Real Business Cycles or Sticky Prices? The Impact of Technology Shocks on US Manufacturing*

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Abstract

In this paper we estimate industry-level VAR models at the 4-digit SIC level for a number of US manufacturing sectors, using TFP series which allow for variable factor utilisation over the cycle. This allows us to verify the relevance of alternative theoretical modelling approaches to the business cycle. Our results support standard RBC models, and models of nominal rigidity based on sticky wages. They offer little support to dynamic general equilibrium models based on imperfect competition and sticky prices. Our results extend those obtained recently by other researchers using aggregate data.

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1 Introduction

The real business cycle (RBC) approach to macroeconomics heralded a new approach to the analysis of business cycle fluctuations. Unlike previous approaches, RBC theorists developed a theory of cycles based on intertemporal optimising behaviour. In the fifteen years since RBC theory was first developed (Kydland and Prescott, 1982; Long and Plosser, 1983) it has been the subject of numerous methodological critiques.

One of the main criticisms of RBC models is that, in their simplest form, they find it difficult to characterise the co-movement of key macroeconomic aggregates over the cycle (see for instance Millard *et al.*, 1997). A key problem with the RBC approach is the fact that the main business cycle propagation mechanism is the consumer's intertemporal income-leisure decision. This in turn implies a strong positive contemporaneous correlation over the cycle between real wages, output and employment. Introducing labour hoarding into RBC models (see for example Burnside *et al.*, 1993) can help to explain why employment may be less responsive over the cycle. Other modifications such as the introduction of a search-theoretic model of the labour market (see Andolfatto, 1996; den Haan *et al.*, 1997; Walsh, 1998a) can also help to bring the prediction of RBC models closer to observed correlations in macroeconomic data.

One of the most innovative areas in business cycle research in the 1990s has been the integration of RBC-type models with Keynesian-type models of wage and price rigidity.[1] Not surprisingly, given their inclusion of product

[1]See Cho and Cooley (1995), Benassy (1995), King and Watson (1995), King and Wolman (1996), Chari *et al.* (1996), Kimball (1995), and Galí (1999) for examples of dynamic general equilibrium (DGE) models with sticky prices. Some economists (notably Goodfriend and King, 1997) have claimed that macroeconomics is heading for a new consensus, or a new neoclassical synthesis.

and labour market imperfections, such integrated models are in a better position to explain the low correlation at the aggregate level between output and the real wage.

The empirical verification of RBC-type models has been a major source of controversy. As Prescott (1998) notes, RBC theorists have felt that their use of calibrated models has much in common with deductive or quantitative inference in the natural sciences (e.g. Newton's laws of motion). Ultimately the argument is that deductive inference is a more useful tool when a researcher wishes to verify the importance of models describing the fundamental underlying forces in the economy. Econometric inference *per se* is unlikely to detect the fundamental forces at work.

However, econometric estimation becomes more useful when alternative hypotheses regarding the essential forces underlying business cycles are considered. Dynamic General Equilibrium (DGE) models generalise RBC models by including an important new element (nominal rigidities) and the two approaches have different and distinct predictions regarding the correlation of macroeconomic variables. It stands to reason that econometric evidence may then be useful in discriminating between these two distinct hypotheses. As well as discriminating between different propagation mechanisms, the econometric verification of business cycle facts is also useful as a way of quantifying the importance of technology shocks in driving cycles.

This paper makes a contribution to the empirical literature on business cycles by estimating VAR models containing output, employment, hours, wages and total factor productivity, using the NBER productivity database. The aim of the paper is two-fold: the first is to evaluate the relative importance of pure-RBC type effects and sticky wages and prices in the propagation of technology shocks in US manufacturing. This is done by examining the patterns of impulse responses of output, employment, hours and wages to technology shocks in the manufacturing sectors of our sample. The second aim is to re-evaluate the importance of technology shocks in explaining business cycle behaviour once we allow for cyclical changes in factor utilisation in measuring total factor productivity (TFP) growth.[2]

The rest of the paper in structured as follows. Section 2 motivates the paper and sets it in the context of the existing empirical literature. Section 3 describes the factor-utilisation adjustments made to our TFP series. Section 4 describes our econometric framework. Section 5 presents our results for both the aggregate and the disaggregated data and Section 6 concludes.

2 Motivation and Context

2.1 The current literature

There are very few empirical contributions which examine the impact of technology shocks on industry-level variables. We are not aware of any similar attempts to estimate industry-level VARs at the 4-digit SIC level to verify the predictions of alternative business cycle models. This paper is therefore best seen as an extension of a small number of existing papers in this area which examine the role and importance of technology shocks in explaining aggregate business cycles.

For instance, Galí (1999), in addition to proposing a prototype sticky-price DGE model, estimates aggregate economy-level VARs of labour productivity and labour input variables for the G7 economies. Gali finds in general that a technology shock has a positive impact on output, but a nega-

[2]The adjustments we make to TFP follow the approach taken by Basu (1996).

tive impact on labour input. This is seen as supportive of supportive of sticky prices: a positive technology shock will increase the productive capacity of a given labour input and hence, absent an increase in aggregate demand due to sticky prices, firms will choose to reduce their total labour input.

Basu *et al.* (1998) examines the impact of technology shocks on factor inputs, factor utilisation, and output. They use the Jorgenson-Fraumeni data on industry inputs and outputs for non-farm industries (manufacturing and services) over the period 1950-89. Following Basu and Kimball (1997) they first of all produce adjusted measures of technology shocks by adjusting TFP growth to take account of variable factor utilisation. The Basu-Kimball corrections involve estimating Hall-type output growth regressions but adding terms to capture variations in hours and in capital utilisation. Unlike the approach followed in Basu (1996) which corrects for factor utilisation using the fact that raw material inputs has a limited intensity dimension,[3] the Basu-Kimball adjustment seeks to estimate the factor intensity adjustment parameters. The resulting technology shock series are aggregated up to obtain an economy-wide utilisation-adjusted series for technical change. They find that output, factor inputs, and factor utilisation fall following a technology shock. Output subsequently recovers, but as in Gali, the negative response of factor inputs persists for 2-3 years. The negative response of input levels (and even of aggregate output on impact) again points against a standard RBC interpretation. Basu *et al.* (1998) note that the interpretation of their results could be supportive of sticky-price DGE model like Galí

[3] The Basu (1996) approach requires the assumption of a given elasticity of substitution between value added and raw materials in the production function. This is explained further below. Burnside *et al.* (1995) follow a similar approach to Basu, but using data on electricity usage from manufacturing sectors. This seems a more limited approach because it is only likely to capture the intensity of capital use.

(1999), but may also support sectoral shift models,[4] or the reverse-causal effects of 'cleansing' from recessions.[5]

The final contribution on the empirics of technology shocks is Shea (1998). Rather than using Solow-based residuals as measures of technology sbocks, Shea (1998) combines the NBER productivity database and industry data on innovative activity (R&D spending and patent applications) to build VAR models which include the innovative activity variables, TFP, and measures factor input use. He finds that technology shocks (interpreted as shocks to the measures of innovative activity) tend to increase input use in the short run, but to reduce it in the long run. They also seem to induce a substitution towards capital and non-production labour, and away from production labour and materials. However, these fundamental technology shocks do not seem to have a significant positive impact on measured TFP, which is measured using the unadjusted Solow residual. Shea's approach is not strictly comparable to ours as it focuses on alternative measures of technology shocks and 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.

By not using aggregate data, or aggregating industry technology shocks, we extend the Galí (1999) and Basu *et al.* (1998) papers. As we shall see, this leads to a very different perspective on the co-movements of key variables over the business cycle. Using industry-level data, we are able to check whether individual manufacturing industries respond differently to technology shocks, and whether these responses can be rationalised in terms of

[4]Because it is costly to reallocate resources following technology shocks, both output and input levels can fall (Ramey and Shapiro, 1997).

[5]So that we observe a negative response of output to technology shocks because the impact is the opposite: recessions cause less-productive firms to exit and hence enhance aggregate productivity (Caballero and Hammour, 1994).

particular patterns (e.g. pure RBC, DGE with sticky wages and DGE with sticky-prices). Second, as noted[6] in Goodfriend and King (1997) if prices are not sticky to the same degree across different industries, relative price effects will ensue which will cause a misallocation of aggregate output across different final-good industries. To put this another way, the behaviour of the mark-up over the cycle will be very different across industries. This type of distortion produces effects that are analogous to those of a productivity shock. Aggregating technology shocks across industries when prices are not equally sticky in all industries might therefore involve an important aggregation bias. Third, unlike all previous authors who have ignored the role of real wages in the propagation of cycles, we include the real consumer wage in our VAR models. As noted in the introduction, the behaviour of wages over the cycle provides a useful check for different explanations of the cyclical effect of technology shocks.

Our main results are the following. First, we find that our empirical results are much more supportive of RBC-type models, or DGE models with sticky wages rather than sticky-price imperfect competition DGE models. Second, we find that there are markedly distinct responses to technology shocks in different manufacturing sectors. This suggests that aggregate studies which seek to verify the validity of RBC or DGE models are likely to be subject to aggregation bias.

Before turning to a detailed description of our econometric method and results, we first describe a basic stylised model of a multi-sector economy with varying degrees of price stickiness between sectors. This will help us to identify the expected impact of technology shocks in different sectors under alternative assumptions about wage and price stickiness. Our stylised model

[6] See also Yun (1996).

will be a summary of existing DGE-type models with nominal rigidities (see Galí, 1999; Goodfriend and King, 1997; Rotemberg and Woodford, 1997).

2.2 A Stylised Model of Technology Shocks

2.2.1 Flexible Prices

We begin by setting out a standard Sidrauski-Brock money in the utility function model. These models have been extensively analysed in the macroeconomics literature (see *inter alia* King *et al.*, 1988; Campbell, 1994; Uhlig, 1995; Walsh, 1998b). They provide a useful way of nesting the consumption-smoothing effects of pure RBC theories within a monetary DGE model.[7]

Aggregate output in the economy is given by a constant-return Cobb-Douglas production function in capital and labour inputs:

$$Y_t = A \exp(z_t) K_{t-1}^{\alpha} L_t^{1-\alpha} \tag{1}$$

where A is total factor productivity and z_t is a stochastic shock to TFP, which is assumed to follow an AR(1) process:

$$z_t = \rho z_{t-1} + \epsilon_t \qquad 0 < \rho < 1. \tag{2}$$

The representative agent maximises the present 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, H:

$$U = \sum_{i=0}^{\infty} \beta^i u(C_t, (M/P)_t, H_t). \tag{3}$$

[7] For an early attempt to incorporate a monetary sector into RBC models, see King and Plosser (1984).

For simplicity, we assume a utility function which is log-separable in consumption and real money balances[8]:

$$u(C_t, (M/P)_t) = log(C_t) + \lambda log((M/P)_t) + \theta \frac{H_t^{1-\mu}}{1-\mu}. \qquad (3)'$$

The resource constraint for the economy is given by:

$$Y_t + (1-\delta)K_{t-1} + (M_{t-1}/P_t) = C_t + K_t + (M_t/P_t). \qquad (4)$$

The consumer's problem can be solved in the usual way to obtain the f.o.c. for consumption, consumers' labour supply, and money balances. The model can be usefully re-written in terms of log-deviations from the steady-state equilibrium, rather than in levels (see Campbell, 1994; Uhlig, 1995; Walsh, 1998b):

$$y_t = \alpha k_{t-1} + (1-\alpha) l_t + z_t \qquad (5)$$

$$k_t = (1-\delta)k_{t-1} + \left(\frac{\bar{Y}}{\bar{K}}\right) y_t - \left(\frac{\bar{C}}{\bar{K}}\right) c_t \qquad (6)$$

$$r_t = \beta\alpha \left(\frac{\bar{Y}}{\bar{K}}\right) (E_{t-1} y_{t+1} - k_t) \qquad (7)$$

$$r_t + E_t(p_{t+1}) = ((1+\bar{\pi}) - \beta)/\beta)(c_t - m_t + p_t) \qquad (8)$$

[8]This implies that the model will display the superneutrality property.

$$E_t c_{t+1} - c_t - r_t = 0 \tag{9}$$

$$\left(1 + \frac{\mu \bar{L}}{1 - \bar{L}}\right) l_t = y_t - c_t \tag{10}$$

where variables with a bar indicate steady-state values of the levels, $\bar{\pi}$ is the steady-state level of inflation, and lower case are log-deviations of the variables from steady state. Equations (5) and (6) are the production function and resource constraint expressed in log-deviations from equilibrium. Equations (8)-(10) are the first-order conditions of the consumer's maximisation problem with respect to money balances, consumption and leisure, whilst (7) is the intertemporal condition linking the expected marginal product of capital to the expected real interest rate.[9]

Under flexible prices, this money-in-the-utility function model behaves much like a pure RBC model following TFP shocks, but anticipated money balances also affect the business cycle through their impact on the expected rate of inflation. However, the essential picture is very similar to pure RBC models: following a TFP shock, ϵ_t, the marginal product of labour increases, and if the money supply process does not react to this shock, output and consumption rise as consumers supply more labour (see Cooley and Hansen, 1995).

To show how output varies with technology shocks we can use (2), (5), (7) and (9) to obtain:

$$y_t = \psi_1 k_{t-1} - \psi_2 c_{t-1} + \psi_3 z_{t-1} + \epsilon_t \qquad \psi_i > 0 \tag{11}$$

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

where:

$$\psi_1 = \left(\alpha + \frac{(1-\alpha)(\alpha\bar{Y}/\bar{R}\bar{K})}{\left(1+\dfrac{\mu\bar{L}}{1-\bar{L}}\right)}\right)/\Omega;$$

$$\psi_2 = \frac{(1-\alpha)}{\left(1+\dfrac{\mu\bar{L}}{1-\bar{L}}\right)\Omega}; \quad \psi_3 = \rho/\Omega;$$

$$\Omega = \left(1 + \frac{(1-\alpha)(\alpha\bar{Y}/\bar{R}\bar{K})-1}{\left(1+\dfrac{\mu\bar{L}}{1-\bar{L}}\right)}\right).$$

It is clear[10] from (11) 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 negative impact on output at time $t+1$, but this is partially offset by the persistence in TFP (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 labour is given by $w - p = y - l$ in terms of deviations from steady-state, and equation (10) shows that labour supply will rise less than proportionately with output.

Generalising this model to one with many industries is trivial in the case of a model with perfect competition in goods and factor markets and with flexible wages and prices. Providing that labour is perfectly mobile between industries, the presence of industry-specific TFP shocks will produce output patterns similar to those described in equation (11) at the *industry level*.

[10]We know from the steady-state solution of the model that $\Omega > 0$.

As noted in Galí (1999), the presence of labour immobility between sectors might generate declines in *aggregate* employment following an industry specific shock but at the industry level, the RBC-type positive co-movement between technology shocks real wages and total employment should still be observed.

2.2.2 Nominal wage contracts

The model in section 2.2.1 can be generalised to allow for nominal wage contracts, where workers set wages on the basis of their expectations of labour demand. The main difference with the flex-price model is that unanticipated price changes have an impact on output (see Benassy, 1995; Walsh, 1998b). 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 (11) becomes:

$$\begin{aligned} &y_t = ((1-\alpha)/\alpha)(p_t - E_{t-1}p_t) + \xi_1 k_{t-1} - \xi_2 c_{t-1} - \xi_3 z_{t-1} + \epsilon_t \\ &\xi_i > 0 \end{aligned} \tag{11$'$}$$

where the ξ's are similar to the ψ's in (11), but contain additional terms due to the presence of the price surprise term in $(11)'$.

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 equation 8). Hence, employment will tend to rise because of the increase in productivity caused by ϵ, but the unanticipated fall in prices will offset this to some extent, as it raises real product wages, since nominal wages are predetermined in this model. The net outcome for real product wages and employment depends on the parameters of the model. It is even conceivable that the positive technological shock will cause real product wages to rise faster than the marginal product of labour, hence causing employment to fall.[11]

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.[12] We would expect there to be a positive co-movement in output and employment with real consumer wages left unchanged.

2.2.3 Sticky-price models with imperfect competition

A number of authors have recently developed DGE models which incorporate features of imperfect competition. Imperfect competition is built into the model either through the assumption that final goods are produced with a variety of intermediate inputs (see Chari *et al.*, 1996), or by assuming that there is product differentiation in consumption goods (Galí, 1999). In addition, we can build in sticky prices, by assuming that firms set prices prior to observing the realisation of the shocks hitting the economy (monetary or technology shocks).

Consider the case where final output is produced using a continuum of

[11] Essentially the effective labour 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.

[12] 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.

intermediate products distributed over the unit interval:

$$Y_t = \left[\int_0^1 Y_{it}^{\sigma} di\right]^{1/\sigma} \qquad 0 < \sigma < 1. \tag{12}$$

Production in each intermediate goods sector is given by Cobb-Douglas technology, as before (equation 1), and there are assumed to be idiosyncratic technology shocks:

$$Y_{it} = Aexp(z_{it})K_{i,t-1}^{\alpha}L_{i,t}^{1-\alpha}. \tag{13}$$

¿From the usual cost minimisation conditions, labour demand in each sector is given by a mark-up equation (in logs):

$$p_{i,t} = w_t - [y_{i,t} - l_{i,t} + log(\sigma(1-\alpha))] \tag{14}$$

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 realisation of the technology shock $z_{i,t}$ or the nominal money supply. How would a model with these features behave compared to the models in sub-sections 2.2.1-2.2.2?

With sticky prices, an increase in productivity due to $z_{i,t}$ will imply that the firm will be able to produce the same output with less inputs than before. Given sticky prices, aggregate demand in the model will not change following the technology shock (see equation 8), and hence the firm will not wish to increase its output.

What happens to real wages? Prices are sticky and nominal wages determined by aggregate labour demand and supply. With effective labour demand falling when the technology shock hits, the real wage will also fall, so that households supply less labour. 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.

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. If some industry prices are sticky whereas others are not, it will lead to a misallocation of aggregate output across different goods. We would expect those industries where prices adjust quickly downwards following a favourable technology shock to experience an increase in output due to a relative demand effect. Hence output should rise, whilst employment may fall or rise depending on the net increase in output. Basically the outcome will then be closer to that described by the RBC model than that described by the simple sticky price model.

2.2.4 Summary of Theoretical Results

The above discussion can be summarised in Table 1. The RBC models predict that output (Y_i), employment (L_i) and the real consumer wage (W_i/P) are positively correlated with a technology shock (Z_i). The sticky-wage/wage contract model produces a 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 labour inputs following a positive technology shock, whilst output will rise, and the real wage will fall. If we also allow for variations in hours of work (H_i) then most normal specifications of variations of labour input on the intensive margin would predict a positive co-movement over the cycle with employment. A negligible effect on hours would not invalidate the main predictions of the models.

Table 1: Expected Pattern of Sectoral Variables

Model	Z_i	Y_i	L_i	W_i/P	H_i
RBC	+	+	+	+	+/0
Sticky Nominal Wages	+	+	+	0	+/0
Sticky Prices	+	+	-	-	-/0

Before turning to estimate a VAR model which will allow us to verify which of these models provides a better account of cyclical variations in US manufacturing, we first deal with the problem of TFP measurement.

3 TFP and Factor Utilisation Adjustment

It is well known that Solow residuals are markedly procyclical and that this procyclicality 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). A number of possible methods have been proposed to correct standard TFP measures for such unobserved input variations. In this paper, we adopt Basu's (1996) proposal, which involves using materials inputs to correct for the cycle on the assumption that raw material and energy inputs are less subject to variations in intensity of use.

An alternative method would have been to adopt the Basu and Kimball (1997) and Basu *et al.* (1998) solution, which involves modelling utilisation growth directly as a function of variations in hours, investment and materials inputs. Although the two methods are very similar in conception, the estimating equation in Basu and Kimball to derive the measure of technical change requires assuming a constant mark-up over the cycle. This would seem to be problematic, especially as it is known that the mark-up may vary over time. Also, as noted above, as relative prices vary between manufacturing sectors this can induce relative price effects which will impinge on the industry mark-up. For this reason we prefer to use Basu's (1996) original method which does not involve making specific assumptions about the mark-up in correcting the TFP measure.

3.1 Alternative Methods of Calculating TFP

To provide a benchmark, our VAR analysis in the next section compares the behaviour of the standard Solow (1957) and the Basu (1996) utilisation adjusted measures of TFP growth. To calculate the alternative measures from 1958-1994 at the 4-digit SIC level we employ the NBER-CES/Census manufacturing industry productivity database (see Bartelsman, Becker and Gray, 1994).[13] The Solow residual, is calculated based on the following three-factor production function,

$$Y_t = \Theta_t F[K_t, L_t, M_t], \tag{15}$$

where, Y is real gross output; Θ represents an index of Hicks neutral technical progress; F is a homogenous production function of some degree, γ; and K, L, M are real capital, labour and real material inputs respectively. Solving the firm's cost minimisation problem,[14] assuming constant returns to scale and

[13]See the Data Appendix for further information pertaining to definitions, sources and methods.

[14]Note that detailed derivations of the Solow and Basu measures can be found in Malley *et al.* (1999).

perfect competition, the following measure of TFP growth can be obtained

$$\dot{\theta}_t = \dot{y}_t - \alpha_t^k \dot{k}_t - \alpha_t^l \dot{n}_t - \alpha_t^m \dot{m}_t \tag{16}$$

where, lower case denotes logs, $\alpha_t^k = 1 - \alpha_t^l - \alpha_t^m, \alpha_t^n = WL/PY$, and $\alpha_t^m = P_m M/PY$. Note that W, P_m, and P are defined as the nominal wage, price of material inputs and price of gross output respectively.[15]

In contrast to (15), Basu (1996) employs the following production function

$$Y_t = \Theta_t F[V(K_t Z_t, L_t G_t), H(M_t)] \tag{17}$$

where the V and H are constant returns to scale value-added and material costs functions and Z and G are the levels of labour and capital utilisation. Note that the function F is assumed to have the same properties as in (15). Exploiting the fact that material inputs do not have a utilisation dimension, Basu uses changes in the input of materials relative to measured capital and labour to derive a measure of TFP growth which controls for cyclical utilisation in both factors, e.g.

$$\dot{\theta}_t = \dot{y}_t - \gamma[\dot{m}_t - \sigma(\alpha_t^l + \alpha_t^k)(\dot{p}_{vt} - \dot{p}_{mt})] \tag{18}$$

where all variables and parameters are defined as above, $\dot{m}_t$ is real material costs growth, σ is the (local) elasticity of substitution between value-added and materials[16] and $\dot{p}_{vt}$ and $\dot{p}_{mt}$ are value-added and materials inflation respectively.

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

[16]Note that $\sigma = 0$ and $\sigma = 1$ refer to the Leontief and Cobb-Douglas cases respectively.

3.2 Estimating the Adjusted TFP Series

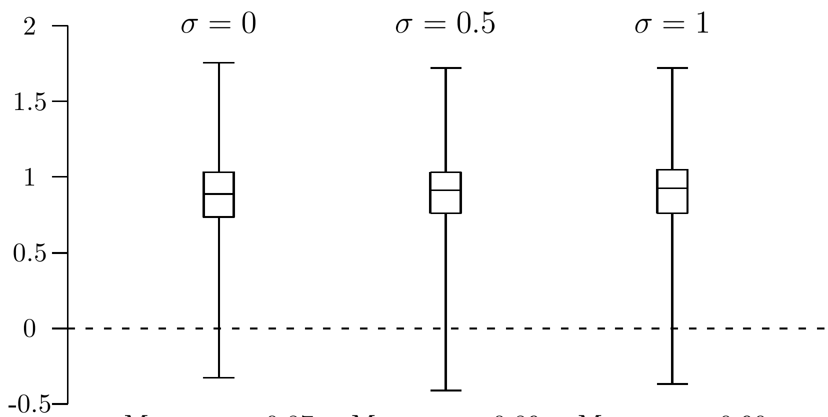
To calculate the above utilisation adjusted measure of TFP growth, we undertake instrumental variable (IV) estimation of (18) to identify γ. These estimations are carried out conditioning on values of σ between 0 and 1.[17] IV estimation is required in this context due to the obvious endogeneity of the 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). These include the growth rate of Military Spending; the growth rate of the World Price of Oil (deflated by both the price of Manufacturing Durables and Non-Durables); and the Political Party of the President. Note that the instruments have been chosen as ones which can explain movements in employment, material costs, capital accumulation and output but are orthogonal with the random component of TFP growth.

The box-plots in Figure 1 below report the results of estimating returns to scale for all 4-digit manufacturing industries for alternative values of σ.[18] These results indicate that (i) returns to scale are equal to or less than unity for most industries and (ii) the estimates are robust to alternative values of σ.

[17] This range for σ at the manufacturing level covers the one reported in the literature. For example, Bruno (1984) reports a consensus range for σ between 0.3 and 0.4 respectively. More recently Rotemberg and Woodford (1992) estimate σ to be 0.7.

[18] Note that two industries (i.e. 177 and 250) were omitted due to missing values.

Figure 1: Distribution of Returns to Scale, $\gamma_i, i = 1, \dots, 448$ for $\sigma = 0, 0.5, 1$



Mean	0.87	Mean	0.89	Mean	0.90
Median	0.89	Median	0.91	Median	0.93
Max.	1.75	Max.	1.72	Max.	1.72
Min.	-0.33	Min.	-0.41	Min.	-0.37
Std.Dev.	0.28	Std.Dev.	0.2	Std.Dev.	0.26

As expected, based on the discussion in Basu (1996) and Basu and Kimball (1997), Table 2 shows that our utilisation-adjusted TFP series at the aggregate level[19] tends to display a much smaller relative variance, and a much less marked positive co-movement with other cyclical series such as output and total hours worked.

Table 2: Descriptive Statistics Aggregate Manufacturing

		Solow	Basu		
			$\sigma = 0$	$\sigma = 0.5$	$\sigma = 1$
Correlation between TFP	Output	0.95	0.24	0.16	0.17
and Output & Hours Growth	Hours	0.84	0.25	0.12	0.08
Variance of TFP to	Output	0.52	0.02	0.02	0.03
Variance Output & Hours Growth	Hours	0.50	0.02	0.02	0.03

[19]Note that the same correlation and relative variance pattern emerges at the sub-aggregate level. To preserve space, these results have not been reported but will be made available on request.

4 Econometric Methodology

Having obtained our adjusted series, we next fit a 5 variable VAR in log levels for each 4-digit sector. The endogenous variables are output (y), employment (l), hours (h), and the real consumer wage (w). Total factor productivity θ follows an exogenous $AR(1)$. The VAR is given by

$$\mathbf{x}_t = \begin{pmatrix} \mathbf{c} & \mathbf{b} & \boldsymbol{\delta} \end{pmatrix} \begin{pmatrix} 1 \\ t \\ \theta_t \end{pmatrix} + \sum_{j=1}^{p} \mathbf{A}_p \mathbf{x}_{t-j} + \mathbf{u}_t, \tag{19}$$

where $\mathbf{c}$ is a (4×1) vector of constants, $\mathbf{b}$ is a (4×1) vector with the slopes for the linear time trend, and $\boldsymbol{\delta}$ is the (4×1) coefficient vector for θ. The (4×1) vector of distrubances $\mathbf{u}_t$ follows the usual assumptions: $\mathrm{E}[\mathbf{u}_t] = \mathbf{0}; \mathrm{E}[\mathbf{u}_t \mathbf{u}_t'] = \boldsymbol{\Sigma}; \mathrm{E}[\mathbf{u}_t \mathbf{u}_{t'}'] = 0 \ \forall \ t \neq t'$. We determine the order p using AIC, with the maximum order fixed at 2, and focus on stationary VARs.[20]

To analyse the impact of TFP innovations on the variables of interest, we calculate impulse responses. They are obtained from the infinite MA representation of the VAR in equation (19), after adjusting the estimated parameter matrices appropriately to take into account the exogenous AR(1) process for θ:

$$\mathbf{x}_t = \sum_{j=0}^{\infty} \mathbf{B}_j \mathbf{u}_{t-j}; \ \mathbf{B}_0 = \mathbf{I}; \ \mathbf{B}_j = \sum_{k=1}^{p} \mathbf{A}_k \mathbf{B}_{j-k}; \ j = 1, 2, \ldots \tag{20}$$

[20]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, p. 9-13). We found when using the Solow residual, that 403 of the 448 industry VARs are stationary. In the case of the Basu residual, 422.

If the error variance-covariance matrix $\mathbf{\Sigma}$ is diagonal, i.e. if the system is identified, the parameter matrices of the MA representation can be interpreted as responses to past shocks. Despite the restrictions we impose with respect to the evolution of TFP, our model is still under-identified. Therefore we employ Generalised Impulse Responses, which have recently been proposed by Pesaran and Shin (1998) and Koop *et al.* (1996). If we interpret the impulse response function at lag h as the difference between a h-step VAR forecast assuming a shock on the variable j, δ_j, and a VAR forecast without a shock, we obtain generalised impulse (**GI**) responses:

$$\begin{aligned} \boldsymbol{GI}\left(h, \delta_j, \mathbf{\Omega}_{t-1}\right) =& \mathrm{E}\left[\mathbf{x}_{t+h} | \epsilon_{t,j} = \delta_j, \mathbf{\Omega}_{t-1}\right] - \mathrm{E}\left[\mathbf{x}_{t+h} | \mathbf{\Omega}_{t-1}\right] = \\ =& \mathbf{B}_h \mathrm{E}\left[\boldsymbol{\epsilon}_t | \epsilon_{t,j} = \delta_j\right], \end{aligned} \tag{21}$$

where $\mathbf{\Omega}_{t-1}$ is the information set available at time t. To compute the forecasts for the other variables $i, i \neq j$, we need starting values at time t, conditional on the fact that there is a shock to series j. If the distribution of $\mathbf{u}_t$ is multivariate normal, the conditional expectation of $\mathbf{u_{t,i}}$ given that there is a shock in the jth equation is

$$\mathrm{E}\left[u_{t,i} | u_{t,j} = \delta_j\right] = \frac{\sigma_{ij}}{\sigma_{jj}} \delta_j. \tag{22}$$

As generalized impulse response we obtain

$$\boldsymbol{GI}\left(h, \delta_j, \mathbf{\Omega}_{t-1}\right) = \mathbf{B}_h \begin{pmatrix} \sigma_{1j} \\ \vdots \\ \sigma_{jj} \\ \vdots \\ \sigma_{nj} \end{pmatrix} \frac{\delta_j}{\sigma_{jj}} = \left. \frac{\mathbf{B}_h \mathbf{\Sigma} \boldsymbol{e}_j}{\sqrt{\sigma_{jj}}} \right|_{\delta_j = \sqrt{\sigma_{jj}}}, \tag{23}$$

where $\mathbf{e}_j$ is an $(n \times 1)$ vector with unity as jth element.

We can broadly compare our empirical results to those obtained by Basu et al. (1998) and Gali (1999) with the obvious caveat that the scope and method of our study is very different from theirs. With respect to measurement, we use sectoral data and a different measure of productivity. Unlike the other studies, our aim is to assess whether different business cycle patterns emerge in different industries and how these square with the patterns predicted by different business cycle theories. Furthermore our method of model identification is different. Since we are not interested in the identification of structural disturbances to variables other than TFP we maintain that the GIR method is particularly appropriate. Finally, unlike these other authors we consider a wider range of variables. For instance Galí (1999) largely restricts his attention to labour productivity and total employment (hours worked). Basu *et al.* (1998) concentrate mainly on total factor inputs, output, and manhours. However, as we saw previously, one distinguishing feature of different business cycle series is the difference in their predictions about the behaviour of the real wage over the cycle. Hence our sectoral 5-variable VAR analysis offers an alternative perspective in discriminating between different accounts of the business cycle.

5 Results

One way to display our estimated impulse response functions is shown in Figures 2 and 3. These show, for the Solow TFP residual, and the Basu TFP residual (using σ=0.5), the range of the impulse response functions for each of the four other variables. It is apparent that using the Solow residual persistent significant positive shocks to output are generated for most sectors

(81% of industries experience a rise in output in period 0, and 43% continue to experience a significant increase even after 5 years). Employment and hours are less procyclical, but after 3 years still 37% of all 403 industries continue to experience an increase in total hours worked, and in 32% employment is still higher. Real wages show no marked pro or counter-cyclical pattern. In 14% of the 403 industries real wages are significantly higher five years after the technology shock, whilst in 23% of industries they are significantly lower.

Looking at the Basu-residual case (Figure 3) some interesting features emerge. First, as we expected, the size of the impact on output is smaller on average across industries, and we find that less industries experience a persistent cyclical effect (30% of 422 industries after 5 years). This, as expected, casts some doubt on the significance of technology shock as a propulsive mechanism for business cycles on aggregate. Second, in apparent contrast to Basu *et al.* (1998) and Galí (1999), the response of employment (total number of workers and total hours) does not seem to be uniformly negative. In comparison with the Solow TFP measure about the same number of industries experience a positive response in l and h after 3-5 years. Few industries seem to follow the negative impact following a technology shock which sticky-price DGE models would suggest. This puzzle, in our view, is best explained by either an aggregation bias effect: (both these previous studies used aggregate data), or because our VAR is larger and includes other labour market variables.

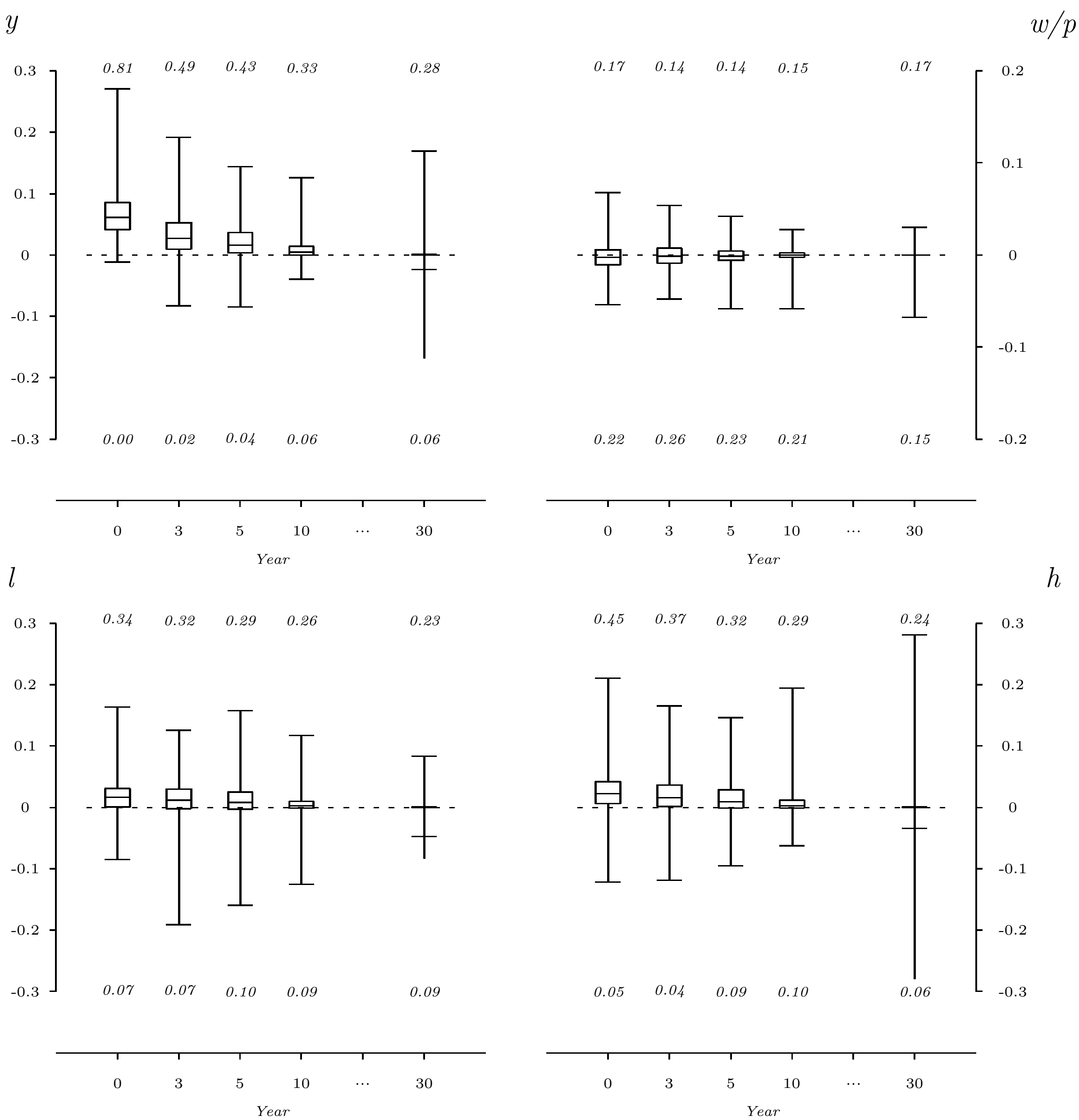
However, Figures 2 and 3 might not give us an accurate picture of what is happening because each industry's position in the cross-sectional distributions shown in these figures will not remain constant over time. A better test of which business cycle model fits best for each industry is found by matching 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.

The result of this mapping is shown in Tables 3 and 4 for the Solow and Basu TFP measures. In each table 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 2-digit category the proportion of 4-digit industries which display the pattern predicted by the alternative theories at different lags.[21]

The results in Tables 3 and 4 are very clear. First, the two preferred explanations for the responses to technology shocks are clearly the pure RBC model and the sticky wage model. The imperfect competition-sticky price model comes a very poor third. This is in sharp contrast to the results in Galí (1999) and Basu *et al.* (1998). Second, the correction for factor utilisation effects tends to reduce the degree to which the results match the pure RBC model. This is as might be anticipated given that the Basu correction reduces the procyclicality of the TFP measure. But interestingly the RBC model still fits the results for a reasonable proportion of the industries considered. Third, the few observations which match the imperfect competition-sticky price case seem to emerge following the Basu correction. The last two points illustrate the importance of the factor utilisation correction.

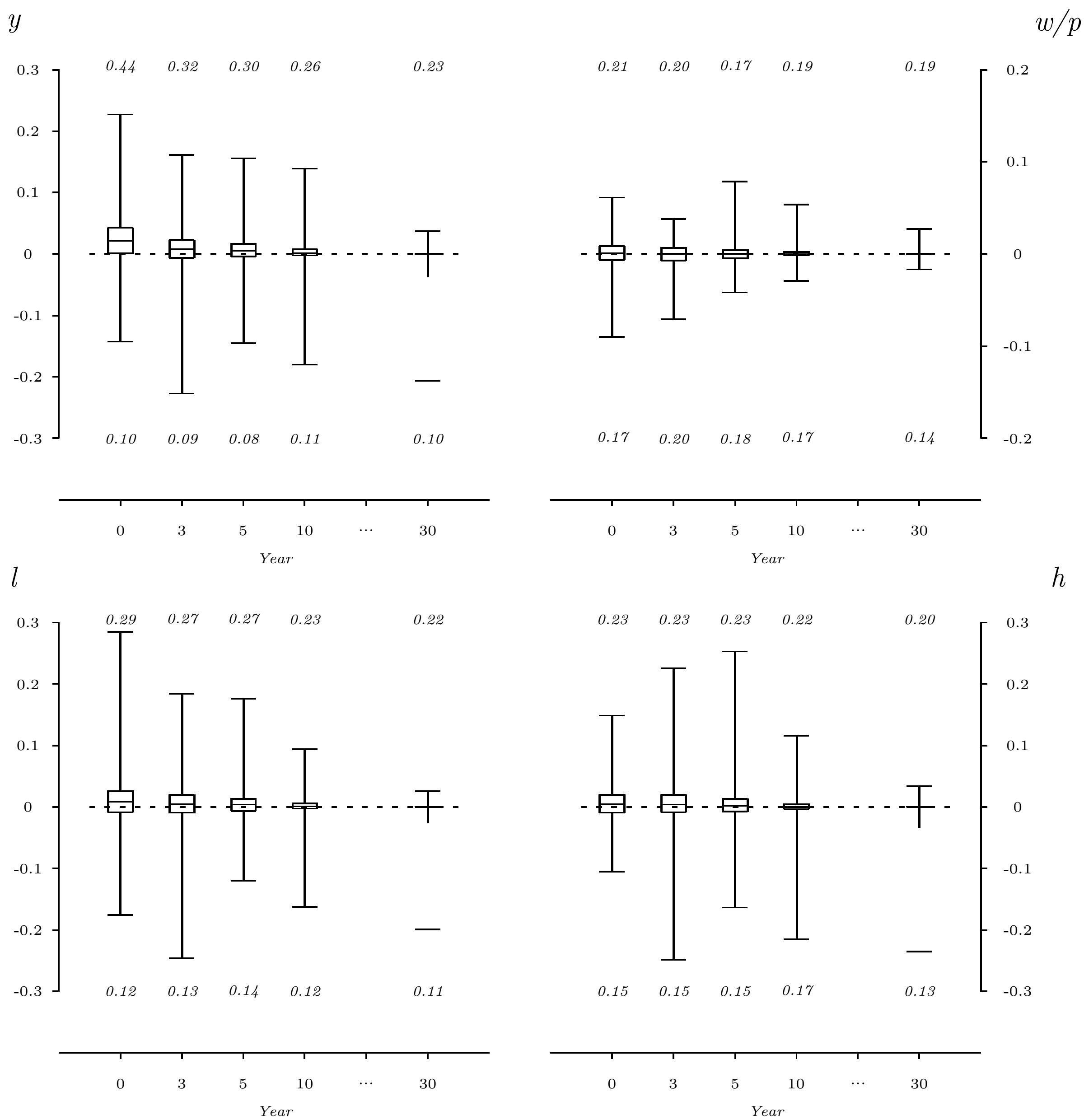
[21]Note that these proportions are for significant impulse responses only. However, we take an insignificant response of real wages as consistent with the sticky nominal wage hypothesis.

Figure 2: Distribution of Impulse-Responses, Solow Residual



Number of Industries: 403. The numbers in italics denote the proportion of significantly positive/negative responses (10 per cent significance level).

Figure 3: Impulse-Responses, Basu Residual ($\sigma = 0.5$)



Number of Industries: 422. The numbers in italics denote the proportion of significantly positive/negative responses (10 per cent significance level).

Table 3: Pattern of Sectoral Variables, Solow Residual

			RBC			Sticky Wages			Sticky Prices		
	SIC	Obs	Lag 1	Lag 2	Lag 5	Lag 1	Lag 2	Lag 5	Lag 1	Lag 2	Lag 5
Nondurables	20	42	0.05	0.02	0.02	0.14	0.05	0.05	0.02	0	0
	21	4	0.25	0	0	0	0	0	0	0	0
	22	29	0.10	0.10	0.10	0.10	0	0	0	0	0
	23	32	0.13	0.03	0.03	0.16	0.06	0.03	0	0	0
	26	16	0.06	0	0	0.06	0.06	0.06	0	0	0
	27	12	0.17	0.17	0.17	0.08	0	0	0	0	0
	28	25	0	0	0	0.08	0.04	0	0	0	0
	29	5	0	0	0	0	0	0	0	0	0
	30	4	0	0	0	0	0	0	0	0	0
	31	11	0.09	0	0	0.09	0	0	0	0	0
Durables	24	14	0	0	0	0	0	0	0	0	0
	25	11	0.09	0.09	0	0.09	0	0	0	0	0
	32	22	0	0	0	0.05	0.05	0	0	0	0
	33	24	0	0	0	0.08	0	0	0	0	0
	34	33	0	0	0	0.06	0	0	0	0	0
	35	36	0.03	0.03	0.03	0.03	0	0	0	0	0
	36	39	0.03	0.03	0	0.05	0.03	0	0	0	0
	37	15	0	0	0	0.07	0.07	0	0	0	0
	38	12	0	0	0	0	0	0	0	0	0
	39	17	0	0	0	0.06	0	0	0	0	0

Table 4: Pattern of Sectoral Variables, Basu Residual, $\sigma = 0.5$

			RBC			Sticky Wages			Sticky Prices		
	SIC	OBS	Lag 1	Lag 2	Lag 5	Lag 1	Lag 2	Lag 5	Lag 1	Lag 2	Lag 5
Nondurables	20	46	0.11	0.09	0.04	0.09	0.07	0.04	0.02	0	0
	21	4	0	0	0	0.25	0	0	0	0	0
	22	29	0.03	0.03	0	0.03	0.03	0	0	0	0
	23	31	0.10	0.03	0	0.13	0	0	0	0	0
	26	15	0	0	0	0.13	0	0	0	0	0
	27	14	0.14	0.07	0.07	0.07	0.07	0.07	0	0	0
	28	28	0	0	0	0.11	0.07	0	0	0	0
	29	5	0	0	0	0	0	0	0	0	0
	30	5	0	0	0	0	0	0	0	0	0
	31	11	0	0	0	0.36	0	0	0	0	0
Durables	24	14	0	0	0	0	0	0	0.07	0.07	0
	25	11	0	0	0	0	0	0	0	0	0
	32	25	0	0	0	0.04	0	0	0	0	0
	33	23	0	0	0	0.04	0	0	0.04	0	0
	34	35	0	0	0	0.09	0.06	0	0	0	0
	35	42	0.02	0	0	0.17	0.07	0.02	0	0	0
	36	38	0.03	0.03	0.03	0.08	0.03	0.03	0	0	0
	37	14	0	0	0	0	0	0	0	0	0
	38	13	0	0	0	0.08	0.08	0	0	0	0
	39	19	0.05	0.05	0	0.11	0	0	0	0	0

6 Conclusions

In this paper we have estimated some industry-level VAR models to verify the relevance of alternative theoretical modelling approaches to the business cycle. Our estimates have been conducted using US manufacturing data at the 4-digit SIC level, correcting the TFP growth series to take account of varying factor utilisation over the cycle.

Our results offer a different perspective to those obtained in other studies which have examined the aggregate impact of technology shocks on the macroeconomy (Basu *et al.*, 1998; Galí, 1999). We show that there is little 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 imperfect competition-sticky price model of a negative response of factor input levels (such as employment) to technology shocks. This prediction does not seem to match many industry-level VARs. Instead, we find much greater support for the pure RBC approach or a nominal rigidity approach which focuses instead on nominal wage stickiness. These seem to be best placed to explain the positive employment effects and the positive/insignificant real consumer wage response to technology shocks.

A subsidiary conclusion is that, despite its lower variance over the cycle, the Basu corrected TFP series does not lead to dramatically different results regarding the co-movement of employment and output over the cycle. Again, in this our results differ sharply from those of Basu *et al.* (1998). The explanation lies either in our use of disaggregated data, or in the richer specification of our VAR.

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Data Appendix

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

Productivity Data:

L	total employment (1,000s)
W	nominal wage per employee
M	real material 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_m	price deflator for material inputs (1987=1)

Instruments:
Military Spending (bill chained $1992) from 1959 is taken from the May 1997 SCB. Based on quantity indexes 1992=100, provided by the Department of Commerce, movements in the quantity index series were spliced to the billions of chained 1992 dollar series to obtain 1958. The World Price of Oil from 1965 onwards is taken from 1995 International Financial Statistics Yearbook Average Crude Price, spot (US$/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 Venezuelan. Implicit price deflators for manufacturing durables and non-durables were calculated using the NBER database. Political Party of the President: D=1 for Democrat and D=0 for Republican.

[22]See www.nber.org/nberprod.html