Cyclical productivity in Europe and the United States

Inklaar, Robert

Published in:
Economica

DOI:
10.1111/j.1468-0335.2006.00554.x

Economica (2007) **74**, 822–841
doi:10.1111/j.1468-0335.2006.00554.x

Cyclical Productivity in Europe and the United States: Evaluating the Evidence on Returns to Scale and Input Utilization

By Robert Inklaar

University of Groningen

Final version received 3 February 2006.

This paper studies procyclical productivity growth at the industry level in the United States and three European countries (France, Germany and the Netherlands). Industry-specific demand-side instruments are used to examine the prevalence of non-constant returns to scale and unmeasured input utilization. For the aggregate US economy, unmeasured input utilization seems to explain procyclical productivity. However, this correction still leaves one in three US industries with procyclical productivity. This failure of the model can also be seen in Europe and is mostly concentrated in services industries.

Introduction

In the short run, output growth and productivity tend to move together in many countries and across a wide range of industries. In recent years this observation has gained increased prominence, as each proposed explanation for the observed procyclicality has important implications for modelling the business cycle and measuring productivity growth.

The goal of this paper is to evaluate the role of increasing returns to scale and unmeasured input utilization in explaining procyclical productivity growth, as earlier research finds these factors to be important (Basu and Fernald 2001). The eventual aim is to better understand short-run changes in productivity growth and how firms adjust to [adverse] changes in demand. The analysis is carried out in a production function framework using a recent, internationally consistent, data-set for three European countries and the United States.

This paper is the first to test directly whether the Basu–Fernald (2001) model is similarly successful in reducing output-productivity correlations outside the United States, and the extent to which it is successful not only at the aggregate but also at the industry level. I confirm the main finding of Basu and Fernald (2001) for the aggregate US economy, but also show that the Basu–Fernald model does not explain much beyond this. Even after correcting for possible non-constant returns to scale and unmeasured input utilization, around one in three US industries still show significant procyclical productivity growth, and a considerable number of these are located outside of manufacturing.

In France and Germany aggregate cyclicality decreases as in the United States, but the failure of the Basu–Fernald (2001) model for many industries can be seen in each of the European countries (France, Germany and the Netherlands). One possible reason for this finding is that the proxy for unmeasured input utilization—average hours worked per person—is not very relevant in Europe or in service industries. Better proxies and more attention to cross-industry heterogeneity, as in Hart and Malley (1999), would probably be helpful.

The second finding is of a more technical nature, but is nevertheless important for the analysis in this paper. Identification of the production functions estimated in this literature tends to rely on relatively weak demand-side instruments. Following Shea (1993) and Baily *et al.* (2001), I construct a set of industry-specific instruments capturing downstream intermediate demand. A recently developed statistical test confirms that these are less prone to weak-instrument bias than the more commonly used instruments such as the real oil price. Therefore the use of these downstream indicators allows for a greater degree of confidence in the estimates presented here than in some of the other studies in this literature.

The rest of this paper is organized as follows. First, the main stylized facts of cyclical productivity are introduced alongside the most important proposed explanations for this phenomenon from the literature. Section II then presents the theoretical framework for the analysis. Section III discusses the estimation framework and the data used in this study. Results are shown in Section IV, first with regards to the production function estimates, and then focusing on the cyclicality of the productivity residuals. Section V summarizes and discusses some of the implications of the results.

I. Background

One of the more robust stylized facts in the macroeconomic literature is that output and productivity move together in the short run. Table 1 illustrates this by showing the correlation between output growth and total factor productivity (TFP) growth in European countries and the United States. With few exceptions, the correlations are positive and highly significant. Although other filtering methods could have been used, I focus on these correlations mainly because Basu and Fernald (2001) do so.

Three explanations for cyclical productivity are popular in the literature: (i) procyclical technology shocks, (ii) increasing returns to scale and (iii) unmeasured input utilization.[1] The first explanation is the most obvious: if technology shows transitory, high-frequency fluctuations, it should not come as a surprise that output will show similar fluctuations, and hence productivity will be procyclical. This argues in favour of models where technology drives the business cycle as in Real Business Cycle theory (e.g. Cooley and Prescott 1995). Under increasing returns to scale, a decline in inputs in a recession will lead to a more than proportionate decline in output and hence will lower output per unit of input. If these increasing returns are related to imperfect competition,

TABLE 1

CORRELATION BETWEEN TOTAL FACTOR PRODUCTIVITY AND GDP GROWTH, EUROPE AND THE UNITED STATES 1979–2001

Austria	0.59*	Italy	0.46*
Belgium	0.53*	Netherlands	0.42
Denmark	0.56*	Portugal	0.51*
Finland	0.75*	Spain	– 0.46*
France	0.56*	Sweden	0.65*
Germany	0.67*	UK	0.54*
Greece	0.71*	USA	0.89*
Ireland	0.68*		

Notes: *Denotes a correlation significantly different from zero at the 5% level.
Source: Timmer and van Ark (2005).

changes in government expenditure can lead directly to procyclical productivity.[2] Increasing returns can also be due to external effects, implying that output in an industry can affect output in other industries, and these effects need to be modelled.[3] If the third explanation holds, firms adjust not only measured inputs such as capital and labour, but also unmeasured inputs such as the utilization rate of capital or the labour effort per hour worked. Therefore, during a growth slowdown or a recession, the decline in productive inputs will be understated and observed productivity will be procyclical.

Differences in the importance of these explanations can also shed important light on the effect of the institutional structure across countries. For example, as Vecchi (2000) shows, Japanese firms hoard more labour than American firms because of lower transaction costs in Japan, and this affects the dynamics of the economies in question.

Different explanations for cyclical productivity also have different implications for the interpretation of productivity growth. Researchers such as Gordon (1993, 2000) try to separate the 'cyclical' from the 'structural' part of productivity growth. This approach might be useful to isolate a more accurate measure of productivity growth if unmeasured input utilization were the leading cause for procyclical productivity growth. However, as Basu and Fernald (2001) argue, if reallocations are important, cyclical productivity is a 'structural' phenomenon since it reflects the ability of firms to produce output given a certain level of inputs. As a result, a more formal analysis is needed to identify movements in production possibilities.

There is an extensive literature that tries to distinguish between the various explanations of procyclical productivity.[4] Most of these papers focus on the US, but there is international evidence as well, most notably from Caballero and Lyons (1990), Oliveira Martins *et al.* (1996), Vecchi (2000) and Marchetti and Nucci (2005), but these studies are mostly confined to production function and related estimates. In a recent study for the US, Basu and Fernald (2001) use production function estimates to evaluate whether these can decrease the correlation between output and the technology residual they estimate. On the basis of this exercise Basu and Fernald (2001) conclude that there is only a limited role for increasing returns to scale outside durable manufacturing and that unmeasured input utilization and reallocations explain the cyclicality of aggregate US productivity.[5] In this paper the same approach is used to see whether their conclusions extend apply to individual industries and other countries as well. First I discuss the production model that lies at the basis of the empirical analysis.

II. A Model of Cyclical Productivity

This section discusses a model that is commonly used to study the cyclicality of productivity growth.[6] A firm produces using the following production function:

$$(1) \qquad Y = F(zK, eHN, M, A)$$

Output, denoted by Y, is produced using capital K, workers N, average hours worked H and intermediate inputs M, given the state of production technology A. Additional choice variables for the firm are the intensity of capital use z and the level of labour effort e. In a model with costless input adjustment, these last variables are irrelevant. However, if labour and capital are quasi-fixed inputs, firms adjust to shocks in the short run by varying average hours worked, labour effort and the intensity of capital use. Following Basu and Fernald (2001), we think of the z as being determined by the number of shifts and higher intensity of capital use is costly due to a shift premium.[7]

Along similar lines, the firm can pay its workers more in order to ensure higher effort levels, given the number of hours worked per worker. If this extra compensation is in the form of better promotion chances or spread out over several years, it will not fully show up in the labour compensation figures of any single year. Furthermore, the level of effort can be interpreted directly as the intensity of work, but reasoning along similar lines, an employee might divide his time between immediately productive work and training or other learning activities. In that case, the firm might simply shift workers from non-productive to productive work without having to pay a higher wage immediately. The cost would lie in the fact that future labour productivity improvements will be lower as less human capital will have been accumulated.[8]

If the firm is a price taker on the market for factor inputs and minimizes cost, inputs will be purchased up to the point where the marginal product equals factor prices. This means we can construct an input growth index (see e.g. Basu and Fernald, 1997):

$$\text{(2)} \qquad \mathrm{d}X = s_L(\mathrm{d}e + \mathrm{d}H + \mathrm{d}N) + s_K(\mathrm{d}z + \mathrm{d}K) + s_M \mathrm{d}M,$$

where $\mathrm{d}(\cdot)$ denotes the percentage growth of the variable and s_x is the two-period average share input x in total cost.[9] Note that equation (2) gives the Törnqvist approximation to the continuous-time Divisia index of input growth. This way, very few restrictions are placed on the underlying production function.

The standard calculation of total factor productivity growth as the Solow residual subtracts the growth of inputs from the growth of output, but this will give a valid measure of technical change only under constant returns to scale. In general, if we assume neutral technical change, the relationship is as follows:

$$\text{(3)} \qquad \mathrm{d}Y = \gamma \mathrm{d}X + \mathrm{d}A,$$

where γ denotes the returns to scale. The problem with estimating (3) is that effort levels and the intensity of capital use are usually not observable and we measure only a biased version of equation (2):

$$\text{(4)} \qquad \mathrm{d}X^* = s_L(\mathrm{d}H + \mathrm{d}N) + s_K \mathrm{d}K + s_M \mathrm{d}M = \mathrm{d}X - s_L \mathrm{d}e - s_K \mathrm{d}z.$$

The usual solution to this problem is to find a proxy for input utilization. For the manufacturing sector, a number of researchers have used survey measures of capacity utilization (i.e. Shapiro 1996). Other studies have proposed energy use or materials use as a proxy for capital utilization (e.g. Burnside *et al.* 1995). However, such measures are silent on labour utilization or are not available outside manufacturing, so alternatives are needed. Abbott *et al.* (1998) proposed using changes in average hours worked as a proxy for both labour and capital utilization. This was later formalized in the model of Basu and Kimball (1997), whose rationale for this proxy is that, if optimizing firms adjust inputs along one margin, namely average hours worked, they will also adjust along unobserved margins. As long as labour effort increases if average hours worked are increased, growth in average hours worked will be a valid proxy for labour utilization. Similarly, if the only way to increase capital utilization in the short run is to increase the number of shifts, and hence average hours worked, the growth in average hours worked will also be a good proxy for capital utilization. Equation (3) can then be written entirely in terms of observable variables:[10]

$$\text{(5)} \qquad \mathrm{d}Y = \gamma \mathrm{d}X^* + \gamma\xi \mathrm{d}H + \mathrm{d}A.$$

Although data on average hours worked are available for all sectors of the economy, the interpretation of this variable as a proxy for unmeasured input utilization seems to be most relevant for manufacturing industries. Most non-manufacturing industries do not work in shifts, and many workers are not paid by the hour, leading to less reliable measures of hours worked. Another proxy, which is also available economy-wide, is intermediate inputs use. The reasoning for this proxy, as originally advanced by Basu (1996), is that if capital and labour utilization go up this is reflected partly in higher use of intermediates such as energy or raw materials. However, intermediate inputs make up on average nearly half of all input cost, so one would expect parameter γ adequately to pick up any utilization effects as well. Adding changes in intermediate use per hour worked, as done by Vecchi (2000), may be problematic, since intermediate use is then included as part of input growth and as a separate explanatory variable.[11]

No explicit role is given to external effects in equation (5), although some researchers such as Caballero and Lyons (1990, 1992) and Vecchi (2000) argue their importance. There are two reasons for this. First, adding aggregate output growth to (5) may indeed pick up the effect of growth in other industries, but, as Sbordone (1997) argues, it could also be a proxy for demand-induced utilization changes. Second, while it is interesting to know whether increasing returns to scale are internal or external to the firm or industry, in the present paper the main focus is on whether returns to scale can explain procyclical productivity growth. Equation (5) gives the general estimation framework to analyse the cyclicality of productivity growth.[12] A number of data and econometric issues need to be dealt with first, however.

III. Methods and Data

Econometric methodology

We estimate two specifications, one including only the returns-to-scale parameter γ, and another including both returns to scale and the correction for unmeasured input utilization in the form of parameter ξ:

$$\text{(6a)} \qquad \mathrm{d}Y_{i,j,t} = \mu_{i,j} + \gamma_j^1 \mathrm{d}X^*_{i,j,t} + \varepsilon^1_{i,j,t},$$

$$\text{(6b)} \qquad \mathrm{d}Y_{i,j,t} = \mu_{i,j} + \gamma_j^2 \mathrm{d}X^*_{i,j,t} + \xi_j \mathrm{d}H_{i,j,t} + \varepsilon^2_{i,j,t}.$$

Output growth of industry i in country j at time t is the dependent variable in both regressions. In (6a) measured input growth is the only explanatory variable, while in (6b) the growth in average hours worked is included to proxy for unmeasured input utilization changes. Input growth is a weighted average of the growth in labour, capital and intermediate inputs (equation (4)). In both specifications a country/industry fixed effect, $\mu_{i,j}$ is also included.

One of the main goals of this exercise is to determine the extent to which European countries show different results from the United States, so the parameters are allowed to vary by country. Productivity growth is accounted for partly in the fixed effect and partly in the residuals $\varepsilon_{i,j}$. The results from Basu and Fernald (2001) suggest that (6a) should give returns-to-scale estimates significantly greater than 1, while in (6b), significant increasing returns should disappear and instead give significantly positive estimates of ξ. Note that in equation (5), parameter ξ was interacted with γ. In practice, taking this nonlinearity into account has little effect on the results, as γ is close to one.

One of the objectives of this paper is to come up with comparable estimates to those of Basu and Fernald (2001), but in specification (6b) growth in average hours worked is included both as part of input growth and as a separate explanatory variable. This is likely to bias the elasticity estimates, so a modified version of (6b) is also estimated, where input growth is calculated excluding growth in average hours worked.

An important problem with estimating (6a) and (6b) is that optimizing firms set their levels of inputs and outputs simultaneously in response to productivity shocks. Therefore we need variables unrelated to industry productivity shocks to identify γ and ξ. Most of the literature has relied on relatively weak instruments, such as the world price of oil (Hall 1988), to estimate variants of (6a) and (6b) and some have even decided to rely on OLS estimates to avoid small-sample bias in IV estimates (e.g. Diewert and Fox 2004). To lessen the weak-instrument problem, in this paper I use downstream indicators of industry demand. Shea (1993) proposed the use of input–output tables to identify industries with close demand links but relatively modest reverse links. Take for example the metal industry and the car industry: output changes in the car industry will likely induce higher demand in the metal industry, so growth in the car industry is certainly relevant. In this case, however, it is not clear whether output changes in the car industry are also exogenous to productivity shocks in the metal industry, because a notable part of intermediate inputs of the car industry come from the metal industry. Baily *et al.* (2001) constructed a weighted average of growth in downstream industries using all industries that buy output from a certain industry and for which these purchases represent less than 5% of intermediate inputs. In constructing the downstream indicators for the present paper, I followed the same procedure.

It is useful at this point to compare how the various instrument sets fare when confronted with the data (described in more detail below). As shown by Stock and Yogo (2004), the *F*-statistic from the first-stage regression of the explanatory variable and the instruments is a useful test statistic with which to gauge the strength of the instruments. The first and third columns of Table 2 show the average *F*-statistic across industries based on the first-stage regressions that try to explain (measured) input growth by the current value and one lag of the downstream indicator for each industry in each country. The second and fourth columns show the same results from regressions with the so-called 'Hall–Ramey' instruments as explanatory variables.[13] As the table shows, in each country the downstream indicators generate a considerably better fit than the more

TABLE 2

COMPARING THE FIT OF FIRST-STAGE REGRESSIONS OF INSTRUMENT SETS ON THE GROWTH OF INPUTS: DOWNSTREAM INDICATOR *v.* HALL–RAMEY INSTRUMENTS

	Average first-stage *F*-statistic		Number of industries with IV bias less than 10% of OLS bias	
	Downstream indicator	Hall–Ramey	Downstream indicator	Hall–Ramey
France	13.5	3.7	15	0
Germany	11.3	3.7	11	1
Netherlands	13.6	4.3	12	1
USA	13.6	6.2	9	4

Notes:
First and third columns: regression with the growth of inputs as dependent variable and the current value and one lag of the downstream indicator as independent variables. Second and fourth columns: regression with the growth of inputs as dependent variable and the current value and one lag of oil price change and growth of real government spending as independent variables. Third and fourth columns: number of industries where the first-stage *F*-statistic exceeds the critical value of 9.08 (third column) and 10.85 (fourth column), using Table 1 of Stock and Yogo (2004).

widely used Hall–Ramey instruments.[14] In quite a number of the 24 industries in this study, the simultaneity bias inherent in OLS estimation can be reduced by 90% or more by using the downstream indicators, while the Hall–Ramey instruments lead to estimates that are much more biased towards the OLS estimates.[15] On the basis of these results, we will rely on the downstream indicators to estimate equations (6a) and (6b).

Data

A quite extensive data-set is needed to estimate the model discussed in Section I. Data are collected on gross output, intermediate inputs, capital services and labour input for 24 market industries in France, Germany, Netherlands and the United States. The period covered is 1979–2001.

For data on capital by asset type and hours worked by skill type in this paper I rely on previous work (see Inklaar *et al.* 2005). For each country, investment data are available for six asset types: computers, communications equipment, software, non-IT machinery, transport equipment and non-residential structures. For France, Netherlands and the United States, these investment data are available as detailed investment matrices from the national statistical offices. In the case of Germany, investment figures from the National Accounts are supplemented with results from investment surveys by the Ifo Institut (see Appendix A of Inklaar *et al.* 2005). From those data, capital stocks are estimated using the perpetual inventory method and asset depreciation rates from the US Bureau of Economic Analysis (see Fraumeni 1997). Given the large differences in how statistical offices across countries account for quality change of ICT products, I used US price indices to deflate ICT investment and the output of ICT-producing industries, after adjusting for differences in the general inflation level. To aggregate across asset types, the gross rate of return on each capital asset is calculated as

$$(7) \qquad r_t^i = R_t^E + \delta_t^i - \dot{P}_t^i.$$

The gross return of asset *i* for industry *j* at time *t* is equal to an external rate of return *R*, assumed equal to the government bond yield (from the IMF's *International Financial Statistics*) plus the asset depreciation rate δ minus the investment price change of the asset $\dot{P}$.[16]

Data on labour input by educational attainment are from national labour force surveys. Owing to differences in the educational system, we do not have the same number of categories in each country: they vary between three categories for Germany and seven for the Netherlands. Information on the wages of each labour type was used to aggregate across different skill categories. Finally, average hours worked by industry are from the GGDC (2003) 60-industry database.

The data from Inklaar *et al.* (2005) are supplemented with information on gross output at current and constant prices from the National Accounts of the various countries. Especially for the 1980s, prices for gross output are frequently not given in the National Accounts. In such cases I either used producer price indexes or estimated prices on the basis of implicit value added deflators. Intermediate inputs were implicitly estimated from gross output and value added at constant prices. In addition to the growth of each input, the share of labour, capital and intermediate inputs are also needed to compute an aggregate input index. The main issue lies in estimating self-employed labour income, as this is included as part of capital income. As in Inklaar *et al.* (2005), data for the United States from Jorgenson *et al.* (2005) were used to estimate that at the aggregate level self-employed wages are on average 70% of employee wages. This ratio is applied to each industry and country.

To construct the downstream indicator for each country, information is needed on deliveries by industry x to industry y. For this I used benchmark input–output tables for each of the countries.[17] Although the sales shares of industries are likely to change over time, experiments using annual input–output tables for the Netherlands show that the impact on the indicators is limited. Therefore only a single input–output table is used for 1995 (France and the Netherlands), 1997 (United States) and 2000 (Germany). The downstream indicators are calculated at the industry detail of the 60-industry database and then aggregated to the level of the 24 market industries in this paper. Finally, the indicators are limited to intermediate demand.

IV. Results

Production function estimates

In this subsection the estimation results from equations (6a) and (6b) are presented. In all cases, two-stage least squares is used to estimate the parameters with the current value and one lag of the industry-specific downstream indicators as instruments. To improve efficiency, first-stage coefficients are allowed to vary by industry.[18] The standard errors of the parameters have been corrected for autocorrelation and heteroscedasticity using the procedure of Newey and West (1987).

As discussed in the previous section, three specifications are considered: equation (6a), equation (6b) with growth of average hours worked included in the aggregate input measure, and equation (6b) with growth in average hours worked excluded. To save space, Table 3 shows these three specifications only for the United States.[19] The results are shown for groups of industries, as the time-series dimension (21 observations) is too short for reliable inference at the industry level; indeed, for some individual industries very large, very small and even negative returns to scale are found (see Appendix Table A3).

The first column of results in Table 3 shows that, without a utilization proxy, returns to scale are significantly greater than 1 at the level of the market economy and in durable manufacturing. By adding the growth of average hours worked, the returns-to-scale estimates go down in nearly all industry groups, and they become insignificant for the market economy and the non-farm, non-mining market economy. However, the utilization proxy is significantly different from zero only for the market economy. The exclusion of average hours worked from aggregate input growth raises the utilization coefficients, so that they are significantly different from zero for all industry groups except services.

To see the extent to which the results in Table 3 depend on the specific data-set used, Table 4 presents a series of estimates using the data from Basu, Fernald and Kimball (2004), hereafter referred to as BFK. The analysis of BFK is concerned not primarily with the relation between productivity growth and output growth, but instead with the correlation between productivity and input growth. However, their paper presents their most recent estimates of equation (6b), and their data could be acquired for comparison purposes.[20]

Column (1) of Table 4 shows results directly taken from BFK, while column (6) shows comparable results from Table 3. Columns (2)–(5) show, step by step, the effects of moving from BFK's estimation to the estimation in this paper by changing the estimation method, the instruments used, the time period covered and whether or not changes in

TABLE 3
ESTIMATES OF RETURNS TO SCALE AND A CORRECTION FOR UNMEASURED INPUT UTILIZATION FOR THE UNITED STATES

		Ave. hours included		Ave. hours included	
	RTS	RTS	Util.	RTS	Util.
Market economy	1.11*	0.96	0.92*	0.97	1.17*
	(0.05)	(0.09)	(0.36)	(0.09)	(0.34)
Market economy excluding agriculture	1.16*	1.08	0.44	1.09	0.72*
& mining	(0.03)	(0.06)	(0.22)	(0.06)	(0.21)
Durable manufacturing	1.26*	1.17*	0.49	1.18*	0.84*
	(0.05)	(0.08)	(0.35)	(0.08)	(0.33)
Non-durable manufacturing	1.07	0.88	0.77	0.91	0.93*
	(0.06)	(0.15)	(0.47)	(0.15)	(0.44)
Non-manufacturing	0.82	0.73	1.27	0.74	1.49*
	(0.13)	(0.16)	(0.76)	(0.16)	(0.72)
Services	0.99	1.02	– 0.26	1.02	0.13
	(0.07)	(0.08)	(0.37)	(0.08)	(0.35)

Notes:
Table shows parameter estimates from regressions using US data with output growth as the dependent variable and growth of inputs (RTS) as the independent variable and with both growth of inputs (RTS) and growth of average hours worked (Util.) as explanatory variables. For the results labelled 'Ave. hours included', growth in average hours worked is included in growth of inputs, while for 'Ave. hours excluded' this is not the case. Estimation is done for a panel of industries, with industry fixed effects included (not shown) using two-stage least squares with the current value and one lag of the downstream indicator for each industry as instruments. Parameters in the first-stage regression are allowed to vary across industries. Standard errors, consistent for heteroscedasticity and autocorrelation, are shown in parentheses.
*Denotes parameters significantly different from one (RTS) or from zero (Util.) at the 5% level. See Table A3 for definitions of industry groupings

average hours worked are included in aggregate inputs.[21] The table shows that these changes do not have a strong effect on the parameter estimates. When restricting the sample to the post-1979 period, durable manufacturing shows increasing instead of constant returns to scale, but there are no other statistically significant differences. The point estimates for the utilization correction change noticeably from column to column, especially in services, but for the most part this reflects the greater uncertainty surrounding these estimates. Given the stability of the main findings, we now move to the international evidence in Table 5.

A few results stand out in Table 5. First, the evidence on returns to scale is very mixed. Those for France resemble those for the United States, with some significantly increasing returns in manufacturing but returns to scale that are indistinguishable from 1 in the rest of the economy. Germany, though, shows significant increasing returns in all sectors, while all industry groups in the Netherlands have constant returns to scale. When it comes to the proxy for unmeasured input utilization, only the US coefficients are consistently positive and significant in nearly all industry groups. In the other countries, the point estimates suggest that there are both positive and negative effects of extra hours worked on output, but, with the exception of durable manufacturing in Germany, none of the coefficients is significant. This suggests that European firms do not vary the average number of hours worked in response to short-run fluctuations in demand in a

TABLE 4
ESTIMATES OF RETURNS TO SCALE AND A CORRECTION FOR UNMEASURED INPUT UTILIZATION FOR THE UNITED STATES: DIFFERENT VARIANTS USING BFK DATA

	(1)	(2)	(3)	(4)	(5)	(6)
Returns to scale						
Durable manufacturing	1.01	1.05	1.06	1.16*	1.15*	1.18*
		(0.03)	(0.05)	(0.05)	(0.05)	(0.08)
Non-durable manufacturing	0.87	0.86	0.96	0.90	0.90	0.91
		(0.08)	(0.06)	(0.09)	(0.10)	(0.15)
Services	1.16	0.98	0.99	0.92	0.92	1.02
		(0.06)	(0.06)	(0.10)	(0.10)	(0.08)
Utilization correction						
Durable manufacturing	1.34*	0.82*	0.53*	0.54*	0.92*	0.84*
	(0.22)	(0.17)	(0.15)	(0.18)	(0.18)	(0.33)
Non-durable manufacturing	2.13*	1.92*	0.54*	0.94*	1.16*	0.93*
	(0.38)	(0.51)	(0.20)	(0.42)	(0.41)	(0.44)
Services	0.64	0.62	0.67	2.29	2.57	0.13
	(0.34)	(0.61)	(0.61)	(1.36)	(1.35)	(0.35)

Notes:
BFK refers to Basu, Fernald and Kimball (2004).
*Denotes parameters significantly different from 1 (returns to scale) or from 0 (utilization) at the 5% level.
Col. (1): Results from BFK, Table 1, using Hall–Ramey instruments, period 1949–1996, average hours included. For returns to scale parameters, the means of industry-specific estimates for each group are shown. As a result, no standard errors are shown.
Col. (2): Hall–Ramey instruments, period 1949–96, estimation method as in Table 3, average hours included.
Col. (3): Downstream indicators, period 1949–96, estimation method as in Table 3, average hours included.
Col. (4): Downstream indicators, period 1979–96, estimation method as in Table 3, average hours included.
Col. (5): Downstream indicators, period 1979–96, estimation method as in Table 3, average hours excluded.
Col. (6): Results from Table 3, downstream indicators, period 1979–2001, average hours excluded.

systematic way. A possible explanation is that adjustment instead takes place by reducing the number of (temporary) workers. A more complete answer would require further research, but I now turn to the question of whether the estimated models help reduce the cyclicality of the productivity residuals.

Cyclicality of productivity residuals

Basu and Fernald (2001) estimate a similar model as BFK and use the results to look at the cyclicality of productivity growth. As is the case with traditional growth accounting, productivity growth is a residual. Basu and Fernald show that the traditional Solow residual (assuming constant returns to scale and well measured inputs) is positively correlated with output growth while the productivity residuals from their regression are not.[22] BFK show that the correlations between output and productivity residuals are lower than the correlations between the Solow residual and output growth, but the correlations remain significantly positive in a number of sectors.

Although most of the estimates show returns to scale that are statistically indistinguishable from constant and few significant utilization effects, the point estimates can be used to see whether these can decrease the observed procyclicality. To compare the results in this paper with those in Basu and Fernald (2001), it is useful to start the analysis at the level of the aggregate economies. As Basu and Fernald discuss, aggregate

TABLE 5

RETURNS TO SCALE AND A CORRECTION FOR UNMEASURED INPUT UTILIZATION, EXCLUDING AVERAGE HOURS WORKED FROM AGGREGATE INPUT GROWTH

	Returns to scale			
	France	Germany	Netherlands	USA
Market economy	1.12	1.16*	1.02	0.97
	(0.07)	(0.04)	(0.05)	(0.09)
Market economy excluding agriculture & mining	1.12	1.16*	1.04	1.09
	(0.06)	(0.04)	(0.04)	(0.06)
Durable manufacturing	1.17*	1.11*	1.03	1.18*
	(0.07)	(0.05)	(0.08)	(0.08)
Non-durable manufacturing	1.32*	1.14*	1.03	0.91
	(0.10)	(0.06)	(0.08)	(0.15)
Non-manufacturing	0.93	1.18*	0.88	0.74
	(0.10)	(0.06)	(0.11)	(0.16)
Services	0.89	1.20*	0.99	1.02
	(0.09)	(0.06)	(0.08)	(0.08)
	Utilization correction			
Market economy	– 0.31	0.31	0.10	1.17*
	(0.47)	(0.18)	(0.12)	(0.34)
Market economy excluding agriculture & mining	– 0.21	0.29	– 0.02	0.72*
	(0.47)	(0.18)	(0.08)	(0.21)
Durable manufacturing	– 0.81	0.77*	– 0.20	0.84*
	(0.53)	(0.23)	(0.22)	(0.33)
Non-durable manufacturing	0.71	0.24	0.05	0.93*
	(0.45)	(0.27)	(0.13)	(0.44)
Non-manufacturing	– 0.71	– 0.08	0.50	1.49*
	(0.68)	(0.28)	(0.26)	(0.72)
Services	– 0.68	– 0.42	0.17	0.13
	(0.67)	(0.32)	(0.16)	(0.35)

Notes:
Table shows parameter estimates from a regression with output growth as the dependent variable and growth of inputs and growth of average hours worked as independent variable. The growth of inputs is modified to exclude growth in average hours worked. Parameters are estimated for a panel of industries, with industry fixed effects included (not shown). Parameters are estimated using two-stage least squares with the current value and one lag of the downstream indicator for each industry as instruments. Parameters in the first-stage regression are allowed to vary across industries. Standard errors, consistent for heteroscedasticity and auto correlation, are shown in parentheses.
*Denotes parameters significantly different from 1 (returns to scale) or 0 (utilization correction) at the 5% level.
See Table A3 for definitions of industry groupings.

productivity growth is calculated by aggregating industry-level residuals. However, since these residuals are based on a gross output production function, an adjustment needs to be made to deal with the double counting of output. Following Rotemberg and Woodford (1995), a value-added-based productivity growth measure can be calculated as

$$\text{(8)} \qquad \mathrm{d}A_i^V = \frac{\mathrm{d}A_i}{1 - \gamma s_{Mi}},$$

TABLE 6

CORRELATION BETWEEN OUTPUT AND PRODUCTIVITY GROWTH FOR INDUSTRY GROUPS UNDER VARIABLE RETURNS TO SCALE AND CORRECTED FOR UNMEASURED UTILIZATION

	France	Germany	Netherlands	USA
Output/productivity correlations, industry groups				
Market economy	0.30	0.27	0.55*	0.42
Market economy excluding agriculture & mining	0.36	0.05	0.26	0.37
Durable manufacturing	0.37	0.26	0.54*	0.12
Non-durable manufacturing	0.30	0.21	0.81*	0.80*
Non-manufacturing	0.57*	0.66*	0.77*	0.60*
Services	0.59*	0.57*	0.58*	0.67*
No. of industries with correlation significantly different from zero (5% level)				
Market economy (24 industries)	9	6	14	7
Market economy excluding agriculture & mining (22)	10	4	11	4
Durable manufacturing (6)	0	1	3	1
Non-durable manufacturing (7)	1	0	2	3
Non-manufacturing (11)	7	5	10	7
Services (9)	6	3	7	4

Note:
Top panel: correlations between output growth and technical change residuals from the regressions in Table 4. *Denotes a correlation significantly different from zero at the 5% level.
Bottom panel: number of industries with significantly non-zero correlations. See Table A3 for definitions of industry groupings.

where dA_i is the residual from either (6a) or (6b). This residual is adjusted using the returns-to-scale estimate γ and the share of materials in gross output s_{Mi} of the industry in question. The value-added-based productivity residuals can then be aggregated across industries using the industry's share in value added and correlated with value-added growth for broad sectors or the market economy. This procedure is a more general form of Domar (1961) aggregation, taking non-constant returns into account. Table 6 shows the correlations between output growth and productivity residuals for all the industry groups from Table 5. In all cases the residuals are from the full model, including both variable returns to scale and hours worked as a proxy for input utilization.

As the top panel of Table 6 shows, in all countries but the Netherlands market economy productivity is not significantly correlated with output growth, and this finding holds for (most of) manufacturing in the same set of countries. However, productivity in non-manufacturing is still strongly procyclical in all countries, which casts some doubt on the scope of the Basu–Fernald (2001) results.[23] These doubts become even stronger when we look at the cyclicality of individual industries. Although there are only 21 observations per industry, Hart and Malley (1999) have shown that in general there is important heterogeneity in the cyclicality of productivity across industries, making it an important issue to examine.

The bottom panel of Table 6 shows the number of industries for which the correlation is significantly different from zero, with the total number of industries in the group. In most groupings a considerable fraction of industries has a significantly positive correlation, despite the fact that the cyclicality for the aggregate sector has disappeared in many cases. Furthermore, Appendix Table A4 shows that this finding remains even when allowing for all coefficients to vary by industry. The share of industries with significantly positive correlations is also higher in services than in manufacturing, which is consistent

TABLE 7

SHARE OF US INDUSTRIES WITH SIGNIFICANTLY POSITIVE CORRELATION BETWEEN OUTPUT AND PRODUCTIVITY GROWTH FOR VARIOUS SPECIFICATIONS

Specification	Market economy	Market economy excl. agriculture & mining
Baseline (downstream indicators, industry dummies)	46%	36%
Hall–Ramey instruments (industry dummies)	58%	55%
BFK productivity residuals		38%
BFK data, downstream industries, 1979–96, ave. hours excluded		34%
Single constant (downstream indicators)	46%	32%
Time dummies (downstream indicators)	50%	32%
Industry and time dummies (downstream indicators)	71%	59%

Notes:
Shows percentage of US industries where the productivity residual is significantly positively correlated with output growth. Different coefficients are estimated for durable manufacturing, non-durable manufacturing and non-manufacturing or services. The number of industries with significant correlations is added across sectors and divided by the total number of industries in the sector (24 for the market economy, 22 if agriculture and mining are excluded). For the specifications based on the BFK data (rows 3 and 4), the total number of industries is 29.

with the significant correlations for the sector as a whole, as well as the lack of significant utilization effects in the United States.

To further evaluate the robustness of this finding, Table 7 shows the share of industries with significantly positive correlations in the United States for a number of alternative specifications.[24] The setup is the same as for Table 6: coefficients are allowed to vary across broad industry groups, but for brevity the number of significant correlations is added across groups. So the 46% in the first cell of the table is calculated by adding the one durable manufacturing industry, three non-durables and seven non-manufacturing industries, with significant positive correlations and dividing by the maximum of 24 industries in the market economy. Six different specifications are considered. First, the Hall–Ramey instruments, as discussed in Table 2, are used instead of the downstream indicators. Next, the productivity residuals from BFK are used, and then in the fourth row the productivity residuals from column (5) in Table 4 are used.[25] The last three specifications first drop the industry dummies and include only a single constant, next include year dummies, and finally include both year and industry dummies. The main result is that, irrespective of the specification, a noticeable fraction of industries still shows significantly positive correlations between output growth and the productivity residuals. Although not shown, the significant correlations can be found across all industry groups. In all, this raises serious questions about the ability of the Basu–Fernald (2001) model to explain the observed cyclicality of productivity growth, especially when looking at individual industries and European countries.

V. CONCLUSIONS

It is important to understand why productivity growth is procyclical, both for understanding the business cycle and for measuring productivity. This paper extends the current literature by analysing not only the United States but also France, Germany and the Netherlands, using an up-to-date and internationally consistent industry data-set covering the entire market economy. The analysis follows along similar lines as in Basu and Fernald (2001): production functions are estimated to allow for non-constant returns to scale and unmeasured input utilization, and the cyclicality of the productivity residuals is examined.

While this study is not the first to cover countries outside the United States, none of those other studies have tested whether the estimated models lead to lower correlation between growth of output and the technology residual from the production model estimates as in Basu and Fernald (2001). Furthermore, I have introduced industry-specific demand-side instruments to better correct for simultaneity bias in estimation than with the more traditional aggregate demand-side variables such as oil price changes.

The results cast doubt on the success of the Basu–Fernald (2001) model in accounting for procyclical productivity growth. At the level of the market economy and in most of manufacturing, the correlation between the productivity residuals from the production function estimates and output growth is no longer significant in France, Germany and the United States, but in services productivity growth is still significantly procyclical. Furthermore, the results show that even in France, Germany and the United States a sizeable fraction of industries still has procyclical productivity residuals, and this is especially noticeable in services. Since the underlying theoretical model tries to explain firm behaviour, the failing of the empirical model for many industries is worrisome.

This is not the first paper to cast doubt on the popular explanations for procyclical productivity growth. Basu and Fernald (1997) raised questions about the prevalence of increasing returns to scale in the United States, while Sbordone (1997) showed that the dynamic behaviour of output and productivity is not consistent with externalities. The main justification for looking at input utilization is the presence of adjustment costs for labour and capital. However, in recent work using annual industry data, Hall (2004) found evidence against important adjustment costs to labour and capital over a time horizon of a year or more. As a result, it is not clear whether firms will vary utilization very much in response to shocks at the frequency for which we observe the data. The finding of Baily *et al.* (2001) that long-run downsizing plants show more procyclicality during downturns than upsizing plants also argues against input utilization: downsizers would have far fewer incentives to hoard labour or conserve capital.

This paper provides some direct evidence that unmeasured input utilization is unable to account for procyclical productivity growth in many settings. One possible reason for this may be that average hours worked per person is not a very good proxy for unmeasured input utilization in most industries, especially outside the United States and in the services sector. It is not clear whether this can be attributed to different work practices outside manufacturing and the United States, problems in accurately measuring average hours worked, or a combination of the two.

This raises the question of where to go from here. One avenue might be to try to find better measures for unmeasured input utilization, especially outside manufacturing. The type of customers of an industry (business versus consumers) may be important too, as Hart and Malley (1999) find less evidence of procyclicality in investment goods industries. Further theoretical research may also provide useful new directions for empirical research. Ultimately, firm-level studies, especially extending the work of Baily *et al.* (2001) beyond US manufacturing, may be needed to understand how firms adjust to changing demand.

APPENDIX

Tables A1–A4 give industry-level details and robustness checks of the paper's findings.

TABLE A1

CORRELATION BETWEEN ANNUAL OUTPUT GROWTH AND TOTAL FACTOR PRODUCTIVITY GROWTH AT THE INDUSTRY LEVEL: FRANCE, GERMANY, NETHERLANDS AND THE UNITED STATES, 1979–2001

	France	Germany	Netherlands	USA
Agriculture, forestry & fishing	0.87*	0.92*	0.65*	0.93*
Mining & quarrying	0.82*	0.65*	0.45*	0.32
Food products	0.05	0.32	0.38	0.54*
Textiles, clothing & leather	0.50*	0.63*	0.32	0.39
Wood products	0.44*	0.69*	0.31	0.45*
Paper, printing & publishing	0.30	0.66*	0.64*	0.50*
Petroleum & coal products	0.82*	0.39	0.40	– 0.01
Chemical products	0.82*	0.47*	0.63*	0.58*
Rubber & plastics	0.86*	0.51*	0.37	0.35
Non-metalic mineral products	0.39	0.88*	0.45*	0.65*
Metal products	0.64*	0.59*	0.84*	0.78*
Machinery	0.61*	0.75*	0.77*	0.73*
Electrical and electronic equipment & instruments	0.78*	0.70*	– 0.09	0.78*
Transport equipment	0.68*	0.57*	0.68*	0.35
Furniture & miscellaneous manufacturing	0.68*	0.79*	0.14	0.53*
Electricity, gas & water	0.69*	0.77*	0.42	0.31
Construction	0.58*	– 0.12	0.07	0.67*
Wholesale trade	0.19	0.44*	0.75*	0.35
Retail trade	0.61*	0.19	0.68*	0.17
Hotels & restaurants	0.44*	0.60*	0.74*	0.10
Transport & storage	0.73*	0.54*	0.78*	0.36
Communications	0.31	0.70*	0.73*	0.66*
Financial intermediation	0.80*	0.54*	0.66*	0.26
Business services	0.17	0.71*	0.05	0.35
Market economy	0.64*	0.82*	0.55*	0.77*

Note:
Total factor productivity growth is calculated as the growth of gross output minus the growth of a Törnqvist aggregate of intermediate inputs, capital and labour.

TABLE A2

F-STATISTICS FOR THE FIRST-STAGE REGRESSION OF INSTRUMENTS ON INPUT GROWTH

	France	Germany	Netherlands	USA
Agriculture, forestry & fishing	2.67	13.5*	1.46	1.56
Mining & quarrying	1.08	9.40*	0.29	1.51
Food products	19.4**	3.36	13.8*	11.1*
Textiles, clothing & leather	8.84	18.3**	6.76	5.99
Wood products	2	1.04	2.08	5.6
Paper, printing & publishing	18.9**	26.4**	6.53	16.7**
Petroleum & coal products	1.54	2.4	0.91	1.2
Chemical products	8.63	4.75	6.26	6.69

TABLE A2
CONTINUED

	France	Germany	Netherlands	USA
Rubber & plastics	17.0**	25.5**	14.7**	40.1**
Non-metalic mineral products	15.0**	0.48	2.56	7.63
Metal products	4.47	26.4**	3.13	8.67
Machinery	9.22*	12.9*	21.5**	7.69
Electrical and electronic equipment & instruments	22.5**	18.7**	29.6**	18.6**
Transport equipment	29.3**	11.5*	5.92	7.06
Furniture & miscellaneous manufacturing	0.23	2.97	8.31	5.96
Electricity, gas & water	10.3*	5.25	8.95	1.02
Construction	9.91*	4.71	10.8*	5.03
Wholesale trade	3.08	6.12	28.0**	6.04
Retail trade	12.8*	0.89	19.1**	12.2*
Hotels & restaurants	27.9**	32.4**	12.5*	17.2**
Transport & storage	35.2**	6.74	12.2*	26.8**
Communications	9.93*	4.57	15.7**	20.1**
Financial intermediation	14.4**	4.83	41.9**	7.39
Business services	39.6**	26.8**	53.0**	83.3**
Market economy	13.5*	11.2*	13.6*	13.5*

Note:
*Bias is less than 10% of OLS bias.
**Bias is less than 5% of OLS bias.
Instruments are the current value and one lag of industry-specific downstream indicators.
Significance is determined using critical values from Table 1 of Stock and Yogo (2004). Critical 5% value is 13.91, the 10% value is 9.08.

TABLE A3
RETURNS-TO-SCALE ESTIMATES AT THE INDUSTRY LEVEL, BASED ON EQUATION (6a)

	Ind. group	France	Germany	Netherlands	USA
Agriculture, forestry & fishing	NMFG	1.69	2.1	0.49	1.41
Mining & quarrying	NMFG	1.53	1.65	− 0.23	− 0.73*
Food products	NDUR	0.26*	0.64	− 1	1.93
Textiles, clothing & leather	NDUR	1.64	1.19*	1.02	1.19
Wood products	NDUR	1.09	1.21	0.75	0.99
Paper, printing & publishing	NDUR	1	1.15	1.21	1.12
Petroleum & coal products	NDUR	1.19	1.12	0.93	0.15*
Chemical products	NDUR	1.25	1.3	0.75	1.3
Rubber and plastics	NDUR	1.57*	1.11	1.18	1.1
Non-metalic mineral products	DUR	0.99	1.59*	1.13	1.28
Metal products	DUR	1.19	1.1	1.37*	1.20*
Machinery	DUR	1.14	1.20*	1.28*	1.25*
Electrical and electronic equipment & instruments	DUR	1.37*	1.08	0.94	1.44*
Transport equipment	DUR	1.31*	1.16	1.15*	1.11
Furniture & miscellaneous manufacturing	DUR	2.27	1.41*	0.8	1.44
Electricity, gas & water	SER/NMFG	0.17*	1.09	1.2	0.01
Construction	SER/NMFG	1.18	0.88	0.92	1.11

TABLE A3
CONTINUED

	Ind. group	France	Germany	Netherlands	USA
Wholesale trade	SER/NMFG	1.13	1.25*	1.31	1.07
Retail trade	SER/NMFG	0.76	− 2.31	1.27	1.54
Hotels & restaurants	SER/NMFG	1.22	1.38*	1.1	0.82
Transport & storage	SER/NMFG	1.24	1.24*	1.22	0.84
Communications	SER/NMFG	0.83	0.95	0.86	0.71
Financial intermediation	SER/NMFG	0.55	0.79	0.37	0.63
Business services	SER/NMFG	1.02	1.34*	1.05	1.08
Market economy		1.15*	1.09	1.01	1.11*

Notes:
Ind. group denotes the group in which the industry is included; DUR = durable manufacturing; NDUR = non-durable manufacturing; SER = services; NMFG = non-manufacturing.
Table shows parameter estimates from a regression with output growth as the dependent variable and growth of inputs as independent variable; a constant was also included. Estimation is industry-by-industry using two-stage least squares with the current value and one lag of the downstream indicator for each industry as instruments. Standard errors, consistent for heteroscedasticity and autocorrelation, are shown in parentheses.
*Denotes parameters significantly different from 1 at the 5% level.

TABLE A4
CORRELATION BETWEEN OUTPUT AND PRODUCTIVITY GROWTH, BASED ON INDUSTRY-BY-INDUSTRY ESTIMATES OF RETURNS TO SCALE AND UNMEASURED INPUT UTILIZATION

	France	Germany	Netherlands	USA
Market economy				
Constant returns to scale	0.72*	0.82*	0.51*	0.85*
Variable returns to scale	0.17	0.37	− 0.00	0.25
Variable returns to scale and utilization correction	0.04	0.12	− 0.10	− 0.02
No. of market industries with correlation significantly different from zero (5% level)				
Constant returns to scale	18	20	14	13
Variable returns to scale	11	9	12	8
Variable returns to scale & utilization correction	5	8	8	5

Note:
Correlations between output growth and technical change residuals.
*Denotes a correlation significantly different from zero at the 5% level. The definitions of productivity residuals are similar to Table 5, but in this table the parameters are allowed to vary for each industry.

ACKNOWLEDGMENTS

I would like to thank Michela Vecchi (National Institute of Economic and Social Research), Robert McGuckin (Conference Board), Bart van Ark (University of Groningen), Marcel Timmer (University of Groningen), Silvia Sgherri (European Central Bank), Jakob de Haan (University of Groningen), participants at the EABCN workshop on 'Productivity and the Business Cycle' and two anonymous referees for helpful comments and suggestions. The help of John Fernald (Federal Reserve Bank of San Francisco) in providing data is also gratefully acknowledged.

NOTES

1. See Basu and Fernald (2001) for a more extensive overview of these explanations; they also include reallocation of resources across sectors as an explanation at the aggregate level. As the focus of this chapter is mostly on the limits of their model at the industry level, it is not discussed any further here.
2. Increases in government expenditure increase (future) taxes, and thereby reduce labour income and hence labour supply. However, increases in government expenditure also increase output and thereby labour supply. Under imperfect competition the former effect dominates the latter, leading to a larger effect of government expenditure increases on output than on employment; see the survey by Rotemberg and Woodford (1995).
3. The literature on short-run externalities is rather unclear about the exact nature of these spillovers. Long-run externalities are generally related to knowledge spillovers, but to explain short-run externalities the authors at most state that 'thick markets' are responsible; in other words, more activity in one market 'spills over' to other markets. See Bartelsman *et al.* (1994) for a discussion.
4. See e.g. Hall (1988, 1990); Roeger (1995); Oliveira Martins *et al.* (1996); Basu and Fernald (1997) and Diewert and Fox (2004) on returns to scale and markups. Markups and returns to scale are comparable as economic profits are generally modest. See Caballero and Lyons (1990, 1992); Bartelsman *et al.* (1994); Sbordone (1997) and Vecchi (2000) on externalities. See e.g. Berndt and Fuss (1986); Basu and Kimball (1997); Burnside *et al.* (1995); Burnside (1996); Hart and Malley (1996); Vecchi (2000); Basu and Fernald (2001) and Basu *et al.* (2001) on labour hoarding and correcting for unmeasured input utilization. Finally, Basu and Fernald (2001) and Basu *et al.* (2001) stress the importance of reallocations between sectors.
5. Marchetti and Nucci (2005) use firm-level data for Italy to look also at correlations of productivity residuals and the cycle, but their approach is somewhat different.
6. Similar types of model are presented in many of the referenced papers. A model that leads to the same estimating equation is given in Basu and Fernald (2001).
7. Another theoretical mechanism commonly used is to assume that if capital is used more intensively machinery wears out more quickly and depreciation is higher (see e.g. Imbs 2003). However, the shift premium fits more closely with the utilization proxy used here. See Basu and Kimball (1997) for a model that explicitly combines both mechanisms.
8. See Hart and Malley (1996) for arguments along these lines.
9. An alternative would be to use constant shares over the full period, but this has only a small impact on the results discussed in Section III.
10. Basu *et al.* (2001, 2004) use the cyclical part of average hours worked instead of the growth in average hours worked. In practice, they estimate close to a linear trend, so only the mean growth of average hours worked is removed, with no impact on parameter estimates.
11. The next section also discusses an adjustment to equation (5) to take this problem into account for growth in average hours worked.
12. Basu *et al.* (2001) also spend considerable effort on including adjustment costs in their output and input measures, calibrated using the estimates of Shapiro (1996). While in theory this has merit, Hall (2004) finds relatively strong evidence against adjustment costs for capital or labour using US industry data. Outside the United States, the evidence is even scarcer so such adjustments are omitted.
13. These instruments are the current value and one lag of the change in the oil price relative to the GDP deflator and the growth of real government spending. The political party of the president is excluded, as it has no straightforward counterpart in other countries and is usually the weakest instrument of the three (e.g. Hall 1988). Similarly, military expenditure is broadened to all government spending for easier cross-country comparability. Monetary policy shocks have also been used sometimes in studies in the United States, but comparable measures are not available for the European countries.
14. *F*-statistics for individual industries in each country are shown in Appendix Table A2.
15. As Basu and Fernald (1997, p. 258) note, the first-stage *F*-statistic of equation (6a) using the Hall–Ramey instruments is around 3 using their data, which is comparable to the results in Table 2.
16. Usually a term reflecting corporate taxes and investment credits is also included in equation (7). However, as Erumban (2004) shows, taxes have only a limited effect on capital input growth, so these terms are omitted here.
17. To be precise, both industry-by-industry and product-by-industry [use] tables are used. Industry-by-industry tables are conceptually to be preferred, but in practice differences will be modest.
18. It would also be efficiency-enhancing to explicitly take into account any cross-sectional dependence of the residuals in a three-stage least squares or GMM procedure. However, the cross-sectional dimension is not large enough to yield reliable estimates. Pesaran (2004) suggests an alternative procedure if the errors have a factor structure, which involves adding the cross-industry (weighted) averages of the dependent and independent variables to the regression. However, in an economic sense this would be a specification that attempts to test for external effects as in Caballero and Lyons (1990, 1992). To avoid such complications, two-stage least squares is used.
19. The full country results are included in the working paper version, which can be found as GGDC Research Memorandum GD-74 at www.ggdc.net.

20. Many thanks go to John Fernald for making these data available.
21. BFK use a GMM procedure to enhance efficiency. The instruments that they use are oil price increases, growth in real defence spending and monetary policy shocks. The monetary policy shocks are available only for the United States, so they are not used in Table 2 when comparing the relevance of the instruments. The relatively modest differences between columns (2) and (3) suggest that these monetary policy shocks are relatively relevant, although first-stage *F*-statistics suggest that downstream indicators still have an advantage.
22. In general, productivity growth from these regressions is equal to the constant plus the residual. However, average productivity growth is not relevant for cyclicality.
23. They show comparable correlations only for the private economy and the overall manufacturing sector.
24. The results for other countries are very similar, and are available upon request from the author.
25. Results for the intermediate specifications are similar.

REFERENCES

ABBOTT, T. A., GRILICHES, Z. and HAUSMAN, J. (1998). Short-run movements in productivity: market power versus capacity utilization. In Z. Griliches (ed.), *Practicing Econometrics: Essays in Method and Application*. Cheltenham: Edward Elgar.

BAILY, M. N., BARTELSMAN, E. J. and HALTIWANGER, J. (2001). Labor productivity: structural change and cyclical dynamics. *Review of Economics and Statistics*, **83**, 420–33.

BARTELSMAN, E., CABALLERO, R. J. and LYONS, R. K. (1994). Customer- and supplier-driven externalities. *American Economic Review*, **84**, 1075–84.

BASU, S. (1996). Procyclical productivity: increasing returns or cyclical utilization? *Quarterly Journal of Economics*, **111**, 719–51.

——— and FERNALD, J. (1997). Returns to scale in US manufacturing: estimates and implications. *Journal of Political Economy*, **105**, 249–83.

——— and ——— (2001). Why is productivity procyclical? Why do we care? In C. R. Hulten, E. R. Dean and M. J. Harper (eds.), *New Developments in Productivity Analysis*, NBER Studies in Income and Wealth, vol. 63, pp. 225–96. Chicago: University of Chicago Press.

——— and KIMBALL, M. (1997), *Cyclical Productivity with Unobserved Input Variation*. NBER Working Paper no. 5915.

———, ——— and SHAPIRO, M. D. (2001). Productivity growth in the 1990s: technology, utilization or adjustment. *Carnegie–Rochester Conference Series on Public Policy*, **55**, 117–65.

BASU, S., FERNALD, J. and KIMBALL, M. (2004), *Are Technology Improvements Contractionary?* NBER Working Paper no. 10,592; forthcoming in *American Economic Review*.

BERNDT, E. R. and FUSS, M. A. (1986). Productivity measurement with adjustments for variations in capacity utilizations and other forms of temporary equilibrium. *Journal of Econometrics*, **33**, 7–29.

BURNSIDE, C. (1996). Production function regressions, returns to scale, and externalities. *Journal of Monetary Economics*, **37**, 177–201.

———, EICHENBAUM, M. and REBELO, S. (1995). Capital utilization and returns to scale. In B. S. Bernanke and J. J. Rotemberg (eds.), *NBER Macroeconomics Annual*.

CABALLERO, R. F. and LYONS, R. K. (1990). Internal versus external economies in European industry. *European Economic Review*, **34**, 805–26.

——— and ——— (1992). External effects in US procyclical productivity. *Journal of Monetary Economics*, **29**, 209–25.

COOLEY, T. F. and PRESCOTT, E. C. (1995). Economic growth and business cycles. In T. F. Cooley (ed.), *Frontiers of Business Cycle Research*. Princeton: Princeton University Press.

DIEWERT, W. E. and FOX, K. J. (2004). On the estimation of returns to scale, technical progress and monopolistic markups. Downloadable from http://www.econ.ubc.ca/discpapers/dp0409.pdf

DOMAR, E. (1961). On the measurement of technical change. *Economic Journal*, **71**, 710–29.

ERUMBAN, A. A. (2004), Twenty ways to aggregate capital: does it really matter for a study of economic growth? Paper given at the 28th conference of the International Association for Research in Income and Wealth, Cork, Ireland, 22–28 August 2004.

FRAUMENI, B. M. (1997). The measurement of depreciation in the US National Income and Product Accounts. *Survey of Current Business*, **77/7**, 7–23.

GGDC (2003), *60-industry database, October 2003*. Downloadable from www.ggdc.net

GORDON, R. J. (1993). The jobless recovery: does it signal a ne era of productivity-led growth? *Brookings Papers on Economic Activity*, **24**, 271–316.

——— (2000). Does the new economy measure up to the great inventions of the past? *Journal of Economic Perspectives*, **14**, 49–77.

HALL, R. E. (1988). The relation between price and marginal cost in US industry. *Journal of Political Economy*, **96**, 921–47.

——— (1990). Invariance properties of Solow's productivity residual. In P. A. Diamond (ed.), *Growth/Productivity/Employment: Essays to Celebrate Bob Solow's Birthday*. Cambridge, Mass.: MIT Press.

——— (2004). Measuring factor adjustment costs. *Quarterly Journal of Economics*, **119**, 899–927.

HART, R. E. and MALLEY, J. R. (1996). Excess labour and the business cycle: a comparative study of Japan, Germany, the United Kingdom and the United States. *Economica*, **63**, 325–42.

——— and MALLEY, J. R. (1999). Procyclical labour productivity: a closer look at a stylized fact. *Economica*, **66**, 533–50.

IMBS, J. M. (2003). Technology, growth and the business cycle. *Journal of Monetary Economics*, **44**, 65–80.

INKLAAR, R., O'MAHONY, M. and TIMMER, M. P. (2005). ICT and Europe's productivity performance: industry-level growth account comparisons with the United States. *Review of Income and Wealth*, **51**, 505–36.

JORGENSON, D. W., HO, M. and STIROH, K. J. (2005). Growth of US industries and investments in information technology and higher education. In C. Corrado, J. Haltiwanger and D. Sichel (eds.), *Measuring Capital in a New Economy*. Chicago: University of Chicago Press.

MARCHETTI, D. J. and NUCCI, F. (2005). Price stickiness and the contractionary effect of technology shocks. *European Economic Review*, **49**, 1137–63.

NEWEY, W. K. and WEST, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation-consistent covariance matrix. *Econometrica*, **55**, 703–8.

OLIVEIRA MARTINS, J., SCARPETTA, S. and PILAT, D. (1996). *Markup Ratios in Manufacturing Industries: Estimates for 14 OECD Countries*. OECD Economics Department Working Paper no. 162.

PESARAN, M. H. (2004). *Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure*. Downloadable from http://www.econ.cam.ac.uk/faculty/pesaran/CDlargePesaran.pdf

ROEGER, W. (1995). Can imperfect competition explain the difference between primal and dual productivity measures? Estimates for US manufacturing. *Journal of Political Economy*, **103**, 316–30.

ROTEMBERG, J. J. and WOODFORD, M. (1995). Dynamic general equilibrium models with imperfectly competitive product markets. In T. F. Cooley (ed.), *Frontiers of Business Cycle Research*. Princeton, NJ: Princeton University Press.

SBORDONE, A. M. (1997). Interpreting the procyclical productivity of manufacturing sectors: external effects or labor hoarding. *Journal of Money, Credit and Banking*, **29**, 26–45.

SHAPIRO, M. D. (1996). Macroeconomic implications of variation in the workweek of capital. *Brookings Papers on Economic Activity*, **2**, 79–119.

SHEA, J. (1993). The input–output approach to instrument selection. *Journal of Business and Economic Statistics*, **11**, 145–55.

STOCK, J. H. and YOGO, M. (2004). *Testing for Weak Instruments in Linear IV Regression*. Downloadable from http://ksghome.harvard.edu/~JStock/ams/websupp/rfa_7.pdf

TIMMER, M. P. and VAN ARK, B. (2005). IT in the European Union: a driver of productivity divergence. *Oxford Economic Papers*, **57**, 693–716.

VECCHI, M. (2000). Increasing returns, labour utilization and externalities: procyclical productivity in the United States and Japan. *Economica*, **67**, 229–44.