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Real business cycles, sticky wages or sticky prices? The impact of technology shocks on US manufacturing

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Abstract

In this paper, we examine empirically the predictions of a range of theoretical models which give a prominent role to technology shocks in explaining business cycles. To this end, we estimate (4-digit SIC) industry-level VAR models for US manufacturing using real output, the real wage and utilization corrected measures of technology and labor input. Our results support both sticky-wage DGE and RBC models over sticky-price DGE models. Moreover, they cast some doubt on the importance of technology shocks as propulsive mechanism for business cycles at the industry level.

JEL classification: E32; O47

Keywords: Real business cycles; Sticky-price DGE models; Technology shocks; Total factor productivity

1. Introduction

The purpose of this paper is to examine empirically the predictions of a range of theoretical models, which give a prominent role to technology shocks in explaining business cycles. The theoretical representations include RBC-type (see, e.g. Kydland and Prescott, 1982; Long and Plosser, 1983; King and Plosser, 1984) and New Keynesian DGE-type models which allow for wage and price rigidity (see, e.g. Goodfriend and King, 1997; Rotemberg and Woodford, 1997; Galí, 1999). Notable empirical contributions which examine the impact of technology shocks include Galí (1999),

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Basu et al. (1998) and Shea (1998).[1] This paper makes a contribution to the empirical literature on business cycles by estimating (4-digit SIC) industry level VAR models using real output, the real wage and utilization corrected measures of technology and labor input.

Our main findings are the following. First, in contrast to Galí (1999) and Basu et al. (1998) whose results support the sticky-price DGE model, we find that our results are much more supportive of RBC-type models, or DGE models with sticky wages. Second our utilization and effort adjustments actually strengthen the empirical support for the RBC and sticky-wage models, despite the fact that the utilization-adjusted TFP innovations are markedly less procyclical. Third, there are markedly distinct responses to technology shocks in different manufacturing sectors.

The rest of the paper is structured as follows. To help identify the expected impact of technology shocks predicted by alternative theories, Section 2 describes a stylized general equilibrium model with varying degrees of wage and price stickiness. Section 3 discusses the factor-utilization adjustments made to our TFP and labor input series. Section 4 outlines our econometric method and presents our VAR results. Finally, Section 5 concludes.

2. A stylized model of technology shocks

2.1. Flexible prices

We begin by setting out a standard Sidrauski–Brock money in the utility function model.[2] Aggregate output in the economy is given by a constant-return Cobb–Douglas production function in capital and labor inputs:

$$Y_t = A\exp(z_t)K_{t-1}^{\alpha}L_t^{1-\alpha}, \quad z_t = \rho z_{t-1} + \varepsilon_t,\ 0 < \rho < 1, \tag{1}$$

where A is total factor productivity and z_t is a stochastic shock to TFP, which is assumed to follow an AR(1) process.[3] The representative agent maximizes the present

[1] Shea's approach is not strictly comparable to ours since his empirical analysis is not aimed at the debate between different business cycle theories. However, the positive response of factor inputs to technology shocks is supportive of RBC-type models.

[2] These models have been extensively analyzed in the macroeconomics literature (see inter alia King et al., 1988; Campbell, 1994; Uhlig, 1995; Walsh, 1998). They provide a useful way of nesting the consumption-smoothing effects of pure RBC theories within a monetary DGE model. For an early attempt to incorporate a monetary sector into RBC models, see King and Plosser (1984).

[3] Note that here we interpret the variables K and L broadly, as being measures of effective capital and labor input, respectively. This is since our empirical work takes seriously the notion that the Solow residual is not an accurate measure of technology due to fluctuations in unobservable labor and capital utilization. For convenience, we do not explicitly model the intensive margins along which labor and capital are varied in the theory. Not doing so could have non-trivial quantitative implications for the theoretical responses of the total effective labor input to a technology shock. However, we believe that the qualitative implications would be relatively robust.

value of total utility over an infinite horizon, where the instantaneous utility function $u(.)$ depends on current consumption, C, real money balances (M/P) and leisure, V:[4]

$$U = \sum_{i=0}^{\infty} \beta^i \left(\log(C_t) + \lambda \log(M_t/P_t) + \phi \frac{V_t^{1-\mu}}{1-\mu} \right). \tag{2}$$

The resource constraint for the economy is given by

$$Y_t + (1-\delta)K_{t-1} + (M_{t-1}/P_t) = C_t + K_t + (M_t/P_t). \tag{3}$$

The consumer's problem can be solved in the usual way to obtain the f.o.c.'s for consumption, labor supply, and money balances. The model can be usefully re-written in terms of log-deviations from the steady-state equilibrium

$$y_t = \alpha k_{t-1} + (1-\alpha) l_t + z_t, \tag{4}$$

$$k_t = (1-\delta)k_{t-1} + (\bar{Y}/\bar{K})y_t - (\bar{C}/\bar{K})c_t, \tag{5}$$

$$\begin{aligned} &r_t = \beta\alpha(\bar{Y}/\bar{K})(\mathrm{E}_{t-1}(y_{t+1}) - k_t), \\ &r_t + \mathrm{E}_t(p_{t+1}) = (((1+\bar{\pi}) - \beta)/\beta)(c_t - m_t + p_t), \\ &\mathrm{E}_t(c_{t+1}) - c_t - r_t = 0, \\ &(1 + \mu\bar{L}/(1-\bar{L}))l_t = y_t - c_t, \end{aligned} \tag{6}$$

where π is inflation, variables with a bar indicate steady-state values of the levels and lower case indicates log-deviations of a variable from its steady state. Eqs. (4) and (5) are the production function and resource constraint, respectively. Eq. (6) contains the f.o.c.'s of the consumer's maximization problem with respect to money balances, consumption and leisure, and the intertemporal condition linking the expected marginal product of capital to the expected real interest rate.[5]

Under flexible prices, this model behaves much like a pure RBC model following TFP shocks, but anticipated money balances also affect the business cycle through their impact on expected inflation. Following a TFP shock, ε_t, the marginal product of labor increases, and if the money supply process does not react to this shock, output and consumption rise as consumers supply more labor (Cooley and Hansen, 1995). To show how output varies with technology shocks we can use the above equations to obtain

$$y_t = \psi_1 k_{t-1} - \psi_2 c_{t-1} + \psi_3 z_{t-1} + \varepsilon_t, \quad \psi_i > 0, \tag{7}$$

where the ψ's are non-linear convolutions of the underlying structural parameters of the model. It is clear from (7) that following an unexpected shock to TFP at time t, output rises immediately, and this triggers off a dynamic adjustment in output in the following period. In the ensuing periods the rise in consumption at time t will have a

[4] For simplicity, we assume a utility function which is log-separable in C and M/P. This implies that the model will display the superneutrality property.

[5] In this we have made use of the fact that in steady state $\bar{R} = (1/\beta)$.

negative impact on output at time $t+1$, but this is partially offset by the persistence in TFP (i.e. ρ). The pattern of output cycles is that typical of RBC-type models.

Employment and the real wage are also procyclical, as in standard RBC-type models. The marginal product of labor is given by $w-p=y-l$ in terms of deviations from steady state, and the last equation in (6) shows that labor supply will rise less than proportionately with output. Whilst these conclusions have been derived using a one-sector model, the same procyclical pattern in employment and the real wage will still broadly hold in a multi-sector model, providing there is some labor mobility across sectors. This will ensure that a positive TFP shock in one sector will lead to a rise in labor demand, and hence employment, real wages and an output pattern similar to that described in Eq. (7).[6]

2.2. Nominal wage contracts

The model in Section 2.1 can be generalized to allow for nominal wage contracts, where workers set wages on the basis of their expectations of labor demand. The main difference with the flex-price model is that unanticipated price changes have an impact on output (see Benassy, 1995; Walsh, 1998). In a one-sector model, firms will set employment equal to the marginal product, and hence an unanticipated increase in prices depresses the real wage and allows output to increase. In this model, it can be shown that (7) becomes

$$y_t = ((1-\alpha)/\alpha)(p_t - \mathrm{E}_{t-1}(p_t)) + \xi_1 k_{t-1} - \xi_2 c_{t-1} - \xi_3 z_{t-1} + \varepsilon_t, \quad \xi_i > 0, \quad (7')$$

where the ξ's are similar to the ψ's in (7), but contain additional terms due to the presence of the price surprise term in (7′).

To find the impact of a technology shock in this model, we have to consider the two separate impacts which this has on output and employment. On the one hand, a positive unanticipated shock to TFP will increase output directly, as before. On the other hand, following a positive TFP shock, given a fixed nominal money supply, prices will fall, as money demand increases with consumption (see Eq. (6)). Hence, employment will tend to rise because of the increase in productivity caused by ε_t, but the unanticipated fall in prices will offset this to some extent, as it raises real wages, given that nominal wages are predetermined in this model. The net outcome for real wages and employment depends on the value of the parameters. It is conceivable that the positive technological shock will cause real wages to rise faster than the marginal product of labor, hence causing employment to fall.[7] However, it is more likely that there will be an outcome

[6] Limited labor mobility between sectors will mean that following a positive sectoral TFP shock, real wages will rise more than employment as firms in the sector increase employment on the intensive margin. Conversely, perfect labor mobility may actually lead to little movement in the real wage if the sector is sufficiently small or the sectoral TFP shock is uncorrelated with TFP shocks in other sectors. The procyclicality of real wages and employment will depend on a number of factors but, in general, we would expect the RBC positive co-movement between technology shocks and real wages and total employment to hold.

[7] Essentially, the effective labor supply curve shifts to the left in the real wage–employment space as nominal wages are fixed before the outcome of the technology shock on the price level is known.

similar to the flexible wage case, with a less marked procyclicality in employment and real wages than the flexible wage model predicts.

If we move away from a single-good world to one with many sectors, we have to distinguish clearly between the real consumer wage and the real product wage. If technology shocks are idiosyncratic, we would not expect to observe a countercyclical movement in the real consumer wage and employment.[8] We would expect there to be a positive co-movement in output and employment with real consumer wages left unchanged.

2.3. Sticky-price models with imperfect competition

Imperfect competition can be built into the model in a variety of ways. Consider the case where final output is produced using a continuum of intermediate products distributed over the unit interval,

$$Y_t = \left[\int_0^1 Y_{it}^{\sigma} \, \mathrm{d}i \right]^{1/\sigma}, \quad 0 < \sigma < 1. \tag{8}$$

Production in each intermediate goods sector is given by Cobb–Douglas technology, as in Eq. (1), and there are assumed to be idiosyncratic technology shocks. From the usual cost minimization conditions, labor demand (post-aggregation) is given by a mark-up equation (in logs)

$$p_t = w_t - [y_t - l_t + \log(\sigma(1-\alpha))], \tag{9}$$

where the final term captures the mark-up over marginal costs. As noted earlier, with sticky prices, firms are assumed to set prices prior to the realization of the technology shock ε_t or the nominal money supply. An increase in productivity due to ε_t will imply that the firm will be able to produce the same output with less inputs than before. Aggregate demand in the model will not change following the technology shock (see Eq. (6)), and hence the firm will not wish to increase its output.

With effective labor demand falling when the technology shock hits, the real wage will also fall, so that households supply less labor. So, overall, we would expect technology shocks in such a model to cause a rise in output and a temporary fall in employment and real wages.[9]

2.4. Summary of theoretical results

As stated in Section 2.1, the theoretical models do not distinguish between the various margins along which effective labor is varied. As a result, if we define effective labor input, L as $L = EHN$, where E is effort, H is hours per worker, and N is the number

[8] The impact on consumer prices of an idiosyncratic TFP shock is likely to be negligible unless there is an extremely high correlation between TFP shocks across sectors.

[9] There are two caveats to this conclusion: first, the introduction of a monetary policy rule which reacts contemporaneously to the technology shock (see Basu et al., 1998; Galí, 1999) can attenuate some of these effects. Second, as noted by Yun (1996) and Goodfriend and King (1997), the above conclusions only hold when we assume a symmetric equilibrium in which relative prices do not differ across industries.

of workers, we cannot derive the theoretical implications for the response of measured total hours worked, HN, to a technology shock. Instead, we compare the model's implications for effective labor's (L) response to a utilization adjusted technology shock.

Given the above, the RBC models predict that output (y), effective labor (l) and the real consumer wage ($w-p$) are positively correlated with a technology shock (ε). The sticky-wage/wage contract model produces a very similar pattern, although due to sticky nominal wages, real consumer wages may not change very much. The sticky-price/imperfect competition model advanced by Galí (1999) and others predicts a decline in labor inputs following a positive technology shock, whilst output will rise, and the real wage will fall.

Before turning to estimate VAR models, which will allow us to verify which model provides a better account of cyclical variations in US manufacturing, we first describe the correction to the Solow residual that allows us to appropriately measure technology and second how we derive our measure of effective labor input.

3. TFP and factor utilization adjustment

It is well known that Solow residuals are markedly procyclical and that this largely reflects variations in the intensity of factor use over the cycle (see Burnside et al., 1995; Basu, 1996; Basu and Kimball, 1997; Basu et al., 1998; Basu and Fernald, 2000). A number of possible methods have been proposed to correct standard TFP measures for such unobserved input variations. In this paper, we adopt the approach set out in Basu and Fernald (2000) which provides a method for estimating a first-order approximation to the production function using theoretically motivated proxies for unobserved labor and capital utilization. We prefer this method since it not only allows us to obtain utilization-adjusted TFP but also a measure of effective labor input.

3.1. Alternative methods of calculating TFP

To provide a benchmark, our VAR analysis in the next section compares the behavior of the standard Solow (1957) and the Basu–Fernald utilization-adjusted measures of TFP growth. To calculate the alternative measures from 1958 to 1994 at the 4-digit SIC level we employ the NBER-CES/Census manufacturing industry productivity database.[10] The Solow residual for each industry is calculated based on the following production function:

$$Y_t = \Theta_t F[K_t, H_t N_t, MC_t, EC_t], \tag{10}$$

where Y is real gross output; Θ represents an index of Hicks-neutral technical progress; F is a homogenous production function of degree one; and K, H, N, MC and EC are real capital, hours per production worker, number of production workers, real (non-energy) material costs and real energy costs, respectively. Solving the firm's cost

[10] See the appendix for further information pertaining to definitions, sources and methods.

minimization problem, assuming constant returns to scale and perfect competition, the following measure of TFP growth can be obtained:

$$\dot{\theta}_t = \dot{y}_t - \alpha_t^k \dot{k}_t - \alpha_t^n(\dot{n}_t + \dot{h}_t) - \alpha_t^{mc}\dot{mc}_t - \alpha_t^{ec}\dot{ec}_t, \tag{11}$$

where lower case denotes logs, $\alpha_t^k = 1 - \alpha_t^n - \alpha_t^{mc} - \alpha_t^{ec}$; $\alpha_t^n = WN/PY$; $\alpha_t^{mc} = P_{mc}MC/PY$; and $\alpha_t^{ec} = P_{ec}EC/PY$. Note that W, P_{mc}, P_{ec} and P are defined as the nominal compensation of production workers, price of non-energy materials, price of energy inputs and price of gross output, respectively.[11]

In contrast to (10), Basu and Kimball (1997) and Basu and Fernald (2000) employ a production function incorporating unobservable capital and labor utilization, e.g.

$$Y_t = F[U_t K_t, E_t H_t N_t, MC_t, EC_t; \Theta], \tag{12}$$

where U is capital utilization, E is work intensity (hourly effort expended) and all other variables are defined as above. Minimizing the appropriate cost function for the representative firm subject to (12) (employing Cobb–Douglas preferences with Hicks-neutral technical progress) and evolution equations for capital and labor, the following measure of cyclically adjusted TFP growth can be derived:[12]

$$\dot{\theta}_t = \dot{y}_t - \mu^* \dot{x}_t - \mu^* \left(\zeta \alpha_t^n + \frac{\eta}{v} \alpha_t^k\right) \dot{h}_t, \tag{13}$$

where $\dot{x}_t = \alpha_t^k \dot{k}_t + \alpha_t^n(\dot{n}_t + \dot{h}_t) + \alpha_t^{mc}\dot{mc}_t + \alpha_t^{ec}\dot{ec}_t$; μ^* is the (steady-state) returns to scale parameter; $\dot{x}_t$ is a measure of observable input growth; ζ is the steady-state elasticity of labor utilization (hourly effort) with respect to hours; η is the rate at which the elasticity of labor costs with respect to hours increases; v is the rate at which the elasticity of labor costs with respect to capital utilization increases; and all other variables are defined as above.

3.2. Estimating adjusted TFP and effective labor

To calculate the utilization-adjusted measures of TFP growth and effective labor, *EHL*, we undertake instrumental variable (*IV*)[13] estimation of the following model:[14]

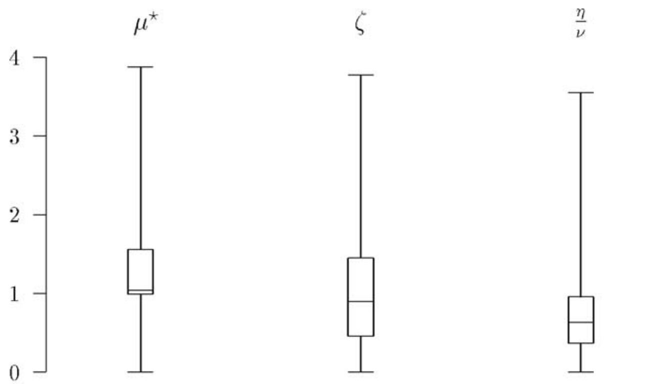
$$\begin{aligned} &\dot{y}_t = a_1 \dot{x}_t + a_2 \alpha_t^n \dot{h}_t + a_3 \alpha_t^k \dot{h}_t + \dot{\theta}, \\ &a_1 = \mu^* > 0, \;\; a_2 = \mu^* \zeta > 0, \;\; a_3 = \mu^* \eta / v > 0. \end{aligned} \tag{14}$$

[11] We follow Diewert (1976) and use a 2-year moving average discrete time approximation for the factor shares in our empirical work.

[12] See Basu and Kimball (1997) and Basu and Fernald (2000) for details of the optimization problem.

[13] *IV* estimation is required in this context due to the obvious endogeneity of the regressors. We employ the same set of instruments proposed by Ramey (1989) and Hall (1990) and augmented by Caballero and Lyons (1992) and Basu (1996) (see the appendix).

[14] Given that in the Basu–Fernald setup $E = E(H)$, where $E'(H) > 0$, $0 < E < 1$ and ζ is defined as $[E'(H)H]/E$, E is simply $H^{(a_1/a_2)}$. Note that to construct an E index which is bounded between zero and unity, we use industry specific information to arrive at the appropriate base year, i.e. we normalize the series by the year in which H was the greatest. Further, note that experimentation with alternative base years does not alter the VAR results reported in the Section 4.



	$\mu^{\star}$		ζ		$\frac{\eta}{\nu}$
Mean	1.36	Mean	1.06	Mean	0.69
Median	1.04	Median	0.90	Median	0.63
Min.	0.00	Min.	0.00	Min.	0.00
Max.	3.87	Max.	3.77	Max.	3.55
St.Dev.	0.64	St.Dev.	0.77	St.Dev.	0.50
> 4	8	> 4	2	> 4	2

Fig. 1. Distribution of parameter estimates, $i = 1, \ldots, 448$.

To estimate the model, we rewrite Eq. (14) in state space form, allowing the parameters $a_{1,\ldots,3}$ and TFP growth to be time dependent:

$$\dot{y}_t = \tilde{a}_{1,t}\dot{x}_t + \tilde{a}_{2,t}\alpha_t^n\dot{h}_t + \tilde{a}_{3,t}\alpha_t^k\dot{h}_t + \dot{\theta}_t,$$

$$\theta_t = \alpha\theta_{t-1} + \psi_t, \qquad \psi_t \sim \mathrm{N}(0, \sigma_\psi^2),$$

$$a_{i,t} = \bar{a}_i + \alpha a_{i,t-1} + \varepsilon_{i,t}, \qquad \varepsilon_{i,t} \sim \mathrm{N}(0, \sigma_{\varepsilon_i}^2), \qquad i = 1, 2, 3, \tag{15}$$

where $\tilde{a}_{i,t} = \exp(a_{i,t})$, thus restricting the parameters to be greater than zero. The parameters of the state vector in Eq. (15) are assumed to follow a damped AR(1) process ($\alpha = 0.9$) which allows some degree of persistence. Besides the estimate of the time path of TFP growth, we also obtain estimates representing the steady-state parameters from Eq. (13). Since the link between the transition and measurement equation is non-linear, we calculate the likelihood of the above model using the extended Kalman filter (Harvey, 1992, pp. 160–162).

The box plots in Fig. 1 summarize the results of estimating returns to scale, μ^*, the effort elasticity with respect to hours, ζ and the ratio of the rate at which the elasticity of labor costs with respect to hours increases to the rate at which the elasticity of labor costs with respect to capital utilization increases, η/v for 448 industries.[15] The box plots show the maximum and minimum values for each parameter (i.e. the lower and

[15] Note that two industries (i.e. 177 and 250) were omitted due to missing values. Further, note another 11 industries are excluded since the estimation procedure produced parameter estimates in excess of 4. The number of industries excluded, for each parameter, is reported in the final row underneath Fig. 1. These 11 excluded industries include 107, 122, 148, 160, 310, 332, 351, 390, 392, 393, and 437.

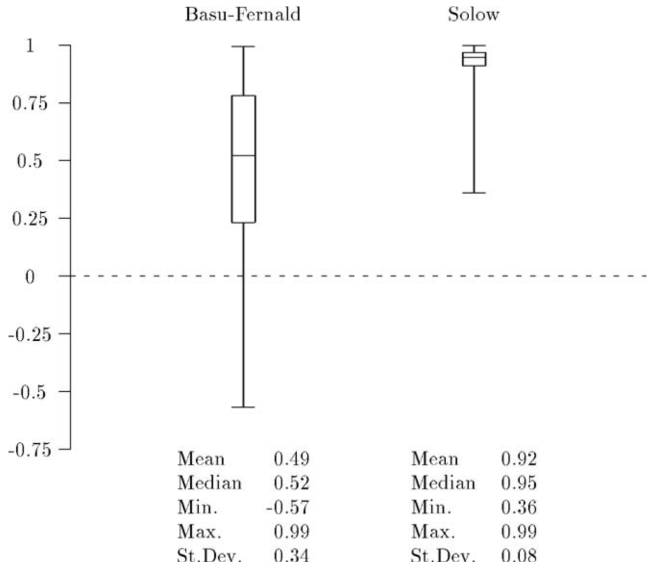


Fig. 2. Distribution of correlations of TFP and output growth.

upper horizontal line, respectively), the median (i.e. the horizontal line in the middle of the box) and the concentration of where the estimates lie in the distribution. For example, for the returns to scale parameter, μ^*, 25% of the estimates lie between the lower edge of the box (i.e approximately 0.95) and the minimum (approximately zero);[16] 50% between the median (i.e. 1.04) and the minimum and 75% between the upper edge of the box (approximately 1.6) and the minimum.

These results appear to be quite sensible and are broadly consistent with the orders of magnitude reported in other more aggregate studies using manufacturing sector or 2-digit data (see, e.g. Basu, 1996; Basu and Kimball, 1997; Malley et al., 2000, 2003; Basu and Fernald, 2000). Although there is much less scope for comparison, the results for ζ and η/v also appear to be sensible and well behaved. For example, 50% of the industries for ζ are between 1.5 and approximately 0.3 with a median value of 0.9 and for η/v, 50% of the estimates lie between roughly 1 and 0.5 with a median value of 0.63.

Fig. 2 shows the distribution of correlations of alternative measures of TFP with output growth. The well-known result, found in numerous aggregate and 2-digit level studies pertaining to the Solow residual, certainly appears to hold at the 4-digit level. That is, there is an extremely strong procyclical relationship between the Solow residual and output growth (e.g. the median correlation is 0.95). Fig. 2 also shows that in the Solow case, the distribution of correlations is extremely concentrated with 75% of the observations lying between approximately 0.93 and 0.99. In contrast, as expected, given the theory developed in Basu and Kimball (1997) and Basu and Fernald (2000), the

[16] Note that there are only four industries where $\mu^* < 0.5$.

spurious cyclical link between adjusted TFP has been weakened considerably. Fig. 2 shows that 50% of the observations lie between approximately a -0.6 and the median of 0.52 and spread of these correlations is over four times greater than in the Solow case.

4. Econometric methodology and results

Having obtained our adjusted TFP and effective labor series, we next fit a 4-variable VAR in log levels for each 4-digit sector. The endogenous variables are output (y), effective labor (l), and the real consumer wage ($w - p$). As a benchmark, we also estimate a VAR in which we use the unadjusted Solow TFP series and the unadjusted labor series (n). Total factor productivity θ follows an exogenous AR(1).[17] The VAR is given by

$$\mathbf{x}_t = (\mathbf{c} \quad \mathbf{b} \quad \delta)\begin{pmatrix} 1 \\ t \\ \theta_t \end{pmatrix} + \sum_{j=1}^{p} \mathbf{A}_p \mathbf{x}_{t-j} + \mathbf{u}_t, \tag{16}$$

where $\mathbf{c}$ is a (3×1) vector of constants, $\mathbf{b}$ is a (3×1) vector with the slopes for a linear time trend, and δ is the (3×1) coefficient vector for θ. The (3×1) vector of disturbances $\mathbf{u}_t$ follows the usual assumptions: $\mathrm{E}[\mathbf{u}_t] = \mathbf{0}$; $\mathrm{E}[\mathbf{u}_t\mathbf{u}_t'] = \mathbf{\Sigma}$; $\mathrm{E}[\mathbf{u}_t\mathbf{u}_{t'}'] = 0\ \forall t \neq t'$.[18] To analyze the impact of TFP innovations on the variables of interest, we calculate impulse responses.[19]

Figs. 3 and 4 show, for the Solow TFP residual and the Basu–Fernald TFP residual, the range of the impulse response functions for each of the three other variables (y, $w - p$, l[20]). It is apparent that using the Solow residual persistent significant positive shocks to output are generated for most sectors (69% of industries experience a rise in output in period 0, and 45% continue to experience a significant increase even after 3 years). Real wages show a much more mixed picture, with some leaning towards a counter-cyclical pattern. Overall, 87% of the 400 industries show some significant change (increase or decrease) in period 0, and even after three years in 41% of the

[17] Given the discussion in Section 2, the theoretical motivation for this structure is clear; however, in an attempt to provide some empirical justification we performed a Granger causality test for the Solow– and the Basu–Fernald model (Lütkepohl, 1991, pp. 35–39, 93–94). The results can be summarized as follows: y does not cause θ: 60% of industries (Solow), 70% of industries (Basu–Fernald); n/ehn does not cause θ: 82% of industries (Solow), 76% of industries (Basu–Fernald); $w - p$ does not cause θ: 84% of industries (Solow), 79% of industries (Basu–Fernald).

[18] To ensure that the estimated system is stationary, we computed the roots of the characteristic polynomial $|\mathbf{A} - \lambda\mathbf{I}| = 0$, where $\mathbf{A}$ is the companion matrix of the parameter matrices $\mathbf{A}_1, \ldots, \mathbf{A}_p$, and checked whether the moduli are inside the unit circle (Lütkepohl, 1991, pp. 9–13). We found when using the Solow residual, that 400 of the 448 industry VARs are stationary. In the case of the Basu–Fernald residual, 386.

[19] Given our model, these impulse responses are the same as those obtained if ordering θ first in a Cholesky decomposition. Since we are not interested in the identification of structural disturbances to variables other than TFP, we maintain that our method is particularly appropriate. The confidence intervals are constructed using the small sample bias correction proposed by Kilian (1998).

[20] Or n in the Solow case.

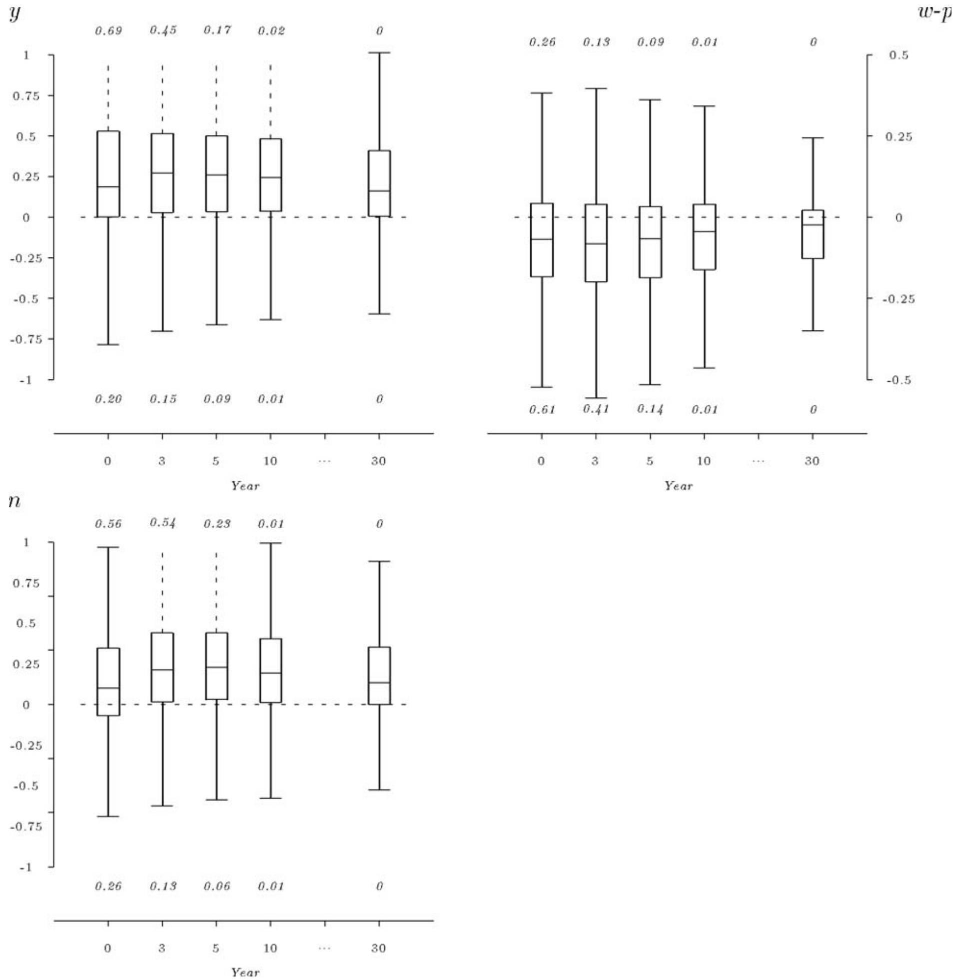


Fig. 3. Distribution of impulse responses, Solow residual. Number of Industries: 401. The numbers in italics denote the proportion of significantly positive/negative responses (10% significance level). The dashed lines in the boxplots indicate whiskers beyond the scale of the graphs.

industries real wages were significantly lower, whilst in 13% they were significantly higher. Overall, employment (n) tends to increase significantly in over 50% of industries, in line with the pattern in standard RBC models and sticky-wage DGE models.

Looking at the Basu–Fernald residual case (Fig. 4), some interesting features emerge. First, as expected, the size of the impact on output is smaller (only 32% experience an increase), and we find that less industries experience a persistent pro-cyclical effect (30% of 386 industries after 3 years). This casts some doubts on the significance of technology shocks as a propulsive mechanism for business cycles. Second, in contrast to Basu et al. (1998) and Galí (1999), the response of effective labor (l) is less significant and does not seem to be uniformly negative. It is only significant in the

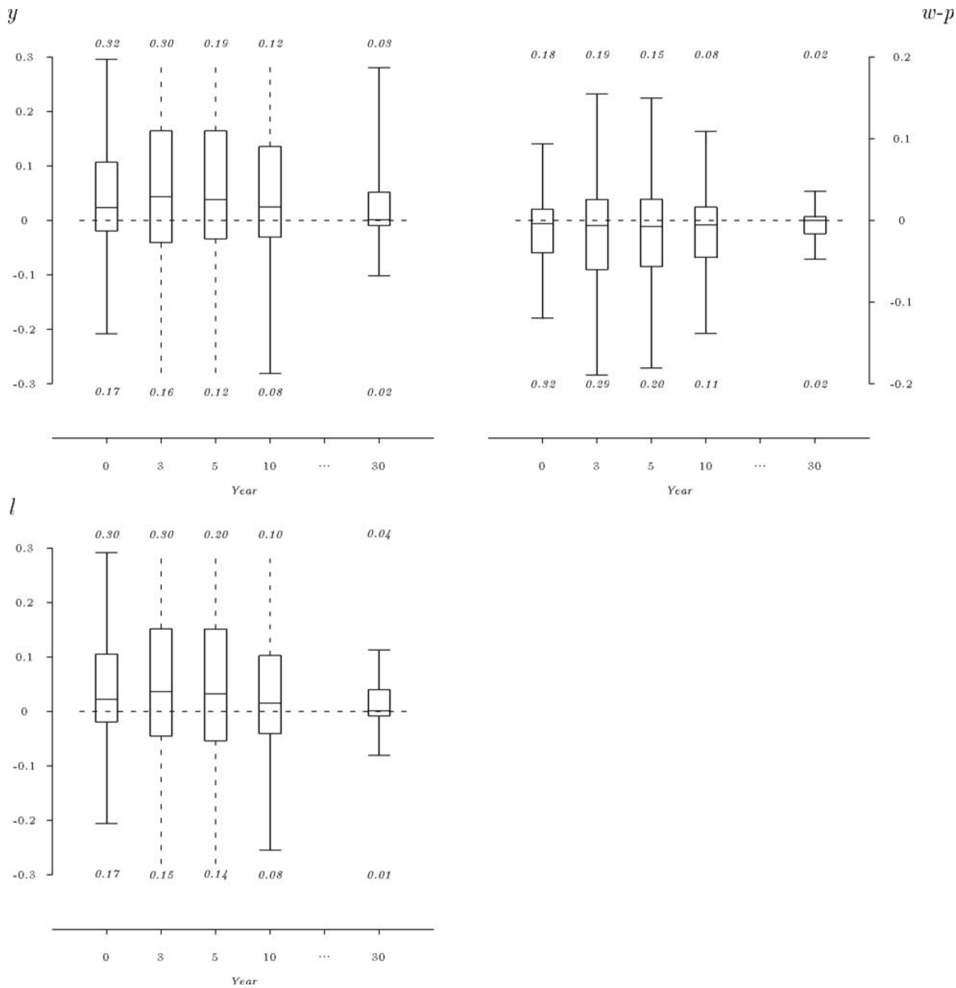


Fig. 4. Distribution of impulse responses, Basu–Fernald residual (rescaled). Number of Industries: 386. The numbers in italics denote the proportion of significantly positive/negative responses (10% significance level). The dashed lines in the boxplots indicate whiskers beyond the scale of the graphs.

case of 47% of 386 industries reported, with a slight tendency towards increasing employment. This difference with the results in favor of sticky-price DGE models obtained by previous authors is best explained, in our view, by not only a significant aggregation bias effect (both Basu et al. (1998) and Galí (1999) used aggregate data), but also by the fact that our VAR incorporates impulse (i.e. utilization adjusted TFP innovations) and transmission mechanisms (i.e. the real wage and effort-adjusted labor) not jointly considered in the other studies.

Since each industry's position in the cross-sectional distribution shown in these figures may not remain constant over time, a complementary test is to consider which

Table 1
Expected pattern of sectoral variables

Model	ε	y	l	$w-p$
RBC	+	+	+	+
Sticky nominal wages	+	+	+	0
Sticky prices	+	+	−	−

Table 2
Pattern of sectoral variables

	Obs	RBC			Sticky wages			Sticky prices		
		Lag 1	Lag 2	Lag 3	Lag 1	Lag 2	Lag 3	Lag 1	Lag 2	Lag 3
Solow										
Manufacturing	401	0.13	0.09	0.07	0.11	0.05	0.03	0.04	0.01	0.01
Nondurables	176	0.13	0.09	0.04	0.09	0.05	0.02	0.04	0.01	0.02
Durables	225	0.13	0.09	0.11	0.12	0.06	0.03	0.05	0.01	0
Basu–Fernald										
Manufacturing	386	0.16	0.08	0.07	0.17	0.05	0.02	0.01	0.01	0.01
Non-durables	168	0.17	0.07	0.07	0.23	0.05	0.01	0.03	0.02	0.02
Durables	218	0.16	0.09	0.07	0.13	0.05	0.02	0	0	0

The number of results in line with the theoretical predictions is reported as a proportion of significant results at lag 1, 2, 3.

business cycle model fits best for each industry. This is found by matching the predicted signs of the cyclical co-movements of the variables from the various theoretical models (Table 1) to the impulse responses of the individual industries.

Table 2 summarizes the results for the Solow- and Basu–Fernald measures by aggregating the 4-digit industries into three broad categories: total manufacturing, non-durables, and durables.[21] Using the predicted signs reported in Table 1, we show how many industries seem to follow the pure RBC pattern, and in how many we find the pattern predicted by the presence of sticky nominal wages and sticky prices. The tables show for each category the proportion of (significant) industries which display the pattern indicated by the alternative theories at different lags.

The results in Table 2 are very clear. First, the two preferred explanations for the responses to technology shocks are clearly the sticky-wage and RBC models. At lag 1, these two models between them explain the behavior of 24% of all manufacturing industries using the Solow TFP measure, and 33% using the Basu–Fernald TFP and adjusted labor measures. In sharp contrast to Basu et al. (1998) and Galí (1999) the

[21] The results at the 2-digit level are reported in the working paper version of this paper (Malley et al., 1999). The two-digit results confirm that for all but one of the industries the RBC and sticky-wage models dominate the sticky-price model. In addition, the Basu–Fernald adjustments tend to strengthen the case for the RBC and sticky-wage models.

imperfect competition–sticky prices model comes a very poor third, explaining the behavior of only 1–4% of all manufacturing industries.

5. Conclusions

In this paper, we have estimated industry-level VAR models to verify the relevance of alternative theoretical modeling approaches to the business cycle. By not using aggregate data, or aggregating industry technology shocks, we extend the Galí (1999) and Basu et al. (1998) papers. As we have seen, this leads to a very different perspective on the co-movements of key variables over the business cycle. We have shown that there is only limited support for a sticky-price/imperfect competition approach to the business cycle, despite the popularity of this approach in recent theoretical models. The main problem seems to lie in the prediction of the sticky-price model of a negative response of factor input levels (such as employment) to technology shocks. In contrast our results are much more supportive of sticky-wage DGE and RBC models.

The differences in our findings with those in the literature are probably best explained by not only a significant aggregation bias effect but also by the fact that our VAR models incorporate impulse (i.e. utilization-adjusted TFP innovations) and propagation mechanisms (i.e. the real wage and effort-adjusted labor) not jointly considered in the other studies. Another noteworthy point is that the utilization and effort adjustments actually strengthen the empirical support for the RBC and sticky-wage models, despite the fact that the utilization-adjusted TFP innovations are markedly less procyclical.

Even with the utilization adjustments, only 30–40% of all industries are correctly characterized by the RBC and DGE models discussed here. This suggests that there is a gap in our collective understanding of the factors driving business cycle fluctuations, which needs to be bridged in future work. An inevitable conclusion is that further empirical research on business cycles at the industry level is necessary to verify the sources of business cycle impulses, and the nature of the propagation mechanisms.

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Appendix.

The following data (1958–1994) are provided by Bartelsman, Becker and Gray, NBER-CES/Census Manufacturing Industry Productivity.[22]

[22] See http://www.nber.org/nberces.

Productivity data:

L	number of production workers (thous.)
H	hours per production workers (thous.)
W	compensation per production worker (thous., current \$)
MC	real (non-energy) material costs (mill., \$1987)
EC	real energy costs (mill., \$1987)
K	real capital stock (start of year); (mil., \$1987)
Y	real value of shipments (mill., \$1987)
P	price deflator for shipments (1987 = 1)
P_{mc}	price deflator for material inputs (non-energy, 1987 = 1)
P_{ec}	price deflator for material inputs (energy, 1987 = 1)

Instruments:

Military spending (bill chained \$1992) from 1959 is taken from the May 1997 Survey of Current Business (SCB). Based on quantity indexes 1992 = 100, provided by the Department of Commerce, movements in the quantity index series were spliced to the billions of chained 1992 dollar series to obtain 1958. The World price of oil from 1965 onwards is taken from 1995 International Financial Statistics Yearbook Average Crude Price, spot (US\$/barrel). It is calculated using UK Brent (light), Dubai (medium) and Alaska North Slope (heavy), equally weighted. Prior to 1965 it is taken from 1983 International Financial Statistics Yearbook. Average price (US\$/barrel) is calculated as a weighted average of the three oil prices listed: Saudi Arabia; Libya from 1961; and Venezuela. Implicit price deflators for manufacturing durables and non-durables were calculated using the NBER database. The political party of the President variable is defined as follows: $D = 1$ for Democrat and $D = 0$ for republican.

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