The Interaction Between Business Cycles and Productivity Growth: Evidence from US Industrial Data

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Abstract

In this paper, we employ total factor productivity data adjusted for factor utilisation over the cycle, to model the dynamic interaction between TFP and employment. Our data spans twenty 2-digit SIC code manufacturing sectors in the US. There are two key results. First, we show that the impact of technology shocks on employment cycles is much weaker than suggested by real business cycle-type models, and that in a number of cases employment responds negatively to technology shocks. Second, in examining the impact of employment shocks on TFP, we find some evidence for both opportunity cost and learning-by-doing effects.
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1. Introduction

Policy-makers in OECD economies are increasingly focusing on the determinants of long-run productivity growth. Indeed, institutional reforms in a number of countries[1] have attempted to ensure a more stable macroeconomic environment on the grounds that this is conducive to long-run growth (see Balls, 1998). The key to understanding how business cycles impact on long-run growth comes from recent theoretical research in endogenous growth. There are numerous theoretical contributions which highlight the implications of this linkage for the desirability of stabilisation policy (see for instance Stadler, 1990, Martin and Rogers, 1995, Muscatelli and Tirelli, 1996).

However, very little is known at the empirical level about the extent to which long-run productivity growth depends on fluctuations in output and/or employment. Economic theory has identified various potential channels through which recessions and booms can affect productivity growth, but empirical work in this area is still quite rare (see Saint-Paul, 1997 for a survey). Existing empirical work also suffers from serious shortcomings. As Saint-Paul points out, one of the key problems is the lack of reliable data on total factor productivity growth. Standard constructions of total factor productivity (TFP) ignore considerations pertaining to market power, returns to scale and variations in factor utilization over the cycle. A second problem is that existing work commonly uses VAR models with just-identifying assumptions which involve imposing strong (and often arbitrary) *a priori* causal links on the interactions between business cycles and TFP growth. A final problem is that the vast majority of

[1] There have been monetary and fiscal policy reforms in a number of countries: not only moves to granting Central Banks greater independence, but in addition a number of economies have attempted to limit the fiscal actions of governments (*cf*. recent UK reforms and the Stability Pact for prospective EMU members).

existing studies are conducted on aggregate data, and so ignore the possibility of serious aggregation bias.

This paper addresses these problems, and investigates the dynamic interaction between employment cycles and TFP growth using US manufacturing data from the NBER productivity database. Our main results are as follows. First, there seems to be little evidence of a significant impact of temporary employment shocks on the level of TFP at the aggregate manufacturing level. This is consistent with existing aggregate economy studies which only occasionally find significant effects of business cycles on long-run productivity. Second, we find that the use of cyclically-adjusted TFP series dramatically alters the results normally obtained using standard Solow residuals. Third, we find that our adjusted TFP data also shed some light on the separate but related issue of how technology shocks affect employment[2]. We find that, the impact of technology shocks on employment varies considerably between sectors, in contrast to existing results obtained using unadjusted TFP data. This result suggests that technology shocks are less important in driving aggregate employment fluctuations than assumed in standard real business cycle models. Finally we provide evidence that technology shocks have temporary or even permanent negative effects on employment. This last result can be explained by sticky-price general-equilibrium macroeconomic models and the presence of 'creative destruction' effects.

The rest of the paper is divided as follows. Section 2 provides a brief survey of the theoretical literature which underpins our empirical models, and surveys the existing empirical literature. Section 3 sets out the methodology which we follow in constructing cyclically-adjusted TFP. Section 4 describes our modeling approach and our econometric results, and section 5 concludes.

2. The Interaction between Business Cycles and Growth: Technology and Employment Shocks

In examining the interaction between business cycles and growth we have to allow for the possibility of bi-directional causal links. We first consider how business cycles (employment shocks[3]) affect TFP. Here the central issue is whether cyclical downturns are periods of opportunity or waste. Indeed the debate on the impact of business cycles on growth goes back to Keynes, Robertson and Schumpeter. A useful survey of the various theoretical models which address this issue is provided by Saint-Paul (1997), we only provide a summary here. One general approach in this literature is to argue that productivity-enhancing activities are most likely to occur in periods of cyclical upswing, through learning-by-doing effects (LBD) whereby individual productive units tend to generate new ideas and design better ways of organising production whilst they are actually engaged in productive activities (see Arrow, 1962, Argote and Epple, 1990, Solow, 1997). Similarly, it is argued that where R&D expenditures have to be financed from retained profits, R&D activity is more likely to take place in booms than in recessions (see Stiglitz 1993).

An alternative approach is to argue that reorganization activities usually take place within firms during recessions, when the opportunity cost (OC) in terms of lost production is lower (see Bean, 1990, Hall, 1991). In addition, firms may respond to greater financial discipline in downswings by resorting to innovation, and resource reallocation may take place between firms in recessions as the least efficient productive units exit from the industry (see Caballero and Hammour, 1994). The notion that there is a process of 'Darwinian Selection' in recessions is also at the heart of the Schumpeterian approach to cycles and growth.

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[2] For recent empirical work on this issue see Gali (1996) and Malley and Muscatelli (1996).

However, empirical evidence on the links between cycles and long-run productivity growth is still extremely thin. There are only a handful of econometric studies which analyse the impact of cyclical shocks on TFP levels in the long-run (Gali and Hammour, 1991, Saint-Paul, 1993, Malley and Muscatelli, 1996). All of these studies estimate bivariate semi-structural VARs for variations in employment and TFP to detect the link between demand shocks and productivity, be it labour productivity or TFP. They examine the impulse responses of TFP levels to temporary employment shocks, and find some support for the 'opportunity cost' approach, suggesting that cyclical downturns tend to have a positive impact on total factor productivity in the long run.

It is notable that all these studies use variations in employment to identify business cycle shocks, rather than a measure of output. The advantage of employment as a measure of cyclical disturbances is that OC or LBD effects are more likely to be correlated with actual changes in a firm's production organisation (which often comes with variations in employment or job reallocation) than with variations in production levels. Davis and Haltiwanger (1990, 1992) show that the job destruction cycle does not quite match the output cycle, and therefore identifying business cycle shocks with employment fluctuations may provide a more accurate measure of the mechanism through which organisational capital is accumulated[4].

We should also point out that, in concentrating on bivariate VARs which are specified in variations of employment and TFP we are not able to differentiate between aggregate demand shocks, and other real shocks (e.g. shocks to labour supply or

[3] The issue of why we focus on employment shocks rather than output shocks in examining the impact of business cycles on productivity growth is dealt with below.

[4] Although not reported here, we find that using an industry output measure as our cyclical variable does not lead to significant OC or LBD effects for any industries in the long run. Again, this suggests

taxation policy) which might cause employment to vary. Thus, when we assert that these models are designed to pick up the interaction between business cycles and growth, we are *not* restricting ourselves to a particular source of cycles in employment.

All the previous studies cited above (with the exception of Malley and Muscatelli, 1996) use aggregate macroeconomic data, as opposed to industry-level data whilst the phenomena described above may clearly differ considerably across industrial sectors. Intuitively we might expect OC effects to be predominant in some sectors, and LBD effects in others. In addition, it may be easier to obtain a more accurate measure of TFP at a more disaggregated level.

Furthermore, none of these studies make any systematic allowance for the mis-measurement of TFP due to factor utilisation, market power and returns to scale effects over the cycle. It is now recognised that this is an extremely important issue (see Hall, 1990, Burnside *et al.*, 1995, Basu, 1996), in that factor mismeasurement may be up to 20% of the total change in measured factor use (see Basu, *op cit*.).

Finally, the VAR models estimated in previous work have generally used the standard Choleski decomposition approach to just-identifying the impulse responses of TFP to employment shocks, or an alternative just-identifying assumption based on assuming a particular lagged impact of employment shocks on TFP. The problem with these just-identifying restrictions is that they involve imposing a causal structure on the model which cannot be tested.

Next, we turn our attention to the way in which shocks to TFP (technology shocks) affect employment. The study of the impact of technology shocks on employment has generally been the domain of real business cycle models, and more

that most of the effect of business cycles shocks on TFP occur through variations in employment levels.

recently of sticky-price general equilibrium models (see, *inter alia*, King and Watson, 1995, Gali, 1996). The effect of technology shocks on employment in these models is due to a standard shift effect on labour demand and the accompanying impact on capital accumulation. But in general such models do not focus on the long-run effects of technology shocks on employment[5].

Labour market search theory has also analysed the impact of productivity growth on employment. These models (see Mortensen and Pissarides, 1994, Aghion and Howitt 1991, 1994) have focused on how changes in the growth rate of productivity can affect inflows and outflows from unemployment, and hence the equilibrium unemployment/employment rate. Whether technology impacts positively or negatively on employment depends partly on whether a positive technology shock leads to the destruction of low-productivity jobs, the creation of new jobs in new firms as technological innovation fosters firm creation, or capital-labour substitution effects. The strength of these effects may again differ markedly between sectors, and this provides an additional incentive to estimate industry-level VARs. Direct empirical evidence on these effects is again difficult to find, but at the *aggregate* level, there seems to be evidence that technology shocks cause employment to fall (at least temporarily)[6].

Of course there is nothing to rule out RBC type shocks co-existing with a labour market search based propagation mechanism. Indeed, recently de Haan *et al.* (1997) have shown using a calibrated model that job destruction dynamics may play an important role in explaining the persistence of output effects arising from technology shocks. Ultimately, one cannot rule out a permanent effect of technology shocks on

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[5] Also, it is important to note that long-run LBD or OC effects are ruled out *by assumption* in such models. In fact VAR models based on RBC models or dynamic sticky price models generally *assume* that the unit root in productivity is due solely to productivity shocks (see Gali, 1996).

employment (or unemployment). If a unit root is present in the employment data, this may be partly due to shifts in agent preferences or in wage and price-setting mechanisms, but one cannot rule out *a priori* the effect of technology shocks in driving the trend in employment.

In Section 4 we shall return to the issue of how our econometric methodology allows us to capture the dynamic interrelationship between TFP and employment, and the response of these variables to demand and technology shocks. We now turn our attention to the construction of adjusted TFP series.

3. Total Factor Productivity: Solow Residuals and Adjusted Series

In virtually all empirical work employing the growth accounting framework (including the studies cited in Sections 1 and 2), TFP growth is measured as in Solow (1957). However, it is well know that the Solow residual may not be an accurate measure of 'true' multi-factor productivity since it ignores considerations pertaining to market power, non-constant returns to scale and variable factor utilisation over the cycle (see Hall, 1991 and Basu, 1996). Clearly any research which hopes to accurately gauge the link between employment cycles and growth requires a measure of TFP which, at least, accounts for the points raised by Hall and Basu[7]. Accordingly, in the VAR analysis which follows in the next Section, we will use cyclically adjusted TFP based on the measure developed in Basu (1996)[8].

In order to illustrate the relationship between the traditional Solow residual and the Basu measure of TFP, it is convenient to start by restating the standard definitions which are commonly used in the literature. First, consider the following production function:

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[6] See Forni and Reichlin (1995), Blanchard *et al.* (1995), Gali (1996), Malley and Muscatelli (1997).
[7] This point is also forcefully made by Saint-Paul (1997).

$$Y_t = \Theta_t F[\,N_t, M_t, K_t\,] \tag{1}$$

where, Θ_t represents an index of Hicks neutral technical progress; F is a homogenous production function of some degree, γ; Y_t is real gross output; and N_t, M_t and K_t are labour and real material and capital inputs respectively.

Taking logs of both sides of (1) and then differentiating with respect to time gives

$$\frac{\dot{Y}}{Y} = \frac{\dot{\Theta}}{\Theta} + \frac{\Theta F_N N}{Y}\left(\frac{\dot{N}}{N}\right) + \frac{\Theta F_M M}{Y}\left(\frac{\dot{M}}{M}\right) + \frac{\Theta F_K K}{Y}\left(\frac{\dot{K}}{K}\right). \tag{2}$$

where, ΘF_N, ΘF_M and ΘF_K are the marginal products of labour, material inputs and capital respectively. The firm is assumed to minimise the following cost function in order to determine the optimal levels of capital and labour to employ,

$$C = wN + P_m M + rK \tag{3}$$

subject to the production constraint in (1). The symbols w, P_m and r are defined as the nominal wage per worker, the price of material inputs and the rental rate of capital respectively. Note that via Euler's Theorem (1) can be equivalently expressed as

$$Y = \frac{1}{\gamma}\left[\Theta F_N N + \Theta F_M M + \Theta F_K K\right]. \tag{4}$$

The first-order conditions resulting from minimising (3) subject to (4) are

$$\Theta F_N = \frac{w\gamma}{\lambda},\ \Theta F_M = \frac{P_m\gamma}{\lambda} \text{ and } \Theta F_K = \frac{r\gamma}{\lambda} \tag{5}$$

where, the Langrangian multiplier λ is defined as marginal cost.

3.1 Revenue Based Total Factor Productivity

The original Solow (1957) residual is derived assuming (i) constant returns to scale and (ii) perfect competition in the factor and product markets. To measure

[8] Note that Basu's measure is an extension of Hall (1991) and hence allows for the possibility of both

marginal cost, Solow assumes that it is *observable* at the market price of output, P. Accordingly the marginal products of capital and labour in (6) can be rewritten as

$$\Theta F_N = \frac{w}{P},\ \Theta F_M = \frac{P_m}{P} \text{ and } \Theta F_K = \frac{r}{P} \quad . \tag{6}$$

Substituting the marginal products in (6) back into (2) gives

$$\frac{\dot{Y}}{Y} = \alpha_t^n \left(\frac{\dot{N}}{N}\right) + \alpha_t^m \left(\frac{\dot{M}}{M}\right) + \alpha_t^k \left(\frac{\dot{K}}{K}\right) + \frac{\dot{\Theta}}{\Theta}, \text{ where} \tag{7}$$

$$\alpha_t^n = \frac{wN}{PY},\ \alpha_t^m = \frac{P_m M}{PY} \text{ and } \alpha_t^k = [1 - \alpha_t^n - \alpha_t^m] = \frac{rK}{PY}.$$

The discrete time approximation to (7) is given by (see Diewert, 1976)

$\Delta y_t = \tilde{a}_t^n \Delta n_t + \tilde{a}_t^m \Delta m_t + \tilde{a}_t^k \Delta k_t + \Delta q_t$, where

$$\begin{gathered}\Delta y_t = \log\left(\frac{Y_t}{Y_{t-1}}\right),\ \Delta n_t = \log\left(\frac{N_t}{N_{t-1}}\right),\ \Delta m_t = \log\left(\frac{M_t}{M_{t-1}}\right),\ \Delta k_t = \log\left(\frac{K_t}{K_{t-1}}\right), \\ \Delta q_t = \log\left(\frac{\Theta_t}{\Theta_{t-1}}\right),\ \tilde{a}_t^n = \left[a_t^n + a_{t-1}^n\right]/2,\ \tilde{a}_t^m = \left[a_t^m + a_{t-1}^m\right]/2,\ \tilde{a}_t^k = \left[a_t^k + a_{t-1}^k\right]/2.\end{gathered} \tag{8}$$

Total factor productivity growth or the Solow residual is therefore derived as the difference between output growth and weighted input growth, e.g.

$$\%\Delta \mathrm{TFP}_{\mathrm{Solow}} \equiv \Delta\theta_t + \varepsilon_t = \Delta y_t - \tilde{\alpha}_t^n \Delta n_t - \tilde{\alpha}_t^m \Delta m_t - \tilde{\alpha}_t^k \Delta k_t . \tag{9}$$

Note that a random term, e_t has been added in (9) to reflect the stochastic nature of productivity growth. Under this view, TFP growth is the sum of a constant underlying growth rate, $\Delta\theta_t$ plus a random component, ε_t.

3.2 Cost Based Total Factor Productivity

To address the problems of mis-measurement associated with imposing constant returns to scale, Hall (1990) derives an alternative measure of TFP which does not require an assumption regarding competition. In contrast to Solow, Hall

market power and non-constant returns to scale.

assumes that marginal cost, λ is not observable as the market price of output, *P*. Instead of measuring each input's shares in revenue, (*PY*) he uses their shares in cost[9].

Using the cost-shares, the marginal products in (5) can be rewritten as

$$\Theta F_N = \frac{w\gamma Y}{wN + P_m M + rK},\ \Theta F_M = \frac{P_m \gamma Y}{wN + P_m M + rK} \text{ and } \Theta F_K = \frac{r\gamma Y}{wN + P_m M + rK}. \quad (10)$$

Again, output growth is found by substituting (10) into (2) and solving for Δy_t, e.g.

$$\Delta y_t = g\,[\tilde{a}_t^{n'} \Delta n_t + \tilde{a}_t^{m'} \Delta m_t + \tilde{a}_t^{k'} \Delta k_t] + \Delta q'_t + e_t, \quad (11)$$

where the α' denote cost shares,

$$\tilde{\alpha}_t^{n'} = \left[\alpha_t^{n'} + \alpha_{t-1}^{n'}\right]/\,2;\ \tilde{\alpha}_t^{m'} = \left[\alpha_t^{m'} + \alpha_{t-1}^{m'}\right]/\,2;\ \tilde{\alpha}_t^{k'} = \left[\alpha_t^{k'} + \alpha_{t-1}^{k'}\right]/\,2;$$
$$\alpha_t^{n'} = \frac{wN}{C};\ \alpha_t^{m'} = \frac{P_m M}{C};\ \alpha_t^{k'} = (1 - \alpha_t^{n'} - \alpha_t^{m'}) = \frac{rK}{C};\ C = wN + P_m M + rK.$$

Using the cost-based shares, TFP growth (adjusted for non-constant returns and market power) can now be expressed as

$$\%\Delta \mathrm{TFP}_{\mathrm{Hall}} = \%\Delta \mathrm{TFP}' - \{(\gamma - 1)[\tilde{\alpha}_t^{n'} \Delta n_t + \tilde{\alpha}_t^{m'} \Delta m_t + \tilde{\alpha}_t^{k'} \Delta k_t]\} \equiv \Delta\theta'_t + \varepsilon_t \quad (12)$$

Note that if γ=1 and PY=C then $\%\Delta \mathrm{TFP}_{\mathrm{Hall}} = \%\Delta \mathrm{TFP}' \equiv \%\Delta \mathrm{TFP}_{\mathrm{Solow}}$.

3.3 Cost-Based (Utilisation Adjusted) Total Factor Productivity

Building directly on Hall's cost-based measure, Basu (1996) provides a method for obtaining a measure of TFP growth which is net of cyclical changes in factor utilisation. Basu's proposed adjustment relies on using data on material inputs as an indicator of cyclical factor utilisation. The argument he puts forward is that unlike employment and capital material inputs do not have an utilisation dimension, and hence one can use relative changes in the input of raw materials and other measured factor

[9] Note that the cost shares are defined as (C=wN+P_mM+rK). Further note that if PY>C, due to pure monopoly profits, then Solow's revenue shares will underestimate the elasticity of output with respect to all inputs.

inputs (capital and labour) to deduce the extent to which factor utilisation changes over the cycle.

In contrast to (1), we follow Basu and employ the following production function

$$Y_t = \Theta_t F[(G_t \cdot N_t), M_t, (Z_t \cdot K_t)] \tag{13}$$

where, G and Z are the levels of labour and capital utilisation. Using the same methods as employed in (2)-(9) the following alternative cost-based Solow residual, net of factor utilisation, can be derived

$$\%\Delta\mathrm{TFP}_{\mathrm{Basu}} = \underbrace{\Delta y_t - \gamma\mathbf{[}\tilde{\alpha}_t^{n'}\Delta n_t + \tilde{\alpha}_t^{m'}\Delta m_t + \tilde{\alpha}_t^{k'}\Delta k_t\mathbf{]}}_{\%\Delta\mathrm{TFP}_{\mathrm{Hall}}} - \underbrace{\gamma[\tilde{\alpha}_t^{n'}\Delta g_t + \tilde{\alpha}_t^{k'}\Delta z_t]}_{u_t} \tag{14}$$

where the shares are defined as in Hall.

In other words, $\%\Delta\mathrm{TFP}_{\mathrm{Basu}}$ in (14) is equal to $\%\Delta\mathrm{TFP}_{\mathrm{Hall}}$ net of changes induced by capacity utilisation. Note however, that the problem with (14) in its current form is that this measure of TFP growth cannot be calculated since some of the components of u_t are *unobservable* (i.e. Δg and Δz). To derive the relationship between *unobserved* capital and labour inputs and *observable* or measured material inputs Basu makes use of the following more restricted production function

$$Y = \Theta F[\mathrm{V}\{(G \cdot N), (Z \cdot K)\}, H\{M\}] \tag{15}$$

where the value-added function, V and the material costs functions, H are assumed to have constant returns to scale. Note that the function F, however, still has the same properties as set out in (1). Log-linearising (15) and using the first-order conditions for cost minimisation the growth rate in value added, Δv_t can be expressed as

$$\Delta v_t = \Delta m_t - \sigma(\Delta p_{vt} - \Delta p_{mt}) \tag{16}$$

where, Δm_t is material cost growth, $\sigma \geq 0$ is the (local) elasticity of substitution between value-added and materials (with $\sigma = 0$ representing the Leontief case and

$\sigma = 1$ the Cobb-Douglas unit-elastic case), and $\Delta p_{vt}, \Delta p_{mt}$ measure value-added and materials inflation, respectively[10].

The growth in value-added can next be expressed as a Divisia index in terms of the growth in observed capital and labour input and unobserved utilisation, e.g.

$$\Delta v_t = \frac{\tilde{a}_t^{n'}(\Delta n_t + \Delta g_t) + \tilde{a}_t^{k'}(\Delta k_t + \Delta z_t)}{\tilde{a}_t^{n'} + \tilde{a}_t^{k'}} \tag{17}$$

Substituting (17) into (16) for Δv_t, rearranging and substituting the resulting expression, which is equal to $u_t(= \tilde{a}_t^{n'}\Delta g_t + \tilde{a}_t^{k'}\Delta z_t)$, into (14) gives

$$\%\Delta \mathrm{TFP}_{\mathrm{Basu}} = \Delta \mathrm{y}_\mathrm{t} - \gamma[[\Delta \mathrm{m}_\mathrm{t} - \sigma(\tilde{\alpha}_\mathrm{t}^{\mathrm{n}'} + \tilde{\alpha}_\mathrm{t}^{\mathrm{k}'})(\Delta \mathrm{p}_{\mathrm{vt}} - \Delta \mathrm{p}_{\mathrm{mt}})]] + \varepsilon_\mathbf{t} \tag{18}$$

Note that unlike (14), TFP growth in (18) is defined in terms of only *observable* magnitudes.

3.4 Estimating Cyclically Adjusted TFP

To derive the utilisation adjusted measure of TFP growth, we next (using U.S. manufacturing data from 1959-91) undertake instrumental variable (*IV*) estimation of (18) to identify γ and hence $\%\Delta\mathrm{TFP}_{\mathrm{Basu}}$. *IV* estimation is required in this context due to the obvious endogeneity of the regressors. We will employ the same set of instruments proposed by Ramey (1989) and Hall (1990) and augmented by Caballero and Lyons (1992) and Basu (1996)[11]. Table 1 below reports the results of estimating (via 3SLS) returns to scale for aggregate manufacturing and two major sub-aggregates. The results of Table 1 indicate for the chosen aggregations that (i) returns

[10] Bruno (1984) reviews a number of papers and reports a consensus range for σ between 0.3-0.4. A more recent study by Rotemberg and Woodford (1992) provide an estimate σ of 0.7 (which is the baseline value used by Basu (1996)).

[11] 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 cause important movements in employment, material costs, capital accumulation and output but are orthogonal with the random component of TFP growth.

to scale are decreasing (but in an economic context, not far from constant) and (ii) the estimates are extremely robust to alternative values of σ.

Tables 2 and 3 provide several different views on the extent to which the Basu measure has succeeded in removing cyclical variation in Solow based TFP. For example, Table 2 reveals, regardless of the value of σ, that the correlation of the Basu measure with alternative measures of the cycle is uniformly lower than the Solow residual. Additionally, Table 3 shows that the variance of TFP relative to alternative measures of the cycle is uniformly lower for the Basu based measure. This lower correlation of the adjusted TFP measure and the cycle implies smaller technology shocks and therefore has been interpreted by some as a problem for real-business cycle (RBC) type models. However, a lower variance of TFP shocks might still correlate well with output and employment cycles: this would depend on the strength of the propagation mechanism. Our VAR results in the next section will offer some insights into this issue.

Finally Table 4 reports estimates of returns to scale for twenty 2-digit industries over the period 1959-1991. Not surprisingly, given the limited degrees of freedom relative to the 3SLS estimations, returns to scale are not significantly different from unity for nearly all industries[12].

4. The Econometric Model and Results

4.1 Econometric Methodology

As explained in the introduction, previous empirical verification of the relationship between business cycles and growth (Gali and Hammour, 1991, Saint-

Paul, 1993, and Malley and Muscatelli, 1996) has used semi-structural VAR analysis. Consider the following p^{th}-order structural or primitive VAR for TFP growth, Δz_{it}, and the percentage change in total employment, Δl_{it}, for each sector i,

$$\mathbf{x}_{it} = \begin{bmatrix} \Delta z_{it} \\ \Delta l_{it} \end{bmatrix} :$$

$$\mathbf{x}_{it} = \sum_{j=1}^{p} \mathbf{A}_j \mathbf{x}_{i,t-j} + \mathbf{u}_{it}; \quad t = 1, \ldots T \tag{19}$$

where $\mathbf{x}_{it}$ is the (2 x 1) vector of dependent variables, $\mathbf{A}_j$, j = 1, ... , p are the (2 x 2) parameter matrices[13], and $\mathbf{u}_{it}$ is an (2 x 1) vector of disturbances, following the usual assumptions: $\mathrm{E}(\mathbf{u}_{it}) = \mathbf{0}$, $\mathrm{E}(\mathbf{u}_{it}\mathbf{u}'_{it}) = \mathbf{\Sigma}$, $\mathrm{E}(\mathbf{u}_{it}\mathbf{u}'_{it'}) = \mathbf{0}\ \forall\ t \neq t'$.

From our discussion in Section 2, the structural disturbance corresponding to the TFP variable (Δz_{it}) corresponds to technological shocks to TFP growth, and the structural disturbance corresponding to the employment variable (Δl_{it}) captures demand-side or business cycle disturbances.

However, a number of issues have to be addressed. The first concerns the long-run properties of the model. Our VAR is specified in differences. Given that both TFP and employment will display a stochastic trend, then our LBD and OC theories suggest we should not restrict the model so as to rule out the possibility of employment shocks driving the stochastic trend in the TFP variable (in contrast to standard RBC models). Vice-versa, as discussed in Section 2, we have to allow for the possibility of technology shocks driving the trend in employment. This is especially important when

[12] This confirms earlier results obtained using a different method by Burnside *et al.* (1995). They use electricity consumption as a proxy for capital utilisation. For a comparison of the two techniques see the discussion to Burnside *et al.* (1995).

[13] The order of the VAR is decided using the AIC criterion; the maximum lag is fixed at 2, the minimum at 1. To ensure that the estimated system is stationary, we computed the roots of the characteristic polynomial $|\mathbf{A}\text{-}\lambda\ \mathbf{I}|=0$, where $\mathbf{A}$ is the system matrix of the VAR(1) representation of

using sectoral data, as in some industries technology shocks may have helped to drive negative trends in employment (labour substitution effects), or positive trends (labour complementarity effects). This has implications for the identification of the VAR. Unlike VAR modelling approaches where long-run effects are constrained *a priori* by theoretical considerations (e.g. Blanchard and Quah, 1989), the questions posed by OC and LBD theories require no long-run restrictions to be imposed on the effects of technology and business cycle shocks.

Let us now consider the identification issue in more detail. Provided that the above model is stationary, it has an infinite MA representation

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

If the error variance-covariance matrix $\mathbf{\Sigma}$ is diagonal, the parameter matrices of the MA representation can be interpreted as responses of the system to past shocks. However, if $\mathbf{\Sigma}$ is not diagonal, the VAR is not identified. To solve this problem, orthogonalized impulse responses can be derived by using, amongst others, the Cholesky (see Sims, 1980) or the Blanchard and Quah (1989) decompositions.
As already noted the Blanchard-Quah identification is inappropriate to our case because we wish to test the long-run impact of employment and technology shocks. Most previous authors (see Gali and Hammour, 1991, Malley and Muscatelli, 1996) have used a Choleski decomposition, or an alternative restriction on the short-run impact of shocks (Saint-Paul, 1993). However, all of these procedures require the imposition of *a priori* knowledge regarding the contemporaneous or the long-run dynamic interaction of the variables. The economic implications of the Choleski

equation (19), and checked whether the moduli are inside the unit circle (see Lütkepohl (1991), p. 9-13; results are available on request).

identification might seem reasonable in our context, given that effects considered in LBD or OC models (e.g. reorganisation, on-the-job training, the introduction of new techniques, R&D activity) typically only impact TFP with a lag. However, this restriction might be inappropriate, especially when using annual data if reorganisation effects following employment shocks feed on to productivity improvements within a year (see Saint-Paul, 1993). An alternative Choleski just-identifying restriction would reverse the assumption regarding contemporaneous causation, thus assuming that productivity shocks do not impact immediately on employment levels. But again, this seems an arbitrary restriction.

Here we pursue an alternative identification scheme which overcomes these problems, and which has 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 ($\mathbf{\Omega}_{t-1}$ is the information set available at time t)

$$\mathbf{GI}(h, d_j, \mathbf{\Omega}_{t-1}) = \mathrm{E}\left(\mathbf{x}_{t+h} \middle| u_{t,j} = d_j, \mathbf{\Omega}_{t-1}\right) - \mathrm{E}\left(\mathbf{x}_{t+h} \middle| \mathbf{\Omega}_{t-1}\right). \tag{21}$$

In order 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. To obtain these starting values, we use the contemporaneous relationship between the error terms given by the estimated error variance covariance matrix. The assumption of a multivariate normal distribution of the error terms leads to the following expression for the starting value in series i

$$\mathrm{E}\left(u_{t,i} \middle| u_{t,j} = d_j\right) = \frac{s_{ij}}{s_{jj}} d_j. \tag{22}$$

i.e. we make use of the expected values for $u_{t,i}$, i = 1, ... , n, conditional on the shock on variable j. Setting δ_j equal to the standard deviation of $\mathbf{u}_j$, we obtain for the generalised impulse responses

$$\boldsymbol{\psi}^{\mathrm{G}}_{j,h} = \mathbf{B}_h \begin{pmatrix} s_{1j} \\ \vdots \\ s_{jj} \\ \vdots \\ s_{nj} \end{pmatrix} \frac{d_j}{s_{jj}} = \left.\frac{\mathbf{B}_h \boldsymbol{\Sigma} \mathbf{e}_j}{\sqrt{s_{jj}}}\right|_{d_j=\sqrt{s_{jj}}} , \tag{23}$$

where $\mathbf{e}_j$ is an (n x 1) vector of zeroes with unity as jth element. The generalised long-run multiplier is defined as

$$\overline{\boldsymbol{\Psi}}^{\mathrm{G}}_{j,\infty} = \sum_{k=0}^{\infty} \overline{\boldsymbol{\Psi}}^{\mathrm{G}}_{j,k} = \frac{\sum_{k=0}^{\infty} \mathbf{B}_k \boldsymbol{\Sigma} \mathbf{e}_j}{\sqrt{s_{jj}}} . \tag{24}$$

Finally, the generalised forecast error decomposition is defined as

$$q_{k,j}(h) = \frac{\sum_{l=0}^{h-1} s_{jj}^{-1} \left(\mathbf{e}'_k \mathbf{B}_l \boldsymbol{\Sigma} \mathbf{e}_j\right)^2}{\sum_{l=0}^{h-1} \left(\mathbf{e}'_k \mathbf{B}_l \boldsymbol{\Sigma} \mathbf{B}'_l \mathbf{e}_k\right)} ; k, j = 1, \ldots, n . \tag{25}$$

The above expression is calculated as the percentage decrease in the forecast error variance of variable k, due to conditioning on the innovations to variable j by using the contemporaneous relationship between the variables given by equation (25) (see Pesaran and Shin, 1998).

4.2 Results

We now present the results from our VAR analysis. We have estimated the VAR model (19) using both aggregate manufacturing data, and disaggregated data for twenty two-digit SIC code industries comprising the aggregate. We report estimates using both the standard Solow measure for TFP as set out in (9), and the adjusted

Basu TFP measure in (18). For reasons of space, we only tabulate the results for the case where $\sigma = 0.5$[14].

First, let us turn to the aggregate data for manufacturing, and to a basic disaggregation into durable and non-durable product industries. Tables 5 and 6 show the cumulated impulse responses and the forecast error decompositions for these three cases using the Solow and Basu measures. There are two important points to note about the impulse responses. The first is that, although the Solow case confirms the results in favour of the OC hypothesis found in earlier work, the total effect of employment shocks on the level of TFP[15] is insignificant. The second important point to note is that the results using the Basu measure of TFP are, generally, weaker for aggregate manufacturing. For the durable sector a significant LBD effect can be detected, and for non-durables we have a negatively-signed long-run effect, but this is not statistically significant at the 10% level. These disaggregated results cast some doubts on the validity of earlier evidence on the prevalence of OC effects (see Saint-Paul, 1997), and suggest much greater variability across different sectors. Note also that our disaggregated models are also given greater statistical weight since the forecast error decompositions indicate that our aggregate models generally explain a smaller proportion of the total forecast variance than the industry results examined below.

A natural reaction to these results is to examine a finer disaggregation of the data. There is no reason to expect that OC or LBD-type effects or the impact of technology shocks on employment are likely to be the same in different industries, given their different susceptibility to the economic cycle, differences in technology, and

[14] Note however that these results, like those in Tables 5-8 are robust to changes in σ from 0 to 1. The VAR results pertaining to alternative values of σ are available on request from the authors.

the differing degree of labour reallocation and re-organisation within each sector. As noted in the introduction aggregation bias is likely to be an important issue when testing for LBD and OC effects.

The impulse responses using the 20 two-digit SIC industries are tabulated in Table 7, and the forecast error decompositions in Table 8. The first key point to note by comparing the results using the Solow and Basu definitions of TFP is that adjusting the TFP data for factor utilisation over the cycle tends to change the impulse response analysis markedly. Looking first at the impact of employment shocks on long-run TFP, we see that using Solow TFP there is an initial positive impact, which is probably due to increasing factor utilisation[16]. Then OC-type effects seem to set in, so that the long-run multipliers are negative. This seems to confirm the results in the earlier literature, except that for all but one industry the 95% confidence intervals for the impulse responses include zero. The Basu TFP measure takes account of factor utilisation effects, and in this case the contemporaneous impact on TFP of employment shocks is no longer positive for all industries. Interestingly, a variety of different significant long-run effects can be found. There seems to be clear evidence of LBD effects in the case of three industries (SIC 23, 25, and 37), and OC effects in the case of three industries (SIC 24, 30 and 38). For some industries there seem to be some temporary impacts on changes in TFP, but no significant long-run effect on the level of TFP. This result suggests that the OC effects detected in earlier work might have been the by-product of using pro-cyclical TFP data.

The second point to note, looking at the reaction of employment to technology shocks using the Solow TFP measures, is that we see a significant positive short- and

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[15] To be more precise, the cumulated growth rate of TFP.

long-run response. The short-run response is typical of the results predicted by RBC-type models. However, results based on the using the Basu measures again produce a variety of different results, with a prevalence of short-run negative employment effects following technology shocks. These short-run negative effects cannot be explained through standard RBC labor demand shifts. Instead the explanation must lie in technology shocks causing either greater factor utilisation and a fall in employment in the presence of sticky prices (see Gali, 1996), or technology shocks inducing labour-substitution effects. Thus, the initial intuition in Basu (1996) that adjustments for factor utilisation might weaken the role for technology shocks, seems to be borne out by our VAR models. Our results are also consistent with the findings in other papers, such as Blanchard *et al.* (1995) in that they support a sticky-price non-RBC interpretation of business cycles. Our findings of a significant long-run negative impact of technology shocks in a small number of industries seems indicative of 'creative destruction' type-effects.

Finally, the forecast error decompositions in Table 8 are much larger than those calculated for the aggregate series, suggesting that disaggregation leads us to explain a greater percentage of the forecast error. Once again, this suggests that our VARs fit the disaggregated data better.

Overall, our industry-level results seem to suggest that the results in the existing literature may be seriously distorted by a failure to measure true productivity shocks in the presence of factor utilisation effects. Also, it appears clear that LBD and OC effects may prevail in different measures in different industries and that previous studies on aggregate data may suffer from severe aggregation bias.

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[16] Note that in earlier papers (Gali and Hammour, 1991, Saint-Paul, 1993, and Malley and Muscatelli, 1996), the impact effect of employment shocks is set at zero or reduced through the use of the Choleski identification scheme or an alternative scheme putting a low weight on impact effects.

Another interesting aspect of our results is the implication for the response of employment to technology shocks. Early work on TFP adjustment (see Basu, 1996) seemed to suggest that factor utilisation could account for a large amount of the covariation between technology and the business cycle. Our VAR analysis shows that in fact, for a number of industries, technology shocks produce reasonably persistent responses in employment. This is consistent with technology shocks accounting for aggregate fluctuations in a number of industries. Moreover, the negative impact of technology shocks on employment in a number of industries is suggestive that variants of RBC models embodying job destruction effects in the propagation mechanism (see de Haan *et al.*, 1997) may be well-founded empirically.

5. Conclusions

In this paper we have extended the recent empirical literature on the interaction between business cycles and growth by tackling some of the key difficulties in earlier work (see Saint-Paul, 1997). The key difficulties include obtaining an accurate measure of TFP over the cycle and the problem of identifying business cycle and technology shocks in the absence of any obvious *a priori* theoretical identifying restrictions which can be imposed on the basic VAR model. Our results shed light on the effect of technology shocks on employment, an issue which is central to both RBC-type models and labour search models.

Our results tend to show that the interaction between employment and TFP growth is much more diverse in different industries than might appear at first sight. The common practice of including Solow residuals in VARs picks up an artificial correlation over the cycle between TFP and employment which arises due to factor utilisation effects. Such correlations have the effect of creating an artificial homogeneity across sectoral VARs. The use of Basu TFP measures shows instead that business cycles (employment shocks) have very different effects across different industries. This runs counter to all existing empirical evidence in this area (see Saint-Paul, 1997). Also, the apparently uniform positive response of employment to technology shocks found using Solow residuals disappears. This new evidence points against the usual real business cycle mechanism, and favours alternative interpretations for the propagation of technology shocks, which include a role for sticky prices.

One possible future extension of our work is to examine the interaction between TFP, output fluctuations and labour re-allocation at the industry level. As shown in Davis *et al.* (1997), most labour re-allocation between firms takes place within industrial sectors rather than between sectors. Using data on job creation and job destruction at the 2-digit SIC level it might be possible to examine the role played by labour reallocation in production-enhancing activities. One might expect to find that labour reallocation plays a role for those industries where OC effects are found.

Finally, another potential extension would be to carry out a comparison similar industries in different OECD economies. If the presence of LBD or OC effects is, as we suspect, a function of the industry technology, one might expect similar patterns to emerge across different countries.

DATA APPENDIX

The following data are provided by Bartlesman and Gray (1994), NBER Manufacturing Productivity Database (see http://www.nber.org/productivity.html):

N	total employment (1,000s)
w	nominal wage per employee (mill., $)
Hp	hours of production workers (mill. of hours)
M	real cost of materials inputs (mill., $1987)
K	real capital stock (start of year); (mill., $1987)
Y	real shipments (mill., $1987)
P	price deflator for value of shipments (1987=1)
P_m	price deflator for value of materials (1987=1)

GDP (bill chained $1992) is taken from the May 1997 Survey of Current Business (SCB), BEA, U.S. Department of Commerce.

Defence 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.

Following Jorgenson and Sullivan (1981), Hall (1990), Cabellero and Lyons (1992), Nadiri and Mamuneas (1994), and Basu (1996) the rental price of capital, r is calculated as follows[17]:

$$r_i = (R + \delta_{K,i})\left(\frac{1 - i_K - u_c z}{1 - u_c}\right) PK_i, \text{ where}$$

i refers to industries the two-digit industries {20, 21…39},

$$z = \frac{\rho(1 - \omega \cdot i_K)}{(R + \rho)},$$

PK_i is the individual industry physical capital deflator and is taken from the BEA Fixed Reproducible Tangible Assets Database (FRTA).

R is the discount rate (10-year Treasury Notes) and is taken from the 1997 Economic Report of the President (ERP).

$d_{K,i}$ is the individual industry physical capital depreciation rate and is taken from BEA's FRTA.

[17] Note however that our measure additionally incorporates individual industry for data for several key components of the user cost.

i_K is the investment tax credit and is taken from Jorgenson and Sullivan (1981) until 1980. Following Naadiri and Mamuneas (1994); for 1981 8% is used and for 1982 to 1986 7.5% is used. Post 1986 the rate is set to 0 due to tax code changes in the U.S..

u_C is the corporate income tax rate and is taken from Jorgenson and Sullivan (1981) and Auerbach (1983) up to 1983. Following Nadiri and Mamuneas (1994) the rate is set to 0.46 after 1983.

z is the present value of capital consumption allowances.

ρ is the capital consumption allowance rate obtained by dividing adjusted capital consumption allowances by the capital stock and is obtained from the 1997 ERP.

ω is a dummy variable which takes the value of 0.5 in 1962-63 and 0 elsewhere. Under the Long Amendment (1962-63) firms were required to reduce the depreciable base of their assets by half the amount of the investment tax credit (see Nadiri and Mamuneas, 1994).

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Table 1: Estimates of Return to Scale for Alternative Values of σ

	Manufacturing	Durables	Non-Durables
σ=0.0	0.94	0.92	0.92
σ=0.3	0.95	0.93	0.94
σ=0.5	0.95	0.94	0.95
σ=0.7	0.96	0.94	0.95
σ=1.0	0.96	0.95	0.96

Note that the above estimates are obtained by applying *3SLS* to the relevant industries comprising a particular aggregation. Based on standard *t-tests*, all of the above estimates are significantly different from zero at less than the 1% level. Finally note that, based on standard *Wald-tests*, all of the above estimates are significantly different from unity.

Table 2: Correlation between TFP and Output/Hours Growth

	Solow	Basu				
		σ=0	σ=0.3	σ=0.5	σ=0.7	σ=1
Manuf.Output	0.95	0.24	0.19	0.16	0.16	0.17
Durable Output	0.95	-0.09	-0.19	-0.24	-0.28	-0.32
Non-Durable Output	0.92	0.43	0.40	0.38	0.36	0.33
Manuf. Hours	0.84	0.25	0.16	0.12	0.09	0.08
Durable Hours	0.84	-0.02	-0.13	-0.20	-0.25	-0.31
Non-Durable Hours	0.79	0.41	0.37	0.34	0.32	0.28

Note, that based on standard *t-tests*, the bi-variate correlation coefficients which tested significantly different from zero at the 5% level include the Solow residuals and the Basu residuals for Non-Durable Output when σ=0, 0.3, 0.5 and 0.7 and for Non-Durable Hours when σ=0 and 0.3).

Table 3: Variance of TFP to Variance Output/Hours Growth

	Solow	Basu				
		σ=0	σ=0.3	σ=0.5	σ=0.7	σ=1
Manuf.Output	0.52	0.02	0.02	0.02	0.03	0.03
Durable Output	0.39	0.02	0.02	0.02	0.02	0.02
Non-Durable Output	0.71	0.14	0.14	0.14	0.14	0.15
Manuf. Hours	0.50	0.02	0.02	0.02	0.02	0.03
Durable Hours	0.42	0.02	0.02	0.02	0.02	0.02
Non-Durable Hours	0.71	0.14	0.14	0.14	0.14	0.15

Table 4: Estimates of Return to Scale, $\hat{\gamma}_{i=20..39}$ for Alternative Values of σ

	Durable Goods Industries					
{σ=		**0.0**	**0.3**	**0.5**	**0.7**	**1.00}**
sic24	Lumber and wood	0.97	0.98	0.98	0.99	1.00
sic25	Furniture and fixtures	1.00	1.02	1.02	1.03	1.04
sic32	Stone, clay and glass	0.90	0.92	0.93	0.94	0.96
sic33	Primary metals	0.99	0.98	0.96	0.95	0.94
sic34	Fabricated metals	1.12	1.12	1.12	1.12	1.13
sic35	Industrial machinery & equipment	0.96	0.95	0.94	0.94	0.93
sic36	Electronic & electric equipment	1.18	1.16	1.15	1.13	1.11
sic37	Transportation equipment	0.83	0.84	0.85	0.86	0.87
sic38	Instruments & related products	1.12	1.10	1.08	1.07	1.05
sic39	Miscellaneous industries	1.03	1.04	1.04	1.05	1.06
	Nondurable Goods Industries					
{σ=		**0.0**	**0.3**	**0.5**	**0.7**	**1.00}**
sic20	Food and kindred products	1.20	1.20	1.21	1.21	1.22
sic21	Tobacco products	1.44	1.41	1.39	1.37	1.34
sic22	Textile mill products	1.08	1.09	1.09	1.09	1.09
sic23	Apparel & other textile	0.91	0.93	0.94	0.95	0.96
sic26	Paper & allied	1.21	1.19	1.17	1.16	1.14
sic27	Printing & publishing	0.85	0.89	0.91	0.95	1.00
sic28	Chemicals & allied	1.25	1.22	1.20	1.18	1.15
sic29	Petroleum & coal products	1.11	1.10	1.09	1.08	1.06
sic30	Rubber & misc. plastics products	1.11	1.11	1.11	1.11	1.10
sic31	Leather & leather products	1.33	1.32	1.32	1.32	1.31

Note that, based on standard *t-tests*, all of the above IV estimates of $\hat{g}_i$ are significantly different from zero at less than the 1% level except for sic21. Further note that, based on standard *Wald-tests*, none of the estimates of $\hat{g}_i$ are significantly different from unity except sic26 and sic37.

Table 5: Aggregate Series - Impulse Responses

Solow

	Technology → N					N → Technology				
	Horizon					Horizon				
	0	1	2	3	∞	0	1	2	3	∞
Aggregate	0.026**	0.010**	-0.004	-0.006	0.027**	0.021**	-0.012**	-0.014*	-0.004	-0.004
Durables	0.034**	0.019**	-0.010	-0.009	0.035**	0.026**	-0.011**	-0.023**	-0.011	-0.017
Non-Durables	0.016**	0.005	-0.001	-0.001	0.019**	0.015**	-0.009**	-0.007**	-0.002	-0.002

Basu (σ=0.5)

	Technology → N					N → Technology				
	Horizon					Horizon				
	0	1	2	3	∞	0	1	2	3	∞
Aggregate	0.004	0.002	0.000	0.000	0.006	0.001	0.000	0.000	0.000	0.000
Durables	-0.007	-0.009	0.000	0.003	-0.012	-0.001	0.004*	0.002	0.002	0.005*
Non-Durables	0.005	0.006	0.002	0.000	0.012**	0.003	-0.003	-0.001	0.000	-0.002

Notes:

a) Superscript **/*: impulse responses significant at the 5%/10% level.

b) The confidence intervals are obtained by employing the bootstrap method using 1000 replications for each step.

Table 6: Aggregate Series - Forecast Error Decomposition

Solow

	Technology → N				N → Technology			
	Horizon				Horizon			
	1	2	3	∞	1	2	3	∞
Aggregate	0.663	0.689	0.655	0.658	0.663	0.637	0.703	0.699
Durables	0.683	0.741	0.736	0.738	0.683	0.679	0.776	0.789
Non-Durables	0.541	0.561	0.551	0.551	0.541	0.562	0.597	0.598

Basu (σ=0.5)

	Technology → N				N → Technology			
	Horizon				Horizon			
	1	2	3	∞	1	2	3	∞
Aggregate	0.013	0.014	0.014	0.014	0.013	0.014	0.015	0.015
Durables	0.023	0.052	0.048	0.052	0.023	0.255	0.283	0.344
Non-Durables	0.055	0.120	0.124	0.124	0.055	0.118	0.130	0.130

Table 7: Industry VARs - Impulse Responses

Solow TFP

Industry	Technology → N Horizon 0	1	2	3	∞	N → Technology Horizon 0	1	2	3	∞
20	0.006**	-0.001	0.005**	-0.001	0.009**	0.008**	-0.007**	-0.001	0.000	0.001
21	0.008	0.006	0.002	0.001	0.018	0.010	-0.003	-0.002	-0.001	0.004
22	0.016**	0.021**	-0.001	-0.004	0.043**	0.012**	-0.016**	-0.018**	0.000	-0.026
23	0.019**	0.013	0.006	-0.004	0.044	0.014**	-0.004	-0.008*	-0.007	-0.022
24	0.018*	0.013	0.006	-0.006	0.029**	0.013*	-0.016**	-0.022**	-0.001	-0.015
25	0.032**	0.025**	-0.019**	-0.013	0.036**	0.023**	-0.002	-0.015**	-0.003	0.008
26	0.018*	0.002	-0.006	0.001	0.016	0.020*	-0.018**	-0.011	0.004	-0.006
27	0.015**	0.004	0.000	0.000	0.019*	0.007**	-0.008	-0.002	0.000	-0.003
28	0.009**	0.010**	0.004	0.000	0.021**	0.021**	-0.015**	-0.013**	-0.005	-0.010
29	0.019**	-0.010**	0.006	0.010*	0.025**	0.026**	-0.007	-0.005	-0.017	-0.021
30	0.036**	0.016	-0.023**	-0.009	0.028**	0.025**	-0.007	-0.024**	-0.016*	-0.013
31	0.017*	0.017**	0.004	0.001	0.039**	0.014*	-0.005	-0.002	0.000	0.007
32	0.028**	0.009*	-0.004	-0.006	0.027**	0.021**	-0.012**	-0.015**	-0.006	-0.007
33	0.052**	0.025*	-0.010	0.001	0.067**	0.057**	-0.015	-0.021	-0.006	0.006
34	0.036**	0.023**	-0.004	-0.011*	0.047**	0.025**	0.000	-0.014**	-0.007	0.010
35	0.039**	0.018**	0.003	-0.004	0.049**	0.024**	-0.013**	-0.021**	-0.015*	-0.027**
36	0.038**	0.026**	0.002	-0.006	0.057**	0.021**	-0.005	-0.008*	-0.003	0.007
37	0.038**	0.017*	-0.003	-0.005	0.047**	0.042**	-0.023**	-0.017*	0.000	0.006
38	0.014**	0.023**	0.008	-0.007	0.034**	0.008**	-0.001	-0.009**	-0.004	-0.001
39	0.026**	0.011	0.003	-0.006	0.031**	0.020**	0.005	-0.022**	-0.004	0.006

Basu TFP (σ=0.5)

Industry	Technology → N Horizon 0	1	2	3	∞	N → Technology Horizon 0	1	2	3	∞
20	0.001	-0.004	-0.001	0.000	-0.004	0.002	0.001	0.000	0.000	0.002
21	0.002	0.002	0.000	-0.013*	-0.004	0.002	0.009	-0.003	0.005	0.011
22	-0.007	0.009	-0.001	0.001	0.001	-0.003	0.001	0.000	0.000	-0.003
23	0.017*	-0.006	-0.003	-0.001	0.008	0.008*	0.002	0.000	0.000	0.010*
24	-0.020**	0.008	0.001	0.000	-0.010	-0.006	-0.004	0.000	0.000	-0.009*
25	0.017*	0.000	0.000	0.000	0.017	0.005*	0.002	0.000	0.000	0.007**
26	-0.010**	0.009**	0.003	-0.005	-0.003	-0.004**	0.002	-0.001	-0.001	-0.004
27	-0.002	-0.004	-0.001	0.000	-0.006	-0.001	0.001	0.000	0.000	0.000
28	-0.006**	0.002	0.003	0.001	0.001	-0.009**	-0.011	0.009**	0.005	-0.003
29	-0.001	-0.004	0.000	0.000	-0.006	-0.001	-0.016*	0.000	-0.001	-0.019
30	-0.023*	-0.009	0.012	0.008	-0.019**	-0.010*	-0.008**	0.011*	0.005	-0.007**
31	-0.029*	-0.008	-0.009	-0.004	-0.057**	-0.021*	-0.001	0.012**	0.005	-0.010
32	0.006	0.003	0.001	0.000	0.011	0.002	-0.001	0.000	0.000	0.000
33	0.007	0.008	0.000	0.000	0.015	0.002	-0.002	0.000	0.000	0.000
34	-0.015**	-0.012	-0.003	0.003	-0.025*	-0.005**	-0.003	0.005**	0.005**	-0.001
35	-0.012	-0.007	-0.002	-0.001	-0.022	-0.004	0.001	0.000	0.000	-0.002
36	-0.034*	-0.024*	0.014	0.008	-0.045*	-0.015*	0.003	0.012*	0.005	0.002
37	0.019	-0.001	0.002	-0.002	0.018	0.004**	0.003	0.005**	-0.002	0.011*
38	-0.027*	-0.007	-0.003	-0.001	-0.040*	-0.022*	0.006	-0.001	0.000	-0.016**
39	-0.001	-0.003	0.000	0.000	-0.005	-0.001	-0.002	0.000	0.000	-0.003

Notes:

a) Superscript **/*: impulse responses significant at the 5%/10% level.

Table 8: Industry VARs - Forecast Error Decomposition

Solow

	Technology → N				N → Technology			
	Horizon				Horizon			
Industry	1	2	3	∞	1	2	3	∞
20	0.241	0.233	0.331	0.331	0.241	0.323	0.324	0.322
21	0.071	0.102	0.107	0.108	0.071	0.068	0.070	0.070
22	0.220	0.448	0.421	0.403	0.220	0.408	0.541	0.477
23	0.358	0.423	0.407	0.383	0.358	0.376	0.424	0.462
24	0.113	0.164	0.131	0.136	0.113	0.227	0.380	0.393
25	0.691	0.658	0.701	0.711	0.691	0.514	0.556	0.551
26	0.409	0.411	0.435	0.435	0.409	0.546	0.582	0.584
27	0.115	0.121	0.121	0.121	0.115	0.218	0.225	0.225
28	0.221	0.346	0.364	0.363	0.221	0.294	0.344	0.347
29	0.481	0.517	0.528	0.589	0.481	0.460	0.443	0.544
30	0.628	0.634	0.701	0.659	0.628	0.640	0.748	0.734
31	0.142	0.238	0.243	0.243	0.142	0.157	0.158	0.158
32	0.659	0.648	0.585	0.583	0.659	0.538	0.603	0.609
33	0.754	0.781	0.786	0.786	0.754	0.735	0.756	0.759
34	0.713	0.778	0.774	0.783	0.713	0.671	0.722	0.724
35	0.611	0.649	0.643	0.630	0.611	0.573	0.666	0.705
36	0.537	0.632	0.612	0.614	0.537	0.490	0.524	0.522
37	0.520	0.563	0.550	0.552	0.520	0.548	0.575	0.573
38	0.155	0.388	0.407	0.428	0.155	0.154	0.255	0.264
39	0.284	0.310	0.291	0.301	0.284	0.289	0.463	0.465

Basu ($\sigma = 0.5$)

	Technology → N				N → Technology			
	Horizon				Horizon			
Industry	1	2	3	∞	1	2	3	∞
20	0.011	0.099	0.102	0.102	0.011	0.013	0.013	0.013
21	0.005	0.010	0.010	0.171	0.005	0.048	0.050	0.060
22	0.031	0.078	0.079	0.079	0.031	0.030	0.030	0.030
23	0.237	0.236	0.239	0.240	0.237	0.254	0.254	0.254
24	0.096	0.107	0.108	0.108	0.096	0.130	0.130	0.130
25	0.096	0.096	0.096	0.096	0.096	0.105	0.105	0.105
26	0.135	0.211	0.217	0.247	0.135	0.151	0.127	0.132
27	0.002	0.010	0.010	0.010	0.002	0.004	0.004	0.004
28	0.094	0.071	0.082	0.085	0.094	0.188	0.246	0.262
29	0.001	0.017	0.017	0.017	0.001	0.106	0.106	0.106
30	0.242	0.253	0.264	0.267	0.242	0.332	0.441	0.483
31	0.386	0.349	0.370	0.368	0.386	0.381	0.431	0.451
32	0.027	0.032	0.033	0.033	0.027	0.032	0.034	0.034
33	0.013	0.027	0.027	0.027	0.013	0.026	0.026	0.026
34	0.117	0.159	0.156	0.155	0.117	0.142	0.225	0.287
35	0.049	0.062	0.062	0.063	0.049	0.055	0.055	0.055
36	0.441	0.508	0.524	0.538	0.441	0.422	0.540	0.558
37	0.115	0.107	0.106	0.106	0.115	0.148	0.254	0.262
38	0.417	0.403	0.403	0.402	0.417	0.426	0.426	0.426
39	0.000	0.005	0.005	0.005	0.000	0.004	0.005	0.005