# Perspectives on productivity and business cycles in Europe

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# Chapter 5 Cyclical productivity[136]

## *5.1 Introduction*

In the short run, output and productivity tend to move together in many countries and across a wide range of industries.[137] In recent years this observation has gained increased prominence, as each proposed explanation for the observed procyclicality of productivity has important implications for modelling the business cycle and measuring technical change. The goal of this chapter is to evaluate the role of increasing returns to scale and unmeasured input utilization in explaining procyclical productivity growth. This is motivated by the success of the model by Basu and Fernald (2001), who find that these two factors can fully account for cyclical productivity of the aggregate U.S. economy. The analysis also serves as a test for the assumptions of constant returns to scale and well-measured inputs inherent in the growth accounting results presented in the previous chapter.

Although there is a large and growing empirical literature looking at returns to scale and input utilization, the exercise in this chapter is the first to directly test whether the Basu-Fernald (2001) model is similarly successful in reducing output-productivity correlations outside the U.S. and to what extent the model applies 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 eliminate procyclicality in many industries. Even after correcting for possible non-constant returns to scale and unmeasured input utilization, around one quarter of U.S. industries still show significant procyclical productivity growth.

For European countries, the evidence on the Basu-Fernald model is more mixed, with some success at the aggregate level while it again falls short at the industry level. One possible reason for these findings is that the analysis relies on a proxy for unmeasured input utilization, hours worked per person. If the change in

[136] This chapter is largely based on Inklaar (2005). See the acknowledgements for further details.
[137] This effect is distinct from the Verdoorn effect, where larger cumulative output leads to higher productivity through learning-by-doing.

average hours worked is not a good indicator of changes in unmeasured inputs, the explanatory power of the model will fall short. The original arguments for this proxy were largely based on work practices in U.S. manufacturing and this may not be very relevant in Europe and in services industries.

Even though the Basu-Fernald model is far from perfect, it does provide a good opportunity to evaluate the impact of adjustments for variable returns to scale and unmeasured input utilization on measured productivity growth. The main result is that although the estimated growth rates change, the adjustments are not large enough to affect the main stylized facts as presented in the previous chapter. For example, the lead of the U.S. in market services TFP growth after 1995 remains unchanged. This suggests that the standard growth accounting assumptions do not give a misleading picture of productivity growth.

The final finding of this chapter is of a more technical nature, but nevertheless important for the analysis. 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 instruments 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 earlier studies in this literature.

The remainder of this chapter 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 5.4 discusses the estimation framework and the data used. The results are shown in Section 5.5, first with regards to the production function estimates. The next part focuses on the cyclicality of the technical change residual while the final part of the section discusses the sensitivity of the standard TFP growth measure. Section 5.6 summarizes and discusses some of the implications of the results.

## 5.2 Background

One of the more robust stylised facts in the macroeconomic literature is that output and productivity move together in the short run. Table 5.1 illustrates this phenomenon 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 exist, we focus on these correlations mainly because Basu and Fernald (2001) do so.

**Table 5.1 Correlation between annual total factor productivity and GDP growth, Europe and the U.S., 1979-2003**

| | | | |
|---|---|---|---|
| Austria | 0.62* | Italy | 0.54* |
| Belgium | 0.64* | Luxembourg | 0.78* |
| Denmark | 0.47* | Netherlands | 0.48* |
| Finland | 0.78* | Portugal | 0.61* |
| France | 0.7* | Spain | -0.42* |
| Germany | 0.92* | Sweden | 0.61* |
| Greece | 0.82* | UK | 0.55* |
| Ireland | 0.78* | US | 0.75* |

Notes: * denotes a correlation significantly different from zero at the 5% level
Source: GGDC Total Economy Growth Accounting Database (2005a)

Three explanations for cyclical productivity are popular in the literature: 1) procyclical technology shocks, 2) increasing returns to scale and 3) unmeasured input utilization.[138] 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 lower output per unit of input. If these increasing returns are related to imperfect competition, changes in government expenditure can directly lead to procyclical productivity.[139] Increasing returns can also be due to external effects,

[138] 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.

[139] Increases in government expenditure increases (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

implying that output in an industry can affect output in other industries and these effects need to be modelled.[140] If the third explanation holds, firms adjust not only measured inputs such as capital and labour, but also unmeasured inputs like 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 due to lower transaction costs in Japan, which affects the dynamics of the economies in question.

Different explanations for cyclical productivity also have implications for the interpretation of productivity growth as technical change. 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 measure of technical change 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 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 technical change.

There is an extensive literature that tries to distinguish between the various explanations of procyclical productivity.[141] 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) which so far

effect of government expenditure increases on output than on employment; see the survey by Rotemberg and Woodford (1995).

[140] 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 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.

[141] 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 (2001) on labour hoarding and correcting for unmeasured input utilization. Finally, Basu and Fernald (2001) and Basu, Fernald and Shapiro (2001) stress the importance of reallocations between sectors.

is confined to production function and related estimates. In a recent study for the U.S., Basu and Fernald (2001) use production function estimates to evaluate whether these reduce 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 U.S. productivity. In this chapter the same approach is used to analyze whether their conclusions also apply to individual industries and other countries. First, I discuss the production model that underlies the empirical analysis.

## *5.3 A model of cyclical productivity*

This section discusses a model that is commonly used to study the cyclicality of productivity growth.[142] A firm produces according to the following production function:

(5.1) $$Y = F(zK, eHN, M, A).$$

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*.[143] 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, the latter two variables are irrelevant. However, when we assume that labour and capital are quasi-fixed inputs, firms can adjust to shocks in the short run only by varying average hours worked, labour effort and the intensity of capital use. Following Basu and Fernald (2001), we think of *z* as being determined by the number of work shifts. Higher intensity of capital use is costly due to a shift premium.[144]

The firm can pay its workers more in order to ensure higher effort levels, given the number of hours worked per worker. If pay is raised immediately, labour compensation could be used as an indicator of labour utilization. However, if the extra compensation is by way of better promotion chances or when it is spread out

[142] 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).

[143] In this concept, gross output is the output concept instead of value added as in Chapter 4. The reason is that while this choice is not crucial for analyzing TFP growth, it does affect the econometric analysis that follows.

[144] 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.

over several years, it will not fully show up in the labour compensation figures of a single year. The level of effort can be interpreted directly as the intensity of work, but an employee might also divide his time between productive work and training or other learning activities. In the latter case, the firm might respond to a positive demand shock by shifting workers from non-productive to productive work without having to pay a higher wage immediately. This will be costly because future labour productivity improvements will be lower as less human capital will have been accumulated.[145]

If the firm minimizes costs and is a price taker on the market for factor inputs, 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):

(5.2) $$dX = s_L(de + dH + dN) + s_K(dz + dK) + s_M dM \ ,$$

where *d(.)* is an operator giving the percentage growth of the variable and $s_x$ is the two-year average share input $x$ in total cost.[146] Note that equation (5.2) 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. 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:

(5.3) $$dY = \gamma dX + dA,$$

where $\gamma$ denotes the returns to scale. The problem with estimating equation (5.3) is that neither effort levels nor the intensity of capital use is easily observable so that one only measures a biased version of equation (5.2):

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

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 do not reflect changes in labour utilization and are often not available

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

[146] 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 5.4.

outside manufacturing. Abbott, Griliches and Hausman (1998) propose to use changes in average hours worked as a proxy for both labour and capital utilization. This was formalised in the model of Basu and Kimball (1997). Their 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 with the rise in average hours worked, growth of the latter variable 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 (5.3) can then be written entirely in terms of observable variables:[147]

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

In this equation, $\xi$. is the effect of changes in the utilization proxy on output growth. 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 rationale for using 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. Intermediate inputs make up on average nearly half of all input cost, so one would expect parameter $\gamma$ to adequately pick up any utilization effects as well. Adding changes in intermediate inputs per hour worked as done by Vecchi (2000) may be problematic since intermediate inputs are then included as part of input growth and as a separate explanatory variable.[148]

No explicit role is given to external effects in equation (5.5), 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

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[147] Basu, *et al.* (2001) use the cyclical part of average hours worked instead of the growth in average hours worked. In practice, they estimate this cyclical part using a Hodrick-Prescott filter with a very high smoothing parameter, removing an almost linear trend (see Chapter 3), so only the mean growth of average hours worked is removed, with no impact on parameter estimates.

[148] The next section also discusses an adjustment to equation (5.5) to take this problem into account for growth in average hours worked.

equation (5.5) may indeed pick up the effect of growth in other industries. However, 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 analysis the main focus is on whether returns to scale can explain procyclical productivity growth. Equation (5.5) gives the general estimation framework to analyse the cyclicality of productivity growth.[149] A number of econometric issues need to be dealt with first, however.

## 5.4 Methods and data

### Econometric methodology

We estimate two specifications, one including only the returns to scale parameter $\gamma$, and another specification which includes both returns to scale and the correction for unmeasured input utilization in the form of parameter $\xi$:

(5.6a) $$dY_{i,j,t} = \mu_{i,j} + \gamma_j^1 dX_{i,j,t}^* + \varepsilon_{i,j,t}^1 ,$$

(5.6b) $$dY_{i,j,t} = \mu_{i,j} + \gamma_j^2 dX_{i,j,t}^* + \xi_j dH_{i,j,t} + \varepsilon_{i,j,t}^2 .$$

Output growth of industry *i* in country *j* at time *t* is the dependent variable in both regressions. In (5.6a), measured input growth is the only explanatory variable while in (5.6b) 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 (5.4)). In both specifications a country/industry fixed effect, $\mu_{i,j}$, is included as well. One of the goals of this work is to see to what extent European countries show different results from the U.S., so the parameters are allowed to vary by country. Productivity growth is partly accounted for through the fixed effect and it partly ends up in the residuals $\varepsilon_{i,j}$. The results from Basu and Fernald (2001) suggest that (5.6a) should give returns to scale estimates significantly greater than 1, while (5.6b) should give significantly positive estimates of $\xi$. Note that in equation (5.5), parameter $\xi$ was interacted with

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

$\gamma$. In practice taking this nonlinearity into account has little effect on the results as $\gamma$ is close to one.

One of the objectives of this chapter is to provide comparable estimates to Basu and Fernald (2001). However, in specification (5.6b), 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 (5.6b) is also estimated where input growth, $dX^*$, is calculated excluding the growth in average hours worked.

An important problem with estimating equations (5.6a) and (5.6b) 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 but relevant for input growth to identify $\gamma$ and $\xi$. Most of the literature has relied on relatively weak instruments, such as the world price of oil (Hall, 1988), to estimate variants of equations (5.6a) and (5.6b). Some have even relied on OLS estimates to avoid small-sample bias in IV estimates (e.g. Diewert and Fox, 2004). To lessen the weak instrument problem, downstream indicators of industry demand are used here.

Shea (1993) proposed to use input-output tables to identify industries with close demand links but relatively modest reverse links. If one takes, for example, the metal industry and the car industry, higher output in the latter industry will likely induce higher demand in the former industry. As a result, growth in the car industry is a relevant indicator for output in the metal industry, which satisfies the first requirement for a good instrument. In this case, however, it is not clear whether output changes in the car industry are sufficiently 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 here, the same procedure was followed.

### Data

A quite extensive dataset is needed to estimate the model described in Section 5.3. For the most part, the same industry growth accounting database is used as in the previous chapter, but there are some differences. First, to estimate full production functions, data on gross output and intermediate inputs are collected, in addition to the value added, capital and labour data from Chapter 4. Since the UK does not apply double deflation procedures in most of their value added estimates, no gross output series can be constructed that is consistent with value added, at least at constant prices. The UK is therefore omitted from the analysis in this chapter. A further change is in the calculation of the gross return on capital assets:

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

Instead of an internal rate of return ($R$), an external rate is used here, which is assumed equal to the government bond yield (from the IMF's *International Financial Statistics*). This adaptation was made in order to avoid assuming constant returns to scale in one part of the analysis and estimating those same returns later on.

Finally, information is collected 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 either producer price indexes are used or price indexes are estimated based on implicit value added deflators. Intermediate inputs at constant prices are implicitly estimated based on gross output and value added at constant prices.

To construct the downstream indicator for each country, information is needed on deliveries by industry $x$ to industry $y$. Benchmark input-output tables are used for each of the countries.[150] 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 GGDC 60-industry database and then aggregated to the level of the 25 market industries covered here.

## 5.5 Results

First of all, it is useful at this point to compare how the various instrument sets perform when confronted with the data. As shown by Stock and Yogo (2004), the F-statistic from the first-stage regression where the endogenous variable is explained by

[150] 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.

the instruments, is a useful statistic to test for instrument weakness.[151] The first column of Table 5.2 shows the average F-statistic across industries based on the first-stage regressions that aim to explain (measured) input growth by the current value and one lag of the downstream indicator for each industry in each country. The second column shows the same results from regressions with the so-called 'Hall-Ramey' instruments as explanatory variables.[152] As the table shows, in each country the downstream indicators generate a considerably better fit than the more widely used Hall-Ramey instruments.[153] As the last two columns show, in many of the 25 industries used here, 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.[154] Based on these results, we may confidently rely on the downstream indicators to estimate equations (5.6a) and (5.6b).

**Table 5.2 Comparing the fit of first-stage regressions explaining input growth, 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 | 15.8 | 6.7 | 13 | 3 |
| Germany | 11.9 | 3.5 | 12 | 1 |
| Netherlands | 14.6 | 4.7 | 12 | 1 |
| U.S. | 13.2 | 5.7 | 8 | 2 |

First and third column: 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 column: Regression ith 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 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).

[151] To be precise, this is the F-test of joint significance of the explanatory variables, or the explained sum of squares over the residual sum of squares, corrected for degrees of freedom.
[152] 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.
[153] F-statistics for individual industries in each country are shown in Appendix Table A2.
[154] 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 5.2.

## Production function estimates

In this section, the estimation results from equations (5.6a) and (5.6b) 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.[155] 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 (5.6a), equation (5.6b) with growth of average hours worked included in the aggregate input measure and equation (5.6b) with growth in average hours worked excluded from the aggregate inputs. Table 5.3 shows the estimates of returns to scale based on the first specification. Estimates that are significantly different from one (constant returns to scale) are marked by an asterisk.[156] The results are shown for groups of industries, as the time series dimension (23 observations) is too short for reliable inference at the industry level.[157] Indeed, for individual industries some very large, very small and even negative returns to scale are found (see Appendix Table 5.A3). As Table 5.3 shows, there is evidence of increasing returns to scale in each of the countries, with significant returns in particular for the market economy as a whole and in durable manufacturing. Excluding agriculture and mining tends to increase the parameter estimates. The largest effect of this can be seen in French non-manufacturing, where decreasing returns to scale are found. When looking only at the services sector (by excluding agriculture and mining), returns to scale are insignificantly different from one.

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[155] 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, since the number of industries is larger than the number of years, the estimated covariance matrix is not of full rank. 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.

[156] Appendix Table 5.A4 shows the same results, but using Hall-Ramey instruments instead of downstream indicators. There only durable manufacturing shows significant increasing returns.

[157] The period between 1979 and 2003 is 24 years, but one year is omitted because a lagged value of the downstream indicator is used as an instrument.

**Table 5.3 Estimates of returns to scale to inputs, unadjusted for unmeasured input utilization, for France, Germany, Netherlands and U.S., 1979-2003**

| | France | Germany | Netherlands | U.S. |
|---|---|---|---|---|
| Market economy | 0.98 | 1.12* | 1.01 | 1.13* |
| | (0.06) | (0.04) | (0.07) | (0.04) |
| Market economy excluding agriculture & mining | 1.06 | 1.15* | 1.08* | 1.12* |
| | (0.06) | (0.04) | (0.04) | (0.04) |
| Durable manufacturing | 1.10* | 1.08 | 1.04 | 1.16* |
| | (0.03) | (0.05) | (0.05) | (0.05) |
| Non-durable manufacturing | 0.81 | 1.10 | 1.04 | 0.93 |
| | (0.13) | (0.05) | (0.04) | (0.07) |
| Non-manufacturing | 0.76* | 1.04 | 0.97 | 0.98 |
| | (0.10) | (0.07) | (0.06) | (0.05) |
| Services | 0.88 | 1.04 | 1.06 | 1.01 |
| | (0.09) | (0.08) | (0.06) | (0.04) |

Notes: Table shows parameter estimates from a regression with output growth as the dependent variable and growth of inputs as independent variable. 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 at the 5% level. See Table 5.A3 for definitions of industry groupings.

In earlier work, Basu *et al.* (2001) have shown that adding changes in average hours worked as a proxy for unmeasured input utilization reduces the estimates of returns to scale. Table 5.4 shows the results for the same specification. In most cases, the estimates of returns to scale have decreased compared to Table 5.3, although especially in France and Germany, the differences are relatively small. Indeed, for these two countries, the same industry groups show returns to scale estimates that are significantly different from one. However, in the Netherlands and the U.S., estimates have gone down to such an extent that the constant returns to scale hypothesis is not rejected for any industry group. Still, the U.S. is the only country where the utilization parameter is positive and significant, while the other countries show many negative and sometimes even significantly negative parameter estimates.

**Table 5.4 Returns to scale of inputs with a correction for unmeasured input utilization, 1979-2003**

| | *Returns to scale* | | | |
|---|---|---|---|---|
| | France | Germany | Netherlands | U.S. |
| Market economy | 0.98 | 1.12* | 0.97 | 1.04 |
| | (0.06) | (0.04) | (0.07) | (0.06) |
| Market economy excluding agriculture & mining | 1.06 | 1.15* | 1.05 | 1.03 |
| | (0.05) | (0.04) | (0.04) | (0.06) |
| Durable manufacturing | 1.12* | 1.07 | 1.02 | 1.12 |
| | (0.03) | (0.04) | (0.04) | (0.07) |
| Non-durable manufacturing | 0.80 | 1.10 | 1.01 | 0.87 |
| | (0.13) | (0.05) | (0.05) | (0.08) |
| Non-manufacturing | 0.76* | 1.03 | 0.96 | 0.95 |
| | (0.09) | (0.06) | (0.06) | (0.07) |
| Services | 0.87 | 1.10 | 1.08 | 1.02 |
| | (0.09) | (0.07) | (0.06) | (0.05) |
| | *Utilization correction* | | | |
| Market economy | -0.40 | 0.03 | -0.34* | 0.64* |
| | (0.34) | (0.23) | (0.14) | (0.23) |
| Market economy excluding agriculture & mining | -0.81 | -0.10 | -0.29* | 0.63* |
| | (0.45) | (0.23) | (0.11) | (0.23) |
| Durable manufacturing | -0.37* | 0.17 | -0.26* | 0.29 |
| | (0.11) | (0.18) | (0.08) | (0.26) |
| Non-durable manufacturing | 0.06 | -0.08 | -0.13 | 0.45* |
| | (0.15) | (0.14) | (0.07) | (0.22) |
| Non-manufacturing | -0.01 | -0.40* | 0.08 | 0.30 |
| | (0.25) | (0.20) | (0.14) | (0.27) |
| Services | -0.51* | -0.93* | -0.29* | -0.07 |
| | (0.19) | (0.29) | (0.09) | (0.18) |

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. 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 5.A3 for definitions of industry groupings.

The U.S. results are different from those of Basu *et al.* (2001) who find strongly significantly positive parameters for each of the industry groupings from Table 5.4. For comparison, Appendix Table 5.A5 shows the same estimation results as Table 5.4, using Hall-Ramey instruments as Basu *et al.* (2001) instead of using downstream indicators. As the utilization effect is not uniformly significant in this specification either, it suggests that differences between the Basu *et al.* (2001) results and the results presented in Table 5.4 are due to the use of a different dataset.[158] Specifically, their dataset, which is based on the work of Jorgenson and Stiroh (2000), contains more industries (33 vs. 25) and more years (31 vs. 23). As a result their estimates are

[158] In addition, some persistently decreasing returns to scale are also apparent, which demonstrates some of the problems with weak instruments.

likely to be more precise.[159] Furthermore, even though the utilization proxy performs badly in all industry groups, the negative 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 therefore also be important.

**Table 5.5 Returns to scale of inputs with a correction for unmeasured input utilization, excluding average hours worked from aggregate inputs, 1979-2003**

| | *Returns to scale* | | | |
|---|---|---|---|---|
| | France | Germany | Netherlands | U.S. |
| Market economy | 0.97 | 1.13* | 0.99 | 1.05 |
| | (0.06) | (0.04) | (0.07) | (0.06) |
| Market economy excluding agriculture & mining | 1.06 | 1.16* | 1.07 | 1.04 |
| | (0.05) | (0.04) | (0.04) | (0.06) |
| Durable manufacturing | 1.12* | 1.07 | 1.04 | 1.12 |
| | (0.03) | (0.04) | (0.04) | (0.07) |
| Non-durable manufacturing | 0.80 | 1.10 | 1.04 | 0.88 |
| | (0.13) | (0.05) | (0.05) | (0.08) |
| Non-manufacturing | 0.76* | 1.03 | 1.01 | 0.97 |
| | (0.09) | (0.06) | (0.06) | (0.07) |
| Services | 0.87 | 1.09 | 1.09 | 1.02 |
| | (0.09) | (0.07) | (0.06) | (0.04) |
| | *Utilization correction* | | | |
| Market economy | -0.09 | 0.41 | -0.12 | 0.92* |
| | (0.35) | (0.23) | (0.14) | (0.22) |
| Market economy excluding agriculture & mining | -0.48 | 0.27 | -0.02 | 0.90* |
| | (0.46) | (0.23) | (0.10) | (0.22) |
| Durable manufacturing | -0.06 | 0.50* | -0.00 | 0.64* |
| | (0.11) | (0.18) | (0.08) | (0.25) |
| Non-durable manufacturing | 0.25 | 0.19 | 0.02 | 0.62* |
| | (0.14) | (0.14) | (0.07) | (0.22) |
| Non-manufacturing | 0.25 | -0.03 | 0.36* | 0.61* |
| | (0.25) | (0.18) | (0.12) | (0.25) |
| Services | -0.19 | -0.49 | 0.14 | 0.31 |
| | (0.21) | (0.29) | (0.09) | (0.17) |

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 5.A3 for definitions of industry groupings.

[159] Another reason is probably that Basu *et al.* (2001) could use system estimation methods to increase efficiency; see footnote 155.

As discussed in Section 5.3, including growth in average hours worked both in aggregate inputs and as a separate explanatory variable may bias the estimate of $\xi$. Table 5.5 therefore shows estimation results based on equation (5.6b), but without the growth of average hours worked being included in aggregate inputs.[160] Compared to Table 5.4, the utilization proxy in the U.S. is now also significantly positive in non-manufacturing. Furthermore the estimates of scale returns are almost unchanged, but the significantly negative utilization effects from Table 5.4 have now disappeared. However, except in the case of durable manufacturing in Germany and non-manufacturing in the Netherlands, the estimates on the utilization correction are not significantly positive either. These results suggest 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 could be that adjustments in Europe take place by changing the number of temporary workers instead of average hours per worker. A more complete answer, however, would need further research. Given these estimates though, we turn to the question of whether the estimated models help reduce the cyclicality of the productivity residuals.

### Cyclicality of productivity growth

Basu and Fernald (2001) estimate a similar model to Basu *et al.* (2001) 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. When the regression results presented above are used to account for non-constant returns to scale and corrected for unmeasured input utilization, the residuals from this regression give an adjusted productivity growth measure. This adjusted measure will be a more accurate measure of technical change than TFP growth, but as it is a residual, there may still be other factors included as well. 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.[161]

Although most of the estimates show returns to scale that are statistically indistinguishable from constant and few significant utilization effects, the point

[160] Appendix Table 5.A6 shows the same estimation results using Hall-Ramey instruments. These specifications show a few more significant utilization effects, but also more significantly decreasing returns to scale.

[161] 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.

estimates can be used to see whether these can decrease the observed procyclicality. To compare the results from this analysis to those in Basu and Fernald (2001), it is useful to start at the aggregate level of the market economies. Basu *et al.* (2001) calculate aggregate adjusted productivity growth 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:

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

In this equation, $dA_i$ is the residual from either (5.6a) or (5.6b). This residual is adjusted using the returns to scale estimate $\gamma$ 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. These residuals are then correlated with value added growth for broad sectors or the market economy.

Table 5.6 presents the evidence on the cyclicality of the productivity residuals in three panels. Panel A shows the correlations for the market economy, excluding agriculture and mining for different specifications. Panel B shows correlations for each industry group, based on the residuals of the models presented in Table 5.5. Panel C shows the number of industries within each industry group with significantly positive correlations.

**Table 5.6 Correlation between output growth and adjusted productivity growth for industry groups under variable returns to scale and corrected for unmeasured utilization**

| | France | Germany | Netherlands | U.S. |
|---|---|---|---|---|
| ***A: Output/productivity correlations: different specifications*** | | | | |
| *Market economy excluding agriculture & mining* | | | | |
| Constant returns to scale | 0.64* | 0.71* | 0.44* | 0.51* |
| Variable returns to scale | 0.59* | 0.14 | 0.18 | 0.33 |
| Variable returns to scale & utilization correction | 0.37 | 0.15 | -0.09 | 0.21 |
| | | | | |
| ***B: Output/productivity correlations, industry groups*** | | | | |
| Market economy | 0.73* | 0.16 | 0.67* | 0.20 |
| Market economy excluding agriculture & mining | 0.37 | 0.15 | -0.09 | 0.21 |
| Durable manufacturing | 0.38 | 0.43* | 0.65* | 0.38 |
| Non-durable manufacturing | 0.73* | 0.40 | 0.69* | 0.86* |
| Non-manufacturing | 0.89* | 0.87* | 0.76* | 0.54* |
| Services | 0.79* | 0.62* | 0.32 | 0.50* |
| | | | | |
| ***C: Number of industries with significantly positive correlations (5% level)*** | | | | |
| Market economy (25 industries) | 16 | 7 | 17 | 5 |
| Market economy excluding agriculture & mining (23) | 12 | 6 | 12 | 4 |
| Durable manufacturing (6) | 3 | 2 | 3 | 1 |
| Non-durable manufacturing (7) | 5 | 1 | 2 | 5 |
| Non-manufacturing (12) | 12 | 9 | 9 | 4 |
| Services (10) | 8 | 6 | 7 | 4 |

Note: Top panel: correlations between output growth and technical change residuals from the regressions in Tables 5.3 to 5.5. * denotes a correlation significantly greater than zero at the 5% level. Bottom panel: number of industries with significantly non-zero correlations/number of industries in group. See Table 5.A3 for definitions of industry groupings.

As Panel A shows, at the aggregate level the Basu-Fernald (2001) model reduces the procyclicality of the technical change residuals, with correlations becoming mostly insignificant when allowing for variable returns to scale (Table 5.3) and correlations dropping even further when the utilization proxy is included (Table 5.5). The evidence is more mixed when looking at the main industry groups in Panel B. Although the aggregate correlations have become insignificant, in each of the countries three out of four industry groups still show a significantly positive correlation between output growth and technical change. This result casts some doubt on the scope of the Basu and Fernald (2001) results.[162] These doubts become even stronger when looking at the cyclicality of individual industries. 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.

[162] They show comparable correlations only for the private economy and the overall manufacturing sector.

Panel C of Table 5.6 shows the number of industries where the correlation is significantly different from zero.[163] In most groupings a considerable fraction of industries shows a significant positive correlation, even in cases where the industry group as a whole shows no sign of procyclicality anymore. Appendix Table 5.A7 shows that this finding remains, even when allowing all coefficients to vary across industries.

**Table 5.7 Share of U.S. industries with significantly positive correlation between output growth and adjusted productivity growth for various specifications**

| *Specification* | *Market economy* | *Market economy excl. agriculture & mining* |
|---|---|---|
| Baseline (downstream indicators, industry dummies) | 40% | 43% |
| Hall-Ramey instruments (industry dummies) | 68% | 65% |
| Basu *et al.* (2001, Table 1) parameters | | 26% |
| Single constant (downstream indicators) | 32% | 35% |
| Time dummies (downstream indicators) | 64% | 52% |
| Industry and time dummies (downstream indicators) | 76% | 65% |

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 (25 for the market economy, 23 if agriculture and mining are excluded).

To further evaluate the robustness of this finding, Table 5.7 shows the share of industries with significantly positive correlations in the U.S. for a number of alternative specifications.[164] The set-up is the same as for Table 5.6: coefficients are allowed to vary across broad industry groups, but for brevity, the number of significant correlations is added across groups. For example, the 40 percent in the first cell of the table is calculated by adding the one durable manufacturing industry, five non-durables and four non-manufacturing industries with significant positive correlations, divided by the maximum of 25 industries in the market economy. Five different specifications are considered, first the Hall-Ramey instruments, as discussed in Table 5.2, 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

[163] After the name of the industry grouping, the total number of industries in that group is shown in brackets.
[164] The results for other countries are very similar.

change residuals. Although not shown here, 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 26 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.

### Adjusted productivity growth

Up to here, the focus of the analysis has been on the cyclicality of technical change residuals. A related question is to what extent the estimated models affect the stylized productivity growth facts that were presented in the previous chapter. The results in the previous chapter all relied on standard growth accounting assumptions of constant returns to scale and well-measured inputs. The estimates in Table 5.5 show that these assumptions are not uniformly supported by the data, so it is useful to see the effect of relaxing these assumptions on productivity growth estimates. Table 5.8 shows two different productivity growth estimates for the period 1995-2003 for both the market economy and the market economy, excluding agriculture and mining. In addition, the contribution of market services to aggregate growth is shown. To make it easier to compare the results to those presented in the previous chapter, the parameters from Table 5.5 are applied on a value added basis, instead of in a gross output framework. Hence the parameters from Table 5.5 are converted to a value added basis:

(5.9) $$\gamma^V = \gamma \frac{1 - s_{Mi}}{1 - \gamma s_{Mi}} .$$

Equation (5.9) shows how the returns to scale parameter is converted from gross output to value added and the same equation is used for the utilization parameter.

**Table 5.8 Productivity growth relaxing growth accounting assumptions**

| | *Market economy* | | *Market economy excluding agriculture & mining* | |
|---|---|---|---|---|
| | Solow | Adjusted | Solow | Adjusted |
| ***Average TFP growth, 1995-2003*** | | | | |
| France | 0.79 | 1.25 | 0.76 | 1.04 |
| Germany | 0.88 | 0.91 | 0.84 | 0.77 |
| Netherlands | 0.14 | 0.10 | 0.14 | -0.36 |
| U.S. | 1.78 | 1.86 | 1.76 | 1.64 |
| ***Contribution of market services, 1995-2003*** | | | | |
| France | -0.18 | 0.33 | -0.19 | 0.13 |
| Germany | 0.14 | 0.10 | 0.14 | 0.01 |
| Netherlands | -0.19 | -0.22 | -0.20 | -0.70 |
| U.S. | 0.93 | 1.03 | 0.96 | 0.87 |

Notes: The columns labelled 'Solow' show productivity growth under constant returns to scale and without utilization adjustments. 'Adjusted' applies the estimated returns to scale and utilization correction from Table 5.5, adjusted to a value added basis.

The columns labelled ‘Solow’ show (total factor) productivity growth under the assumptions of constant returns to scale and well-measured inputs. The ‘Adjusted’ columns apply the returns to scale parameters and utilization correction from Table 5.5 for the main industry groups.[165] As Table 5.8 show, the adjustment are sometimes sizeable with adjusted productivity growth coming out half a percentage point lower in the case of the market economy excluding agriculture and mining in the Netherlands. In contrast, growth is almost half a percentage point higher in the case of the market economy in France.

However, the adjustments have no large impact on the main stylized facts from the previous chapter. The U.S. shows the highest aggregate growth for this group of countries after 1995. Similarly, market services make much larger contributions to aggregate growth in the U.S. than in the European countries. It is also important to note the effect of excluding agriculture and mining. Germany and the U.S. provide the clearest cases with growth compared to the Solow residual coming out higher if agriculture and mining are included and lower when they are excluded. Also, in some sense the adjustments represent an upper-bound since for most industry groups and countries, the returns to scale were not significantly different from one, and the utilization adjustment statistically indistinguishable from zero.

[165] Nearly all of the difference in average growth can be traced to the effect of applying the returns to scale parameters.

## 5.6 Concluding remarks

It is important to understand why productivity growth is procyclical, both for understanding the determinants of the business cycle and productivity growth. This chapter extends the current literature by not only analyzing this phenomenon for the U.S. but also for France, Germany and the Netherlands using an up-to-date and internationally consistent dataset covering the entire market economy. The analysis follows the approach of 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 analyze this issue for countries outside the U.S., none of the earlier studies have followed Basu and Fernald (2001) and tested whether the estimated models lead to lower correlation between growth of output and the adjusted productivity residual using the production model estimates. Furthermore, industry-specific demand-side instruments are introduced to correct for simultaneity bias in the estimation of production functions.

The results cast some doubt on the ability of the Basu and Fernald (2001) model to account for procyclical productivity growth beyond their specific case. At the level of the market economy (excluding agriculture and mining), the correlation between adjusted productivity growth and output growth is no longer significant. But in some individual industry groups, technical change is still significantly procyclical. Furthermore, the results show that in all countries, a sizeable fraction of individual industries show procyclical productivity. Since the underlying theoretical model tries to explain firm behaviour, the failure of the empirical model in many industries is particularly worrisome.

There have been other studies that cast doubt on the popular explanations for procyclical productivity growth. Basu and Fernald (1997) themselves 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 the input utilization hypothesis. In their view, downsizing establishments would have fewer incentives to hoard labour or conserve capital. This chapter 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. For example, the type of customers of an industry (business versus consumers) may be important, as Hart and Malley (1999) find less evidence of procyclicality in investment-goods industries than in other industries. More theoretical research may also provide useful new directions for empirical research. Ultimately, firm-level studies, especially extending the work of Baily, Bartelsman and Haltiwanger (2001) beyond U.S. manufacturing, may be needed to understand how firms adjust to changing demand.

More encouraging are the results on the robustness of the stylized productivity growth facts. Relaxing the assumptions of constant returns to scale and well-measured inputs has a noticeable impact on productivity growth estimates. However, the stylized facts from Chapter 4 are not affected. U.S. TFP growth remains higher than in the European countries, especially in market services. Furthermore the regression parameters, and therefore the adjusted productivity estimates, are strongly affected by relatively minor changes to the data, such as excluding agriculture and mining from the set of industries. This suggests that relaxing some of the growth accounting assumptions may be warranted by the data, but it can give a false sense of precision. A more robust approach is to acknowledge that total factor productivity growth is a concept that captures many different phenomena, such as technical change and returns to scale.

## *Appendix 5.A Appendix tables*

**Appendix Table 5.1 Correlation between annual output growth and total factor productivity growth at the industry level, France, Germany, Netherlands and U.S., 1979-2003**

| | France | Germany | Netherlands | US |
|---|---|---|---|---|
| Agriculture, forestry and fishing | 0.82* | 0.74* | 0.65* | 0.84* |
| Mining and quarrying | 0.74* | 0.48* | 0.46* | 0.19 |
| Food products | -0.22 | 0.08 | 0.38 | 0.28 |
| Textiles, clothing and leather | 0.29 | 0.62* | 0.32 | 0.40 |
| Wood products | 0.52* | 0.71* | 0.34 | 0.39 |
| Paper, printing and publishing | 0.05 | 0.63* | 0.68* | 0.34 |
| Petroleum and coal products | 0.57* | 0.52* | 0.42* | -0.19 |
| Chemical products | 0.84* | 0.44* | 0.63* | 0.45* |
| Rubber and plastics | -0.04 | 0.33 | 0.40 | 0.45* |
| Non-metalic mineral products | 0.38 | 0.88* | 0.48* | 0.57* |
| Metal products | 0.16 | 0.54* | 0.83* | 0.7* |
| Machinery | 0.68* | 0.63* | 0.77* | 0.69* |
| Electrical and electronic equipment & instruments | 0.58* | 0.29 | 0.13 | 0.69* |
| Transport equipment | 0.63* | 0.53* | 0.67* | 0.19 |
| Furniture and miscellaneous manufacturing | 0.66* | 0.64* | 0.19 | 0.56* |
| Electricity, gas and water | 0.65* | 0.82* | 0.40 | 0.27 |
| Construction | 0.60* | -0.14 | 0.22 | 0.56* |
| Wholesale trade | 0.33 | 0.49* | 0.76* | -0.17 |
| Retail trade | 0.73* | 0.73* | 0.70* | 0.56* |
| Hotels and restaurants | 0.39 | 0.67* | 0.72* | 0.06 |
| Transport & storage | 0.53* | 0.55* | 0.80* | 0.24 |
| Communications | 0.35 | 0.60* | 0.71* | 0.55* |
| Financial intermediation | 0.23 | 0.53* | 0.55* | 0.02 |
| Business services | 0.06 | 0.76* | 0.17 | 0.07 |
| Other services | 0.57* | 0.37 | 0.64* | 0.47* |
| Market economy | 0.66* | 0.69* | 0.62* | 0.57* |

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

**Appendix Table 5.2 F-statistics for the first-stage regression of instruments on input growth**

| | France | Germany | Netherlands | US |
|---|---|---|---|---|
| Agriculture, forestry and fishing | 3.31 | 9.59* | 0.75 | 2.31 |
| Mining and quarrying | 2.81 | 8.73 | 0.29 | 0.55 |
| Food products | 15.9** | 1.19 | 8.28 | 3.92 |
| Textiles, clothing and leather | 12.4* | 17.9** | 9.99* | 7.54 |
| Wood products | 1.87 | 1.07 | 2.29 | 8.92 |
| Paper, printing and publishing | 15.7** | 24.9** | 8.36 | 7.59 |
| Petroleum and coal products | 4.27 | 2.97 | 1.07 | 2.40 |
| Chemical products | 16.9** | 4.94 | 7.03 | 5.84 |
| Rubber and plastics | 2.54 | 17.9** | 16.3** | 23.6** |
| Non-metalic mineral products | 10.6* | 0.88 | 1.71 | 8.58 |
| Metal products | 7.19 | 20.5** | 4.12 | 6.93 |
| Machinery | 8.49 | 15.1** | 24.8** | 7.47 |
| Electrical and electronic equipment & instruments | 14.8** | 23.9** | 29.1** | 15.8** |
| Transport equipment | 25** | 9.58* | 6.13 | 9.90* |
| Furniture and miscellaneous manufacturing | 0.66 | 2.08 | 8.22 | 8.74 |
| Electricity, gas and water | 7.58 | 10.8* | 9.83* | 0.23 |
| Construction | 7.78 | 5.73 | 13.4* | 4.48 |
| Wholesale trade | 30.3** | 7.93 | 30.6** | 5.12 |
| Retail trade | 16.8** | 15.8** | 22.6** | 15.6** |
| Hotels and restaurants | 22.8** | 42.0** | 8.40 | 27.1** |
| Transport & storage | 18.0** | 4.34 | 14.1** | 28.1** |
| Communications | 10.6* | 2.68 | 18.5** | 20.4** |
| Financial intermediation | 8.02 | 5.58 | 47.3** | 4.48 |
| Business services | 63.3** | 32.9** | 54.8** | 66.3** |
| Other services | 67.3** | 8.91 | 15.9** | 38.6** |
| Market economy | 15.8** | 11.9* | 14.5** | 13.2* |

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.

**Appendix Table 5.3 Estimates of returns to scale of inputs for individual industries, 1979-2003**

| | *Ind. Group* | France | Germany | Netherlands | US |
|---|---|---|---|---|---|
| Agriculture, forestry and fishing | NMFG | 1.55 | 0.88 | 0.74 | 1.15 |
| Mining and quarrying | NMFG | -2.48 | 0.61 | -0.21 | -1.64* |
| Food products | NDUR | 0.46* | 0.59 | 0.3 | 1.35 |
| Textiles, clothing and leather | NDUR | 1.85 | 1.19* | 1.01 | 1.24 |
| Wood products | NDUR | 1.04 | 1.15 | 0.87 | 0.92 |
| Paper, printing and publishing | NDUR | 1.04 | 1.15 | 1.29* | 1.23 |
| Petroleum and coal products | NDUR | 0.62 | 1.23 | 0.97 | 0.45* |
| Chemical products | NDUR | 1.68* | 1.15 | 0.76 | 1.21 |
| Rubber and plastics | NDUR | 1.06 | 1.04 | 1.18 | 1.22* |
| Non-metalic mineral products | DUR | 0.96 | 1.54* | 1.62 | 1.21* |
| Metal products | DUR | 1.05 | 1.08 | 1.31* | 1.27* |
| Machinery | DUR | 1.32 | 1.15* | 1.28* | 1.23* |
| Electrical and electronic equipment & instruments | DUR | 1.20* | 0.94 | 1.03 | 1.42 |
| Transport equipment | DUR | 1.25* | 1.09 | 1.15* | 1.00 |
| Furniture and miscellaneous manufacturing | DUR | 1.57 | 1.30* | 0.88 | 1.40 |
| Electricity, gas and water | SER/NMFG | 0.12* | 0.84 | 1.08 | 0.43 |
| Construction | SER/NMFG | 1.25* | 0.93 | 1.01 | 1.07 |
| Wholesale trade | SER/NMFG | 0.93 | 1.46* | 1.34* | 1.10 |
| Retail trade | SER/NMFG | 0.25 | 1.67* | 1.35 | 1.33 |
| Hotels and restaurants | SER/NMFG | 1.28 | 1.49 | 1.47 | 0.74 |
| Transport & storage | SER/NMFG | 1.21 | 1.30* | 1.36* | 0.81* |
| Communications | SER/NMFG | 0.99 | 1.12 | 0.93 | 0.61 |
| Financial intermediation | SER/NMFG | 0.83 | 0.88 | 0.42* | 1.21 |
| Business services | SER/NMFG | 0.96 | 1.37* | 1.07 | 0.96 |
| Other services | SER/NMFG | 0.83 | 1.25 | 2.47 | 1.20 |
| 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.

**Appendix Table 5.4 Estimates of returns to scale of inputs without a utilization correction, using Hall-Ramey instruments, 1979-2003**

| | Hall-Ramey instruments | | | |
|---|---|---|---|---|
| | France | Germany | Netherlands | US |
| Market economy | 0.99 | 0.85* | 1.11 | 0.90* |
| | (0.06) | (0.04) | (0.07) | (0.04) |
| Market economy excluding agriculture & mining | 0.97 | 0.98 | 1.12* | 0.94 |
| | (0.06) | (0.04) | (0.04) | (0.04) |
| Durable manufacturing | 1.08* | 0.94 | 1.07 | 1.13* |
| | (0.03) | (0.05) | (0.05) | (0.05) |
| Non-durable manufacturing | 0.87 | 1.05 | 1.06 | 0.88 |
| | (0.13) | (0.05) | (0.04) | (0.07) |
| Non-manufacturing | 0.72* | 0.82* | 1.08 | 0.69* |
| | (0.1) | (0.07) | (0.06) | (0.05) |
| Services | 0.52* | 0.99 | 1.11 | 0.72* |
| | (0.09) | (0.08) | (0.06) | (0.04) |

Notes: Table shows parameter estimates from a regression with output growth as the dependent variable and growth of inputs as independent variable. 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 at the 5% level. See Table 5.A3 for definitions of industry groupings.

**Appendix Table 5.5 Returns to scale of inputs with a correction for unmeasured input utilization using Hall-Ramey instruments, 1979-2003**

| | Hall-Ramey instruments | | | |
|---|---|---|---|---|
| | *Returns to scale* | | | |
| | France | Germany | Netherlands | US |
| Market economy | 1.00 | 0.87 | 1.11 | 0.86* |
| | (0.06) | (0.08) | (0.06) | (0.06) |
| Market economy excluding agriculture & mining | 0.96 | 1.07 | 1.11* | 0.93 |
| | (0.07) | (0.07) | (0.04) | (0.06) |
| Durable manufacturing | 1.12* | 0.98 | 1.06 | 1.11 |
| | (0.02) | (0.08) | (0.04) | (0.06) |
| Non-durable manufacturing | 0.88 | 1.05 | 1.06 | 0.88 |
| | (0.08) | (0.06) | (0.04) | (0.07) |
| Non-manufacturing | 0.73* | 0.82 | 1.08 | 0.68* |
| | (0.12) | (0.10) | (0.07) | (0.06) |
| Services | 0.54* | 1.02 | 1.11 | 0.74* |
| | (0.14) | (0.08) | (0.06) | (0.06) |
| | *Utilization correction* | | | |
| Market economy | 0.04 | -0.15 | 0.02 | 0.39* |
| | (0.23) | (0.19) | (0.11) | (0.19) |
| Market economy excluding agriculture & mining | 0.11 | -0.51* | -0.13 | 0.11 |
| | (0.24) | (0.22) | (0.07) | (0.20) |
| Durable manufacturing | -0.40* | -0.28 | -0.21* | 0.18 |
| | (0.11) | (0.36) | (0.05) | (0.25) |
| Non-durable manufacturing | -0.08 | -0.26 | -0.05 | 0.12 |
| | (0.15) | (0.24) | (0.07) | (0.16) |
| Non-manufacturing | -0.24 | -0.28 | 0.01 | 0.19 |
| | (0.13) | (0.16) | (0.15) | (0.19) |
| Services | -0.27 | -0.63* | -0.17 | -0.21 |
| | (0.15) | (0.14) | (0.09) | (0.19) |

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. 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 5.A3 for definitions of industry groupings.

**Appendix Table 5.6 Returns to scale of inputs with a correction for unmeasured input utilization, excluding average hours worked from aggregate input growth using Hall-Ramey instruments, 1979-2003**

| | Hall-Ramey instruments | | | |
|---|---|---|---|---|
| | *Returns to scale* | | | |
| | France | Germany | Netherlands | US |
| Market economy | 0.99 | 0.88 | 1.12 | 0.87* |
| | (0.06) | (0.08) | (0.05) | (0.06) |
| Market economy excluding agriculture & mining | 0.95 | 1.07 | 1.13* | 0.94 |
| | (0.07) | (0.07) | (0.04) | (0.06) |
| Durable manufacturing | 1.12* | 0.98 | 1.07 | 1.11 |
| | (0.02) | (0.08) | (0.04) | (0.06) |
| Non-durable manufacturing | 0.88 | 1.05 | 1.07 | 0.89 |
| | (0.08) | (0.06) | (0.04) | (0.07) |
| Non-manufacturing | 0.73* | 0.82 | 1.08 | 0.69* |
| | (0.12) | (0.10) | (0.05) | (0.06) |
| Services | 0.54* | 1.02 | 1.14* | 0.76* |
| | (0.14) | (0.09) | (0.06) | (0.06) |
| | *Utilization correction* | | | |
| Market economy | 0.33 | 0.12 | 0.26* | 0.61* |
| | (0.22) | (0.19) | (0.1) | (0.18) |
| Market economy excluding agriculture & mining | 0.4 | -0.17 | 0.15* | 0.39* |
| | (0.23) | (0.22) | (0.06) | (0.19) |
| Durable manufacturing | -0.09 | 0.02 | 0.06 | 0.53* |
| | (0.1) | (0.38) | (0.05) | (0.24) |
| Non-durable manufacturing | 0.1 | -0.02 | 0.1 | 0.31* |
| | (0.14) | (0.27) | (0.05) | (0.14) |
| Non-manufacturing | 0.01 | 0.00 | 0.32* | 0.38* |
| | (0.12) | (0.16) | (0.14) | (0.18) |
| Services | -0.08 | -0.24 | 0.25* | 0.05 |
| | (0.14) | (0.13) | (0.08) | (0.17) |

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 5.A3 for definitions of industry groupings.

**Appendix Table 5.7 Correlation between output and adjusted productivity growth, based on industry-by-industry estimates of returns to scale and unmeasured input utilization**

| | France | Germany | Netherlands | US |
|---|---|---|---|---|
| *Market economy* | | | | |
| Constant returns to scale | 0.66* | 0.69* | 0.62* | 0.57* |
| Variable returns to scale | -0.01 | 0.21 | 0.53* | 0.21 |
| Variable returns to scale & utilization correction | -0.34 | -0.09 | 0.35 | 0.19 |
| *Number of market industries with correlation significantly different from zero (5% level)* | | | | |
| Constant returns to scale | 13 | 20 | 15 | 11 |
| Variable returns to scale | 10 | 8 | 8 | 8 |
| Variable returns to scale & utilization correction | 5 | 7 | 8 | 7 |

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 5.6, only in this table the parameters are allowed to vary for each industry.