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CYCLICAL PRODUCTIVITY IN EUROPE AND THE UNITED STATES, EVALUATING THE EVIDENCE ON RETURNS TO SCALE AND INPUT UTILIZATION

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ABSTRACT

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

This paper studies procyclical productivity growth at the industry level in the U.S. and in 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 U.S. economy, unmeasured input utilization seems to explain procyclical productivity. However, this correction still leaves one in three U.S. industries with procyclical productivity. This failure of the model can also be seen in Europe and is mostly concentrated in services industries.

JEL Classification: D24, E32 and O47
Keywords: cyclical productivity, input utilizations, instrumental variables and returns to scale

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I. *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 technical change. 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 dataset for three European countries and the United States.

This paper is the first to directly test whether the Basu-Fernald (2001) model is similarly successful in reducing output-technology correlations outside the U.S. and to what extent 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 U.S. 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 U.S. industries still show significant procyclical productivity growth.

In France and Germany the aggregate cyclicality decreases as in the U.S., but the failure of the Basu-Fernald (2001) model for many industries can also be seen in France, Germany and the Netherlands. One possible reason for this finding is that the proxy for unmeasured input utilization, hours worked per person, is not very relevant in Europe and in services 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 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, Bartelsman and Haltiwanger (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, using 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 stylised facts of cyclical productivity are introduced alongside the most important proposed explanations for this phenomenon from the literature. The next section presents the theoretical framework for the analysis. Section IV discusses the estimation framework and the data used in this study. Results are shown in Section V, first with regards to the production function estimates, while the second part focuses on the cyclicality of the technical change residual. Section VI summarizes and discusses some of the implications of the results.

II. BACKGROUND

One of the more robust stylised facts in the macroeconomic literature is that output and productivity move together in the short run. Table 1 illustrates this fact 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, we focus on these correlations mainly because Basu and Fernald (2001) do so.

Table 1, Correlation between total factor productivity and GDP growth, Europe and the U.S., 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*	US	0.89*
Ireland	0.68*		

Notes: * denotes a correlation significantly different from zero at the 5% level
Source: Timmer, Ypma and van Ark (2003)

Three explanations for cyclical productivity are popular in the literature: 1) procyclical technology shocks, 2) increasing returns to scale and 3) unmeasured input utilization.[1] The first explanation is the most obvious: if technology shows 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 lower output per unit of input. If this is related to imperfect competition, changes in government expenditure can generate business cycles (see the survey by Rotemberg and Woodford, 1995). Increasing returns can also be due to external effects, implying that linkages between firms and industries are important and need to be modelled.[2] If the third explanation holds, firms adjust not only measured inputs such as capital and labour, but also unmeasured inputs like the workweek 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 due to lower transaction costs in Japan, and this will affect the dynamics of the economies in question.

Different explanations for cyclical productivity also have different implications for the interpretation of productivity growth as technical change. Researchers such as Gordon (2000) try to separate the 'cyclical' from the 'structural' part of productivity growth. This approach might have some merit if unmeasured input utilization were the leading cause for procyclical productivity growth. However, as Basu and Fernald (2001) argue, if increasing returns to scale and reallocations are important, cyclical productivity is a 'structural' phenomenon in that 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 technical change.

There is an extensive literature that tries to distinguish between the various explanations of procyclical productivity.[3] Most of these papers focus on the U.S., but there is international evidence as well, most notably from Caballero and Lyons (1990), Oliveira Martins, Scarpetta and Pilat (1996) and Vecchi (2000). But although this paper is not the first to look at returns to scale and unmeasured input utilization for countries outside the U.S., the international evidence so far is confined to production function and related estimates. However, in a recent study for the U.S., Basu and Fernald (2001) use production function estimates to evaluate whether these estimates can actually decrease the correlation between output and the technology residual they estimate. From 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 can explain the cyclicality of aggregate U.S. productivity. In this paper the same approach is chosen to see whether their conclusions extend across industries and other countries as well. First I discuss the production model that lies at the basis of the empirical analysis.

III. A MODEL OF CYCLICAL PRODUCTIVITY

This section discusses a model that is commonly used to study the cyclicality of productivity growth.[4] A firm produces using the following production function:

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

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 effective labour effort *e*. In a model with costless input adjustment, these last variables are irrelevant. However, we assume that labour and capital are quasi-fixed inputs, so in the short run, firms adjust to shocks 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.[5]

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.[6]

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):

(2) $$dX = s_L(de + dH + dN) + s_K(dz + dK) + s_M dM$$

where *d* denotes the percentage growth of the variable and s_x is the two-period average share input *x* in total cost.[7] Note that equation (2) gives the Törnquist 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 only give a valid measure of technical change under constant returns to scale. In general, if we assume neutral technical change, the relationship is as follows:

(3) $$dY = \gamma dX + dA$$

where γ denotes the returns to scale. The problem with estimating equation (3) is that neither effort levels nor the intensity of capital use is usually observed and we can only measure a biased version of equation (2):

(4) $$dX^* = s_L(dH + dN) + s_K dK + s_M dM = dX - s_L de - s_K dz$$

The usual solution to this problem is to find a proxy for input utilization. For the manufacturing sector, a number of researchers have used capacity utilization measures (i.e. Shapiro, 1996). Other studies have proposed energy use or materials use as a proxy for capital utilization (e.g. Burnside *et al.*, 1996). However, such measures are silent on labour utilization or not available outside manufacturing so alternatives are needed. Abbott, Griliches and Hausman (1998) proposed using changes in average hours worked as a proxy for both labour and capital utilization. This was later formalised in the model of Basu and Kimball (1997), whose rationale for this proxy is that if optimising 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:[8]

(5) $$dY = \gamma dX^* + \gamma \xi dH + dA$$

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 goes up, this is partly reflected 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 to adequately 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.[9]

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 equation (5) may indeed pick up the effect of growth in other industries, but as Sbordone (1997) argues, is may just as well 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.[10] A number of econometric issues need to be dealt with first, however.

IV. METHODS AND DATA

Econometric methodology

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

(6a) $$dY_{i,j,t} = \mu_{i,j} + \gamma_j^1 dX^*_{i,j,t} + \varepsilon^1_{i,j,t}$$

(6b) $$dY_{i,j,t} = \mu_{i,j} + \gamma_j^2 dX^*_{i,j,t} + \xi_j dH_{i,j,t} + \varepsilon^2_{i,j,t}$$

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 included as well. One of the main goals of this exercise is to see to what extent European countries show different results from the U.S., so the parameters are allowed to vary by country. Technical change is partly accounted for in the fixed effect and partly ends up in the residuals $\varepsilon_{i,j,t}$. 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 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 equations (6a) and (6b) is that optimising 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 equations (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, this paper uses downstream indicators of industry demand.

Shea (1993) proposed to use 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, Bartelsman and Haltiwanger (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 five percent of intermediate inputs. In constructing the downstream instruments for this paper the same procedure was followed.

It is useful at this point to compare how the various instrument sets fare when confronted with the data (described in more detail in Section III). 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 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.[11] As the table shows, in each country the downstream indicators generate a considerably better fit than the more widely used Hall-Ramey instruments.[12] In quite a number of the 24 industries in this study the simultaneity bias inherent in OLS estimation can be reduced by 90 percent or more by using the downstream indicators, while the Hall-Ramey instruments lead to estimates that are much more biased towards the OLS estimates.[13] Based on these results, we will rely on the downstream indicators to estimate equations (6a) and (6b).

Table 2, Comparing the fit of first-stage regressions of instrument sets on growth of inputs, downstream indicator vs. 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
U.S.	13.6	6.2	9	4

First and third column: Regression of current and one lag of downstream indicator on the growth of inputs. Second and fourth column: Regression of current and one lag of oil price change and growth of real government spending on growth of inputs. Third and fourth column: Number of industries where the first-stage F-statistic exceeds the critical value of 9.08 (third column) and 10.83 (fourth column), using Table 1 of Stock and Yogo (2004).

Data

A quite extensive dataset is needed to estimate the model discussed in Section 2. Data is collected on gross output, intermediate inputs, capital services and labour input for 24 market industries in France, Germany, Netherlands and United States. The period covered is 1979 to 2001.

For data on capital by asset type and hours worked by skill type, this paper relies on previous work (see Inklaar, O'Mahony and Timmer, 2003). For each country, investment data is available for 6 asset types, namely computers, communication equipment, software, non-IT machinery, transport equipment and non-residential structures. For France, Netherlands and the U.S., 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.*, 2003). From those data, capital stocks are estimated using the perpetual inventory method and asset depreciation rates from the U.S. Bureau of Economic Analysis (see Fraumeni, 1997). Given the large differences across countries in how statistical offices account for quality change of ICT products, we use U.S. 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 we estimate rental prices as follows:

$$R_{i,j,t} = r_t + \delta_i - \dot{p}^I_{i,j,t} \tag{7}$$

The rental price 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*), the asset depreciation rate and the investment price change of the asset.[14]

Data on labour input by educational attainment are from national labour force surveys. Due to differences in educational system we do not have the same number of categories in each country, varying between 3 categories in the case of Germany and 7 in the case of 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.* (2003) 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 those cases we either use producer price indexes or we estimate prices based on implicit value added deflators. Intermediate inputs are implicitly estimated based on gross output and value added at constant prices. Apart from 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.* (2003), data for the U.S. from Jorgenson, Ho and Stiroh (2002) are used to estimate that at the aggregate level, self-employed wages are on average 70 percent 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 we use benchmark input-output tables for each of our countries.[15] 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. Although there are no conceptual problems with including final demand as well, we have not done this.

V. 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.[16] 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, namely 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 U.S.[17] 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 one 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 economy, which is in line with the estimates shown in Basu *et al.* (2001). However, the utilization proxy is only significantly different from zero for the market economy.

Table 3, Estimates of returns to scale and a correction for unmeasured input utilization for the United States

		Hours included		Hours excluded	
	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 & mining	1.16*	1.08	0.44	1.09	0.72*
	(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 U.S. data with output growth as the dependent variable and growth of inputs (RTS) as independent variable and with both growth of inputs (RTS) and growth of average hours worked (Util) as explanatory variables. For the results labelled 'hours included', growth in average hours worked is included in growth of inputs, while for '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.

This result stands in contrast to Basu *et al.* (2001), who do find strongly significant parameters for each of the industry groupings from Table 3. For comparison, Appendix Table A4 shows the same estimation results as Table 3, but then using Hall-Ramey instruments instead of downstream indicators. The fact that the utilization effect is not significant in the second specification either, suggests the difference is due to the use of a different dataset.[18] One possible explanation is that their dataset (based on the work of Jorgenson and Stiroh, 2000) contains more industries (33 vs. 24) and more years (31 vs. 21) and as a result their estimates are likely to be more precise.[19] The utilization proxy performs badly in all industry groups, but the negative point estimates for services suggest that growth in average hours worked is even less suitable in services than in manufacturing. The Jorgenson-Stiroh dataset only includes eight non-manufacturing industries and three of these cover utilities and construction, where work practices are probably more comparable with manufacturing industries than with, say, finance or business services. This difference in composition of the dataset might also be important.

As discussed in Section III, including growth in average hours worked both in aggregate inputs and as a separate explanatory variable may bias the estimate of ξ. The final columns of Table 3 show that excluding growth of average worked from aggregate input growth increases the coefficients on the utilization proxy and the estimates are now significant for all industry groups except services. As the parameter estimates as well as the significance levels are now broadly similar to those reported in Basu *et al.* (2001), Table 4 shows the results for this specification for all countries.[20]

Table 4, Returns to scale and a correction for unmeasured input utilization, excluding average hours worked from aggregate input growth

	Returns to scale				*Utilization correction*			
	France	Germany	Netherlands	US	France	Germany	Netherlands	US
Market economy	1.12	1.16*	1.02	0.97	-0.31	0.31	0.10	1.17*
	(0.07)	(0.04)	(0.05)	(0.09)	(0.47)	(0.18)	(0.12)	(0.34)
Market economy excluding agriculture & mining	1.12	1.16*	1.04	1.09	-0.21	0.29	-0.02	0.72*
	(0.06)	(0.04)	(0.04)	(0.06)	(0.47)	(0.18)	(0.08)	(0.21)
Durable manufacturing	1.17*	1.11*	1.03	1.18*	-0.81	0.77*	-0.20	0.84*
	(0.07)	(0.05)	(0.08)	(0.08)	(0.53)	(0.23)	(0.22)	(0.33)
Non-durable manufacturing	1.32*	1.14*	1.03	0.91	0.71	0.24	0.05	0.93*
	(0.10)	(0.06)	(0.08)	(0.15)	(0.45)	(0.27)	(0.13)	(0.44)
Non-manufacturing	0.93	1.18*	0.88	0.74	-0.71	-0.08	0.50	1.49*
	(0.10)	(0.06)	(0.11)	(0.16)	(0.68)	(0.28)	(0.26)	(0.72)
Services	0.89	1.20*	0.99	1.02	-0.68	-0.42	0.17	0.13
	(0.09)	(0.06)	(0.08)	(0.08)	(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 one (returns to scale) or zero (utilization correction) at the 5% level. See Table A3 for definitions of industry groupings.

A few results stand out in Table 4. First of all, the evidence on returns to scale is very mixed. France looks like the U.S. with significantly increasing returns in manufacturing, but returns to scale that are indistinguishable from one 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 U.S. 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 systematic way. A potential explanation can be that adjustment instead takes place by reducing the number of temporary workers. A more complete answer would need further research, but we now turn to the question whether the estimated models help reduce the cyclicality of the technical change residuals.

Cyclicality of technical change

Basu and Fernald (2001) estimate a similar model to Basu *et al.* (2001) and use the results to look at the cyclicality of technical change. As is the case with traditional growth accounting, technical change is a residual. If the regressions from the previous subsection are used to account for non-constant returns to scale and correct for unmeasured input utilization, the residuals from this regression reflect technical change. Basu and Fernald (2001) show that the traditional Solow residual (assuming constant returns to scale and well-measured inputs) is positively correlated with output growth while the residuals from their regression are not.[21]

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 to those in Basu and Fernald (2001), it is useful to start the analysis at the level of the aggregate economies. As Basu *et al.* (2001) discuss, aggregate technical change 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 technical change measure can be calculated as:

(8) $$dA_i^V = \frac{dA_i}{1-\gamma s_{Mi}}$$

In this equation, 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 technical change 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. Table 5 shows the correlations between output growth and technical change for all the industry groups from Table 4. 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.

Table 5, Correlation between output growth and technical change for industry groups under variable returns to scale and corrected for unmeasured utilization

	France	Germany	Netherlands	US
Correlation between output growth and technical change				
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*	0.8*
Non-manufacturing	0.57*	0.66*	0.77*	0.6*
Services	0.59*	0.57*	0.58*	0.67*
Number of market industries with correlation significantly different from zero (5% level)				
Market economy	9/24	6/24	14/24	7/24
Market economy excluding agriculture & mining	10/22	4/22	11/22	4/22
Durable manufacturing	0/6	1/6	3/6	1/6
Non-durable manufacturing	1/7	0/7	2/7	3/7
Non-manufacturing	7/11	5/11	10/11	7/11
Services	6/9	3/9	7/9	4/9

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/number of industries in group. See Table A3 for definitions of industry groupings.

As the top panel of the table shows, in all countries but the Netherlands, market economy technical change is not significantly correlated with output growth, and this finding holds for (most of) manufacturing in the same set of countries. Technical change in non-manufacturing though is still strongly procyclical in all countries, which already casts some doubt on the scope of the Basu and Fernald (2001) results.[22] These doubts become even stronger when looking 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 5 shows first the number of industries where the correlation is significantly different from zero, and the second figure gives the number of industries in the industry group. In most groupings a considerable fraction of industries has a significant positive correlation, even despite the fact that the cyclicality at the aggregate has disappeared in many cases. Furthermore, Appendix Table A6 shows that this finding remains, even when allowing for all coefficients to vary across industries.

To further evaluate the robustness of this finding, Table 6 shows the share of industries with significantly positive correlations in the U.S. for a number of alternative specifications.[23] The set-up is the same as for Table 5: coefficients are allowed to vary across broad industry groups, but for brevity, the number of significant correlations is added across groups. So the 46 percent 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. Five different specifications are considered, first the Hall-Ramey instruments as discussed in Table 2 are used instead of the downstream indicators. Second, the parameters from the Basu *et al.* (2001) study are used to calculate the residuals. 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 technical change residuals. Although not shown, the significant correlations can be found across all industry groups. When using the Basu *et al.* (2001) parameters, the fraction of significant correlations drops to 27 percent but this is still more than could be expected based on random chance. In all, this raises serious questions about the ability of the Basu and Fernald (2001) model to explain the observed cyclicality of productivity growth, especially when looking at individual industries and European countries.

Table 6, Share of U.S. industries with significantly positive correlation between output growth and technical change 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%
Basu *et al.* (2001, Table 1) parameters		27%
Single constant (downstream indicators)	46%	32%
Time dummies (downstream indicators)	50%	32%
Industry and time dummies (downstream indicators)	71%	59%

Notes: shows percentage of U.S. industries where the technical change residual is significantly positively correlated with output growth. Different coefficients are estimated for durable manufacturing, non-durable manufacturing and non-manufacturing or services. The numer 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).

VI. Conclusions

It is important to understand why productivity growth is procyclical, both for understanding the business cycle and for measuring technical change. This paper extends the current literature by not only analyzing the U.S. but also France, Germany and the Netherlands using an up-to-date and internationally consistent dataset covering the entire market economy. The analysis follows along similar lines as Basu and Fernald (2001): production functions are estimated to allow for non-constant returns to scale and unmeasured input utilization. While this study is not the first to cover countries outside the U.S., 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, industry-specific demand-side instruments are introduced to better correct for simultaneity bias in estimation.

The results cast doubt on the success of the Basu and 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 technology residual from the production function estimates and output growth is no longer significant in France, Germany and the U.S., but in services, technical change 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 technology residuals. 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 U.S., 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, Hall (2004) finds strong 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, Bartelsman and Haltiwanger (2001) that long-run downsizing plants show more procyclicality during downturns than upsizing plants also argues against input utilization: downsizers would have much 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 U.S. and in the services sector.

This raises the question where to go from here. One avenue might be to try and 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 Baily, Bartelsman and Haltiwanger's (2001) work beyond U.S. manufacturing, may be needed to understand how firms adjust to changing demand.

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Table A1, Correlation between annual output growth and total factor productivity growth at the industry level, France, Germany, Netherlands and U.S., 1979-2001

	France	Germany	Netherlands	US
Agriculture, forestry and fishing	0.87*	0.92*	0.65*	0.93*
Mining and quarrying	0.82*	0.65*	0.45*	0.32
Food products	0.05	0.32	0.38	0.54*
Textiles, clothing and leather	0.50*	0.63*	0.32	0.39
Wood products	0.44*	0.69*	0.31	0.45*
Paper, printing and publishing	0.30	0.66*	0.64*	0.50*
Petroleum and coal products	0.82*	0.39	0.40	-0.01
Chemical products	0.82*	0.47*	0.63*	0.58*
Rubber and 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 and miscellaneous manufacturing	0.68*	0.79*	0.14	0.53*
Electricity, gas and 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 and 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 growth of gross output minus growth of a Törnquist aggregate of intermediate inputs, capital and labour.

Table A2, F-statistics for the first-stage regression of instruments on input growth

	France	Germany	Netherlands	US
Agriculture, forestry and fishing	2.67	13.5*	1.46	1.56
Mining and quarrying	1.08	9.40*	0.29	1.51
Food products	19.4**	3.36	13.8*	11.1*
Textiles, clothing and leather	8.84	18.3**	6.76	5.99
Wood products	2.00	1.04	2.08	5.60
Paper, printing and publishing	18.9**	26.4**	6.53	16.7**
Petroleum and coal products	1.54	2.40	0.91	1.20
Chemical products	8.63	4.75	6.26	6.69
Rubber and 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 and miscellaneous manufacturing	0.23	2.97	8.31	5.96
Electricity, gas and 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 and 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	US
Agriculture, forestry and fishing	NMFG	1.69	2.10	0.49	1.41
Mining and quarrying	NMFG	1.53	1.65	-0.23	-0.73*
Food products	NDUR	0.26*	0.64	-1.00	1.93
Textiles, clothing and leather	NDUR	1.64	1.19*	1.02	1.19
Wood products	NDUR	1.09	1.21	0.75	0.99
Paper, printing and publishing	NDUR	1.00	1.15	1.21	1.12
Petroleum and coal products	NDUR	1.19	1.12	0.93	0.15*
Chemical products	NDUR	1.25	1.30	0.75	1.30
Rubber and plastics	NDUR	1.57*	1.11	1.18	1.10
Non-metalic mineral products	DUR	0.99	1.59*	1.13	1.28
Metal products	DUR	1.19	1.10	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 and miscellaneous manufacturing	DUR	2.27	1.41*	0.80	1.44
Electricity, gas and water	SER/NMFG	0.17*	1.09	1.20	0.01
Construction	SER/NMFG	1.18	0.88	0.92	1.11
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 and restaurants	SER/NMFG	1.22	1.38*	1.10	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*

Ind. Group denotes the group in which the industry is included. DUR = Durable manufacturing, NDUR = Non-durable manufacturing, SER = Services, NMFG = Non-manufacturing.

Notes: 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 done 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 one at the 5% level.

Table A4, Estimates of returns to scale and a correction for unmeasured input utilization for the United States using Hall-Ramey instruments

	Hall-Ramey instruments				
		Hours included		Hours excluded	
	RTS	RTS	Util	RTS	Util
Market economy	0.92	0.87	0.29	0.89	0.85*
	(0.06)	(0.07)	(0.18)	(0.07)	(0.15)
Market economy excluding agriculture & mining	0.96	0.94	0.17	0.96	0.81*
	(0.06)	(0.07)	(0.16)	(0.07)	(0.13)
Durable manufacturing	1.19*	1.26*	-0.35	1.25*	0.64*
	(0.07)	(0.1)	(0.32)	(0.1)	(0.28)
Non-durable manufacturing	0.92	0.85	0.58	0.88	1.15*
	(0.12)	(0.14)	(0.36)	(0.14)	(0.28)
Non-manufacturing	0.67*	0.65*	0.18	0.63*	0.63*
	(0.08)	(0.09)	(0.23)	(0.09)	(0.2)
Services	0.72*	0.74*	-0.08	0.75*	0.39*
	(0.09)	(0.1)	(0.15)	(0.1)	(0.14)

Notes: Table shows parameter estimates from regressions using U.S. data with output growth as the dependent variable and growth of inputs (RTS) as independent variable and with both growth of inputs (RTS) and growth of average hours worked (Util) as explanatory variables. For the results labelled 'hours included', growth in average hours worked is included in growth of inputs, while for '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 real oil price and real government spending 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.

Table A5, Returns to scale and a correction for unmeasured input utilization, excluding average hours worked from aggregate input growth using Hall-Ramey instruments

	Hall-Ramey instruments							
	Returns to scale				*Utilization correction*			
	France	Germany	Netherlands	US	France	Germany	Netherlands	US
Market economy	0.83	0.97	1.05	0.89	0.58*	0.77*	0.50*	0.85*
	(0.12)	(0.07)	(0.08)	(0.07)	(0.17)	(0.18)	(0.11)	(0.15)
Market economy excluding agriculture & mining	0.87	1.02	1.11	0.96	0.56*	0.64*	0.61*	0.80*
	(0.11)	(0.06)	(0.06)	(0.07)	(0.16)	(0.18)	(0.1)	(0.13)
Durable manufacturing	1.19	1.17*	1.06	1.25*	0.82*	1.31*	0.83*	0.64*
	(0.1)	(0.05)	(0.1)	(0.1)	(0.21)	(0.12)	(0.27)	(0.28)
Non-durable manufacturing	1.19	0.79*	1.21*	0.88	0.66*	0.5	0.65*	1.15*
	(0.11)	(0.1)	(0.09)	(0.14)	(0.2)	(0.33)	(0.12)	(0.28)
Non-manufacturing	0.22*	0.91	1.12	0.63*	0.2	0.28	0.85*	0.63*
	(0.15)	(0.1)	(0.22)	(0.09)	(0.26)	(0.29)	(0.21)	(0.2)
Services	0.32*	1.07	1.14	0.75*	0.21	-0.31	0.46*	0.39*
	(0.15)	(0.09)	(0.1)	(0.1)	(0.27)	(0.28)	(0.16)	(0.14)

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 real oil price and real government spending 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 one (returns to scale) or zero (utilization correction) at the 5% level. See Table A3 for definitions of industry groupings.

Table A6, Correlation between output and technical change, based on industry-by-industry estimates of returns to scale and unmeasured input utilization

	France	Germany	Netherlands	US
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 & utilization correction	0.04	0.12	-0.10	-0.02
Number 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 technical change residuals is similar to Table 6, only in this table the parameters are allowed to vary for each industry.

[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 paper is mostly on the industry results, it is not discussed any further here.

[2] The literature on short-run externalities is generally vague 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 refer to the idea that 'thick markets' are responsible. In other words, more activity in one market 'spills over' to other markets. See Bartelsman, Caballero and Lyons (1994) for a discussion.

[3] See amongst others: Hall (1988, 1990), Roeger (1995), Oliveira Martins, Scarpetta and Pilat (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, Caballero and Lyons (1994), Sbordone (1997) and Vecchi (2000) on externalities. See e.g. Berndt and Fuss (1986), Basu and Kimball (1997), Burnside, Eichenbaum and Rebelo (1995), Burnside (1996), Hart and Malley (1996), Vecchi (2000), Basu and Fernald (2001) and Basu, Fernald and Shapiro (2002) on labour hoarding and correcting for unmeasured input utilization. Finally, Basu and Fernald (2001) and Basu, Fernald and Shapiro (2002) stress the importance of reallocations between sectors.

[4] Similar types of models are presented in many of the referenced papers. A model that leads to the same estimating equation is given in Basu and Fernald (2001).

[5] 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.

[6] See Hart and Malley (1996) for arguments along these lines.

[7] 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 4.

[8] Basu, *et al.* (2001) 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.

[9] The next section also discusses an adjustment to equation (5) to take this problem into account for growth in average hours worked.

[10] Basu, *et al.* (2001) also spend considerable attention to including adjustment costs in their output and input measures, calibrated using the estimates of Shapiro (1986). While in theory this has merit Hall (2004) finds relatively strong evidence against adjustment costs for capital or labor using U.S. industry data. Outside the U.S., the evidence is even scarcer so such adjustments are omitted.

[11] 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.

[12] F-statistics for individual industries in each country are shown in Appendix Table A2.

[13] As Basu and Fernald (1997, p. 258) note, the first stage F-statistic of equation (6a) using the Hall-Ramey instruments is around three using their data, which is comparable to the results in Table 2.
[14] 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.
[15]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.
[16] In principle, it is also efficiency-enhancing to explicitly take into account any cross-sectional dependence of the residuals in a three-stage least squares procedure. However, the estimated covariance matrix is too close to singular 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, simple two-stage least squares is used.
[17] The full countries results are included in the working paper version, which can be found as GGDC Research Memorandum GD-74 at www.ggdc.net.
[18] In addition, some persistently decreasing returns to scale are also apparent, which demonstrates some of the problems with weak instruments.
[19] Another reason is probably that Basu *et al.* (2001) could use system estimation methods to increase efficiency: their standard errors are about half as those reported in Table 3. However, system methods could not be used here, see endnote 16.
[20] Appendix Table A5 shows the same estimation results using Hall-Ramey instruments. These specifications show more significant utilization effects, but also significantly decreasing returns to scale.
[21] In general, technical change from these regressions is equal to the constant plus the residual. However, average technical change is not relevant for the cyclicality of technical change.
[22] They show comparable correlations only for the private economy and the overall manufacturing sector.
[23] The results for other countries are very similar, and are available upon request from the author.