Note that neither the long-run effects of news shocks nor those of preference shocks are imposed through the identifying assumptions. The responses of activity to monetary shocks are very similar in all systems. All activities display a gradual increase over a year or so in response to a news shock. Clearly, this cannot be attributed to standard factor adjustment costs, because the response of activity to a preference shock is an instantaneous jump. In fact, this difference in the initial responses seems to be an interesting distinguishing feature of news and preference shocks. It can support the interpretation of news shocks as an expectational variable, because news about future technological developments may at first be skeptically received by many agents, except for a few particularly dynamic or risk-loving entrepreneurs. Thus, there may be some sort of sluggishness in the adjustment of expectations responsible for the shape of
Fig. 11. FEVDs of activities in NIPA systems (top panel) and QA systems (bottom panel), identification ID1.
Fig. 12. Selected impulse responses for NIPA$_i$, NIPA$_y$, NIPA$_c$, QA$_iq$, QA$_yq$, QA$_c$ (top to bottom rows), identification ID1. Responses of TFP (left) and activities (right). Impulses are given in columns, responding variables in rows. Solid lines are estimated impulse responses; dashed lines are two standard errors bootstrapped confidence intervals (Hall).
the responses to news shocks, while behavioral changes or changes in the economic environment captured by our notion of a preference shock cause an instantaneous response of activity.

B. Two Cointegrating Vectors

As an additional robustness check we examine what happens if we change assumptions about cointegration. When we estimate the baseline NIPA_h system with only two cointegrating vectors, the results are mostly similar to the case of three cointegrating vectors. This is true for both identification schemes. The most notable change is the impulse response of hours to the monetary shock, which now seems to have a persistent effect (see fig. 13 for ID1). This is also clearly visible in the variance decomposition of hours. As this is not in line with standard theory, we do not follow this approach further. The QA_h system with two cointegrating vectors has similar properties.

C. Overidentifying Restrictions

Up to now we have not imposed any overidentifying restrictions in our estimating procedure. Here we examine the effects of imposing such restrictions. For example, identification ID1 did not impose the restriction $b_{21} = 0$, which is a natural counterpart to the restriction $b_{12} = 0$ implied by assumption A1. We therefore proceed by subjecting the NIPA_h system to identification scheme ID1 and the additional restriction $b_{21} = 0$. We find that the $p$-value of the likelihood-ratio (LR) statistic for overidentifying

![Fig. 13. NIPA_h estimated with two cointegrating vectors, identification ID1](image)
restrictions is 0.081; thus the restriction can be reasonably accepted. Even more important, we find that when imposing the additional restriction there are almost no changes in the estimated FEVDs and IRs.

Identification ID2 did not impose the restriction \( l_{21} = 0 \), which is the natural counterpart to the restriction \( l_{12} = 0 \) implied by assumption C2. Overidentifying the NIPA_\_h system with ID2 and the additional restriction \( l_{21} = 0 \), we find a p-value of the LR statistic of 0.67, so this restriction is easily accepted. There are again no noteworthy changes in the IRs and FEVDs when this restriction is imposed.

We also explored the imposition of the overidentifying restriction \( l_{52} = 0 \) on ID1, that is, a restriction aimed at eliminating the counterintuitive permanent effect of IST shocks on the federal funds rate.\(^6\) This restriction is clearly rejected by the LR test. If, however, we ignore the test result and estimate the structural decomposition nonetheless, we again get results very close to those in figures 3 and 4. Even the response of int to IST shocks does not change by much during the first 32 quarters; that is, the enforced convergence back to zero is quite slow.

D. Short-Run Response of Hours to Monetary Policy

To help identify the monetary shock, we assumed that activity does not respond on impact to monetary policy; that is, \( b_{45} = 0 \) (assumption A3). We here replace this restriction in ID1 by the long-run restriction \( l_{25} = 0 \); that is, monetary policy does not affect IST in the long run. In the case of three cointegrating vectors, the two long-run restrictions, \( l_{15} = l_{25} = 0 \), immediately imply that the monetary shock is a transitory shock; that is, all elements in the last column of \( L \) are zero (with probability one). We find that computing the structural decomposition under this alternative assumption does not change our benchmark results in any remarkable way.\(^7\) We therefore continue to use the \( b_{45} = 0 \) restriction in the following exercise.

E. No Restrictions on IST Shocks

So far, our results suggest that IST shocks are not very important for business cycle fluctuations. Given that this finding may be contentious, we thus explore an alternative identification scheme where we take care not to put any restrictions on the IST shock, neither in the short run nor in the long run. Moreover, the relative price of investment may react on impact to any shock. Rather, identification is achieved by adopting the assumption that in the long run only IST shocks affect IST.
We call this scheme identification ID3, and its restrictions are conveniently summarized in (5). Note that news shocks are taken to be news with respect to TFP but not to IST. Thus, if there is, in fact, IST-specific news, then identification ID3 will project these shocks onto the IST shock since this is the only shock with a long-run effect on IST. In our opinion, ID3 is an identification strategy that is very unlikely to be biased against finding IST shocks to be important if this is actually the case:

\[
B = \begin{pmatrix}
* & * & 0 & 0 & 0 \\
* & * & * & * & * \\
* & * & * & * & * \\
* & * & * & 0 & * \\
* & * & * & * & *
\end{pmatrix}, \quad L = \begin{pmatrix}
* & * & * & 0 & 0 \\
0 & * & 0 & 0 & 0 \\
* & * & * & * & * \\
* & * & * & * & * \\
* & * & * & * & *
\end{pmatrix}.
\] (5)

Yet the results of this structural decomposition for NIPA_h (a selection is given in figs. 14 and 15) are very close to those we obtained under the benchmark identification ID1. In fact, computing the correlation matrices of the shocks retrieved from ID1 with those retrieved from ID3, we find that the diagonal elements are mostly around 0.9 or higher and the off-diagonal elements are mostly small in absolute value (see table 3).


Our results stand in remarkable contrast to the findings of Fisher (2003, 2006), who suggested that investment-specific technical change explains a lot of hours variance. His benchmark system is a VAR in the growth rate of the relative (QA) equipment price, the growth rate of labor productivity, and the level of hours. Fisher uses a Blanchard-Quah (1989) approach

![Fig. 14. FEVDs for NIPA_h, identification ID3](image-url)
Fig. 15. Impulse responses for NIPA_h, identification ID3
that relies exclusively on long-run restrictions. He imposes that only IST shocks affect IST in the long run and only IST shocks or neutral technology shocks affect labor productivity in the long run. Our identification scheme ID3 is very similar in spirit to that of Fisher, as it imposes no restrictions on the IST shock, and it imposes that the investment specific shock is the only shock that drives the relative price of investment in the long run.

To try to understand the difference between our results and those of Fisher, we move to a four-dimensional system (denoted NIPA4_pi) by eliminating stock prices. In line with Johansen tests, we assume two co-integrating vectors; that is, we allow for two stochastic trends—likely trends associated with the two technology processes. Identification is achieved by eliminating the third column and row from both $B$ and $L$ in ID3 and by allowing for $I_{24} \neq 0$ (see eq. [6]). As before, this identification is very close to Fisher’s. It is slightly overidentified in order to make it as similar as possible to the previous identification scheme ID3:

$$B = \begin{pmatrix} * & * & 0 & 0 \\ * & * & * & * \\ * & * & 0 & * \\ * & * & * & * \end{pmatrix}, \quad L = \begin{pmatrix} * & * & 0 & 0 \\ 0 & 0 & * & * \\ * & * & * & * \\ * & * & * & * \end{pmatrix}.$$ (6)

The results for this decomposition (see figs. 16 and 17) are very different from what we obtained so far. If we mechanically use the labels TFP shock, IST shock, preference shock, and monetary shock—dropping any reference to news shocks—we find that the “surprise IST” shock explains roughly 60% of hours variance across all horizons—which is more or less Fisher’s finding. This shock also accounts for an increasing share of TFP variance as time goes by, both qualitatively and quantitatively in much the same way as the news shock did in the five-dimensional systems. It thus seems to be the case that the news shock, which cannot be distinguished from an IST shock in this four-variable system, is mostly

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<th>Shocks Identified by ID1</th>
<th>Shocks Identified by ID3</th>
</tr>
</thead>
<tbody>
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<tr>
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</tr>
<tr>
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<td>-0.29</td>
</tr>
<tr>
<td>0.00</td>
<td>0.07</td>
</tr>
</tbody>
</table>

Table 3: Correlation Matrix for NIPA_h Shocks Identified by ID1 and ID3
being picked up by the shock associated with the second column in equation (6).

To investigate this conjecture we compute the correlations between this “surprise IST” shock and the structural residuals in NIPA_h under benchmark identification ID1. The highest correlations are found with the NIPA_h IST shock (0.61) and the NIPA_h news shock (0.45)—and they are of almost the same order of magnitude. Thus under identification it seems that both the former IST shock and the former news shock are projected on the second column, and this explains the higher explanatory power of “IST shocks” in Fisher-type identification schemes. However, if IST shocks and news shocks are allowed to compete, as in our approach, the IST shock is completely marginalized.

G. Eliminating the Relative Price of Investment

Our analysis suggests that the relative price of investment does not add much to the explanation of macroeconomic fluctuations. We therefore explore how our results change when we drop the relative investment price. (We continue to use standard NIPA concepts and denote this system NIPA4_sp.) The identification in this system is analogous to the five-dimensional case, as we only need to rely on assumptions A1, A2, and A3, as seen in (7), where the restrictions on $B$ and $L$ are made explicit:

\[
B = \begin{pmatrix}
* & 0 & 0 & 0 \\
* & * & * & * \\
* & * & * & 0 \\
* & * & * & *
\end{pmatrix}, \quad L = \begin{pmatrix}
* & * & 0 & 0 \\
* & * & * & * \\
* & * & * & * \\
* & * & * & *
\end{pmatrix}.
\] (7)
Fig. 17. Impulse responses for NIPA4_pi under identification (6). The identified shocks in NIPA4_pi under identification (6) are quite different from the structural residuals retrieved elsewhere in this paper. We mechanically use the same labels to denote the shocks, but it should be understood that the former are better thought of as linear combinations of the latter.
Since the relative price of investment seems to represent a stochastic trend of minor importance for the other variables, we retain the assumption of three cointegrating vectors and estimate the VECM again with five lags in differences. The variance decompositions of TFP and hours are given in figure 18, and a selection of the resulting impulse responses (corresponding to those in fig. 12) is given in figure 19. There is no essential change to the results in the five-dimensional system, except a somewhat greater share of preference shocks in the variances of TFP and hours across all horizons. We again conclude that IST shocks appear rather inessential for business cycle analysis.

H. **The Role of Stock Prices**

Given the seemingly highly important role of news shocks for macroeconomic fluctuations, one might argue that it should be possible to replace the stock price variable used in our analysis by any other macroeconomic variable that responds on impact to the news shock. For instance, if consumption behavior is a rapidly adjusting forward-looking variable as postulated by standard theory, then consumption should be well suited to replace stock prices in our system. We thus examine this conjecture by estimating a four-dimensional system (denoted NIPA4_c) with consumption replacing stock prices as the second variable. The results (see figs. 20 and 21) seem to confirm our conjecture, the only apparent difference being that the money shock response of hours is not significant any more.

A closer analysis, however, reveals that this approach is only moderately successful. The correlation of the suspected news shock extracted

Fig. 18. FEVDs for NIPA4_sp (NIPA_h without \( \pi \))
Fig. 19. Impulse responses for NIPA4_sp (NIPA_h without $\pi$)

Fig. 20. FEVDs for NIPA4_c (c replaces sp)
Fig. 21. Impulse responses for NIPA4, c (c replaces $\gamma$)
from this system with the news shock from NIPA_h is a mere 0.47. While this is clearly more than its correlations with the TFP, IFP, and preference shocks from NIPA_h (which are all zero), its correlation with the NIPA_h monetary shock is \(-0.67\). This and the fact that the response of hours to the monetary shock is not significant in this system indicate that the decomposition may project part of the monetary shock on news; that is, the system may have more trouble extracting news correctly from consumption than from stock prices. This may not be too surprising in view of the vastly different degree of attention real-world consumers and stock market traders typically pay to news about technological advances. The TFP shock, on the other hand, seems to be correctly identified—its correlation with its NIPA_h analogue is 0.95. As such it is interesting to see that TFP shocks explain only a negligible share of hours variance—and mostly less than 10% of the variance of consumption. The combined news/monetary shock clearly dominates the variance of consumption across all horizons and plays an important role in hours variance as well. It still contains a substantial amount of information about future disembodied technology (see the variance decomposition of \(\text{tfp} \)) and causes responses from \(\text{tfp} \) and hours in much the same way as in the NIPA_h system.

I. Robustness with Respect to Identifying Assumptions

Finally, we want to check the robustness of our results for the (five-dimensional) benchmark NIPA_h system with respect to a more systematic exploration of “reasonable” identifying assumptions where ID1, ID2, and ID3 can be seen as special cases. In particular, we want to perform this exercise to illustrate that our results are not knife edged. The intersection of the three sets of identifying assumptions used up to this point is given by the restrictions \(R: b_{13} = b_{14} = b_{15} = b_{45} = l_{14} = l_{15} = 0\). Moreover, we always use either restrictions \(R^c: b_{24} = b_{25} = 0\) or \(R^l: l_{24} = l_{25} = 0\) to express the idea that \(pi\) is a technology process. Thus, we have essentially two basic sets of identifying restrictions, \(R_1 := R \cup R^c\) and \(R_2 := R \cup R^l\), each of which comprises eight restrictions. Just identification requires two additional restrictions. In principle, the logic we have used up to this point (based on the structure of standard macro models) suggests that one should be able to use any two of the following six restrictions in set \(A\) to identify the shocks of interest, where \(A: b_{12} = b_{21} = b_{23} = l_{12} = l_{21} = l_{23} = 0\). Note that ID1, ID2, and ID3 are all based on using restrictions from this set.

There are 15 different pairs of restrictions in \(A\) that can be added to \(R_1\) or \(R_2\) to achieve identification. We will study each of these cases. This
gives 30 different identification schemes (among them ID1, ID2, and ID3). Not all of these schemes actually achieve identification, since in some cases, for example, the rank condition for local identification can be violated (see Lütkepohl 2005, proposition 9.4). But most schemes work, and we summarize the results by reporting the shares of hours variance at 8 quarters explained by the two surprise technology shocks and the news shock (see table 4).

It turns out that 24 of the 30 possible sets of restrictions are sufficient for identification, with 22 of these schemes delivering results very similar to those found so far in terms of FEVDs and impulse responses. In particular, the third shock in the system, which we interpret as news shock, is found to be of major importance for hours variance (around 60%), while the first two shocks, interpreted as surprise technology shocks, are not (less than 10%). In all cases, we find that the monetary and the preference shocks combined account for about 30% of fluctuations. For two identifications, however, it is the second shock that is dominating hours variance. These two cases have in common that they both use the restrictions

Table 4
Robustness with Respect to Identification

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<td>.02</td>
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<td>.62</td>
<td>.66</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( l_{23} = 0 )</td>
<td>.02</td>
<td>.02</td>
<td>n.i.</td>
<td>.01</td>
<td>.03</td>
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<td></td>
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<td>.06</td>
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<td>.70</td>
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Note: Results below (above) the diagonal are for identifications combining \( R_1 \) (\( R_2 \)) and the respective row and column restrictions. Entries give the share of hours variance at 8 quarters for the TFP shock, the IST shock, and the news shock (in descending order). n.i. = not identified.
\( b_{21} = l_{21} = 0 \), which implies that TFP shocks are orthogonal to \( pi \) on impact and in the long run. This result may appear to suggest that IST should not be dismissed too quickly as a potentially important source of fluctuations. However, a closer look suggests that this is likely the wrong inference. First, let us note that under these two identification schemes, it is the third shock that dominates the variance of \( pi \) at all frequencies and not the second shock. This suggests that the third shock may more appropriately be considered the IST shock. Furthermore, we find that the impulse response associated with the second shock in these two cases looks almost identical to what we previously called the news shock. In particular, the impulse responses indicate that following an innovation in the second shock, TFP does not change much for about 8 quarters and then starts growing for several periods. This is precisely the type of pattern we view as being associated with the news shock. The only difference in these impulse responses and those that we previously interpreted as reflecting a news shock is that in these two cases measured TFP falls slightly following an innovation in the second shock (although the effect is not significant). Thus, it seems unreasonable to interpret the second shock in these two cases as representing an IST shock. Instead, we view the two identification schemes based on \( b_{21} = l_{21} = 0 \) as having difficulty properly separating an IST shock and a news shock since the only restriction imposed to separate them in this case is \( b_{12} = 0 \). However, there is no a priori reason not to believe that both the IST shock and the news shock should have no contemporaneous effect on TFP, which explains why this identification scheme should be ruled out.

**VII. Conclusions**

The main driving forces behind macroeconomic fluctuations remain the subject of much debate. After decades of research, not even a consensus on the relative importance of technological versus nontechnological shocks has emerged. In a structural vector error correction exercise designed as a horse race between several main contenders, we find a surprisingly clear result: Technology matters a lot, but it is expected rather than surprise technological progress that drives activity.

In fact, the joint contribution of surprise technology shocks to measures of TFP and IST rarely exceeds 20% of the variance of hours, investment, or consumption. News shocks, however, often account for variance shares exceeding 50% of activity variance and generate patterns in impulse responses and variance decompositions that strongly suggest they are essentially technological.
This result is obtained under identification schemes where news shocks have to satisfy more restrictions than the surprise TFP shocks or the investment specific shocks. Thus, if anything, the horse race seems biased against news shocks. Nevertheless, news shocks not only emerge as more important, they essentially marginalize surprise technology shocks. This result is robust across many possible modifications in terms of specification and identification. Previous results in the literature that emphasized the importance of surprise technology shocks seem to be due to an identification strategy that does not include news shocks and does not include stock prices that reveal information about expectations.

In the short run, the second-most important shock is often what we call a preference shock. This shock has mostly transitory effects, for example, increases in activity and interest rates and decreases in stock prices and, possibly, measured TFP. It may be well explained by a transitory change in consumer demand that stimulates competition. We hasten to add that similar effects might be caused by changes in the economic environment (e.g., deregulation or globalization) rather than preference shocks. The evidence we have on this shock may be compatible with various interpretations. At least some of them can be mapped on a transitory change in a preference parameter and only in this broad sense do we state that preference shocks matter for the short-run dynamics of investment and other activities.

Since money shocks are also found to explain a minor, but not negligible share of business cycle variances, our main finding is one of four relevant macroeconomic shocks: Expectation shocks on future TFP as the main driving force along with smaller roles for preference shocks, monetary shocks, and—particularly in the case of output—surprise TFP shocks. As such, it seems not advisable to reduce structural business cycle analysis to systems of dimension three or lower, as this would make it impossible to properly disentangle the main shocks and analyze their propagation mechanisms.

Endnotes

We thank Daron Acemoglu, Jonas Fisher, Ulrich Fritsche, Thomas Haertel, Helmut Lütkepohl, Andreas Schabert, and Stephanie Schmidt-Grohé for comments. All remaining errors are ours.

1. Since the long-run matrix is singular, 10 restrictions may not be sufficient for identification.

2. For example, Greenwood, Hercowitz, and Krusell (1997) and most others model IST as different vintages of capital goods. A new vintage has the property that a more productive capital good can be produced at the resource cost of one consumption good than in previous vintages. Hence, the price of investment goods in constant (base year) quality
declines over time relative to the price of consumption goods. If the capital stock, $K_t$, is measured in constant quality investment goods, $I_t$, the capital accumulation equation is

$$K_{t+1} = (1 - \delta)K_{t-1} + V_tI_t,$$

where $V_t$ is the inverse of the relative price of investment goods. Since we are interested in identifying shocks to IST, we will include the ratio of the consumer price index to an investment price index in the SVEC.

3. Fisher (2003) states that the relative price of QA equipment may be a better measure of IST than the relative price of quality adjusted total investment.

4. We use the free Jmulti software (see http://www.jmulti.de).

5. The FEVD is similar under ID2.

6. It is not possible to overidentify ID2 with this restriction.

7. In the case of two cointegrating vectors (i.e., with nonzero elements in the last column of $L$) the only noteworthy difference is, again, the permanent effect of monetary policy on activity (see fig. 13).

8. Removing only the third row and column from $B$ and $L$ in (5) results in an invalid set of identifying restrictions, because the number of independent restrictions for any shock must be smaller than the dimension of the system (see Lucke 2008, proposition 2). By lifting $I_{4t} = 0$ we ensure that this condition is satisfied for the money shock.

9. There are also nonzero correlations with the NIPA_h preference (0.40) and money shocks (−0.39). The correlation with the NIPA_h surprise TFP shock is essentially zero (−0.03).

10. A Johansen test of less than three cointegrating vectors has a rather inconclusive p-value of 0.07.

References


