Shocks – Do SVAR Models Justify Discarding the Technology Shock-Driven Real Business Cycle Hypothesis?†

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Abstract

Recent studies by Gali (1999), Gali and Rabanal (2004) and Francis and Ramey (2005) raise a strong objection to the technology shock-driven real business cycle (RBC) hypothesis on empirical grounds. To further investigate the validity of technology shocks as a driving force of U.S. business cycle fluctuations, we revisit some of the most commonly understood structural vector autoregression (SVAR) models of the empirical business cycle: namely, Gali (1999), Shapiro and Watson (1988), and King, Plosser, Stock and Watson (1991). Unlike previous contributions, we utilize these models to analyze how structural shocks are associated with the variations of output and hours worked at business cycle frequencies. Empirical evidence indicates that, across the models, technology shocks remain as an important source of cyclical movements in output even if all other shocks are combined and used against the technology shocks. Furthermore, in contrast to previous studies, our results show that a positive technology shock does not lead to a decline in hours worked. These results remain robust whether hours worked is assumed to be a difference-stationary or trend-stationary process. Our SVAR-based evidence does not support discarding a technology shock-driven business cycle theory.

Keywords: Structural vector autoregressive (SVAR) models, Technology shocks, Demand shocks, Real business cycle theory.

JEL Classification: C32, E32.

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1. Introduction

Is the quest for the dominant driver of economic fluctuations over? Furthermore, should the technology shock-driven real business cycle (RBC) hypothesis be discarded? The RBC hypothesis posits that technology or productivity shocks are the dominant source of fluctuations, propagated through intertemporal substitutions by optimizing households and firms in response to the shocks. The hypothesis implies that government stabilization policies could be counter-productive. In contrast, the New Keynesian models emphasize the role of demand shocks propagated due to the presence of price stickiness and imperfect competition, hence justifying active demand management through short-run stabilization programs. Thus, empirical investigation of the main source of business cycle fluctuations is important not only as a guide for developing a useful positive theory but also because policy implications can vary substantially, depending on which interpretation is correct.

Following the emergence of the New Keynesian research program, there has been a considerable debate as to whether the RBC predictions are borne out by data. Many empirical studies have relied on structural vector autoregression (SVAR) approaches to evaluate the empirical validity of the RBC hypothesis. Notably, Gali (1999), Gali and Rabanal (2004), and Francis and Ramey (2005) all reported that, in SVAR models, positive technology shocks lead to a decline in hours worked, casting serious doubt on the usefulness of RBC theory as a quantitative theory of economic fluctuations. Typically, these studies use long-run restrictions to identify shocks with the interpretation of “technology shocks” and compare how the congruence between the impulse responses from an estimated SVAR model and those of an RBC model. A key yardstick used to evaluate the RBC hypothesis using an estimated SVAR model is whether “technology shocks lead to a rise in hours?” in actual data as predicted by the theory.

However, McGrattan (2004), Christiano et al. (2003), and Chari et al. (2008) all challenged this rejection of technology-shock driven RBC models based on such an
evaluation strategy. Specifically, they argued that the SVAR models used to refute RBC-based explanations are either misspecified or not appropriately designed to evaluate the calibrated general equilibrium business cycle theory. In a similar vein, Wang and Wen (2011) argued that conditional impulse responses generated by SVAR models cannot serve as grounds to reject the technology shock-driven RBC hypothesis because the dimension of such a highly stylized model is different from that of an empirical characterization of data.

In this paper, we utilize several SVAR models and present a set of further results that provide alternative perspectives into the empirical source of fluctuations. Our work is not an attempt to engage in the methodological debate over the best practice to empirically evaluate the RBC theory or, more generally, calibrated macroeconomic models. While our SVAR analysis produces impulse response functions, we do not simply follow what Gali and others did in their analyses. Instead, we focus on business cycle frequencies and estimate the contribution of technology vs. demand (and other) shocks by imposing a minimal number of identifying assumptions. Hence, our work is similar, in spirit, to Cochrane (1994a) in that it is a quest for which empirical shocks drive business cycle fluctuations. Unlike Cochrane’s bivariate setting, however, we employ extended models that accommodate various underlying shocks to allow for different dynamics depending on the nature of the shocks. The results are used to examine the robustness of empirical findings produced by the existing stream of SVAR models.

The SVAR models utilized here are taken from Gali (1999), Shapiro and Watson (1988), and King et al. (1991). These three SVAR models were selected because they are among the best understood and the most popular models in empirical business cycle research. Along with these SVAR models, we use the decomposition of permanent and transitory components as a key analytical tool, similar to that of Beveridge and Nelson (1981). The permanent component determines the long-run movements of the variables, while the transitory component captures the short-run dynamics. Both components can be constructed
after estimating structural models in conjunction with identifying restrictions. This allows us to analyze how the underlying shocks of models are associated with the transitory component of output, which captures fluctuations at business cycle frequencies. Based on the conditional correlations of shocks with cyclical output, we examine how different structural shocks have contributed to postwar U.S. business cycle fluctuations. We also provide detailed findings on two important issues. First, we shed light on whether the importance of technology shocks is sensitive to whether hours worked is specified to be difference-stationary or trend-stationary, as RBC proponents such as Christiano et al. (2004) have argued. The other issue concerns the empirical findings that a positive technology shock leads to a decline in hours, which Gali and others have used as evidence against the RBC theory. Overall, this study provides further and alternative perspectives using the evidence that is clearly at odds with the earlier findings of Gali and others.

The remainder of this paper is organized as follows. Section 2 outlines the three SVAR models explored in the paper, and Section 3 presents our empirical strategy for measuring the relative contribution of structural shocks in accounting for the business cycle fluctuations of the variables. The results are given in Section 4. Section 5 offers further discussion of the results, with particular emphasis on robustness, and revisits the issue raised by Gali concerning the relationship between technology shocks and hours worked. Section 6 summarizes the key results of the paper and concludes the paper.

2. SVAR models

This section reviews the three SVAR models and explains how they are used in our investigation.

Gali investigated whether technology shocks could explain postwar U.S. business cycles using an SVAR model, to conclude that the technology shocks have a limited ability to explain the business cycle. He adopted two models: (i) a bivariate SVAR model comprising labor productivity \((x)\) (defined as output less hours worked) and hours worked \((n)\), i.e. with the vector \([x, n]^\prime\], and (ii) a five-variable SVAR model with the vector of variables \([x, n, m - p, R - \Delta p, \Delta p]^\prime\], where, in addition to labor productivity and hours worked, real money balances (nominal money, \(m\), less the price level, \(p\)), real interest rates (nominal interest rates, \(R\), minus the rate of inflation, \(\Delta p\)), and the inflation rate \((\Delta p)\) enter the system.\(^1\)

In the current paper, we consider only the latter model as the bivariate model does not make a distinction between non-technology supply shocks and demand shocks. The five-variable SVAR model assumes that there are five structural shocks: technology shocks \((v_1)\), labor supply shocks \((v_2)\), and three demand-side shocks \((v_3, v_4, \text{and } v_5)\).

The structural vector moving average (VMA) representation can be compactly written as

\[
\begin{bmatrix}
\Delta x_t \\
\Delta n_t \\
\Delta m_t - \Delta p_t \\
R_t - \Delta p_t \\
\Delta^2 p_t
\end{bmatrix}
= C(L)v_t = 
\begin{bmatrix}
C_{11}(L) & C_{12}(L) & C_{13}(L) & C_{14}(L) & C_{15}(L) \\
C_{21}(L) & C_{22}(L) & C_{23}(L) & C_{24}(L) & C_{25}(L) \\
C_{31}(L) & C_{32}(L) & C_{33}(L) & C_{34}(L) & C_{35}(L) \\
C_{41}(L) & C_{42}(L) & C_{43}(L) & C_{44}(L) & C_{45}(L) \\
C_{51}(L) & C_{52}(L) & C_{53}(L) & C_{54}(L) & C_{55}(L)
\end{bmatrix}
\begin{bmatrix}
v_{1t} \\
v_{2t} \\
v_{3t} \\
v_{4t} \\
v_{5t}
\end{bmatrix}
\]

where \(\Delta\) is the first difference operator, \(L\) is the lag operator, \(C_{ij} = \sum_{k=0}^{\infty} C_{ij,k} L^k\), \(C_{ij,k}\) is the response of the \(i^{th}\) variable to the \(j^{th}\) shock at a horizon \(k\), and the vector of disturbances \(v_t = [v_{1t}, v_{2t}, v_{3t}, v_{4t}, v_{5t}]^\prime\) represents a set of structural shocks driving the system over time.\(^2\) For identification of the underlying shocks, it is assumed that labor productivity and hours are not

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\(^1\) Note that the lowercase variables denote that the variables are logged, e.g. \(y = \log Y\).

\(^2\) The constant term is suppressed for the sake of illustration.
affected by the three demand shocks, $v_{3t}$, $v_{4t}$, and $v_{5t}$, in the long run. The implied restrictions can be imposed by assuming that $C_{1j}(1) = C_{2j}(1) = 0$ for $j = 3, 4$ and $5$, where

$$C_{ij}(1) = \sum_{k=0}^{\infty} C_{jk}$$

measures the long-run response of the $i$th variable to the $j$th shock. This distinguishes the technology and labor supply shocks from the demand shocks. The two supply shocks are identified individually on the assumption that the labor supply shock has no long-run effect on labor productivity by setting $C_{12}(1) = 0$. The three demand shocks are not disentangled individually, and their combined effects are used. As output is obtained through the relationship that $y_t = x_t + n_t$, it is affected by the two supply shocks at all horizons, while none of the demand shocks has long-run effects.

2.2. Shapiro and Watson (1988)

Shapiro and Watson (henceforth SW) present a five-variable SVAR model comprising the variables, $[o_t, n_t, y_t, \Delta p_t, R_t - \Delta p_t]'$, where $o_t$ is the price of oil. In the model, the oil price is assumed to be exogenous to all of the other variables, so that its reduced-form residuals become the oil price shocks. This allows us to reduce the original specification to the four-variable model of $[n_t, y_t, \Delta p_t, R_t - \Delta p_t]'$ with the oil price entering the equations as an exogenous regressor. There are assumed to be four structural shocks governing the economy: labor supply shocks ($v_{1t}$), technology shocks ($v_{2t}$), and two demand shocks ($v_{3t}$ and $v_{4t}$).

The SW model can be written as a structural VMA:

$$
\begin{bmatrix}
\Delta n_t \\
\Delta y_t \\
\Delta^2 p_t \\
R_t - \Delta p_t
\end{bmatrix}
= C(L)
\begin{bmatrix}
v_{1t} \\
v_{2t} \\
v_{3t} \\
v_{4t}
\end{bmatrix}.
$$
The labor supply shock is identified on the assumption that it is the only shock that has a long-run effect on hours. This is equivalent to assuming that $C_{12}(1) = C_{13}(1) = C_{14}(1) = 0$. The technology shock is identified using the long-run output neutrality so that the two demand shocks do not have long-run effects on output. This can be imposed by setting that $C_{23}(1) = C_{24}(1) = 0$. Again, the demand shocks are not identified individually, and their combined effects are considered instead.

### 2.3. King, Plosser, Stock and Watson (1991)

King et al. (henceforth KWSW) analyze a vector error correction model (VECM) comprising the six-variable, $[y_t, \Delta p_t, c_t, i_t, m_t - p_t, R_t]'$, where consumption ($c_t$) and investment ($i_t$) are also included. They suggest that there are three co-integrating relations present in the system. Two of these are the great ratios: that is, $(c_t - y_t)$ and $(i_t - y_t)$ are stationary (after the adjustment for real interest rate effects), while the remaining relation is a long-run money demand relation among real money ($m_t - p_t$), output ($y_t$), and the nominal interest rate ($R_t$).

On the basis of three cointegrating relations, there are assumed to be three structural shocks whose effects are permanent, and they are identified as balanced-growth (productivity) shocks ($\nu_{1t}$), inflation shocks ($\nu_{2t}$), and real interest rate shocks ($\nu_{3t}$). The remaining three shocks ($\nu_{4t}$, $\nu_{5t}$, and $\nu_{6t}$) have only transitory effects on the variables, and are not given specific economic interpretations.\(^3\)

The KPSW model may be expressed in the form of a structural VMA as

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\(^3\) See also Gonzalo and Ng (2001) and Pagan and Pesaran (2008) for the implications of cointegration in the structural identification of the VECM model.
The productivity (technology) shock is identified under the assumption that neither the inflation shock nor the real interest rate shock has a long-run effect on output by setting that $C_{12}(1) = C_{13}(1) = 0$. The shocks to inflation and the real interest rate are individually identified by assuming that the real interest rate shock does not have a long-run effect on the inflation, which implies that $C_{23}(1) = 0$. These three restrictions are sufficient for exact identification of the permanent shocks in the model, as the presence of three transitory shocks implies that all of the elements in the last three columns of $C(1)$ are zero, i.e. $C_{ij}(1) = 0$ for $i=1, 2, \ldots, 6$ and $j=4, 5,$ and 6.

Unlike the Gali and SW models, KPSW allow for investment dynamics to be expressed within the system. Cogley and Nason (1995) showed that investment dynamics plays a central role through adjustment lags or costs in accounting for the propagation mechanism. McGrattan (2004) eloquently argued that technology shocks typically influence the business cycle through investment, rather than hours. Her point casts doubt on the premise of sticky-price models of the business cycle model because such models, including the one studied by Gali, dispense with the role of investment in propagating technology shocks. Fama (1992) also presented evidence that the hump-shaped response of output is largely due to the multiplier effect of variations in investment. A recent work by Fisher (2006) further strengthened the case for the importance of investment and the role of investment-specific technology shocks.

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4 We use the terms productivity and technology interchangeably unless stated otherwise.
Measuring the contribution of structural shocks

Let $Z$ be a $(k \times 1)$ vector of variables consisting of $k_1$ non-stationary variables and $k_2$ stationary variables, i.e. $Z_t = \begin{bmatrix} \Delta X_{1t}, X_{2t}' \end{bmatrix}'$. The structural VMA representation can be compactly expressed as

$$Z_t = \Gamma(L)v_t$$  \hspace{1cm} (1)

where $v_t$ represents a vector of structural shocks, and the lag polynomial matrix $\Gamma(L)$ tracks the response of $Z$ to the structural shocks. For expositional convenience, assume that output in differenced form, $\Delta y$, is the first variable in the vector $Z$. This allows the following decomposition in a manner analogous to Beveridge and Nelson (1981):

$$\Delta y_t = \Gamma_y(L)v_t = \Gamma_{yp}(L)v_t^p + \Gamma_{yc}(L)v_t^c$$  \hspace{1cm} (2)

where $v_t^p$ is a vector of shocks that have permanent effects on output, e.g., technology shocks, and $v_t^c$ is a vector of shocks that exert only transitory effects, e.g., IS and LM shocks.

Equation (2) can be further decomposed as

$$\Delta y_t = \left[ \Gamma_{yp}(1) + \Gamma_{yp}^*(L) \right] v_t^p + \Gamma_{yc}(L)v_t^c = \Gamma_{yp}(1)v_t^p + \Gamma_{yp}^*(L)v_t^p + \Gamma_{yc}(L)v_t^c$$  \hspace{1cm} (3)

where $\Gamma_{yp}^*(L) = \left[ \Gamma_{yp}(L) - \Gamma_{yp}(1) \right]$. $\Gamma_{yp}(1)$ captures the effects of $v_t^p$ on the long-term trend of output, and $\Gamma_{yp}^*(L)$ measures the effects of $v_t^p$ on the short-run dynamics of output. For instance, technology shocks affect long-run output, which is reflected in $\Gamma_{yp}(1)$, and also cause business cycles through changes in capital investment and adjustment costs or lags in labor input, that is captured by $\Gamma_{yp}^*(L)$. Equation (3) can be transformed in levels as

$$y_t = y_t^p + y_t^c = \Gamma_{yp}(1)\sum_{i=0}^L v_{t-i}^p + \Gamma_{yp}^*(L)\sum_{i=0}^L v_{t-i}^p + \Gamma_{yc}(L)\sum_{i=0}^L v_{t-i}^c$$  \hspace{1cm} (4)

In (4), the cyclical component of output corresponds to $y_t^c = \Gamma_{yp}^*(L)\sum_{i=0}^L v_{t-i}^p + \Gamma_{yc}(L)\sum_{i=0}^L v_{t-i}^c$. As it comprises the components separately driven by
permanent shocks and transitory demand shocks, we are able to examine which shock is mainly responsible for fluctuations in output at business cycle frequencies. This may provide a better way of defining determinants underlying business cycles than the typical tool of impulse responses and variance decompositions. For technology shocks, the effect on output is captured by $\Gamma_{3p}(L)$, which can be decomposed into the effect on the short-run dynamics $\Gamma^*_s(L)$ as well as the effect on the long-term trend $\Gamma_{3p}(1)$.

Using the decomposition outlined above, we calculate the conditional correlations of different shocks with the cyclical component of output. To take a five-variable model as an example, let $\rho_{r,i}$ be the correlation coefficient between cyclical output $y^c_i$ and the first shock in the model, say, technology shock $v_{it}$. Then, the coefficient $\rho_{c,2345}$ captures the correlation of $y^c_i$ with all other shocks combined, indexed 2 to 5 combined, e.g., the composite non-technology shocks. The conditional correlation quantifies the extent to which each structural shock is associated with output fluctuations at business cycle frequencies. In addition, by squaring the correlation coefficients, we can analyze the contribution of the shocks to accounting for the variance of $y^c_i$. To see this, rewrite $y^c_i$ in (4) as

$$y^c_i = a_{01}v_{it} + a_{02}v_{2t} + a_{03}v_{3t} + a_{04}v_{4t} + a_{05}v_{5t} + a_{11}v_{it-1} + a_{12}v_{2t-1} + a_{13}v_{3t-1} + a_{14}v_{4t-1} + a_{15}v_{5t-1} + a_{21}v_{2t-2} + a_{22}v_{2t-2} + a_{23}v_{3t-2} + a_{24}v_{4t-2} + a_{25}v_{5t-2} + \ldots$$

Then, the conditional correlation of $y^c_i$ with the $i^\text{th}$ shock $v_{it}$ can be obtained as

$$\rho_{v,i} = \text{Corr}(y^c_i, v_{it}) = \frac{\sqrt{\sum_{i=1}^{5} a_{ii}^2 \sigma_i^2}}{\sqrt{\sum_{i=1}^{5} a_{ii}^2 \sigma_i^2}}$$

Where $\sigma_i^2$ is the variance of the shock $v_{it}$. Squaring the coefficient of the correlation yields
\[ \rho_{v,t}^2 = \left[ \text{Corr}(y_t^c, \nu_t^c) \right]^2 = \frac{\sigma_0^2 \sigma_i^2}{\sum_{i=1}^{\sigma_i} \sigma_i^2} \]

The denominator represents the variance of \( y_t^c \) explained by all shocks in time \( t \) and the numerator measures the contribution of the \( i \)th shock \( \nu_t^i \).

4. **Empirical results**

4.1. **Impulse responses and historical decompositions**

The Gali, SW, and KPSW models in Section 2 are estimated using the same data series, lag lengths, and starting dates as those used in the original contributions. This paper, however, extends the sample period for all models to end in 2008:Q4. We first present the results from impulse responses and historical decompositions. For the former, we examine how a variable responds to the structural shocks and check whether these responses are consistent with the theory. For the latter, we assess the ability of structural shocks to explain the stochastic movement in a variable over time. At the outset it should be remembered that demand shocks in the Gali and SW models, and transitory shocks in the KPSW model were not individually identified (see Section 2). As such, the responses of the variables to these shocks are not reported in the impulse response analysis, while the historical decomposition analysis reports their combined contribution to tracking the stochastic movements of the variables. It should be noted that hours worked is assumed to be a difference-stationary process. In the next section, we will examine how the results differ when hours worked is assumed to be a trend-stationary process.

(i) **Gali SVAR**

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5 The number of lags is 4, 6, and 8, and the starting date is 1959:Q1, 1951:Q1, and 1954:Q1 for the Gali, SW, and KPSW models, respectively.

6 This effectively excludes the full effect of the recent financial crisis as an outlier.
Figure 1.1 depicts the responses of labor productivity, output and hours in levels to the two supply-side shocks identified, that is, technology (TN) and labor supply (LS) shocks. Also reported around each response is the one standard error confidence interval generated by 1,000 bootstrap replications. All of the responses are not different from those presented by Gali. A positive technology shock raises labor productivity and output permanently, while hours show a significant decline at short time horizons. As Gali forcefully argues, this finding is apparently evidence against the RBC theory, which predicts pro-cyclical labor hours in response to technology shocks. A positive labor supply shock increases hours and output permanently, and the effect on labor productivity converges to zero by the identifying assumption. Figure 2.1 shows the historical decompositions of the key variables. Technology shocks explain most of the variation in labor productivity, while the variation of hours is mostly accounted for by labor supply shocks. Interestingly, the result shows that the labor supply shock is also the main determinant of the movements in output. None of the technology or demand shocks plays any significant role. We will discuss these results subsequently in detail.

(ii) Shapiro and Watson SVAR

Figure 1.2 shows the responses of the variables to technology and labor supply shocks estimated from the SW model. Overall, output and hours respond in a very similar manner to the Gali model. The level of hours falls in response to a positive technology shock before converging to zero by the identifying restriction. Positive shocks to labor supply and technology increase output permanently. The historical decomposition yields similar results, as displayed in Figure 2.2. The labor supply shock is the main factor in explaining the stochastic movements in hours and output, while technology and demand shocks contribute little to the movements in output.
(iii) King, Plosser, Stock, and Watson SVAR

Figure 1.3 shows the responses of three real variables - output, consumption, and investment to the three permanent shocks: shocks to technology (TN), inflation (IF), and the real interest rate (RR). A positive technology shock raises output, consumption and investment permanently, as expected *a priori*. The inflation shock has little impact on the variables except at some short time horizons. In response to a positive real interest rate shock, the three variables show strong initial increases. It is difficult to provide precise economic interpretations to these impulse responses, as also acknowledged by KPSW. However, Fisher *et al.* (2000) suggested that a real spending shock, in place of the real interest rate shock, provides a better economic interpretation of the KPSW findings. Under this alternative interpretation, the strong initial increases in the variables in response to the shock are consistent with the predictions of conventional economic theory. Figure 2.3 shows the results of historical decomposition estimated from the KPSW SVAR. Technology shocks account for most of the variations in output and consumption. The other two permanent shocks as well as transitory shocks do not appear to contribute as much. In the case of investment, the technology shock is still a major determinant, but the combined transitory shocks also capture a sizable portion of the movements particularly for the second half of the sample period.

4.2. Cyclical output and shocks

As stated previously, the crux of this paper is an examination of the sources of fluctuations at business cycle frequencies. While the results in the preceding section provide useful insights, they are not complete for an often neglected reason that the impulse response function is designed to capture the combined effects of shocks on both long-term trends and short-run dynamics. To business cycle researchers, one odd observation concerning the Gali and SW models would be that output fluctuations were mostly accounted for by labor supply shocks.
As shown before in this paper, technology and demand shocks contributed relatively little in their models, which is hard to reconcile with the RBC or even with the Keynesian perspective.

When focusing on business cycle fluctuations, as in the current study, it may be more prudent to look at the relationships between underlying shocks and cyclical output, rather than the output variable per se. As RBC models are typically analyzed in terms of the steady state deviations in response to a shock, decomposing output into permanent, defining the steady state, and transitory components is legitimate, justifying the empirical strategy detailed in Section 3. Assuming the transitory component as a measure of cyclical output, we examine how and to what extent cyclical output is associated with the shocks in the model.

(i) Gali SVAR

Table 1.1 reports the conditional correlations of cyclical output with respect to the shocks identified from the Gali model. The correlation coefficient between cyclical output and technology shocks is 0.69; squaring it shows that technology shocks account for about 48 percent of the variance in cyclical output. Demand shocks are almost as highly correlated with cyclical output (\( \rho_{t,345} = 0.68 \)) as technology shocks. In contrast, the correlation coefficient between the labor supply shock and cyclical output is low, at 0.33; only 10 percent of variance in cyclical output is explained by the labor supply shock. To elaborate on these results, Figure 3.1 reports the historical decomposition of cyclical output, and the shaded areas represent periods between peaks and troughs in the U.S. business cycles, dated by the National Bureau of Economic Research (NBER). Indeed, both technology and demand shocks capture the movements in cyclical output equally well, while labor supply shocks perform poorly. The results are quite different from those of the impulse response and variance decomposition analysis in the preceding section. That is, the technology and demand shocks now emerge as the main determinant of output movements at business cycle
frequencies while the contribution of the labor supply shock is substantially reduced once the low frequency component of output is removed. Figure 4.1 displays the cross correlations of cyclical output with the shocks at leads up to eight quarters. The correlations at leads can assess the predictive properties of the shocks over the business cycle. The technology shock is found to lead cyclical output more strongly than demand shocks across the leads while the labor supply shock fails to lead cyclical output.

(ii) Shapiro and Watson SVAR

Table 1.2 reports the conditional correlations between cyclical output and the structural shocks estimated from the SW model. For technology shocks, the correlation coefficient is 0.58, while the coefficient for the combined demand shocks is much higher, at 0.83. Similar to the Gali SVAR, the association between output and labor supply shocks becomes significantly weaker and statistically insignificant over the business cycle. Although the level of correlation between technology shocks and cyclical output is lower than in the Gali SVAR, technology shocks still account for about 34 percent of the variance in cyclical output with the remainder being explained by the demand and labor supply shocks together. The historical decomposition in Figure 3.2 confirms these findings. Demand shocks closely follow the movements in cyclical output over the sample period while labor supply shocks contribute very little. The technology shock still retains a considerable ability to explain cyclical output, although not as well as demand shocks. Again, these results are quite different from those of the historical decomposition for output in which demand and technology shocks played a negligible role. Figure 4.2 displays the cross correlations of cyclical output with the shocks at various leads. Demand shocks better predict cyclical output than technology shock, although the difference is diminished at long leads. The labor supply shock does not exhibit any discernible ability to lead cyclical output across all leads. Overall, the Shapiro and Watson SVAR produces qualitatively similar results to those from the Gali
SVAR. In both models, technology and demand shocks are the main drivers of cyclical output, while the labor supply shock becomes insignificant.

(iii) King, Plosser, Stock and Watson SVAR

Table 1.3 reports the conditional correlation of output with respect to the structural shocks from the KPSW model. The technology shock is the most significant force, with the correlation coefficient of 0.61. The correlation of cyclical output with the two demand shocks combined (shocks to inflation and the real interest rate) is 0.48, while the correlation with the three (unidentified) transitory shocks is 0.56. Although the results depend somewhat on how the transitory shocks are actually identified, they are more likely to originate from the demand side rather than the supply side. This allows us to combine these transitory shocks with the two permanent demand shocks and interpret them as non-technology shocks that mainly reflect changes in demand. As a consequence, the non-technology shock is more highly correlated with cyclical output ($\rho_{v,23456} = 0.77$) than the technology shock. Figure 3.3 shows the decomposition of cyclical output attributable to the structural shocks. The technology and transitory shocks appear to track the movements in cyclical output equally well. When the demand and transitory shocks are combined, the resulting non-technology shock shows a better fit with cyclical output throughout the entire sample period. Figure 4.3 adds an interesting observation concerning the ability of the shocks to predict cyclical output. The non-technology shock outperforms the technology shock for up to three quarters of leads, while the reverse is true thereafter. As the forecasting horizon increases beyond three quarters, the technology shock exhibits better predictive abilities for cyclical output.

5. Issues surrounding hours worked
In the New Keynesian-RBC debate over the importance of technology shocks, there are two important issues concerning the empirical characterization of hours worked. The first issue is the sensitivity of the results to the assumption of whether hours worked is difference-stationary or trend-stationary. The second issue, related to the first one, is whether a positive technology shock does, in fact, lead to a decline in hours worked, as argued by Gali (1999). This section addresses each of these issues with respect to our results from the Gali and SW models.

5.1. Stationary vs. non-stationary hours worked

Theoretically speaking, hours worked is a bounded series, and conventional RBC models predict that in the presence of technology shocks, the substitution and income effects cancel each other out with no clear impact on the steady state level of hours. In finite samples, however, it is debatable whether such theoretical constraints are borne out by the data. Some RBC proponents such as Christiano et al. (2004) argue that the findings of Gali (1999) depend critically on whether the level of hours is assumed to be stationary. This was also noted earlier by Shapiro and Watson (1988) as they observed that the output effects of technology and labor supply shocks may vary depending on whether hours worked is assumed to be difference-stationary or trend-stationary.

In the preceding section, the Gali and SW models adopted the assumption of difference-stationary hours. Figures 5.1 and 5.2 display the impulse responses and historical decompositions estimated from the Gali and SW models when hours worked is assumed to be a trend-stationary process. For both models, the impulse responses remain largely unchanged with two obvious exceptions; the transitory effects of the labor supply shock and the responses of hours converging to zero in the long run, reflecting the assumption of the trend stationary hours. Again, a positive technology shock leads to a decline in hours, analogous to the finding under the assumption of difference-stationary hours. However, the historical
decomposition produces quite a different picture; across the models, the technology shock is now the main source of movements in output, and the contribution of the labor supply shock shrinks considerably, particularly since the mid-1970s. Similar changes are also observed for explaining the variability of hours. Now, the technology shock emerges as the main determinant while the labor supply shock contributes far less than before.

To further illustrate, we re-compute the conditional correlations of the structural shocks with cyclical output under the assumption that hours worked is a trend-stationary process. The results are reported in Tables 2.1 and 2.2. Several changes are worth discussion. Examining the Gali model first, the technology shock is the most highly correlated with cyclical output as documented by the correlation coefficient of 0.87. The correlation between demand shocks and cyclical output is only about 0.2, which is quite low compared with the correlation coefficient of 0.68 when hours was assumed to be difference-stationary. Even when all non-technology shocks are combined, the correlation coefficient is just 0.33, far less than the correlation between the technology shock and cyclical output.

The SW model produces the same implications. The correlation of cyclical output with the technology shock rises considerably to 0.84, while the corresponding figure for demand shocks is diminished to 0.37, in comparison to the result when hours was assumed to be difference-stationary. The historical decomposition of cyclical output reported in Figure 5.3 consolidates the results. The technology shock accounts for most of the movements in cyclical output, while both labor supply and demand shocks contribute little. Figure 5.4 shows that the predictive power of technology shocks is also strengthened under the assumption of stationary hours. For both the Gali and SW models, the technology shock leads cyclical output far better than labor supply and demand shocks across all leads, showing particularly strong effects at short leads. Even over longer leads, such as eight quarters, the coefficient remains higher than 0.5. For the SW model, demand shocks exhibit some
predictability at short leads but only marginally, while the labor supply shock fails to lead cyclical output.

In summary, our results are sensitive to whether hours worked is assumed to be a difference-stationary or trend-stationary process. The RBC hypothesis is more preferred under the trend-stationarity assumption. In addition, the evidence is more pronounced when we decompose the variables into permanent and transitory components and focus only on the latter components, which reflect movements at business cycle frequencies. When hours worked is assumed to be difference-stationary, technology and demand shocks are almost equally important in accounting for cyclical output. Under the assumption of trend-stationary hours, the technology shock becomes the major determinant of cyclical output, outperforming all other shocks, including demand shocks. This finding provides rather strong support for the RBC hypothesis. The results are robust for both Gali and SW models, despite the fact that these models have different structures and identifying assumptions. Therefore, whether hours worked is a difference-stationary or trend-stationary process may be a useful yardstick for discriminating between RBC and New Keynesian models. Policy implications would differ depending on which model is a better description of the real economy. While more comprehensive research is warranted, it could be difficult to draw an empirical distinction concerning the time-series properties of hours, given the well-known low power problem of many unit root tests coupled with the typical sample size of macroeconomic data. Because this issue is beyond the scope of the current paper, we leave it for future research and move on to another related issue.

5.2. Technology shocks and hours worked

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5 For example, the Gali model assumes that technology shocks can affect all of the variables in the long run, but labor supply shocks are not allowed to have a long-run effect on labor productivity. The converse is assumed in the SW model: labor supply shocks can have a long-run impact on all of the variables while technology shocks cannot have permanent effects on labor supply.
Gali (1999) argued that technology shocks lead to a decline in hours worked, whether hours is difference-stationary or trend-stationary, using this as evidence against the RBC hypothesis. In the impulse response analysis, we find results similar to those of Gali, as displayed in Figures 1.1, 1.2, and 5.1. The figures also indicate that the decline in hours is present only in the short time horizon, after which the responses of hours to a positive technology shock are statistically insignificant (Figure 1.1) or converge to zero (Figures 1.2 and 5.1) by the identifying assumptions. As stated earlier, the impulse response analysis reflects the composite effects on both long-term movements and short-term dynamics. To isolate the short-term from the long-term movements, the decomposition outlined in Section 3 was applied to hours worked. In this way, we sought to determine whether Gali’s argument would still hold once confined to movements at business cycle frequencies.

Figure 5.5 displays the conditional correlations between technology shocks and cyclical hours over the leads of one to eight quarters. The technology shock appears to be positively correlated with cyclical hours contemporaneously across the Gali and SW models. This is robust whether hours worked is assumed to be a difference-stationary or trend-stationary process. The correlations range between 0.59 and 0.88 and are particularly strong under the trend-stationarity assumption. It is also notable that the Gali and SW models produce coefficients of a very similar magnitude, validating the robustness of the results. Furthermore, the technology shock is found to lead cyclical hours considerably, displaying positive and statistically significant correlations at most of the leads. Thus, our evidence does not support Gali’s finding that a positive technology shock leads to a decline in hours, when examined over business cycle frequencies. Rather, our finding that a technology shock has a strongly positive association with cyclical variation in hours is quite well explained by the RBC models.8

8 In RBC models, a positive shock to technology leads to a rise in hours worked through an increase in the marginal product of labor and the consequent adjustments in the marginal rate of substitution.
6. Conclusion

This paper examined the empirical sources of business cycle fluctuations in the postwar U.S. economy using three popular variants of SVAR models; those studied by Gali (1999), Shapiro and Watson (1988), and King, Plosser, Stock and Watson (1991). In adopting these models, a minimum set of theoretical restrictions were imposed \textit{a priori} to avoid favoring a particular theory, especially between New Keynesian and RBC paradigms. The current study went significantly further than the original SVAR contributions by making extensive use of the statistical properties of the data and results. In particular, the variables were decomposed into permanent and transitory components; using the latter, we investigated the relationships between underlying structural shocks and movements of the variables at business cycle frequencies. This strategy appeared to pay economically interesting dividends. Technology and demand shocks were both shown to be the most important sources of variation in cyclical output. This finding is different from that suggested by the conventional impulse response and historical decomposition analysis.

This paper also examined two important issues still being debated in the literature: whether the assumption of stationarity of hours worked matters; and whether a positive technology shock leads to a decline in hours, as claimed by Gali (1999). As to the first issue, our results showed considerable changes under the assumption of trend-stationary hours. Of particular interest, we found that a technology shock was the most important determinant of cyclical output, while all other shocks, including demand shocks, showed only marginal contributions. This study provided an equally interesting result with respect to the second issue. While we, like other authors, found a decline in hours in response to a positive technology shock, a very different picture emerged when focused on the movements over the business cycle. The technology shock was positively correlated with the contemporaneous and future values of cyclical hours, invalidating Gali’s claim. The effects were more
pronounced when hours was assumed to be trend-stationary. Our evidence is robust across the models under consideration.

Considering all these results together, we conclude that technology shocks should not be discarded as an important driver of business cycle fluctuations, nor should the RBC be thrown out simply because of its emphasis on technology shocks. Although we may “forever remain ignorant of the fundamental causes of economic fluctuations” as remarked by Cochrane (1994b), technology shocks are never likely to be dropped as an important source of macroeconomic fluctuations. The technology-driven real business cycle hypothesis should be still alive.
References


Table 1.1: Correlations of Shocks with Cyclical Output from Gali SVAR

<table>
<thead>
<tr>
<th>Technology shock ( (\rho_{v,1}) )</th>
<th>Labor supply shock ( (\rho_{v,2}) )</th>
<th>Demand shocks combined ( (\rho_{v,345}) )</th>
<th>Non-technology shocks ( (\rho_{v,2345}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.69 ( (0.31) )</td>
<td>0.33 ( (0.32) )</td>
<td>0.68 ( (0.26) )</td>
<td>0.78 ( (0.23) )</td>
</tr>
</tbody>
</table>

Table 1.2: Correlations of Shocks with Cyclical Output from Shapiro and Watson SVAR

<table>
<thead>
<tr>
<th>Technology shock ( (\rho_{v,2}) )</th>
<th>Labor supply shock ( (\rho_{v,1}) )</th>
<th>Demand shocks combined ( (\rho_{v,34}) )</th>
<th>Non-technology shocks ( (\rho_{v,234}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.58 ( (0.29) )</td>
<td>0.15 ( (0.30) )</td>
<td>0.83 ( (0.25) )</td>
<td>0.86 ( (0.13) )</td>
</tr>
</tbody>
</table>

Table 1.3: Correlations of Shocks with Cyclical Output from KPSW SVAR

<table>
<thead>
<tr>
<th>Technology shock ( (\rho_{v,i}) )</th>
<th>Demand shocks combined ( (\rho_{v,23}) )</th>
<th>All transitory shocks combined ( (\rho_{v,456}) )</th>
<th>Non-technology shocks ( (\rho_{v,23456}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.61 ( (0.28) )</td>
<td>0.48 ( (0.25) )</td>
<td>0.56 ( (0.19) )</td>
<td>0.77 ( (0.17) )</td>
</tr>
</tbody>
</table>

Note: Figures in parentheses are one-standard errors of the estimates generated by 1,000 bootstrap replications.
Table 2.1: Correlations of Shocks with Cyclical Output from Gali SVAR (trend-stationary hours)

<table>
<thead>
<tr>
<th>Technology shock ($\rho_{v,1}$)</th>
<th>Labor supply shock ($\rho_{v,2}$)</th>
<th>Demand shocks combined ($\rho_{v,345}$)</th>
<th>Non-technology shocks ($\rho_{v,2345}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.87  (0.16)</td>
<td>0.27  (0.19)</td>
<td>0.20  (0.14)</td>
<td>0.33  (0.19)</td>
</tr>
</tbody>
</table>

Table 2.2: Correlations of Shocks with Cyclical Output from Shapiro and Watson SVAR (trend-stationary hours)

<table>
<thead>
<tr>
<th>Technology shock ($\rho_{v,2}$)</th>
<th>Labor supply shock ($\rho_{v,3}$)</th>
<th>Demand shocks combined ($\rho_{v,34}$)</th>
<th>Non-technology shocks ($\rho_{v,234}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.84  (0.17)</td>
<td>-0.01  (0.22)</td>
<td>0.37  (0.20)</td>
<td>0.15  (0.21)</td>
</tr>
</tbody>
</table>

Note: Figures in parentheses are one-standard errors of the estimates generated by 1,000 bootstrap replications.
Figure 1.1: Impulse Responses from Gali SVAR

Notes: TN and LS denote technology and labor supply shocks, respectively. Shown around each response (in blue) is the one standard error confidence interval generated by 1,000 bootstrap replications.
Figure 1.2: Impulse Responses from Shapiro and Watson SVAR

Notes: LS and TN denote labor supply and technology shocks, respectively. Shown around each response (in blue) is the one standard error confidence interval generated by 1,000 bootstrap replications.
Figure 1.3: Impulse Responses from KPSW SVAR

Notes: TN, IF, and RR denote shocks to technology, inflation, and real interest rate, respectively. Shown around each response (in blue) is the one standard error confidence interval generated by 1,000 bootstrap replications.
Figure 2.1: Historical Decompositions from Gali SVAR

Notes: In each graph, the solid line is the stochastic movement in a variable. The dotted lines show the contribution of the structural shocks where TN, LS, and DM denote shocks to technology, labor supply, and demand, respectively.
Figure 2.2: Historical Decompositions from Shapiro and Watson SVAR

Notes: In each graph, the solid line is the stochastic movement in a variable. The dotted lines show the contribution of the structural shocks where LS, TN, and DM denote shocks to labor supply, technology, and demand, respectively.
Figure 2.3: Historical Decompositions from KPSW SVAR

Notes: In each graph, the solid line is the stochastic movement in a variable. The dotted lines show the contribution of the structural shocks where TN, IF, RR, and TR denote technology shock, inflation shock, real interest rate shock, and transitory shocks, respectively.
Figure 3.1: Cyclical Output and Shocks from Gali SVAR

Notes: In each graph, the solid line is the stochastic movement of cyclical output, while the dotted lines show the contribution of respective shocks. The shaded areas are periods between peaks and troughs of U.S. business cycles dated by the National Bureau of Economic Research (NBER).
Figure 3.2: Cyclical Output and Shocks from Shapiro and Watson SVAR

Notes: In each graph, the solid line is the stochastic movement of cyclical output, while the dotted lines show the contribution of respective shocks. The shaded areas are periods between peaks and troughs of U.S. business cycles dated by the National Bureau of Economic Research (NBER).
Figure 3.3: Cyclical Output and Shocks from KPSW SVAR

Notes: In each graph, the solid line is the stochastic movement of cyclical output, while the dotted lines show the contribution of respective shocks. The shaded areas are periods between peaks and troughs of U.S. business cycles dated by the National Bureau of Economic Research (NBER).
Figure 4.1: Predictive Properties of Shocks from Gali SVAR

Note: The solid pronounced markers indicate statistically significant point estimates at the 10 percent level.
Figure 4.2: Predictive Properties of Shocks from Shapiro and Watson SVAR

Note: The solid pronounced markers indicate statistically significant point estimates at the 10 percent level.
Figure 4.3: Predictive Properties of Shocks from KPSW SVAR

Note: The solid pronounced markers indicate statistically significant point estimates at the 10 percent level.
Figure 5.1: Impulse Responses with Trend-stationary Hours

(a) Gali SVAR
(b) Shapiro and Watson SVAR

Notes: TN and LS denote technology and labor supply shocks, respectively. Shown around each response (in blue) is the one standard error confidence interval generated by 1,000 bootstrap replications.
Figure 5.2: Historical Decomposition of Output and Hours with Trend-stationary Hours

(a) Gali SVAR
Notes: In each graph, the solid line is the stochastic movement in a variable. The dotted lines show the contribution of the structural shocks where LS, TN, and DM denote shocks to labor supply, technology, and demand, respectively.
Figure 5.3: Shocks over the Business Cycle with Trend-stationary Hours

(a) Gali SVAR
In each graph, the solid line is the stochastic movement of cyclical output while the dotted lines show the contribution of respective shocks. The shaded areas are periods between peaks and troughs of U.S. business cycles dated by the National Bureau of Economic Research (NBER).
Figure 5.4: Predictive Properties of Shocks with Trend-stationary Hours

(a) Gali SVAR

(b) Shapiro and Watson SVAR

Note: The solid pronounced markers indicate statistically significant estimates at the 10 percent level.
Figure 5.5: Cross Correlations between Technology Shocks and Hours Worked

(a) Difference-stationary hours

(b) Trend-stationary hours

Note: The solid pronounced markers indicate statistically significance at the 10% level.