# The Sensitivity of Estimates of UK Manufacturing TFP to Definition and Measurement

By

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*To my parents*

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# DECLARATION

This thesis is submitted to the University of Warwick in accordance with the requirements of the degree of Doctor of Philosophy. I hereby declare that this thesis contains no material which has been submitted for the award of any other degree at any other university or equivalent institution. I also certify that the work described here is entirely my own, except where due acknowledgment has been made in the text.

A preliminary version of Chapter 3 has been presented in seminars at the Economic Department of the University of Warwick, at Warwick Business School (University of Warwick) and at the Economic Department of the University of Valencia. A preliminary version of Chapter 4 has been presented at the 2003 Royal Economic Society Annual Conference (University of Warwick) and at the 18th Annual Congress of the European Economic Association (Stockholm).

# ABSTRACT

This thesis is concerned with the sensitivity of Total Factor Productivity (TFP) estimates in UK manufacturing industries to the use of alternative output concepts –gross output vs. value added- and estimation methods –growth accounting vs. econometrics. The departure point is that differences in methods and assumptions can lead to very different TFP growth estimates. The interpretation of these estimates can be problematic when they reflect factors beyond the theoretical concept of TFP. The central goal of this thesis is to evaluate whether and to what extent these factors have an impact on the measurement of TFP growth, on the estimation of any relationship between TFP and Research and Development (R&D) investment and, finally, on the measurement of the UK manufacturing productivity gap differential.

The empirical results suggest that: First, TFP growth estimates in UK manufacturing are sensitive to both the output concept used and the assumptions underlying the method used to estimate them. It was found when tested for that the assumptions of perfect competition and instantaneous adjustment, which underlie the growth accounting framework, are not valid. Adjusting for the measurement bias associated with the presence of these factors, it is found that the recovery experienced in the 1980s in UK manufacturing productivity growth rates was not as spectacular as implied by the traditional growth accounting approach.

Second, adjusting for measurement bias does not affect markedly the results found in related studies with respect to the relationship between TFP and R&D efforts. The results suggest that R&D investment from the industry itself and from other national industries has a positive impact on the industry's productivity but there is no gain from R&D investment undertaken abroad.

Third, the results indicate that the bias in traditional TFP estimates does not impact greatly on the British productivity gap at the aggregate manufacturing level but does so at a more disaggregated level. Finally, despite the concerns about measurement bias, the results show that the productivity gap still remains significant and the productivity of UK manufacturing still trails behind that achieved in the US, France and Germany, regardless of the sector.

# CHAPTER 1 –
# INTRODUCTION AND OVERVIEW

> *"Productivity growth underpins economic performance and sustained increases in living standards. The Government's long-term goal is that Britain will achieve a faster rate of productivity growth than its main competitors."*
>
> HM Treasury (2003: p. 45)

## 1.1 THE CONTEXT

Productivity growth is often cited as one of the major factors contributing to the continued economic growth of a nation (Jorgenson 1995). As a result, measurement and analysis of productivity change have been areas of great interest for both economists and policy makers. However, despite this interest in productivity, the interpretation and measurement of productivity has been a matter of ongoing controversy. Particularly, this debate has focused on the assumptions and accuracy of the methods used to estimate Total Factor Productivity (TFP henceforth) growth.

The theme of this thesis is that measurement matters. Minor differences in assumptions can lead to very different estimates of TFP growth. The interpretation of any particular measure of TFP growth can be problematic when such estimates reflect factors beyond the theoretical concept of TFP growth. This concept, as it will be seen in Chapter 2, can be given a rigorous foundation in the theory of production.

This thesis is concerned with productivity performance, a topic at the top of the agenda of the present UK Government - *"Improving productivity is the Government's key economic objective for this Parliament"* (DTI 2002: p. 3). Central to the Government analysis of UK productivity performance is growth accounting, the framework traditionally used to benchmark productivity since Solow's (1957) contribution.

Under the growth accounting approach, TFP growth estimates are usually obtained as a residual from the difference between the growth rate of real value added and a weighted average of the growth rates of labour and capital, where the weights are the respective input shares in value added. Under the appropriate assumptions, the accounting residual (also referred as the "Solow residual") provides an appropriate measure of the rate of change of TFP (Solow 1957). However, under more general assumptions, the residual represents a biased measure of the conceptual definition of TFP growth.

One source of this bias arises precisely from the restrictive assumptions about the underlying technology and allocation decisions made in the growth accounting framework. In particular, the accounting approach assumes competitive output and input markets, plus full utilisation and instantaneous adjustment of all inputs. When these assumptions fail a second source of bias can arise. This is due to the common practice of using value added instead of gross output as a measure of real output (see David 1962; Baily 1986 and Basu and Fernald 1997; among others).

During the early seventies, most industrialized countries, among them the UK, experienced a slowdown in the growth rates of TFP as conventionally measured. The growth accounting framework, however, was unable to provide valuable insights into the reasons underlying these events. As a result methodological developments in productivity growth research took new directions to account for technical and market characteristics that affect productivity and which were ignored in traditional measures. These developments implied the use of econometrics as an alternative approach to productivity measurement.

Fruits of these developments were the studies addressing the importance of the role of market power and scale economies in productivity measurement (see Hall 1988; 1990). A second wave of studies departed from the growth accounting methodology allowing for the presence of adjustment costs and variations in capacity utilisation (Mendis and Muellbauer 1984; Berndt and Morrison 1981 and Basu and Kimball 1997). Overall, these studies showed the statistically significance of mark-ups due to non-competitive behaviour and the importance of adjusting for capacity utilisation. These findings imply departures from the assumptions underlying the growth accounting approach, and therefore, the inadequacy of this method to productivity measurement.

Having established the importance of productivity measurement, the next section addresses the main objectives of this study. Then, Section 1.3 presents the structure of the thesis and introduces, in more detail, the five subsequent chapters.

## 1.2 RESEARCH OBJECTIVES OF THE THESIS

The goal of this thesis is not one of obtaining conclusive estimates of the growth rate of TFP; rather it is to assess the sensitivity of TFP estimates to different measurement and methodological concerns. In doing so, this study will look at how, particularly, different output concepts (gross output vs. value added) and estimation methods, distinguished by the distinct underlying assumptions, could affect the measurement and analysis of TFP in UK manufacturing industries. Further, it seeks to determine to what extent taking into account these measurement concerns might have an impact on the study of two relevant areas of productivity analysis. These are the study of TFP determinants and international productivity comparisons.

The research performed through this thesis is empirical and comparative in its nature and concern. Two main features distinguish the empirical analysis of the next chapters from the existing body of empirical literature in the context of the measurement and analysis of UK productivity and its determinants. First, this thesis places greater emphasis on some of the main measurement issues that traditionally are ignored in conventional TFP estimates based on growth accounting. Particularly, the stress is placed upon the use of gross output and the allowance for the role of market power and adjustments in capacity utilisation in measuring TFP. Second, several dimensions of the literature, which are usually studied independently are analysed within a given integrated empirical framework.

The ultimate objective of this thesis is to assess whether and to what extent different methodological and measurement issues are likely to affect: (i) the estimated TFP growth rate itself, (ii) the estimates of the relationship between TFP and its main determinants, particularly R&D investment, and (iii) the measurement of the size and direction of the UK manufacturing productivity differential with respect to other industrialized countries. Each of these research questions will be addressed respectively in separate empirical chapters.

For these purposes, available data on UK manufacturing industries from 1970 to 1997 will be examined. Due to limitations on the data available for certain explanatory variables from 1970 onwards, particularly physical capital stock and R&D spending, the focus of the statistical analysis will be on eight major industrial groups as defined at the two digit Standard Industrial

Classification (SIC) level by the Office for National Statistics (ONS). The industries considered are listed in Table 1.1 and they represent about 95% of total manufacturing production[1].

**Table 1.1**
**UK Manufacturing Industries Considered in the Thesis**

| Industries | Symbol | SIC 1992 |
|---|---|---|
| Food, Beverages & Tobacco | FBT | 15+16 |
| Textile & Leather | TL | 17+18+19 |
| Wood and Wood Products | WWP | 20 |
| Paper and Paper Products | PPP | 21+22 |
| Chemicals, Man-made fibres, Rubber & Plastic Products | CH | 24 |
| Other Non-Metallic Mineral Products | NMM | 26 |
| Manufacture of Basic Metals & Fabricated Metal Products | BFM | 27 + 28 |
| Machinery, Optical Equipment & Transport Equipment | MOT | 29 + 30/1/2/3/4 /5 |

*Source*: Office for National Statistics.

The focus on manufacturing here is because of several reasons. Although the share of manufacturing in total output and employment has declined over the last decades, it still remains a key sector. The Government's view is that manufacturing success is critical to the prosperity of Britain as a leading knowledge economy (DTI 2002a). Nowadays, the manufacturing sector generates two thirds of the value of UK's exports, directly provides 4.3 million jobs and accounts for 20 per cent of the GDP. It is also the sector with greater volume of investment in R&D –around 80% of commercial R&D in the UK is undertaken by manufacturers.

[1] The industries excluded from the analysis are the manufacture of coke, refined petroleum products and nuclear fuel (SIC 23) and manufacturing not elsewhere classified (SIC 36).

It seems appropriate to focus on manufacturing where data to obtain productivity measures is both less difficult to obtain and more reliable. There are further reasons to focus on manufacturing, which are linked to the purpose of this thesis. First, measured R&D expenditures in the manufacturing are both less difficult to obtained and available for early years. Finally, data for manufacturing sectors appears to be more available and reliable for international productivity comparisons.

The next section presents the structure of the thesis and introduces the five subsequent chapters.

## 1.3 OUTLINE OF THE THESIS

In the following chapters, the objectives outlined above are successively addressed. Particularly, the structure of the thesis can be summarized as follows. Chapter 2 is a review of the research on TFP growth measurement. Its aim is to provide a general theoretical foundation on which the remainder of the thesis is built and to critically review the studies that have dealt with the issues addressed in this thesis. By way of introduction, the chapter begins by addressing some general questions associated with the concept, measurement and interpretation of the growth rate of TFP: "What does TFP growth mean?", "How is it measured?", "Which traditional methods have been used?", "What are the limitations of these methods?". The consideration of these questions will clarify the subject of the thesis and outline some of the limits of the formalization of the estimates of TFP growth.

Chapter 2 also unfolds the empirical methodology that will be used through the subsequent chapters. It devotes special attention to the traditional growth accounting approach to measuring changes in TFP and its enhancing assumptions. Further, it presents the insights on methodological extensions to relax the assumptions of growth accounting. Finally, Chapter 2 closes with a critical survey on recent empirical studies on measuring TFP growth in UK manufacturing. This review pays particular attention to how the findings in previous studies relate to the analysis undertaken in the thesis.

The following three empirical chapters represent the core components of this thesis. These chapters have a common structure. First, the most prominent findings reported in the related literature are reviewed. Then, an outline of the methodological and econometric framework is presented. Finally, the empirical section interprets the main results.

Chapter 3 presents a critical review of traditional methods of measuring productivity growth and provides new adjusted measures of UK manufacturing TFP growth rates. In particular, the chapter examines the impact on productivity estimates of using alternative output concepts and estimation methods. It argues that gross output is the superior concept of real output instead of the most frequently used value added. Additionally, it states that parametric measures of TFP growth are to be preferred to growth accounting estimates under general assumptions. A panel regression on UK manufacturing industries over the period 1970-1997 reveals that both market power and adjustment for variations in capacity utilisation have an important influence on TFP growth measurement. This finding implies that the use of growth accounting leads to biased estimates of UK manufacturing productivity growth.

Following on the results obtained in Chapter 3, Chapter 4 takes the analysis a step further by considering the influence of these methodological and measurement concerns on studying the relationship between industry's productivity performance and its main determinants, in particular, Research and Development (R&D) investment. Moreover, as one of the key benefits claimed for R&D investment is that its benefits spill over, so that industries will benefit from both their own R&D efforts as well as the research results of other national and overseas industries, the chapter also assesses empirically the importance and nature of these R&D spillovers in UK manufacturing industries.

Chapter 5 revisits the documented productivity gap in manufacturing between the UK and the rest of the G7 economies. To this end, new international comparative estimates of growth performance and levels of productivity are provided for the aggregate manufacturing sector and for the set of eight manufacturing industries from 1970 to 1998. The stress is placed upon the sensitivity of the size and direction of the productivity differential to the measurement issues and restrictive assumptions considered previously. To this end a different dataset is used, which is based on the STAN (Structural Analysis) OECD database[2].

Chapter 6 begins with a summary of each chapter and underlines the main empirical findings. Then, some aspects deserving further attention are discussed and some ideas for the future research agenda are suggested. The last section of this chapter concludes.

[2] The OECD STAN database is mainly based on national accounts data of individual OECD country members. The use of national accounts for international productivity comparisons has the advantage that its components are harmonised across countries on the basis of the International System of National Accounts.

# CHAPTER 2 –

# A REVIEW OF RESEARCH ON TFP GROWTH MEASUREMENT

*"Productivity isn't everything but in the long run it is almost everything"*
P. Krugman (1990: p. 9)

## 2.1 INTRODUCTION

Economists have long recognised that Total Factor Productivity (TFP henceforth) growth is an important factor in the process of economic growth (Jorgenson 1995). As a result, measurement and analysis of productivity change have been areas of great interest for both economists and policy makers[1]. However, despite its importance and widespread referral in public policy discussions, the interpretation and measurement of TFP growth has been a matter of ongoing controversy. In particular, the debate has focused on the assumptions and the accuracy of the actual methods used in estimating TFP growth[2].

The initial question when modelling and measuring TFP growth is "what does it mean"? Theoretically, as Oulton and O'Mahony (1994: p. 1) pointed out "*TFP growth is the rate at which output would have increased in some period if all inputs had remained constant*". Intuitively, it measures the shift in the production function. Although there is little disagreement on this broad concept, difficulties in measuring TFP growth are soon encountered when one confronts various methodological and measurement problems. These problems are further compounded by difficulties in obtaining relevant data. In addition, productivity measures can be made at the process, plant, firm, industry or, economy level: each of which involves

[1] Raising UK productivity growth is a major Government objective. For example, whole chapters on productivity have appeared in every Budget and pre-Budget report since 1997 and also in separate Treasury documents (HM Treasury 2000).
[2] The literature on TFP measurement is extensive in terms of both theoretical and empirical studies. Important productivity measurement issues have been recently brought together in Hulten (2000) and in the OECD Productivity Manual (OECD 2001).

some specific issues and concepts. This thesis analyses industry performance. Hence, the chapter concentrates on industry level productivity.

Conceptually, TFP growth should be measured as the difference between the growth rate of real output and the weighted growth rate of real factor inputs. The weights should, in principle, reflect the relative importance of each input contribution to production. In practice, one can discern two theoretically distinct methods for computing the index of inputs. These can be distinguished, among others, by the assumptions for determining the weights assigned to the different types of input. The first method, the growth accounting approach, predicts that under some simplifying assumptions, factor income shares should be used as weights[3]. The second approach, the econometric method, weights the different types of inputs on the basis of their relative ability to predict output through regression analysis.

Additionally, in productivity analysis measures of TFP are computed from either of two different concepts of real output. These are gross output and value added. In contrast to gross output, value added is an economic index dependent on theoretical assumptions. Despite its popularity in empirical studies, there is an extensive literature (David 1962; Bruno 1978; Baily 1986; Basu and Fernald 1997) that shows the inadequacy of using value added for productivity measurement, particularly when its underlying assumptions cannot be maintained.

[3] This income shares approximate production elasticities or the effects of a 1% change in individual inputs on outputs.

The theme of this thesis is that measurement matters. The point of departure is that ostensibly insignificant differences in assumptions can lead to very different estimates of TFP growth. The interpretation of measured TFP growth can be problematic when such estimates reflect factors other than shifts in the production function. Examples are mark-ups due to imperfect competition, cyclical variations in capacity utilisation, scale economies, or other measurement errors. The result of these errors is to introduce serious biases not only in the measurement of the "true" TFP growth but also on the analysis of its main determinants, and by implication, on the policy indications derived from the analysis.

The objectives of the present chapter are twofold. The first is to assert whether various methodological and measurement issues are likely to affect the estimated TFP growth rate and if so to what extent. To do so, the chapter first introduces many issues related to the conceptualisation, construction and interpretation of TFP growth measures. Special attention is devoted to the biases in measuring productivity growth using the traditional growth accounting method. This will provide the basis for extensions of the traditional TFP growth measure by relaxing some of its underlying assumptions. The final aim is to set the empirical methodology that will be used through the following chapters.

The second aim is to provide a critical survey of the recent empirical literature on measuring TFP growth in UK manufacturing industries. This provides some examples of how the methods and issues discussed in previous sections have been used. Secondly, it establishes the basis for comparison with the results of the following chapters. This analysis of the literature clarifies various issues regarding the sensitiveness of the empirical results to (i) the chosen theoretical framework, (ii) the relaxation of some the assumptions underlying traditional methods and (iii) the real output concept (value added vs. gross output) used in productivity measurement.

The remainder of this chapter is structured as follows. Section 2.2 tackles the main technical and conceptual issues related to the measurement of TFP growth. Further, it presents the two main theoretical frameworks for productivity measurement – i.e., the primal and the dual approaches. Section 2.3 provides a description of the traditional accounting framework and the econometric approach as alternative methods for productivity measurement. Section 2.4 discusses the implication of potential measurement errors related to the computation of TFP growth using the growth accounting approach. These include: imperfect competition, presence of scale economies, use of value added as measure of output, adjustment for utilisation rates of production capacities, and biased technological change. Section 2.5 presents a survey of empirical studies on UK manufacturing productivity performance. Finally, section 2.6 concludes.

## 2.2 THE INTERPRETATION OF TFP GROWTH: WHAT DOES "TFP" MEAN?

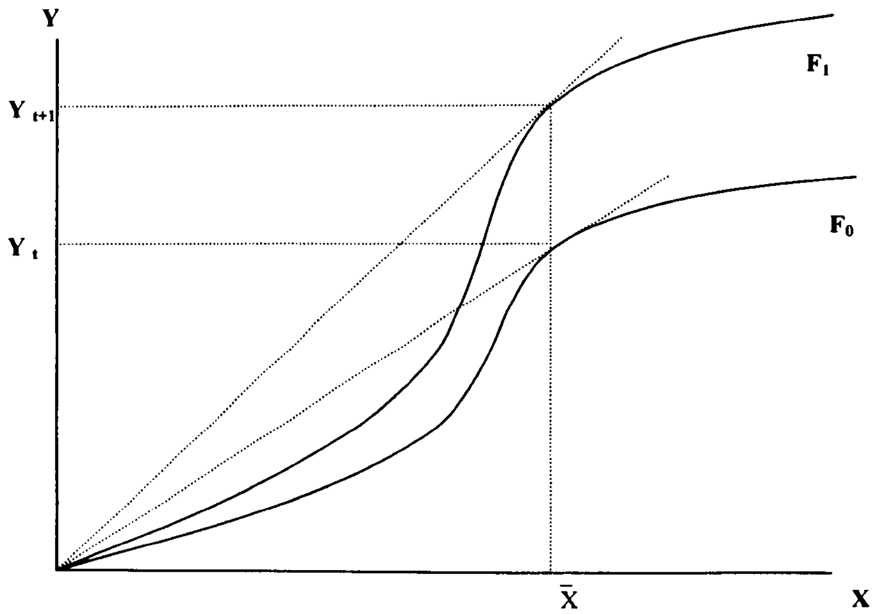
The least controversial definition of productivity is that it is a "*ratio of a volume measure of output to a volume measure of input use*" (OECD 2001: p. 11). Therefore, TFP growth represents the difference between the growth rate of real output and the growth rate of real input use. This idea is, however, not as easy to formalize as it is to express, since observed changes in output production and input use have many underlying determinants. In this section the concept of TFP growth is developed more systematically within the framework of production theory.

### 2.2.1 The Primal Approach

The conceptual framework for productivity growth measurement begins with the assumption that producers face a production function $Y(t)=Y(X(t), t)$, where $Y(t)$ is real output, $X(t)$ is a vector of $J$ aggregate inputs (including labour, capital and intermediate inputs) and $t$ is a time trend, which captures (exogenous) improvements in technology over time. The idea underlying the specification of the production function is that it summarises the state of technology, i.e. the maximum production of output technically possible given a particular amount of inputs. The "pure" productivity growth conceptually arises from a change or shift in the production function over time. This can be illustrated (see Figure 2.1) considering a simple process in which a single input ($X$) is used to produce a single output ($Y$).

The lines $F_0$ and $F_1$ in Figure 2.1 represent production frontiers at different points in time. Each production frontier represents the maximum output ($Y$) attainable for each input level ($X$) at a specific point in time. Hence, it reflects the current state of technology of the firm or industry. The slope of the ray through the origin is $Y/X$, i.e. the ratio of output to input, and hence provides a measure of productivity at a particular data point. An upward shift in the production frontier from $F_0$ to $F_1$ implies that for each level of input industries can technically produce more output. Thus, changes in productivity are expressed by shifts in the production frontier between time periods.

**Figure 2.1**
**Productivity Change between Two Periods**




The primal measure of TFP growth may be interpreted as the increase in output over a period of time (from $Y_t$ to $Y_{t+1}$) for a fixed amount of inputs ($X$). This is typically how productivity growth (and thus measurement) is represented. In order to compute the index of the primal TFP growth rate, the logarithmic differential of the production function $Y(t)=Y(X(t), t)$ is taken.

$$(2.1)\quad \frac{d\ln Y_t}{dt}=\frac{\partial \ln Y_t}{\partial t}+\sum_{j=1}^{J}\frac{\partial \ln Y_t}{\partial \ln X_{jt}}\frac{d\ln X_{jt}}{dt}$$

Defining $\varepsilon_{jt} = \left( \partial Y_t / \partial X_{jt} \right) \left( X_{jt} / Y_t \right) = \partial \ln Y_t / \partial \ln X_{jt}$ as the output elasticity of inputs and rearranging, one obtains:

$$(2.2) \quad \tau_{Y_t} = \frac{\partial \ln Y_t}{\partial t} = \frac{d \ln Y_t}{dt} - \sum_{j=1}^{J} \varepsilon_{jt} \frac{d \ln X_{jt}}{dt}$$

Thus, the primal TFP growth measure ($\tau_{Y_t}$) is expressed in the form of a residual of output growth less factor input growth. This measure ideally reflects only (costless) changes in technology, i.e. shifts in the production frontier as opposed to movements along the frontier.

Before proceeding it is worth clarifying some points with respect to the linkages between TFP growth and technological change. Developing the theoretical links between the two concepts requires formalizing the concept of productivity using a production function representation of the technology, and considering its implications for the definition of technological change.

### 2.2.2 Productivity and Technological Change

While technological change is sometimes identified with productivity change[4], the two are theoretically distinct -albeit related- concepts. Specifically, technological change is a contributor to productivity change. In other words, technical change leads to TFP growth

[4] Frequently, the measurement of technological change is reduced to observing the rate of TFP growth.

by increasing the real output that is attainable with the available productive resources. However, technological change is not the only contributor to productivity change and not all technological change translates into TFP growth.

First, as Oulton (1997) points out there are a number of factors underlying TFP growth besides advances in scientific and technical knowledge. These are organisational and institutional changes, learning by doing and/or legislative and regulatory changes. Moreover, TFP growth in the way is conventionally measured also reflects additional factors that are not genuine causes of TFP growth. These are economies of scale[5], efficiency gains, resource allocation, and measurement errors[6]. Thus, gauging the contribution of technical change to productivity change requires precision in the measurement of TFP growth.

On the other hand, some technological change[7] does not translate into TFP growth. The development of TFP growth as a technical change representation above is based on the notion of disembodied technical change. It reflects progress occurring over time due to costless improvements in production (technical change viewed as exogenous is usually referred to as "manna from heaven"). However, many aspects of technological change have an input-specific nature[8] (embodied technical change).

[5] Gains from scale economies are not TFP growth proper, although they are empirically indistinguishable from TFP except by econometric estimation.
[6] Since TFP growth is the difference between output growth and a weighted average of input growth, any errors in measuring output or inputs will appear in the TFP growth estimate.
[7] In its broad sense, technological change can be thought of as the rate at which new production processes and products are introduced and adopted in the economy.
[8] Solow (1957) is cited as not only providing the foundation of disembodied technological change, but also emphasizing the distinction -as well as the connection- between the notions of disembodied and embodied technological change. Embodied technological changes are advances in the design and quality of new vintages of capital and intermediate products. Disembodied technological change, on the other

When inputs are carefully measured, taking into account their heterogeneity and quality change, the effects of embodied technical change and improved human capital are fully reflected in the measured contribution of each factor of production. It also follows that, in this case, the TFP term captures exclusively the effects of disembodied technological change. However, more often than not, data and resource constraints do not permit a careful differentiation and full coverage of all inputs. As a consequence, a potential identification problem arises, in the sense that some of the embodiment effects of technical change and some of the changes in the skill composition of labour input are actually captured by the TFP residual. In this case, the TFP growth estimate exhibits the effects of both embodied and disembodied technical change.

The conceptual and practical problems associated with measuring technical change are, if anything, even more severe than those associated with measuring productivity change. Indeed, it is difficult to conceive of a single measure that would accurately reflect the complex and heterogeneous nature of technological change. As a result, various proxies have been used in empirical studies. Perhaps the most widely used proxy for technological change is R&D expenditures. The straightforward presumption is that R&D is a necessary, although not sufficient, prerequisite of technological change.

hand, relates to advances in science, and the diffusion of knowledge of how things are done, including better management and organisational change.

### 2.2.3 The Dual Approach

A further extension to productivity growth measurement, encouraged by developments in duality theory from the late 1970s, is to use a cost side rather than a primal side measure. Fundamental contributions include Diewert (1974; 1982) and McFadden (1978). The idea underlying the cost measure is that if a given output can be produced using fewer inputs once productivity growth has occurred, that output may, by definition, be produced at a lower cost. The dual approach expresses advances in productivity as downwards shifts of a cost function.

In what follows, an expression for the dual measure of TFP growth is developed from the cost function. This expression is based on the definition of a total cost function $C_t = C(P_{jt}, Y_t, t)$ as the minimum production cost of producing a certain level of output ($Y_t$), given a set of input prices ($P_{jt}$), at time ($t$). Taking the natural logarithm of both sides of this function and differentiating it with respect to time yields:

$$\text{(2.3)} \quad \frac{d\ln C_t}{dt} = \frac{\partial \ln C_t}{\partial \ln Y_t}\frac{d\ln Y_t}{dt} + \sum_{j=1}^{J}\frac{\partial \ln C_t}{\partial \ln P_{jt}}\frac{d\ln P_{jt}}{dt} + \frac{\partial \ln C_t}{\partial t}$$

The dual rate of productivity change is defined as $\tau_{ct} = \partial lnC(Y_t, P_{jt}, t)/\partial t$, which represents the potential change in costs resulting from a change in $t$ (state of technology) holding output and input prices fixed. Arranging terms and making use of Shephard's lemma, equation (2.3) can be rewritten as:

(2.4) $$\tau_{ct} = \frac{d\ln C_t}{dt} - \sum_{j=1}^{J} \frac{P_{jt}X_{jt}}{C_t}\frac{d\ln P_{jt}}{dt} - \varepsilon_t^{cy}\frac{d\ln Y_t}{dt}$$

where $\varepsilon_t^{cy}$ is the elasticity of cost with respect to output.

Logarithmically differentiating both sides of the cost equation $C_t = \sum P_{jt} X_{jt}$ with respect to time, and rearranging, yields:

(2.5) $$\frac{d\ln C_t}{dt} - \sum_{j=1}^{J} \frac{P_{jt}X_{jt}}{C_t}\frac{d\ln P_{jt}}{dt} = \sum_{j=1}^{J} \frac{P_{jt}X_{jt}}{C_t}\frac{d\ln X_{jt}}{dt}$$

Assuming cost minimisation, $\partial Y_t / \partial X_{jt} = P_{jt} \Big/ \left( \partial C_t / \partial Y_t \right)$ and substituting into equation (2.4), yields:

(2.6) $$-\tau_{ct} = \varepsilon_t^{cy}\left( \frac{d\ln Y}{dt}_t - \sum_{j=1}^{J} \varepsilon_{jt}\frac{d\ln X_{jt}}{dt} \right)$$

From equation (2.6) it can be seen that, in the absence of scale economies or diseconomies ($\varepsilon_t{}^{cy} = 1$), the dual concept of productivity growth is equivalent to the primal specification of the productivity growth measure outlined in equation (2.2). This result was first shown by Ohta (1975)[9].

[9] In addition, under the assumption of constant returns to scale, the cost function can be written as $C_t(P_{Jt}, Y_t, t) = Y_t \cdot AC(P_{Jt}, t)$, where $AC_t = C_t/Y_t$ is average or unit costs. This implies that $d\ln C_t/dt - d\ln Y_t/dt = d\ln(C_t/Y_t)/dt = d\ln AC_t/dt$, which is often used as the basis for the measurement of TFP growth under the dual approach.

The primal and dual productivity growth expressions provide the basis for the measurement of TFP growth from both growth accounting (non-parametric) and econometric (parametric) perspectives, since the accounting practices can theoretically be justified by empirically estimable production and cost functions. The theoretical foundation provides also the basis for extension of the TFP growth measures that relax some of the assumptions that are maintained in the conventional accounting formulations. In what follows the growth accounting and the econometric approaches will be outlined as alternative methods to measure TFP growth.

## 2.3 EMPIRICAL APPROACHES TO THE MEASUREMENT OF TFP GROWTH

Once productivity measures are conceptualised on the basis of economic theory, there are several ways to proceed with their empirical implementation. From a broad methodological point of view, non-parametric and parametric approaches can be distinguished. Non-parametric techniques combine properties of a production function with results from the economic theory of production in order to identify the index of productivity growth. On the other hand, parametric approaches apply econometric techniques to estimate parameters of a production function (cost, profit or revenue function) and therefore, obtain direct measures of productivity growth. The traditional index approach and data envelopment analysis (DEA)[10] are examples of the first category. The econometric estimation and stochastic frontier analysis[11] are examples of the second group.

**Figure 2.2**
**Approaches to TFP Measurement**

| | FRONTIER | NON-FRONTIER |
|---|---|---|
| **PARAMETRIC** | Stochastic Models | Econometrics |
| **NON-PARAMETRIC** | DEA | Index Number Approach |

TFP estimation methods can be alternatively categorized into frontier and non-frontier approaches. Non-frontier approaches to productivity measurement, which include the index number and the econometric approach, assume technical efficiency in production. On the other hand, frontier approaches to the measurement of productivity, which include both the stochastic frontier approach and DEA, take explicitly into account the possible inefficient behaviour of the units analyzed. Under the assumption of perfect efficiency, production growth consists of movements along the production frontier (increased input use) plus the increase in output due to shifts in the production frontier ("pure" TFP growth). If, otherwise, the assumption of technically efficient production is relaxed, one can attribute total production growth to at least three separate factors: efficiency improvement, increased inputs use and technological change or "pure" TFP growth. Further classification is again done along the non-parametric and parametric approaches. Figure 2.2 presents these classifications of approaches to productivity measurement.

[10] For a survey of DEA methodologies see Charnes *et al.* (1994)

In what follows the non-frontier approaches to productivity measurement, which are the focus of this thesis, are addressed. Particularly, the growth accounting approach based on the Divisia index and the econometric approach will be reviewed.

### 2.3.1 The Growth Accounting Approach

The standard growth accounting approach based on the Divisia index is, among the non-parametric techniques, the most frequently adopted. The theoretical framework of growth accounting is rooted in the seminal works of Tinbergen (1942) and, independently, Solow (1957). Since then, it has been developed considerably, particularly by the contributions of Denison (1962), Jorgenson and Griliches (1967), Diewert (1976), and Hulten (1978)[12].

The growth accounting framework departs from a production function:

(2.7) $Y(t) = F(X(t), A(t))$

Where $Y(t)$ is real output, $X(t)$ is a vector of $J$ inputs, and $A(t)$ is a measure of disembodied technological change. If one assumes that the marginal rate of substitution between factors is not affected by shifts in the production function, then technological change is Hicks neutral[13] and the function takes the form:

[11] See Coelli *et al.* (1998) for a review on stochastic frontier analysis.

[12] Griliches (1996) and Hulten (2000) provide an overview of the growth accounting approach, stressing the development of the Solow residual.

[13] Technical change is called Hicks neutral or output augmenting when it can be represented as an outward shift of the production function that affects all factors of production proportionately. As emphasized in the previous section, the difference between the Hicksian shift parameter, $A(t)$, and the rate of technological

(2.8) $Y(t) = A(t)F(X(t))$

The growth accounting approach addresses the key question of measuring the change in the TFP parameter, *A(t)*, using a non-parametric index number approach (an approach that does not impose a specific form on the production function). The solution is based on the total logarithmic differential of the production function (2.8) with respect to time:

(2.9) $$\frac{d\ln Y_t}{dt} = \frac{d\ln A_t}{dt} + \sum_{j=1}^{J} \varepsilon_{jt} \frac{d\ln X_{jt}}{dt}$$

where $\varepsilon_{jt} = \dfrac{\partial F_t}{\partial X_{jt}} \dfrac{X_{jt}}{F_t}$ is defined as the output elasticity of input *J*.

A key assumption in growth accounting is that under perfect competition observable factor prices coincide with social marginal products.

(2.10) $$P_{Yt}\left(\frac{\partial Y_t}{\partial X_{jt}}\right) = P_{Jt}$$

This in turn, converts the unobserved output elasticities into observable income shares. Additionally, inserting equation (2.10) into equation (2.9) and rearranging, one obtains a measure of TFP growth, also called Solow residual:

change arises for many reasons. The most important is that the shift parameter captures only costless improvements in the way that inputs are transformed into real output ("manna from heaven").

$$\frac{d\ln A_t^s}{dt} = \frac{d\ln Y_t}{dt} - \sum_{j=1}^{J} s_{jt} \frac{d\ln X_{jt}}{dt} \tag{2.11}$$

Equation (2.11) represents the Solow residual: the residual growth rate of output not explained by the growth in inputs. Here, TFP growth is positive when the rate of growth of the volume of output rises faster than the rate of growth of all combined inputs.

Solow demonstrated that under the assumptions of a Hicks neutral production function, competitive equilibrium and input exhaustion, the residual is equivalent to the growth rate of the Hicksian parameter. This, in turn, is equivalent to the rate at which the production function is shifting over time. An important implication of this result is that, under the appropriate assumptions, the shift in the production function can be measured using observed data on prices and quantity alone. In this way one can provide a formal definition of (disembodied) technological change that coincides with the conceptual idea of productivity growth, given certain assumptions about the appropriate structural and behavioural assumptions being correctly specified[14].

However, in its current form the function (2.11) is in terms of instantaneous changes, for which economic data is not available. The conventional method of calculation is to estimate the function using annual growth rates as a discrete approximation to the continuous case. The most commonly used discrete approximation is the Törnqvist-Theil approximation

[14] Structural assumptions refer to returns to scale, capacity utilisation and the nature of technological change, whereas behavioural assumptions refer to the market structure, the objective function of the producer, and the importance of various regulations.

(Hulten 1973), which takes into account the changes in the factor shares over time. The Törnqvist approximation[15] for equation (2.11) can be written as:

$$\text{(2.12)} \quad \ln\left(\frac{TFP_t}{TFP_{t-1}}\right) \equiv \ln\left(\frac{A_t}{A_{t-1}}\right) = \ln\left(\frac{Y_t}{Y_{t-1}}\right) - 1/2\sum_{j=1}^{J}\left(s_{jt} + s_{jt-1}\right)\ln\left(\frac{X_t}{X_{t-1}}\right)$$

Interpretation of this index requires some care when the implicit assumptions are not met (Hall 1988; Hulten 2000). In other words, for the growth accounting approach to provide meaningful estimates of the rate of disembodied technological change, rather restrictive assumptions about the underlying technology and allocation decision must be maintained. Particularly, these are: (i) the existence of a production technology that can be represented by an aggregate production function; (ii) Hicks-neutral technical change; (iii) competitive output and input markets and; (iv) static long run equilibrium, which implies full utilisation and instantaneous adjustment of all inputs to their desired demand levels. If these assumptions fail, then productivity measures based on the growth accounting approach will in general yield biased estimates of the rate of technological change. When these assumptions are violated, it is still possible, however, to use econometric techniques to filter out these effects to obtain "pure" TFP growth.

[15] In his seminal article, Diewert (1976) was able to identify the economic assumptions about the underlying aggregation functions that are implicit in the choice of an index number. For example, the use of Laspeyres index number implies the assumption of either a linear production function in which all inputs are substitutes, or a Leontief production function in which all inputs are used in fixed proportions. The geometric index number implies an underlying Cobb-Douglas specification for the production function. Finally, the Tömqvist-Theil index number has been shown to be exact for a homogenous translog production function.

### 2.3.2 The Econometric Approach to Productivity Measurement

The standpoint of the econometric approach to productivity measurement is the estimation of an explicitly specified production (the primal approach) or cost function (dual approach) with the objective of establishing the direct linkage between productivity and the key characteristics or parameters of these functions. The estimated parameters of the underlying production or cost model then are used to derive an index of TFP growth. One important benefit from this approach is that it allows for the careful testing of various features of a postulated model. This is preferable to imposing these features a priori.

In its most naïve form, the econometric framework proceeds by estimating a production (cost, profit or revenue) function, which represents the technology, without imposing any further restriction. Thus, for example, one avoids imposing the relationship between production elasticities and income shares as in the growth accounting approach. Indeed, researchers are able to test for the assumptions underlying the growth accounting approach. Thus, non-competitive price behaviour, scale economies[16], and factor augmenting technical change can be accommodated. Additionally, allowance can be made for adjustment cost and variations in capacity utilisation in order to help to explain the residual[17].

Another advantage of the econometric framework as opposed to the growth accounting approach is that it allows one to identify the sources behind TFP growth. Growth accounting, on the other hand, can only quantify the rate of change of TFP, it cannot

[16] Hall (1986, 1988 and 1990), among others, addresses the importance of the role of market power and scale economies in productivity analysis. Overall, these studies showed that estimated mark-ups are positive and statistically significant, implying departures from the perfect competition assumption, and by implication, the inadequacy of using the growth accounting approach.

explain why it changes[18]. Moreover, regression analysis might shed some light on explaining differences in productivity growth rates across firms, industries or countries.

All these possibilities come at a cost, however. The regression approach is not devoid of problems. For instance, the accurate specification of the functional form and estimation of the parameters of these functions are considered to be crucial to the measurement of TFP growth (Nadiri 1970). Any misspecification or errors in estimating the production or cost function will spill over to the measure of TFP.

The choice among different functional forms is generally based on the type of analysis to be carried out[19]. Most of the empirical studies based on the primal approach adopt a Cobb-Douglas specification while most modern studies based on the dual approach, however, rely on some type of flexible functional form. Nevertheless, it is generally agreed that, unless theory requires a more complicated functional form than the Cobb Douglas, the gain from estimating one is marginal (Griliches and Mairesse 1998). Additionally, there is the basic trade-off in that flexible functional forms require a larger sample size for estimation of more parameters.

Moreover, as will be shown in the following chapters, the series (in levels) under analysis show strong evidence of non-stationarity. Although there has been considerable progress concerning the statistical analysis of linear models for non-stationary time series, the

[17] See Mendis and Muellbauer (1984), Berndt and Morrison (1981) and Basu and Kimball (1997).
[18] TFP growth is entirely exogenous to the growth accounting framework.
[19] Some functions simplify computation of elasticity formulas and specification of constraints such as constant returns to scale, some facilitate consideration of dynamic interactions, some allow curvature conditions to be directly imposed, and some enhance the ability to identify the difference between short-run and long-run behaviour.

complexity of the non-linear interaction among variables that occur in flexible functional forms is still largely unknown as far as statistical analysis is concerned. It is for these reasons that this study has chosen the simpler approach of estimating a Cobb Douglas production function.

Estimation of production functions can raise complex econometric issues. There is often a question about the robustness of the resulting parameters when imposing restrictions. Often, researchers are constrained by the sample size of observations, and have to revert to *a priori* restrictions (for example constant returns to scale) to increase the degrees of freedom for estimation. Additionally, there is the question of the econometric procedures used to obtain these estimates. Finally, since at least as early as Marschak and Andrews (1944), researchers have worried about the potential correlation between input levels and the unobserved firm or industry-specific shocks in the estimation of production function parameters[20].

In other words, the benefits of the parametric approach come at a cost. According to Hulten (2000) there is no reason why the econometric and the index number approach should be viewed as competitors and he quotes examples of synergies that proved particularly productive. These arise in particular when econometric methods are used to further explain the Solow residual.

[20] Econometrically, with simultaneity is generally impossible to sign the biases of the production function coefficients when there are many inputs, all of which may be (to different degrees) correlated with the error.

The following section presents adjusted TFP growth indices by relaxing some of the technical and market assumptions underlying the growth accounting framework. The objective is to compare these new expressions with the conventional Solow residual, and based on this comparison discuss potential sources of bias in the latter measure.

## 2.4 SOURCES OF BIAS IN THE SOLOW RESIDUAL

### 2.4.1 Deviations from Perfect Competition

A source of bias in growth accounting estimates of TFP growth (or Solow residual) may be at work if market power exists. With market power the output price ($P_{Yt}$), or marginal revenue, would be above marginal cost. When imperfect competition leads to a price greater than marginal cost, Hall (1988) shows that the Solow residual from equation (2.11) yields a biased estimate of the Hicksian shift parameter, $d\ln A_t/dt$. There is no way around this problem within the index approach proposed by Solow. The index number approach is by nature non-parametric, meaning that it produces estimates of $d\ln A_t/dt$ directly from observed data on prices and quantities.

In the case of imperfect competition in the goods markets[21] the first order condition for cost minimisation implies that producers set the values of factor's marginal product equal to a mark-up ($\mu_t$) over the factor's input price. Thus formally,

[21] However, producers act as price takers in factors markets when choosing their factors inputs so as to maximize profits (or minimise costs). Therefore, producers take the price of all $J$ inputs, $P_{jt}$, as given.

(2.13) $$P_{Jt} = \left( \frac{\partial Y_t}{\partial X_{jt}} \right) \frac{P_{Yt}}{\mu_t}$$

Using expression (2.13) is straightforward to see that the output elasticities can be described as the mark-up multiplied by the input revenue shares ($s_{jt}$):

(2.14) $$\varepsilon_{jt} = \left( \frac{\partial Y_t}{\partial X_{jt}} \right) \frac{X_{jt}}{Y_t} = \mu_t \frac{P_{jt} X_{jt}}{P_t Y_t} = \mu_t s_{jt}$$

This way, using (2.14) in expression (2.9) one obtains:

(2.15) $$\frac{d \ln Y_t}{dt} = \frac{d \ln A_t}{dt} + \mu_t \sum_{j=1}^{J} s_{jt} \frac{d \ln X_{jt}}{dt}$$

Allowing for imperfect competition the output elasticities are not observable from the data anymore. Thus the estimation strategy changes from the measurement of the residual, towards the estimation of expression (2.15) as a way of jointly identifying the degree of market power and TFP growth.

Comparing expressions (2.11) with (2.15) one can derive the bias in the Solow residual when the assumption of perfect competition is violated:

(2.16) $$\frac{d \ln A_t}{dt} - \frac{d \ln A_t^s}{dt} = (1 - \mu_t) \sum_{j=1}^{J} s_{jt} \frac{d \ln X_{jt}}{dt}$$

Equation (2.16) shows that under perfect competition, ($\mu_t$=1), the traditional Solow residual represents an unbiased measure of the "pure" TFP growth. However, for $\mu_t \neq 1$, the Solow residual produces a biased estimate of the TFP parameter. For instance, in the case of imperfect competition ($\mu_t$>1) and positive input growth the Solow residual will overestimate the "pure" growth rate of TFP.

### 2.4.2 Deviations from Constant Returns to Scale

Before analysing the bias in the residual when the assumption of constant returns does not hold it is important to clarify some points. First, there is the view that the Solow residual is inextricable linked to the assumption of constant returns to scale. However, as pointed out by Hulten (2000), there is nothing in the sequence leading from the production function to the residual that requires constant returns to scale. The assumption of constant returns to scale is needed for another purpose. That is to estimate the return of capital as a residual (Jorgenson and Griliches 1967). If an independent measure of the return to capital is used in constructing the share-weights, the residual can be derived without the assumption of constant returns to scale. However, data on the rental price of capital are seldom available or reliable. As a result, the assumption of constant returns to scale is generally adopted for the estimation of the output elasticity using growth accounting.

When constant returns to scale is assumed equation (2.11) can be re-arranged after applying Euler's theorem in the following way[22]:

[22] Unless otherwise specified the assumption of perfect competition will be maintained through the analysis.

$$(2.17) \qquad \frac{d\ln A_t^s}{dt} = \frac{d\ln Y}{dt}_t - \sum_{j\neq k} s_{jt}\frac{d\ln X_{jt}}{dt} - \left(1 - \sum_{j\neq k} s_{jt}\right)\frac{d\ln X_{kt}}{dt}$$

If the assumption of constant returns to scale is not met then the sum of output elasticities of factors $J$ differs from one and is equal to the scale elasticity (Euler's Theorem). However, one can still compute the capital elasticity as the following difference:

$$(2.18) \qquad \varepsilon_{kt} = (1+\lambda_t) - \sum_{j\neq k}\varepsilon_{jt}$$

where $\lambda_t$ is a convenient measure of the extent to which the production function differs from constant return to scale. Additionally, by assuming perfect competition, then output elasticities coincide with income shares. In this way it can be shown that when the assumption of constant returns to scale is not met the residual produces a biased estimate of the "pure" TFP growth, where the bias can be represented as:

$$(2.19) \qquad \frac{d\ln A_t}{dt} - \frac{d\ln A_t^s}{dt} = -\lambda_t\frac{d\ln X_{Kt}}{dt}$$

From equation (2.19) it can be seen that under constant returns to scale ($\lambda_t=0$) the bias in the Solow residual is zero. If, otherwise, $\lambda_t\neq0$ the residual produces a biased estimate of the true technological change. For example, under increasing returns to scale ($\lambda_t>0$) and positive capital input growth the Solow residual will overestimate technological change.

Additionally, the issue of returns to scale is closely related to the role of market power. To see this, notice that the homogeneity of degree ($1+\lambda_t$) of the production function allows one to write the degree of returns to scale as the sum of the output elasticities with respect to the inputs. Allowing for market power, one obtains the following relationship between returns to scale and market power:

$$(2.20) \qquad (1+\lambda_t) = \mu_t \left( \frac{\text{total cost}}{\text{total revenue}} \right)_t = \mu_t (1 - s_{\pi t})$$

where $s_{\pi t}$ are the pure profits as a percentage of total revenue. One consideration is in order. If pure profits are close to zero, then the degree of returns to scale is equal to the mark up.

When one allows for both market power and return to scale, the bias in the residual can be represented as follows:

$$(2.21) \qquad \frac{d\ln A_t}{dt} - \frac{d\ln A_t^s}{dt} = (1-\mu_t)\sum_{j=1}^{J} s_{jt} \frac{d\ln X_{jt}}{dt} - \lambda_t \frac{d\ln X_{Kt}}{dt}$$

### 2.4.3 Output Concept: Gross Output vs. Value Added

Through the previous sections we have referred to a general concept of real output ($Y_t$). However, in productivity analysis, measures of TFP growth are usually computed using either of two different concepts of output. Namely, gross output, which in nominal terms equals the total value of sales and other operating recipes of an economic unit, and value added, which subtracts from gross output the value of goods and services purchased from other units that are used in the course of production (intermediate inputs). A detailed analysis of both concepts is carried out in the next chapter. In this section the interest lies in the implications of using either of the two concepts to measure TFP growth. To do so, it is useful to refer to a production function.

The gross output representation of the production function, denoted by equation (2.22), relates the maximum quantity of real output ($Q_t$) that can be produced by primary inputs, *i.e.* labour ($L_t$) and capital ($K_t$), as well as intermediate inputs ($M_t$). This function also contains the Hicksian parameter $A(t)$, which represents a measure of disembodied technology.

(2.22) $$Q_t = A(t)F(L_t, K_t, M_t)$$

The other common representation relates *value added* to primary inputs in the following way:

(2.23) $$V_t^D = A^V(t)G(L_t, K_t)$$

In equation (2.23) it is assumed that $V_t^D$ (real value added) is a function of primary inputs with value added augmenting technical change.

Under perfect competition and constant returns to scale, the following relationship between gross output and value added growth rates holds[23]:

[23] This is the Divisia definition of value added discussed by Sims (1969) and is in growth rates in continuous time.

$$\text{(2.24)} \qquad \frac{d\ln V_t^D}{dt} = \frac{1}{1-s_{mt}}\left(\frac{d\ln Q_t}{dt} - s_{mt}\frac{d\ln M_t}{dt}\right)$$

where $d\ln V_t^D/dt$ represents the growth rate of the Divisia index of value added as opposed to gross output, $d\ln Q_t/dt$ . From equation (2.24) it follows that if the ratio of materials to output is constant, then value added grows at the same rate as gross output. But in general, this will not be the case.

On general grounds, gross output and value added output concepts will result in different measures of the rate of productivity growth. However, the value added approach might have a significant shortcoming in the presence of imperfect competition and non-constant returns to scale: it can bias the estimation of technological progress. The respective TFP growth measures are the log change rates of $A_t$ and $A^V{}_t$ respectively, and under general assumptions these are given as follows:

$$\text{(2.25)} \qquad \frac{d\ln A_t}{dt} = \frac{d\ln Q_t}{dt} - \mu_t\left(s_{lt}\frac{d\ln L_t}{dt} + s_{kt}\frac{d\ln K_t}{dt} + s_{mt}\frac{d\ln M_t}{dt}\right)$$

$$\text{(2.26)} \qquad \frac{d\ln A^V{}_t}{dt} = \frac{d\ln V_t^D}{dt} - \mu_t^V\left(s_{lt}^V\frac{d\ln L_t}{dt} + s_{kt}^V\frac{d\ln K_t}{dt}\right)$$

where the $s_{jt}$'s are the shares of factor payments in revenues, and the $s^V{}_{jt}$ are the factor shares in nominal value added

Comparing expressions (2.25) and (2.26) two comments are in order. First, it is not clear what the relationship is between the parameter $\mu_t^V$ and $\mu_t$. Second, the term $d\ln A_t^V/dt$ only identifies the true TFP growth ($d\ln A_t/dt$ in expression (2.25)) under certain conditions. To determine these conditions this subsection proceeds by finding a relationship between the two expressions.

One can rearrange equation (2.25) as follows:

$$\frac{d\ln Q_t}{dt}=\mu_t(1-s_{mt})\left(\frac{s_{kt}}{(1-s_{mt})}\frac{d\ln K_t}{dt}+\frac{s_{lt}}{(1-s_{mt})}\frac{d\ln L_t}{dt}\right)+\mu_t s_{mt}\frac{d\ln M_t}{dt}+\frac{d\ln A_t}{dt} \tag{2.27}$$

Then using (2.24) and cost minimisation conditions for intermediate inputs yield:

$$\begin{aligned}\frac{d\ln V_t^D}{dt}&=\frac{\mu_t(1-s_{mt})}{(1-\mu_t s_{mt})}\left(\frac{s_{kt}}{(1-s_{mt})}\frac{d\ln K_t}{dt}+\frac{s_{lt}}{(1-s_{mt})}\frac{d\ln L_t}{dt}\right)\\&+\frac{(\mu_t-1)}{(1-\mu_t s_{mt})}\frac{s_{mt}}{(1-s_{mt})}\left(\frac{d\ln M_t}{dt}-\frac{d\ln Q_t}{dt}\right)+\\&\frac{1}{(1-\mu_t s_{mt})}\frac{d\ln A_t}{dt}\end{aligned} \tag{2.28}$$

From the comparison of expression (2.28) and (2.26) one can infer that:

1. The coefficient $\mu_t^V = \dfrac{\mu_t(1-s_{mt})}{(1-\mu_t s_{mt})}$ identifies the mark-up if and only there are no materials used in production, (usually far from being true). In addition, under imperfect competition (values of $\mu_t > 1$), one can note that $\mu_t^V > \mu_t$.

2. The term $d\ln A_t^V/dt$ in the value added regression takes the form:

$$
\begin{aligned}
\frac{d\ln A_t^V}{dt} &= \frac{(\mu_t-1)}{(1-\mu_t s_{mt})}\frac{s_{mt}}{(1-s_{mt})}\left(\frac{d\ln M_t}{dt}-\frac{d\ln Q_t}{dt}\right)+\frac{1}{(1-\mu_t s_{mt})}\frac{d\ln A_t}{dt} \\
&= \Phi_t\frac{d\ln(M/Q)_t}{dt}+\omega_t\frac{d\ln A_t}{dt}
\end{aligned} \tag{2.29}
$$

Thus, part of the cyclical movements in the residual of the value added regression does not reflect "pure" TFP growth, but rather a hybrid of several variables ($\Phi d\ln(M/Q)_t/dt$), with the rest being "pure" TFP growth ($d\ln A_t/dt$). The size of the former bias depends on the significance of the degree of imperfect competition and the cyclical behaviour of the ratio of materials to output. The term ($\Phi d\ln(M/Q)_t/dt$) is zero if and only if there is perfect competition ($\mu_t$=1), the share of intermediate inputs to gross output is zero and/or the intermediate inputs over total outputs remain constant over time. The second term, which reflects disembodied technological change, gives a relationship between the gross output-based TFP growth ($d\ln A_t/dt$) and the value added based TFP growth rate ($d\ln A_t^V/dt$). Taking into account the share of intermediate inputs, for a reasonable value of $\mu_t$, this relationship implies that the TFP growth in terms of value added will be higher than the gross output based TFP growth.[24] Notice that, both concepts of TFP growth are equal if and only if there is no intermediate inputs ($s_{mt}$ =0) since in this case value added and gross output are the same.

### 2.4.4 The Rate of Utilisation of Production Capacities and Labour Hoarding

Another of the assumptions underlying the growth accounting approach is that factors adjust instantaneously to the desired demand levels or that industries are in steady state of equilibrium. It should be noted that, in the short term, capacity might not be optimally adjusted in the sense that resources are not always fully employed and the degree to which they are varies considerably with the business cycle. This may be because there are fixed factors of production, costs of adjustment or because forecasting errors lead to incorrect investment and labour hiring decisions. This would imply both that TFP growth as conventionally measured by growth accounting techniques would be biased and that econometric methods are required to distinguish these different impacts.

This fact is recognized in productivity discussions (Berndt and Fuss 1986; Wolff 1985), which indicate that labour hoarding can occur at times of low demand as employers seek to avoid loses of skill labour and human capital investments, as well as avoiding potentially costly delays and search costs that may be incurred when demand recovers. Several authors (Mendis and Muellbauer 1984; Muellbauer 1991, among others) have stressed the importance of taking into account adjustments in capacity utilisation when considering TFP growth in the UK, especially in the context of the turbulent conditions of the 1970s and

[24] Caballero and Lyons (1989) and Burnside (1996), among others, have also emphasized how the

1980s[25]. As Cameron (2003: p. 121) pointed out "*capital scrapping in 1979-80 meant that from 1981 onwards the proportionate increase in the capital stock would be substantially higher than recorded by Official Statistics*". This would lead to an upward bias in the conventional TFP growth figures. Additionally "*the 1980-81 recession led to a major shake-out of labour that had been mistakenly hoarded during the late 1970s*".

This subsection looks at the implications of allowing for cyclical variations in the utilization of both capital and labour in identifying "pure" TFP growth. To do so the analysis focuses on the gross output specification of the production function. As Basu and Kimball (1997) point out what matters for production activities are both capital and labour services ($K_{st}$, $L_{st}$) as opposed to the stock of those variables. In other words, production depends on the quantities of those inputs (hours worked and capital stock) as well as the intensity with which they are used (which is not observed). In general, one can express capital services as the function of the capital stock, $K_t$, and its degree of utilisation, $Z_t$. In addition, labour services can be decomposed in terms of number of employees, $N_t$, the number of hours worked, $H_t$, and the effort of each worker, $E_t$. Formally, one can express input services as follows: $K_{st}=Z_tK_t$, and $L_{st}=N_tH_tE_t=L_tE_t$. Allowing for different utilisation rates of both capital, and labour, leads to a new expression for the output growth regression:

$$(2.30)\quad \frac{d\ln Y_t}{dt}=\mu_t\left(s_{kt}\frac{d\ln K_t}{dt}+s_{lt}\frac{d\ln L_t}{dt}+s_{mt}\frac{d\ln M_t}{dt}\right)+\mu_t\left(s_{kt}\frac{d\ln Z_t}{dt}+s_{lt}\frac{d\ln E_t}{dt}\right)+\frac{d\ln A_t}{dt}$$

presence of external effects can affect this analysis.

[25] For example, Richmond and Lynde (2000) estimate that a substantial part of the improvements in manufacturing TFP growth in the 1980s relative to the 1970s resulted from reduced cost inefficiencies rather than faster technological change.

where $d\ln L_t/dt = \left(d\ln N_t/dt + d\ln H_t/dt\right)$

In addition, defining $\sum_{j=1}^{J} s_{jt}\frac{d\ln X_{jt}}{dt} = \left(s_{kt}\frac{d\ln K_t}{dt} + s_{lt}\frac{d\ln L_t}{dt} + s_{mt}\frac{d\ln M_t}{dt}\right)$, the previous expression can be written in the following more compact way:

$$(2.31) \quad \frac{d\ln Y_t}{dt} = \mu_t \sum_{j=1}^{J} s_{jt}\frac{d\ln X_{jt}}{dt} + \xi_t \frac{d\ln U_t}{dt} + \frac{d\ln A_t}{dt}$$

where $d\ln U_t/dt = s_{kt}\left(d\ln Z_t/dt\right) + s_{lt}\left(d\ln E_t/dt\right)$, is a weighted average of unobserved variation in capital utilisation and effort. Notice that if this effect is present and it is not considered, estimated TFP growth would be contaminated by the cyclical utilisation of inputs. In this case, the bias in the Solow residual when both perfect competition and instantaneous adjustments are not met can be represented as follows:

$$(2.32) \quad \frac{d\ln A_t}{dt} - \frac{d\ln A_t^s}{dt} = \left(1-\mu_t\right)\sum_{j=1}^{J} s_{jt}\frac{d\ln X_{jt}}{dt} - \xi_t \frac{d\ln U_t}{dt}$$

From equation (2.32) one can observe that if industries are in steady state or producing at full capacity, $U_t = 1$, then the Solow residual produces an unbiased estimate of the "pure" TFP growth (if additionally the other growth accounting underlying assumptions are met).

The challenge in estimating expression (2.31) is to relate the unobservable $U_t$ to observable variables. To do so, different proxies have been used in empirical applications. For instance, Denison (1979) used the cyclical deviation in the share of profits; Baily (1981) used unemployment rates, while Jorgenson and Griliches (1967) employed electricity use as a proxy. Additional popular proxies to capture both labour effort and capital utilisation have been material inputs (Basu 1995); energy inputs (Costello 1993; Burnside *et al.* 1995); and movements in hours (Basu and Fernald 1997; Basu and Kimball 1997).

As extensively discussed by Basu and Fernald (1997), using conventional data it is not possible to distinguish between labour effort and variable capital utilisation. Nevertheless, these authors use a cost minimisation problem for the firm to show that a reduced-form estimate of the following form: $U_t=\varphi H_t$, is compatible with this joint effect. In many circumstances this correction for hours will account for capital utilisation as well as unobserved labour effort (see Basu and Fernald (1997) for a detailed exposition).

### 2.4.5 Neutrality of Technological Change

Another issue concerns the implied nature of technological change in the growth accounting approach. In general, the assumption of Hicks neutrality of technological progress represented in the production function (2.8) requires that innovation improve the marginal productivity of all inputs equally. In that case, the production function shifts by the same proportion at all combinations of inputs. This is a rather restrictive assumption, which may well lead to biases if violated. A more general formulation allows (costless) improvements in technology to augment the marginal productivity of each input separately:

(2.33) $$Q_t = F(a_t L_t, b_t K_t, c_t M_t)$$

This is the factor-augmentation formulation of technology. It replaces the Hicksian parameter $A$ with the augmentation parameters $a_t$, $b_t$, and $c_t$. If all the other assumptions of the growth accounting approach are retained, one can show that the residual can be expressed as:

$$\frac{d\ln Q_t}{dt}-\sum_{j=1}^{J}s_{jt}\frac{d\ln X_{jt}}{dt}=s_{kt}\frac{d\ln a_t}{dt}+s_{lt}\frac{d\ln b_t}{dt}+s_{mt}\frac{d\ln c_t}{dt} \tag{2.34}$$

The residual is now the share-weighted average of the rates of factor augmentation, but it still measures changes in TFP. Indeed, when the rates of factor augmentation are equal and the sum of the shares is constant, one returns to the previous Hicksian case.

Problems may arise if the rates of factor augmentation are not equal. In this situation, termed "Hicks biased technical change", it is evident that productivity growth depends on the inputs shares as well as the parameters of innovation. A change in the income shares can cause TFP to increase, even if the underlying rate of technological change remains unchanged.

The methodological development in this section has been based primarily on considering procedures to relax the assumptions inherent in the conventional measure of productivity growth or Solow residual. As has been revealed, this involves the use of econometric techniques. Ignoring these technical and market characteristics yields biased estimates of the firm or industry's TFP growth. The burgeoning literature in the area of productivity growth measurement and explanation includes important contributions dealing with these issues. The next section reviews how these issues have had an impact on the reported estimates of TFP growth in the UK manufacturing industry.

## 2.5 REVIEW OF THE EMPIRICAL LITERATURE ON UK MANUFACTURING PRODUCTIVITY GROWTH

This section discusses a number of recent empirical UK based studies on TFP growth measurement. In particular, the section is primarily devoted to a review of the literature in an attempt to synthesise reported findings and provide some answers to the following questions:

1. What are the main specifications that have been used and how much do they affect the results (growth accounting vs. econometrics; primal vs. dual approach)?
2. Are the assumptions underlying the conventional growth accounting approach valid?
3. Are the results sensitive to the inclusion of other adjustment factors?
4. Are the estimates robust to the output concept (gross output vs. value added)?

Since this thesis uses data at the industry level, the section concentrates at the same level instead of summarising the entire literature. This focus on a more limited number of studies allows a summary of the different specifications, data structure and the ensuing hypothesis of each analysis. Moreover, it establishes a basis for comparison for the results of the following chapters.

**Table 2.1**
**Empirical Studies on UK Manufacturing TFP Growth Measurement**

| Studies | Industry Coverage | Output Concept | Adjustments | Estimated period | TFPG Estimates |
|---|---|---|---|---|---|
| ***Growth Accounting*** | | | | | **(1)** |
| *Oulton & O'Mahony (1994)* | 133 Industries | GO | | 1954-86 | 0.35% |
| | | | | 1973- 86 | -0.47% |
| *Cameron et al. (1998)* | 19 Industries | VA | R&D double counting | 1970-92 | 1.40% |
| *O'Mahony (1999)* | 40 Industries | VA | | 1973-95 | 1.85 % |
| *Oulton (1999)* | Manufacturing | GO | | 1973-95 | 0.90% |
| ***Econometrics*** | | | | | |
| ***Primal Approach*** | | | | | |
| *Muellbauer (1991)* | Manufacturing | VA | Capacity Utilisation<br>Price Bias | 1973-90 | 2.08% |
| *Oliveira Martins et al. (1996)* | Manufacturing | VA | Mark-ups | 1970-92 | 2.47% |
| *Harris & Trainor (1997)* | 13 Industries | VA | Mark-ups | 1969-91 | 2.64% |
| *Cameron (2003)* | Manufacturing | VA | Capacity Utilisation<br>Price Biases | 1973-95 | 2.46% |
| *Malley et al. (2003)* | 13 Industries | GO | Capacity Utilisation<br>Mark-ups<br>Scale Economies | 1971-87 | 0.50% |
| ***Dual Approach*** | | | | | |
| *Berndt & Wood (1986)* | Manufacturing | VA | Capital Utilisation | 1973-82 | 0.42% |
| *Lynde & Richmond (1993)* | Manufacturing | VA | Mark-ups<br>Scale economies<br>Price bias | 1966-90 | 3.22% |
| *Crafts & Mills (2001)* | Manufacturing | GO | Capacity Utilisation<br>Mark-ups<br>Returns to scale | 1974-96 | 2.68% |

*Source:* Author
*Notes:* GO refers to gross output, VA to value added and TFPG to total factor productivity growth
(1) Average annual rates for the UK Manufacturing sector.

Table 2.1 summarises the results of a number of recent studies on productivity measurement focused on the UK manufacturing industry. The first panel of the Table covers the state-of-the-art growth accounting studies of post-war British productivity performance. The second panel shows a number of representative studies using econometric techniques. Comparisons across the different results may be misleading or meaningless. This is due to the fact that studies differ in terms of the empirical approach used, studied periods, econometric specification, data sources and number of economic units. The subsequent challenge is then to determine whether the different results reflect actual differences in TFP growth rates or whether these differences are the outcome of different empirical practices.

Despite the differences in approach, the majority of studies on UK manufacturing productivity performance are generally consistent in indicating:

1. A slowdown of the growth of TFP in the 1970s with an important acceleration in the 1980s. Cameron (2003), for instance, using the growth accounting approach, estimated that the annual rate of TFP growth in UK manufacturing fell from about 2.6% in the 1960s to around 0.2% between 1973 and 1980, before rising to around 3% in the 1980s.

Nevertheless, econometric studies have queried the apparent strength of TFP growth in UK manufacturing in the 1980s and concluded that it may not represent an acceleration of technical progress compared with earlier decades. In other words, this was the result of mis-measurement[26]. In this line, there are the studies by Darby and Wren-Lewis (1991), Linde and Richmond (1993), Crafts and Mills (2001) and Cameron (2003). For example, Cameron

[26] There is another set of explanations besides mis-measurement that argues that the major structural changes in the UK economy had an impact on productivity performance (see Muellbauer 1991; Bean and Crafts 1996 and Crafts 2002 for further discussion).

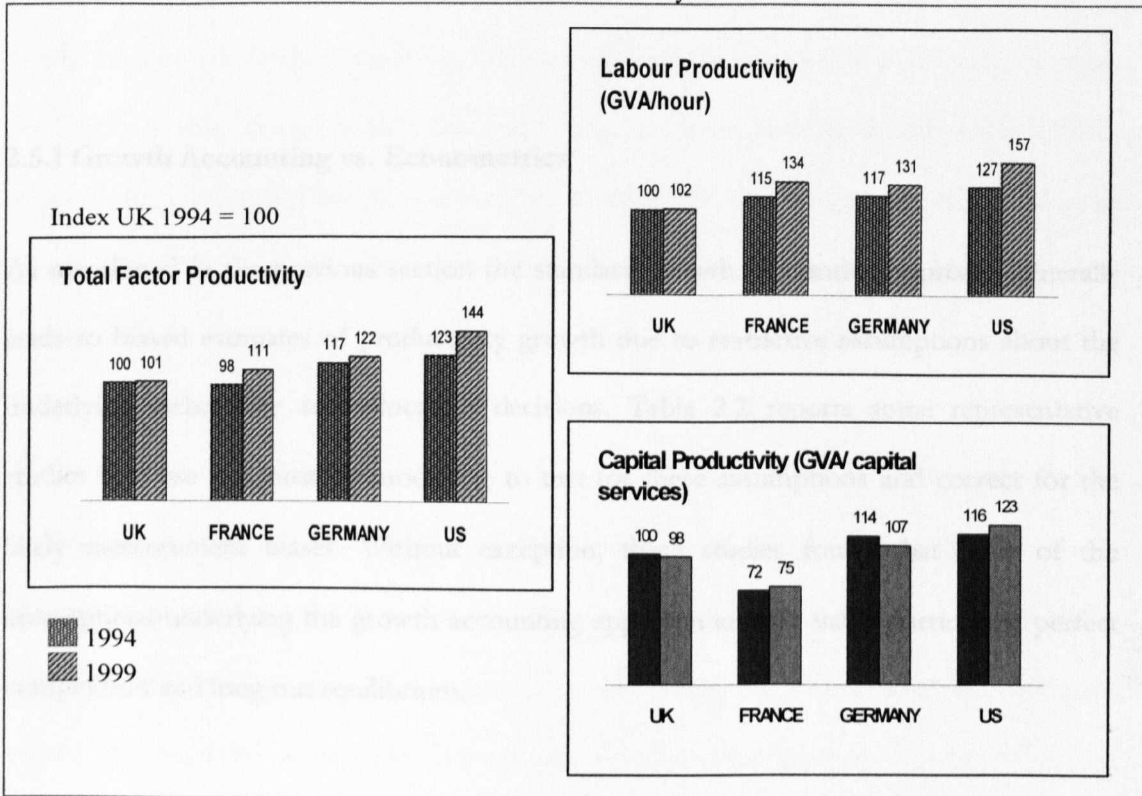
(2003: p. 134) in the same study concludes that when using an econometric approach "*much of the growth upturn in the 1980s was attributable to measurement bias*". Among the measurement issues considered there are: adjustments in capacity utilisation, imperfect competition, scale economies and mis-measurement of output[27].

2. A fairly and persistent lag in TFP levels relative to other industrialized countries. For example, O'Mahony (1999) provides an analysis that documents comparative levels and growth rates of TFP in five countries[28] using the standard growth accounting assumptions. Her study concludes that the level of UK TFP in manufacturing is notoriously lower than that of its primary international competitors. McKinsey (2002) reports the fact that the productivity gap between the UK manufacturing sector and its major competitors is both large and growing (see Figure 2.4). From 1994 to 1999, the gap in TFP increased from 23% to 43% relative to the US, and from 17% to 21% relative to Germany. The UK's lead over France reversed into a 10% lag in 1999.

Moreover, the studies by Crafts and Mills (2001) and Malley *et al.* (2003), using econometric techniques, conclude that adjusting for measurement biases does not affect significantly the growth accounting's results. In other words, adjusting for measurement bias in the productivity residual, although important, does not tend to impact heavily on the British productivity gap. This finding might suggest that measurement biases play an equal part in all the countries considered.

[27] Bruno and Sachs (1985), Stoneman and Francis (1994), and Cameron (2003) argue that errors in the measurement of output led to underestimates of the growth of TFP in the 1970s and overestimates in the 1980s.

**Figure 2.3**
**International Productivity Levels**




Source: McKinsey (2002).

Representative estimates of UK manufacturing TFP growth by the different studies have been brought together in the last column of Table 2.1, with a specific focus on the period 1970-96. Despite the common findings reported above, the results show wide variations in TFP growth estimates across studies and over time. They range from a negative rate of -0.47% to a positive 3.22 percent per annum over different subperiods during the years 1954 to 1996. These differences can be attributed to multiple sources, among them the empirical approach adopted, the assumptions underlying the empirical approach and the output

[28] These countries are France, Germany, Japan, UK and the US.

concept used for productivity measurement. In what follows each of these issues will be considered in more detail.

### 2.5.1 Growth Accounting vs. Econometrics

As mentioned in the previous section the standard growth accounting approach generally leads to biased estimates of productivity growth due to restrictive assumptions about the underlying technology and allocation decisions. Table 2.2 reports some representative studies that use econometric modelling to test for these assumptions and correct for the likely measurement biases. Without exception, these studies found that most of the assumptions underlying the growth accounting approach are not valid, particularly perfect competition and long run equilibrium.

**Table 2.2**
**Bias in the Solow Residual**
(in % terms per annum)

| Studies | Period | Solow residual | Adjusted TFP | Bias |
|---|---|---|---|---|
| **Primal Approach** | | **(1)** | **(2)** | **(2)-(1)** |
| *Oliveira Martins et al. (1996)* | 1970-92 | 1.99 | 2.47 | 0.48 |
| *Harris & Trainor (1997)* | 1969-91 | 1.08 | 2.64 | 1.56 |
| *Cameron (2003)* | 1973-95 | 2.02 | 2.46 | 0.44 |
| *Malley et al. (2003)* | 1971-87 | 0.95 | 0.50 | -0.45 |
| **Average** | | **1.51** | **2.02** | |
| **Dual Approach** | | | | |
| *Berndt & Wood (1986)* | 1973-82 | 0.24 | 0.42 | 0.18 |
| *Lynde & Richmond (1993)* | 1966-90 | 2.40 | 3.22 | 0.82 |
| *Crafts and Mills (2001)* | 1974-96 | 3.24 | 2.68 | -0.56 |
| | | 1.35 (P) | | 1.33 |
| **Average** | | **1.96†** | **2.11** | |

*Source*: Author
*Notes*: (P) refers to the Primal Approach
†: the average excludes the (P) estimate

However, most of the empirical studies in this tradition tend to focus on a particular assumption, either the role of market power or the impact of capacity utilisation instead of jointly testing for both. Based on the reported studies on Table 2.1, there are two exceptions to this. These are the studies by Crafts and Mills (2001) and Malley *et al.* (2003), respectively. The former focuses on the manufacturing sector in aggregate, while the latter directs attention to 13 manufacturing industries although restricts the study to a shorter period.

The last column of Table 2.2 presents the reported estimates of the bias in the Solow residual (or growth accounting based TFP residual) found in different studies. It can be observed that the size of the bias varies across studies and periods. Part of this disparity reflects the extent to which the assumptions underlying the neoclassical approach are relaxed in the different studies. Nevertheless, some interesting facts emerge from the comparison among these studies.

1. For the period 1970 to 1995 the bias was found, on general grounds, to be positive, in the sense that the Solow residual underestimates the true contribution of TFP growth. There are two exceptions to this finding: the study by Crafts and Mills (2001), when the dual measure of the residual is used, and the study by Malley *et al.* (2003), which found that the sign of the bias is negative.

2. Primal estimates of the residual are lower than the respective dual estimates for similar periods. For instance, one can compare the results obtained from Harris and Trainor (1997) with those obtained from Lynde and Richmond (1993) for a similar

period, or the results from Cameron (2003) with those from Crafts and Mills (2001). This is obviously an indication that the assumptions underlying the neoclassical framework do not hold in the context of the UK manufacturing industry (otherwise, as stated above, both measures would be identical).

3. Finally, when adjusted for measurement biases, both primal and dual measures (column 2) tend to converge[29]. For instance, for the period from the end of the sixties to the early nineties Harris and Trainor (1997) and Lynde and Richmond (1993) found that the adjusted TFP growth rate was 2.64% and 3.22%, under the primal and dual approach respectively. Even closer are the estimates found by Cameron (2003) and Crafts and Mills (2001) for the period from the early seventies to the mid-nineties. The averages of the adjusted TFP growth estimates in columns 1 and 2 for the different approaches are 2.02% under the primal approach and 2.11% under the dual approach.

### 2.5.2 Departures from the Growth Accounting Assumptions

This subsection analyses the role of some of the assumptions underlying growth accounting in explaining the bias reported above.

*The Role of Market Power*

Following Hall (1988; 1990) and Roeger (1995) a set of studies departed from the growth accounting approach addressing the importance of the role of market power in measuring

[29] One should be cautious about this note due to the small sample size of our sample of studies.

UK TFP growth. Overall, these studies (see Table 2.3) show that the average estimated mark-up in UK manufacturing industry is positive (about 1.43) and statistically significant. This finding implies a deviation from the perfect competition assumption, and by implication, the inadequacy of using growth accounting. Note also that the one of the lowest mark-up estimate ($\mu$ = 1.21) is obtained using gross output as proxy for real output (Crafts and Mills 2001).

**Table 2.3**
**Average Estimated Mark-ups for UK Manufacturing**

| Study | Period | Avg. Mark-up |
|---|---|---|
| *Bean & Symons (1989)* | 1969-86 | 1.52* |
| *Lynde & Richmond (1993)* | 1966-90 | 1.47 |
| *Haskel et al. (1995)* | 1968-89 | 2.00 |
| *Beccarello (1996)* | 1971-87 | 1.47 |
| *Oliveira Martins et al. (1996)* | 1970-91 | 1.16 |
| *Harris & Trainor (1997)* | 1968-91 | 1.34 |
| *Small (1997)* | 1968-91 | 1.24 |
| *Crafts & Mills (2001)* | 1974-96 | 1.21 |
| **Average** | | **1.43** |
| **Median** | | **1.40** |

*Note:* * The average mark-up estimate of Bean and Symons (1989) is for the whole economy.

### *Scale Economies*

As far as the assumption of economies of scale is concerned, results obtained are mixed depending on the approach adopted, i.e. primal vs. dual approach (see Table 2.3). While most of the estimates within the primal approach imply constant returns to scale, deviations from this assumption are found using the dual approach (Lynde and Richmond 1993; Crafts and Mills 2001).

**Table 2.4**
**Empirical Evidence of Scale Economies in UK Manufacturing**

| Study | Approach | Findings |
|---|---|---|
| *Caballero & Lyons (1990)* | Primal | CRTS |
| *Lynde & Richmond (1993)* | Dual | IRTS |
| *Haskel et al. (1995)* | Primal | CRTS |
| *Oulton (1996)* | Primal | CRTS |
| *Braun (2000)* | Primal | CRTS |
| *Crafts & Mills (2001)* | Dual | IRTS |

*Notes*: CRTS refers to constant returns to scale and IRTS refers to increasing returns to scale.

Two different approaches have been adopted to estimate returns to scale at the industry level using the primal approach. On one side, Haskel *et al.* (1995) opt for the general procedure of estimating returns to scale assuming that they are stable across industries and found that the assumption of constant returns to scale could not be rejected. On the other hand, Caballero and Lyons (1990) allow varying the degree of internal economies of scale and found that only the rubber and plastic industry and the other manufacturing products industry exhibit internal increasing returns to scale. Oulton (1996), in a similar framework, found no evidence for increasing returns internal to the industry. In fact, for the great majority of industries, the hypothesis of constant returns to scale could not be rejected.

### *Capacity Utilisation*

Another wave of studies departed from the growth accounting methodology allowing for the presence of adjustment costs and variation in capacity utilisation. Mendis and Muellbauer (1984), among others, pointed out that the published UK data on labour and capital contain short-term cyclical variations in over and under-utilisation that can be easily misinterpreted as long-term improvements. In order to control for this type of measurement error, different proxies for the unobserved changes in utilisation have been used in past UK based studies. These have been, among others, data on overtime vs. normal hours (Muellbauer 1986; 1991 and Cameron 2003), data from the CBI Industrial Trend Survey (Muellbauer 1986; Cameron 2003) and data on raw materials and energy inputs (Malley *et al.* 2003).

Overall, these studies highlight the importance of taking adjustments in capacity utilisation into account when considering TFP growth in UK, especially in the context of the turbulent conditions of the 1970s and 1980s. For example, according to Cameron's (2003) findings the capacity utilisation adjustment accounted for -0.92% of the growth slowdown in the 1970s. As Muellbauer (1991: p. 105) points out *"one can be seriously led astray by paying too much attention to productivity data not adjusted for utilisation."*

### 2.5.3 Gross Output vs. Value Added

Hitherto, one thing seems clear; that some of the assumptions underlying the growth accounting approach are not valid in the context of UK manufacturing industries when one tests for them. These are, in particular, the assumption of perfect competition and instantaneous input adjustment. This result, on the other hand, implies that the use of value added as a proxy for real output leads to biased estimates of the true TFP growth measure (refer to Section 2.4.3)[30]. Nevertheless, from Table 2.1, one can observe that most of the empirical literature on UK TFP analysis uses value added to proxy real output, instead of the more theoretically correct gross output (exceptions are the studies by Oulton and O'Mahony 1996; Crafts and Mills 2001 and Malley *et al.* 2003).

[30] Note also that the use of value added leads to biased estimates of the true mark-up.

How does the use of value added vs. gross output affect the estimates of TFP growth? From Table 2.2 one can see that, on general grounds, gross output based TFP estimates are lower than those based on value added. The only exception seems to be the estimate reported by Crafts and Mills (2001). As mentioned above their study also provides a primal estimate of TFP growth of 1.35%, which is more in line with other gross output based TFP estimates. Nevertheless, the study proxies intermediate inputs by a measure of energy use, which only represents a proportion of total intermediate inputs in the manufacturing sector. As emphasised previously, any omitted variable (in this case, raw materials and industrial and non-industrial inputs services) will bias the resulting TFP growth estimates.

**Table 2.5**
**Gross Output vs. Value Added Solow Residual Estimates**

| Studies | Period | GO-TFP | VA-TFP | Difference |
|---|---|---|---|---|
| | | (1) | (2) | (1)/(2) |
| *Oulton & O'Mahony (1994)* | 1954-86 | 0.35 | 1.00 | 0.35 |
| *Oulton (1999)* | 1973-95 | 0.90 | 1.85 | 0.49 |
| *Malley et al. (2003)* † | 1971-87 | 0.95 | 2.23 | 0.43 |
| **Average** | | **0.73** | **1.69** | **0.42** |

*Note:* † Data available at http://www.gla.ac.uk/economics/TFP

Table 2.5 reports gross output and value added based TFP growth rates in UK manufacturing respectively. These estimates based on the growth accounting approach, provide a basis for comparisons. From the results presented, one can observe that value added based TFP growth estimates are more than twice as large as those based on gross output.

## 2.6 FIRM LEVEL UK PRODUCTIVITY STUDIES

The focus of this thesis is TFP measurement at the industry level of the economy, and in particular, within manufacturing. At the industry level productivity can grow due to two different sources. First, it can increase due to productivity changes within existing firms belonging to the industry[31]. Second, industry productivity can grow due to "*the process of market selection whereby low productivity establishments exit and are replaced by higher productivity entrants while higher productivity incumbents gain market share*" (Disney *et al.* 2003: p. 666). The recent release of the ARD[32] micro-level database has greatly enhanced the possibilities to study both sources of productivity growth and, therefore, to better understand how UK firms' productivity performance impacts on what is observed at the industry level.

Recent studies using the ARD database have shown that there are indeed large differences in productivity performance across UK manufacturing firms (see Griffith 1999 and Oulton 2000). Part of this literature has focused on the contribution of entry and exit to industry productivity growth. The results in this area are, however, mixed. On one hand, Oulton (2000) finds that exits did not play a significant role in labour productivity growth during the period 1979-89. Low productivity entrants replaced low productivity firms that closed while most of the productivity growth occurred in a small number of survivors that downsized employment. Disney *et al.* (2003), on the other hand, found that around 50% of labour productivity growth and 80-90% of TFP growth in UK Manufacturing over the

[31] Micro-level productivity studies analysing this mechanism focus, for instance, on the role of downsizing (Oulton 2000), new technology and organisational change (Haskel and Szymanski 1993) and increased competition (Nickell 1996).

[32] The ARD or Annual Business Inquire (ABI) Respondent Database contains the micro data underlying the aggregates published annually in the UK Annual Census of Production. Details of the ARD database can be found in Oulton (1997a) and Griffith (1999).

1980s was due to market selection. Particularly, the contribution of entry and exit arose because entrants were more productive than exitors.

Other studies using the ARD database have focused on productivity differentials between domestic and foreign-owned firms (Oulton 1998 and Griffith 1999). These studies found that, overall, foreign-owned establishments have higher productivity rates. According to Oulton (1998) this can be partly explained by higher levels of human capital in the foreign firms.

These findings do not invalidate the theory of productivity measurement in this thesis that essentially treats an industry as if it was a single firm. Rather, they should be regarded as complementary, helping to understand and interpret measured TFP growth at industry level. Moreover, micro-level approaches cannot replace more aggregated productivity studies. This is because many questions of interest to economists and policy makers have to do with general trends in an industry rather than with the performance of a particular firm. Additionally, several data problems arise in using the ARD to obtain productivity estimates. Difficulties arise from the timeliness and exhaustiveness of some of the available series[33]. However, the main problems arise in the measurement of prices, capital stock[34], and average hours worked at the firm level.

[33] For instance, in the study by Disney *et al.* (2003a: p. 94), the authors point out "*data for a large group of small establishments in the 1970s is missing from the ARD records, forcing us to drop 1972-1979 inclusive*".
[34] See the work by Harris and Drinkwater (2000) and Oulton and O'Mahony (1994) on measuring capital stocks.

Particularly, the ARD data do not contain any information on the prices firms charge on output or pay for inputs. The general approach is to use price indices at the 4-digit industry as a proxy for firm prices on outputs and intermediate inputs. Because this is an average of the price over all establishments in the industry, this introduces measurement error in the variables and leads to biased productivity estimates (see Klette and Griliches 1996)[35]. The ARD database does not contain either data on capital stocks, investment deflators, or depreciation rates at firm level. Estimates of the initial capital stock, investment deflators together with depreciation rates are generally obtained using industry level data (Griffith 1999). Finally, estimates of average annual hours worked are only available at the two-digit level.

## 2.7 CONCLUSIONS

With the recognition that productivity growth is the key to sustained economic expansion, the measurement and analysis of productivity represent areas of great importance to economists and policy makers alike. The accurate measurement of productivity growth plays an important role in providing the information economists need to improve policy recommendations and for policy makers to make well-founded decisions. However, despite its importance, the interpretation and measurement of productivity is still a matter of ongoing debate. A debate primarily focused on the methods and assumptions in measuring the rate of change of TFP.

[35] Klette and Griliches (1996) and Ornaghi (2003) have suggested that in order to control for this bias the solution comes from endogenising prices, and therefore modelling the demand side together with the production function.

This chapter has considered some of the issues related to the conceptualisation, measurement and interpretation of TFP growth. First, it has overviewed the conceptual and basic theoretical foundation for measuring productivity growth. Second, it has presented a review of the growth accounting framework in addition to the insights on methodological extensions that relax its underlying assumptions. As has been seen, allowing for different technical and market characteristics assumptions results in "adjusted" productivity growth measures, which may be thought of as more accurate representations of the theoretical concept of TFP growth. Finally, this chapter has reviewed recent UK empirical studies on TFP growth measurement.

Overall, the empirical evidence in this chapter has suggested that TFP growth estimates are very sensitive to different assumptions. There is strong evidence that some of the assumptions underlying the growth accounting approach to measure TFP growth in UK manufacturing industries cannot be sustained. These are, specifically, the assumption of perfect competition and the assumption of instantaneous input adjustment. The evidence with respect to returns to scale is, however, inconclusive. Additionally, productivity measures are highly sensitive to the output measure.

However, the majority of the empirical UK-based studies tend to focus on a particular assumption, either the role of market power or the impact of capacity utilisation, instead of jointly testing for both. Not only that, most of the studies rely on measures of value added to test for these assumptions. This, on the other hand, has been shown to bring additional measurement errors. The recognition of these caveats is the motive of the present study.

The main conclusion is that a comprehensive and integrated framework that accounts for these measurement issues is much needed. Along these lines, in the following chapters we will address whether and to what extent these methodological and measurement issues affect (i) the estimated TFP growth rate (Chapter 3), (ii) the estimated relationship between TFP and its main determinants, in particular R&D investment (Chapter 4), and (iii) the measurement of the size and direction of the UK productivity differential with respect to other industrialized countries (Chapter 5).

As highlighted above there are two studies in the context of UK manufacturing that explore these measurements concerns in an integrated framework. These are the studies by Crafts and Mills (2001) and Malley *et al.* (2003), respectively. The differences of this thesis with respect to the study by Crafts and Mills (2001) are noticeable. The latter focuses exclusively on the manufacturing sector in aggregate while the present study considers 8 manufacturing industries. Second, Crafts and Mills use the dual approach to obtain TFP growth estimates while this study adopts the primal approach. Third, as previously mentioned, Crafts and Mills research proxies intermediate inputs by a measure of the energy use while we do not. Finally, their study focuses exclusively on productivity comparisons between UK and Germany while the focus of the present study is much broader.

This thesis follows an approach similar to that of the contemporaneous study by Malley *et al.* (2003). There are, however, considerable differences that should be mentioned. First, the data sources for gross output and intermediate inputs are different[36]. Second, the proxy for capacity utilisation is also different. Malley and co-authors employ data on raw materials and energy inputs to proxy the capacity utilisation parameter while this study uses deviation from the hours trend. Third, Malley's *et al.* study restricts the period of analysis for the UK to 1970-1987 while this thesis extends it until 1997. Finally, the focus of both studies is different. While the work by Malley and co-authors focuses on international productivity comparisons, this thesis has two other main objectives. As already mentioned, this study additionally considers how different measurement and methodological concerns have an impact on the growth rate estimate of TFP and on the relationship between TFP and R&D in the context of UK manufacturing industries.

[36] Malley *et al.* (2003) obtain the data from the national input-output model database provided by the Inforum Group at the University of Maryland (see Wilson and Mead (1998) for a technical note).

# CHAPTER 3 –

# PRODUCTIVITY GROWTH IN UK MANUFACTURING: OUTPUT CONCEPTS AND ALTERNATIVE ESTIMATION METHODS

*"Improving productivity is the Government's key economic objective for this Parliament. Higher productivity generates prosperity, increases wages and profits, and permits investment in modern, high quality public services."*

*Patricia Hewitt, Secretary of State for Trade and Industry.*
DTI (2002: p. 3)

## 3.1 INTRODUCTION

In Chapter 2 productivity growth was defined as the difference between the growth rate of real output and the growth rate of real factor inputs. Moreover, it was stated that while there is no disagreement on this general concept, there has been extended discussion over the methods and assumptions employed in its various applications. In particular, the accuracy of the conventional measures of productivity growth based on the growth accounting approach has moved centre-stage in the debate about productivity performance. Under the growth accounting approach, Total Factor Productivity (TFP henceforth) growth estimates are usually obtained as a residual from the difference between the growth rate of real value added and a weighted average of the growth rates of primary inputs (labour and capital), where the weights are the respective input shares in value added.

One of the main results emerging from this debate is that the accounting productivity residual (also referred as "Solow residual") is, under general conditions, a biased measure of productivity growth. One source of this bias arises from the common practice of using value added instead of gross output as a measure of real output. There has been a long literature since at least as early as David (1962) that shows the inadequacy of using value added for productivity measurement, especially when perfect competition fails. However, it is only recently that the tide has begun to turn against the use of value added in empirical studies.

Independently of the output concept used for productivity measurement, Chapter 2 indicated that the standard "Solow residual" generally leads to biased estimates of productivity growth. This is due to the restrictive assumptions about the underlying technology and allocation decisions made in the growth accounting framework. In particular, the accounting approach assumes competitive output and input markets, plus full utilisation and instantaneous adjustment of all inputs. In an attempt to correct this measurement bias new trends have emerged in the productivity literature that allow for market imperfections and adjustments for capacity utilisation or quasi-fixed inputs, among others. These new trends have implied the use of econometric modelling as alternative to the growth accounting index number approach.

This chapter directs particular attention to the sensitivity of TFP growth estimates to both alternative output concepts and estimation procedures in the context of UK manufacturing industries. The objective of this chapter is twofold. First, it seeks to examine the importance of using alternative concepts of output. In particular, TFP growth estimates based on the popular value added index are contrasted with those derived from a superior concept of output -gross output. The second aim is to study the implications for UK manufacturing productivity measurement of relaxing some of the assumptions underlying the traditional accounting approach in an integrated framework. To do so, a panel regression is conducted, in which imperfect competition and variations in capacity utilisation are both considered.

The resulting parametric estimates of TFP growth are then compared with those derived from the traditional accounting approach.

In what follows, however, there is no attempt to treat a number of issues, such as aggregation bias[1] or quality adjustment, which may be equally important in measuring industry's productivity growth. First, with respect to the problem of aggregation Cameron *et al.* (1998) produce estimates of the aggregation bias from moving between 2-digit and total manufacturing data and find that it only accounts for around 10% of measured UK Manufacturing TFP growth[2]. Second, ascertaining the bias from not appropriately adjusting for quality improvements is a more difficult task, if not impossible. The understatement of quality change in output[3] leads to an understatement of productivity growth, while the understatement in inputs leads to an overstatement of productivity growth. In what follows we are agnostic as to the overall impact.

The remainder of this chapter is structured as follows. The next section discusses the implications of using either value-added or gross output for productivity measurement. Section 3.3 reviews the traditional accounting framework and the econometric approach as alternative methods for productivity measurement. In section 3.4, conventional accounting

[1] The topic of aggregation bias can be divided into two sets of problems (Maddala 1977). The first one refers to the "aggregation of variables" problem, which includes issues that deal with the index number construction (see Lichtenberg 1990). The second, the "aggregation of relations" problem, includes many issues that deal with the interaction between micro- and macro-relationships (Theil 1954).

[2] To our knowledge, there have been no attempts to provide estimates of the aggregation bias from moving between 3-digit and 2-digit data in the context of UK manufacturing. Morrison and Siegel (1999) in the context of measuring economies of scale in US manufacturing find that the aggregation bias from moving between 4-digit, 2-digit and total manufacturing data is not substantial.

[3] The Hedonic approach is one of the methods used for the treatment of quality adjustments in output. In a simplified way, hedonic methods have in common the use of regression analysis to estimate a hedonic function $P=h(S_1, S_2, \ldots, S_N)$, relating observed prices to quantities of the associated characteristics $S_n$. The objective is to control for those price changes induced by quality improvements and to separate them from pure inflation.

TFP growth estimates are obtained at the industry level for alternative measures of output. A panel regression is presented in section 3.5 in order to see to what extent the assumptions underlying the accounting approach are valid in the context of UK manufacturing, particularly perfect competition and full utilisation of factor inputs. Additionally, a more refined set of parametric estimates of TFP growth is presented and compared with those from the growth accounting approach. To finish, conclusions on the relevance and implications of the results obtained in the previous sections for TFP growth measurement are drawn in section 3.6.

## 3.2 REPRESENTATION OF THE PRODUCTION PROCESS: GROSS OUTPUT VS. VALUE ADDED

In productivity analysis, measures of TFP growth, as stated in the previous chapter, are usually computed using either of two different concepts of output. Namely, gross output and value added. Whether one should be preferred over the other has been an issue of considerable debate since the work of David (1962). Before reviewing the implications of using any of the two concepts it is useful to clarify some concepts.

### 3.2.1 Definitions of Output

*Gross Output*

The OECD (2001: p. 24) defines gross output *(Q)* as *"the goods or services that are produced within a producer unit and that become available for use outside the unit"*. In empirical studies for the UK manufacturing sector, the principal source of nominal gross output data is the Census of Production[4]. The nominal figures represent the value of sales and net additions to inventories. In order to obtain a real measure of gross output, nominal figures are deflated by the appropriate producer price index.

In practice, given the way the data is collected, gross production from the Census is an output measure that includes not only "final output"[5] but double counts those intermediate inputs produced within the industry that are used internally. For productivity analysis at the establishment level there are no intraindustry flows to take into account, thus the published figures provide a good counterpart of the theoretical concept of gross output after some adjustments[6]. At the industry level, however, the problem of double counting arises, in the sense that intraindustry flows are counted in both the input and the output side of the industry production function. In this case, it is suggested that the output measures for intraindustry purchases be adjusted (see Baily 1986 and Oulton and O'Mahony 1994).

On theoretical grounds the published gross output figures should be adjusted for intraindustry transactions. However, in practice this is a cumbersome process and often impossible to perform in time series analysis. UK intraindustry purchases can be derived from the input-output tables. However, these tables, apart from presenting a problem of consistency with the Census data, are not available for every year[7]. In addition, this

[4] From 1997 the Annual Census of Production, together with the Census of Construction, has been incorporated into and replaced by the Annual Business Inquiry (ABI).
[5] By "final output" is meant that part of the industry sales that is not destined to be used as intermediate inputs by the other firms included in the aggregate under study.
[6] In order to arrive at an economic definition of nominal gross output for each establishment, valued at producer prices, the published "gross output" figures (from the Census of Production) should be adjusted. These adjustments are (i) the removal of stock appreciation, and (ii) the elimination of excise payments and subsidies (see Oulton and O'Mahony 1994).
[7] Particularly, UK input-output tables are available for the years 1968, 1972, 1979, 1984, 1985 and 1990. From 1979 to 1990 the tables are based on the 1980-SIC and are in current prices only. In addition, the

adjustment amounts to a process of integration of different units or industries, in which mergers and acquisitions –not always identifiable- play an important role in determining gross output or intermediate inputs in any industry[8].

*Value Added*

When purchases of intermediate inputs are deducted from the value of gross output, one obtains a measure of nominal value added. Thus value added avoids the problem of double counting intra-industry transactions. In principle, there is no disagreement in defining nominal value added as:

$$(3.1) \quad P_t^V V_t^D = P_t Q_t - P_t^M M_t$$

where $V_t^D$ is real value added, $Q_t$ is real gross output and $M_t$ refers to intermediate inputs. The prices of value added, gross output and intermediate inputs are represented respectively by $P_t^V$, $P_t$ and $P_t^M$.

However, the method of deflation used to obtain a measure of real value added is subject to considerable controversy, in that a "price of value added" does not exist. In practice, two methods of deflation have been frequently employed: single and double deflation. Single deflation (used, for example, by Cameron (1996)) consists of deflating nominal value added by the price of gross output. That is,

tables are constructed on a commodity-by-commodity basis instead of on an industry-by-industry basis. Also the level of commodity disaggregation has varied over time.

[8] As Hulten (2000: p. 57) points out "the merger of firms can transform what were once inter-firm flows of goods into intra-firm flows, thereby extinguishing some amount of gross output".

(3.2) $V_t^{SD} = \frac{P_t Q_t - P_t^M M_t}{P_t} = Q_t - \left(\frac{P_t^M}{P_t}\right) M_t$

This method of deflation has been shown to be inadequate, unless output and intermediate input prices are rising at the same rate (Sato 1976; Stoneman and Francis 1994).

Double deflated value added is usually defined as:

(3.3) $V_t^{DD} = \frac{P_t Q_t}{P_t} - \frac{P_t^M M_t}{P_t^M} = Q_t - M_t$

However, Bruno (1978) and Diewert (1978) have showed that this definition has no theoretical foundation, considering the conditions under which an aggregate real value added function can exist. These conditions are either (i) prices of intermediate inputs relative to that of gross output remain constant –which is unlikely to occur-, or (ii) primary inputs and technology are separable from intermediate inputs in the gross output specification of the production function. In the latter case, the production function based on gross output is represented as:

(3.4) $Q_t = G\left(V_t^d, M_t\right)$

where,

(3.5) $V_t^d = V(L_t, K_t, t)$

Under perfect competition and constant returns to scale, a relationship between the gross output and value added growth rates can be obtained by differentiating (3.4) and (3.5) with respect to time (Sato 1976):

$$(3.6) \quad \Delta \ln V_t^D = \frac{1}{1-s_{mt}}\left[\Delta \ln Q_t - s_{mt}\Delta \ln M_t\right] = \Delta \ln Q_t - \frac{s_{mt}}{1-s_{mt}}\left[\Delta \ln Q_t - \Delta \ln M_t\right]$$

Expression (3.6) is the Divisia definition of value added discussed by Sims (1969) (that is, in growth rates in continuous time)[9]. Comparing this expression with (3.2) it can be shown (Sato 1976; Stoneman and Francis 1994) that single deflation and the Divisia method of double deflation will yield the same result only if output and intermediate input prices are rising at the same rate. That is,

$$(3.7) \quad \Delta \ln V_t^{SD} = \Delta \ln V_t^D + \left(\frac{n}{1-s_{mt}}\right)\Delta \ln\left(P_t^M / P_t\right)$$

in which $n = M/Q$, the share of output going to materials in base year prices.

On the other hand, Bruno (1978) and Basu (1995) have showed that the two methods of double deflation (expressions 3.3 and 3.6 respectively) will yield the same result only in two

[9] In practice it may not be possible to construct a chained Divisia index. Instead, the use of a discrete Törnqvist index (the geometric mean of the two estimates) is a good first approximation to the desired figure.

special cases: if gross output and intermediate inputs are rising at the same rate, or if the price of intermediate inputs relative to the price of output always equals one (in which case single deflation would do just as well).

$$(3.8) \quad \Delta \ln V_t^{DD} = \Delta \ln V_t^{D} + \left( \frac{n}{(1-s_{mt})(1-n)} \right) \left( 1 - \left( \frac{P_t^M}{P_t} \right) \right) \left( \Delta \ln Q_t - \Delta \ln M_t \right)$$

Therefore, the common practice of using single deflated value added or the Laspeyres (or Paasche) double deflated value added index will result in biased estimates of real output, unless the conditions stated above are satisfied.

### 3.2.2 Gross Output vs. Value Added Based TFP Growth Measures

On the basis of the output concept definitions, this section briefly reviews the implications of using either gross output or real value-added in the context of productivity measurement. To do so, it is useful to refer to a production function.

In the literature on productivity, both gross output and value added representations of the production function have been adopted. The gross output specification, represented by equation (3.9), relates the maximum quantity of output ($Q_t$) that can be produced by primary inputs, *i.e.* labour ($L_t$) and capital ($K_t$), as well as intermediate inputs ($M_t$). This function also contains a parameter $t$, which represents a measure of technology.

(3.9) $Q_t = Q(L_t, K_t, M_t, t)$

In applications to actual data an alternative special case of (3.9) is often assumed (e.g. Hulten 1978; Griliches and Mairesse 1983; Bruno 1984; Baily 1986; Oulton and O'Mahony 1994; Oulton 1996 and Maley *et al.* 2003).

(3.10) $Q_t = A(t)F(L_t, K_t, M_t)$

Equation (3.10) simply assumes that there is output-augmenting technical change, in the sense that technical change raises the maximum output that can be produced with a given level of inputs without changing the relationship between them. This form of technical change is called "Hicks-neutral" and is represented by the term $A(t)$.

The other common representation relates *value added* to primary inputs in the following way:

(3.11) $V_t^D = A^V(t)G(L_t, K_t)$

In Equation (3.11) it is assumed that $V_t^d$ (real value added) is a function of primary inputs with value added augmenting technical change. Value added production functions have been frequently used in the productivity literature, e.g. Solow (1957), Jorgenson and Griliches (1967) and Jorgenson *et al.* (1987). For UK studies on productivity, this specification has been adopted by Muellbauer (1986), Cameron *et al.* (1998), O'Mahony (1999) and Cameron (2003), among others.

Baily (1986) shows that, with the exception of special functional forms, the gross output and value added specifications are inconsistent with each other and will result in two different measures of the rate of productivity growth. These two measures are logarithmic rates of change of parameters $A_t$ and $A_t^V$ respectively; and under the assumption of perfect competition these are given as follows:

$$(3.12)\quad \Delta \ln A_t = \Delta \ln Q_t - s_{lt}\Delta \ln L_t - s_{kt}\Delta \ln K_t - s_{mt}\Delta \ln M_t$$

$$(3.13)\quad \Delta \ln A^V{}_t = \Delta \ln V_t - \tilde{s}_{lt}\Delta \ln L_t - \tilde{s}_{kt}\Delta \ln K_t$$

where the $s_{Jt}$'s are the shares of factor payments in revenues, and the $\tilde{s}_{Jt}$'s are the factor shares in nominal value added.

Using the Divisia definition of value added (represented in equation (3.6)) there is a direct relation between the gross-output, $\Delta lnA_t$, and the value-added, $\Delta lnA^V{}_t$, productivity measures (see Bruno 1978):

$$(3.14)\quad \Delta \ln A^V{}_t = \left(\frac{1}{1-s_{mt}}\right)\Delta \ln A_t = \frac{1}{S_t^{VA}}\Delta \ln A_t \qquad \text{with } s_t^{VA} = \frac{P_t^v V_t^D}{P_t Q_t}$$

Specifically, the rate of change of value added based TFP equals the rate of change of gross output based TFP, multiplied by the inverse of the nominal share of value added in gross output. Moreover, from (3.14) value added based TFP growth can never be less than and will generally be larger than TFP growth in the gross output sense. However, this relationship only holds under perfect competition and constant returns to scale.

### 3.2.3 Discussion

Whether gross output should be preferred to value added or vice versa has been an issue of considerable controversy, reflected in the works of Bruno (1978; 1984), Baily (1986) and Basu and Fernald (1995; 1997), among others. There is a long literature that argues against the use of value added for studying productivity growth on various grounds. On one hand, Bruno (1978), among others, emphasises the strong separability assumptions necessary for the existence of a stable value added production function. Given these assumptions are satisfied, one could, in principle, obtain correct total productivity estimates from value added. This is valid provided that these are obtained from underlying gross output and intermediate inputs measures based on the Divisia index procedure. In which case, the data requirements are just as great as for the gross output approach. Researchers, however, often rely on the usual national accounts figures obtained by the Laspeyres (or Paasche) method of double or single deflation. This method can bring considerable measurement problems unless certain conditions are satisfied.

Additionally, with the renewed interest in the role of market power in productivity analysis, further objections to the use of value added have arisen. The argument of authors like Basu (1995) and Basu and Fernald (1995; 1997) is focused on the neo-classical assumptions behind the definition of the value-added index. Even if separability holds, with imperfect competition, taking value added to be a function only of primary inputs is generally misspecified: it depends on intermediate input use as well. Value added growth is obtained by subtracting from gross output growth the revenue-share-weighted contribution of intermediate inputs. However, this is only valid under perfect competition. With imperfect competition, the input elasticity of intermediate inputs exceeds its revenue share by the mark-up. Consequently, in the presence of mark-ups some of the productive contribution of the intermediate inputs remains in the measured value-added growth[10].

In conclusion, on theoretical grounds the preferred output measure for studying productivity performance is gross output, use of which does not impose any a priori assumption in the production function. In contrast to gross output, value added is an economic index number without physical interpretation and, because of that, dependent on theoretical assumptions, in particular perfect competition and constant returns to scale. This dependence makes value added an invalid measure of output and, therefore, not appropriate for studying productivity growth. Nevertheless, in practical terms as the focus of study moves to higher levels of industry aggregation the quality of the published gross output figures differs from the ideal. This is due to the problem of intra-industry flows. Therefore, at high levels of aggregation the researcher is confronted with the dilemma of either using the gross output approach, which implies becoming a prisoner of the degree of industrial integration, or otherwise using the implausible value added approach.

[10] See Section 2.4.3 in Chapter 2 for a detailed exposition.

## 3.3 ALTERNATIVE ESTIMATION TECHNIQUES: GROWTH ACCOUNTING VS. ECONOMETRICS

Once productivity measures are conceptualised on the basis of economic theory, there are several ways to proceed with their empirical implementation. In Chapter 2, it was stated that from a broad methodological point of view, non-parametric and parametric approaches could be distinguished. This section summarises the main features found in Chapter 2 with respect to two of the most frequent approaches to obtain TFP growth measures: the growth accounting and the econometric approach.

### 3.3.1 Growth Accounting and Assumptions Underlying the Conceptual Framework

The standard growth accounting approach based on the Divisia index is, among the non-parametric techniques, the most frequently adopted. The theoretical framework of growth accounting is rooted in the seminal works of Tinbergen (1942) and, independently, of Solow (1957). Since then it has been developed considerably, in particular by the contributions of Denison (1962), Jorgenson and Griliches (1967), Diewert (1976) and Hulten (1978)[11].

*Theoretical Background*

The growth accounting framework starts with a production function such as those defined in equations (3.7) and (3.8) and proceeds by differentiating them with respect to time to

[11] Griliches (1996) and Hulten (2000) provide an overview of the growth accounting approach, stressing the development of the Solow residual.

obtain the productivity growth index or "Solow" residual[12]. For instance, logarithmically differentiating the gross output production function (equation (3.7)) with respect to time, one obtains:

$$(3.15)\quad \Delta \ln Q_t = \Delta \ln A_t + \varepsilon_t^{Q,L} \Delta \ln L_t + \varepsilon_t^{Q,K} \Delta \ln K_t + \varepsilon_t^{Q,M} \Delta \ln M_t$$

where $\varepsilon_t^{Q,L}, \varepsilon_t^{Q,K}, \varepsilon_t^{Q,M}$ denote respectively the elasticity of output with respect to labour, capital and intermediate inputs.

Additionally, most growth accounting studies proceed assuming a constant returns technology, but this is not necessary in cases where an independent observation of the rental price of capital is available. Under both assumptions of perfect competition and constant returns to scale, equation (3.15) can be rearranged to yield the basic growth accounting equation for a gross output representation of the production function:

$$(3.16)\quad \Delta \ln A_t = \Delta \ln(Q/K)_t - s_{lt} \Delta \ln(L/K)_t - s_{mt} \Delta \ln(M/K)_t$$

*Advantages and Restrictions of the Growth Accounting Approach*

As Nadiri and Prucha (1999: p. 3) point out the traditional growth accounting approach "*has the advantage of simplicity as well as the benefit of not requiring direct estimation of the underlying technology*". In practice, the residual can be obtained from observed data as the difference

[12] The key result of Solow's analysis is that the residual is, in theory, equal to the growth rate of the Hicksian efficiency parameter.

between the growth rate of real output and a weighted average of the growth rate of factor inputs, where the weights are the respective revenue shares, as shown in equation (3.16).

Additionally, the residual provides a formal definition of (disembodied) technological change that coincides with the conceptual idea of TFP growth. Nevertheless, for the growth accounting approach to provide meaningful estimates of technical change, rather strong assumptions about the underlying technology and allocation decisions must be maintained. In particular, it is necessary to assume: (i) the existence of a production technology that can be represented by a production function, (ii) Hicks-neutral technical change, (iii) competitive output and input markets, and (iv) long run equilibrium, which implies full utilisation and instantaneous adjustment of all inputs to their desired demand levels. If these assumptions are violated, then productivity measures based on the growth accounting approach will in general yield biased estimates of technological change.

*Deviations from Growth Accounting*

The puzzle of the observed slowdown of productivity growth during the 1970s initiated a critical methodological review of the conventional measure of productivity growth[13]. First, a new literature emerged addressing the importance of the role of market power and scale economies in productivity measurement (see Hall 1986; 1988 and 1990, among others). Overall, these studies showed that estimated mark-ups are positive and statistically significant. This implies departures from the perfect competition assumption[14], and by implication, the inadequacy of using the growth accounting approach. A second wave of

[13] See Berndt and Fuss (1986), Denny *et al.* (1981), Hall (1988) and Hulten (1986).

studies departed from the growth accounting methodology assuming economies are not in steady state, thus allowing for the presence of adjustment costs (the possibility that changes in factor inputs are increasingly costly the faster they are implemented) and, variations in capacity utilisation (Mendis and Muellbauer 1984; Berndt and Morrison 1981 and Basu and Kimball 1997). These studies showed that allowing for changes in capacity utilisation the conventional productivity residual resulted in a biased estimate of the rate of technological change.

### 3.3.2 The Econometric Approach

In its most naïve form, the econometric framework proceeds by estimating an equation like (3.15) without imposing any further restriction. Thus, one avoids imposing the relationship between production elasticities and income shares as in the growth accounting approach. Moreover, non-competitive price behaviour, scale economies, and factor augmenting technical change can be accommodated. Additionally, allowance can be made for adjustment cost and variations in capacity utilisation in order to help to explain the residual.

As seen in Chapter 2, the regression approach is not devoid of problems either. The accurate specification of the functional form and estimation of the parameters of the production (or cost) function are considered to be crucial to the measurement of TFP growth (Nadiri 1970). For instance, there is often a question about the robustness of the resulting parameters or about the econometric procedures used to obtain these estimates.

[14] In Roeger (1995) an alternative to Hall's method of estimation is proposed, founded on both the Solow residuals and the dual Solow residuals. The method employed by Roeger is used by Oliveira Martins *et al.* (1996), among others.

Finally, since at least as early as Marschak and Andrews (1944), researchers have worried about the potential correlation between input levels and the unobserved industry-specific shocks in the estimation of production function parameters[15]. To the extent that these exist, conventional OLS estimates of production functions will yield biased parameter estimates, and, by implication, biased estimates of productivity growth.

## 3.4 TFP GROWTH ESTIMATES FOR ALTERNATIVE OUTPUT CONCEPTS USING THE GROWTH ACCOUNTING APPROACH

Using the growth accounting approach, which assumes perfect competition and constant returns to scale, estimates of TFP growth based on the Divisia value added (DVA) index are as valid as those based on gross output, given that separability holds. Additionally, single deflated value added (SDVA) will be an appropriate measure of real output as long as output and intermediate input prices rise at the same rate. Given this condition is satisfied, SDVA and DVA based TFP growth measures coincide. Otherwise, the use of SDVA brings considerable measurement bias.

The main purpose of this section is to check the adequacy of using the traditional SDVA as a measure of real output. To do so, estimates of alternative TFP growth measures based on different concepts of output have been computed using the traditional growth accounting approach[16]. Table 3.1 displays time-averaged rates of growth during the entire sample

[15] Econometrically, with simultaneity it is generally impossible to sign the biases of the production function coefficients when there are many inputs, all of which may be (to different degrees) correlated with the error.
[16] See Table B.1 in the Statistical Appendix B.1 for descriptive statistics of the main variables.

period, while Table 3.2 reports those for different sub-periods (1973-79, 1979-89 and 1989-97). In particular, the TFP growth rates presented are derived from gross output (GO)[17], the Divisia value added (DVA) index[18], and the single deflated value added (SDVA) index, all at 1995 prices. These TFP growth rates have been obtained using the results derived in the previous section for the growth accounting framework. Equations (3.17) and (3.18) represent the basic growth accounting equations to be estimated in terms of gross output and value added respectively.

$$(3.17)\quad \Delta \ln A_t = \Delta \ln(Q/K)_t - s_{lt}\Delta \ln(L/K)_t - s_{mt}\Delta \ln(M/K)_t$$

$$(3.18)\quad \Delta \ln A_t^V = \Delta \ln(V/K)_t - \tilde{s}_{lt}\Delta \ln(L/K)_t$$

From the results presented in Table 3.1 and Table 3.2, some interesting facts emerge. First, it can be observed that the magnitudes of the three alternative estimates of productivity growth are very different. As the theory predicts, gross output based TFP growth rates are lower than those based on the value-added approach. Second, the results confirm that there is considerable disparity in terms of productivity growth both across industry groups and time. This disparity is more accentuated in terms of the value-added approach, and, in general, for the period 1973-1979. Finally, from Table 3.1 and 3.2 one observes that the DVA and SDVA based TFP growth rates rather than being similar, differ substantially. This implies that the use of SDVA brings considerable measurement bias.

[17] In order to minimise the problem of intraindustry flows regarding the official data on gross output, the study focuses on UK two digit manufacturing industries.

**Table 3.1**
**Value-Added vs. Gross-Output based TFP Growth Rates, 1970-1997**
Averages of annual rates of change (in percentage terms)

| **Industry** | | **$\Delta lnA_t$ (GO)** | **$\Delta lnA^V_t$ (DVA)** | **$\Delta lnA^V_t$ (SDVA)** |
|---|---|---|---|---|
| Food, Beverages & Tobacco | FBT | -0.23 | -1.05 | 0.93 |
| Textile & Leather | TL | 1.14 | 3.07 | 2.26 |
| Wood and Wood Products | WWP | 0.23 | 0.75 | 1.11 |
| Paper and Paper Products | PPP | 0.29 | 0.68 | 1.58 |
| Chemicals, man-made fibres, rubber & plastic products | CH | 1.02 | 3.11 | 1.72 |
| Other Non-Metallic Mineral Products | NMM | -0.70 | -1.57 | -0.61 |
| Manufacture of Basic Metals & Fabricated Metal Products | BFM | 0.90 | 2.97 | 2.02 |
| Machinery, Optical Equipment & Transport Equipment | MOT | 1.64 | 4.57 | 3.10 |
| **Mean** | | 0.53 | 1.57 | 1.51 |
| **Standard Deviation** | | 0.78 | 2.20 | 1.10 |

*Sources*: Data on input shares, output, inputs and the corresponding prices are available for eight two-digit manufacturing industries, classified by SIC-1992, over the period 1970-1997. The source for all these figures is a database mainly derived from the Census of Production, and which is described in further detail in the Appendix A.1.

The change in rates of TFP growth between the three periods is equally noticeable. Between 1973-1979, the average TFP growth rate for the industries considered fell at an average annual rate of 1.16 per cent (with 7 of the 8 industries experiencing negative growth rates). Although it is a common finding to obtain negative estimates for the period 1973-1979, it is controversial to associate them to technological regress. Some authors (see, for example, Muellbauer 1991) have argued that negative estimates of TFP growth may reflect measurement problems, especially as regards the capital stock. As emphasized in Chapter 2 there are a number of factors underlying TFP growth besides technological change. Moreover, estimates of TFP growth obtained as a residual may reflect the influence of a

[18] For empirical purposes the discrete Törnqvist approximation is employed.

range of phenomena that are not genuine causes of TFP growth. In this way, negative TFP growth estimates for certain time periods and industries become more plausible.

**Table 3.2**
**Gross-Output and Value-Added based TFP Growth Estimates**
Averages of annual rates of change (in percentage terms)
Sample periods: 1973-79, 1979-89, and 1989-97

| | 1973-1979 | | | 1979-1989 | | | 1989-1997 | | |
|---|---|---|---|---|---|---|---|---|---|
| **Industry** | $\Delta \ln A_t$ (GO) | $\Delta \ln A^V_t$ (DVA) | $\Delta \ln A^V_t$ (SDVA) | $\Delta \ln A_t$ (GO) | $\Delta \ln A^V_t$ (DVA) | $\Delta \ln A^V_t$ (SDVA) | $\Delta \ln A_t$ (GO) | $\Delta \ln A^V_t$ (DVA) | $\Delta \ln A^V_t$ (SDVA) |
| **FBT** | -1.18 | -5.28 | -2.35 | 0.16 | 0.71 | 1.83 | 0.26 | 1.04 | 2.98 |
| **TL** | -0.31 | -0.57 | -0.25 | 1.80 | 4.84 | 3.28 | 1.43 | 3.74 | 3.31 |
| **WWP** | -1.59 | -5.04 | -4.77 | 0.77 | 2.60 | 1.95 | 0.63 | 1.98 | 1.79 |
| **PPP** | -2.28 | -5.03 | -2.42 | 0.89 | 2.08 | 2.77 | 0.29 | 0.65 | 0.93 |
| **CH** | 0.45 | 1.51 | -0.54 | 1.64 | 5.10 | 4.69 | 1.46 | 4.17 | 2.63 |
| **NMM** | -2.81 | -6.10 | -2.72 | 0.38 | 0.97 | 1.54 | -0.60 | -1.46 | -1.95 |
| **BFM** | -1.46 | -4.45 | -3.13 | 2.74 | 8.94 | 6.36 | 1.68 | 4.89 | 3.55 |
| **MOT** | -0.14 | -0.33 | -0.59 | 2.06 | 5.36 | 4.87 | 2.98 | 9.15 | 4.32 |
| **Mean** | -1.16 | -3.16 | -2.10 | 1.31 | 3.82 | 3.41 | 1.02 | 3.02 | 2.19 |
| **St. Dev.** | 1.11 | 2.89 | 1.55 | 0.9 | 2.77 | 1.73 | 1.10 | 3.24 | 1.98 |

*Source*: See Data Appendix A.1.

On the whole, industries experienced faster growth rates in the 1980s under the three alternative output measures, recovering from the poor performance achieved in the period 1973-1979. Moreover, over the 1989-1997 period the manufacturing industries experienced a slow down in their growth rates, the exception being the Food industry. Oulton and O'Mahony (1994) and Cameron (1996), using different approaches, confirm these trends.

In Table 3.3 the rate of gross output growth is decomposed into the contributions of hours worked, capital accumulation, intermediate inputs and TFP growth according to the growth accounting equation (3.17). The Table displays time-averaged rates of growth over the period 1970 to 1997. While the contribution of hours worked to gross output is negative in all the industries considered, the contribution of physical capital accumulation to output growth is positive in six of the eight industries considered (the exceptions being the Textile and Metal industries). Intermediate inputs, on the other hand, have a positive contribution to output growth in five industries (the exceptions being the Textile, Wood and Metal industries).

**Table 3.3**
**Sources of Gross Output Growth in UK manufacturing, 1970-1997**
Average of annual rates of change (in % terms)

| Industry | Gross Output | Labour | Capital | Interm. Inputs | TFP |
|---|---|---|---|---|---|
| **FBT** | -0.14 | -0.25 | 0.10 | 0.25 | -0.23 |
| **TL** | -1.30 | -1.12 | -0.20 | -1.13 | 1.14 |
| **WWP** | -0.45 | -0.37 | 0.08 | -0.39 | 0.23 |
| **PPP** | 1.54 | -0.44 | 0.28 | 1.40 | 0.29 |
| **CH** | 2.54 | -0.26 | 0.18 | 1.60 | 1.02 |
| **NMM** | -0.61 | -0.76 | 0.56 | 0.30 | -0.70 |
| **BFM** | -0.49 | -0.76 | -0.07 | -0.56 | 0.90 |
| **MOT** | 2.05 | -0.95 | 0.10 | 1.26 | 1.64 |
| **Mean** | 0.39 | -0.61 | 0.13 | 0.34 | 0.53 |
| **Std. Dev.** | 1.43 | 0.33 | 0.23 | 1.00 | 0.78 |

*Source:* See Data Appendix A.1.

Gross output in manufacturing industries grew at an average annual rate of 0.39% between 1970 and 1997, while TFP rose at 0.53%. Nevertheless, there is considerable variation in rates of productivity growth across manufacturing sectors. Over the sample period, average annual rates of TFP growth ranged from 1.64% and 1.14% in the Machinery (MOT) and

Textile (TL) industries respectively to -0.70% and -0.23% in Minerals (NMM) and Food (FBT) respectively.

**Table 3.4**
**Sources of Value Added Growth in UK Manufacturing, 1970-1997**
Average of annual rates of change (in % terms)

| Industry | Value Added | Labour | Capital | TFP |
|---|---|---|---|---|
| FBT | 0.29 | -1.09 | 0.44 | 0.93 |
| TL | -1.31 | -3.05 | -0.52 | 2.26 |
| WWP | 0.08 | -1.25 | 0.23 | 1.11 |
| PPP | 1.23 | -1.00 | 0.65 | 1.58 |
| CH | 1.41 | -0.80 | 0.49 | 1.72 |
| NMM | -1.16 | -1.80 | 1.25 | -0.61 |
| BFM | -0.72 | -2.50 | -0.24 | 2.02 |
| MOT | 0.87 | -2.50 | 0.26 | 3.10 |
| Mean | 0.09 | -1.75 | 0.32 | 1.51 |
| Std. Dev. | 1.06 | 0.84 | 0.54 | 1.10 |

*Source*: See Data Appendix A.1.

On the other hand, Table 3.4 shows the rate of value added (SDVA) decomposed into the contributions of the hours worked, capital accumulation and value added based TFP growth according to equation (3.18). The contribution of hours worked to value added is negative in all industries. Physical capital accumulation, on the other hand, has a positive contribution to value added in six of the industries considered (the exceptions being the Textile and Metal industries). The contribution of TFP growth is also positive, except in the case of the Mineral (NMM) industry.

## 3.5 ECONOMETRIC RESULTS: ALLOWANCE FOR IMPERFECT COMPETITION AND CAPACITY UTILISATION

In the previous section, it was showed that the commonly used SDVA as a measure of real output brings considerable measurement bias when applying the growth accounting technique. Nevertheless, GO and DVA were regarded as appropriate measures of output for productivity analysis under the assumptions underlying the growth accounting approach. However, under more general conditions, the use of DVA would generate biased productivity measures.

The purpose of this section is to see to what extent the assumptions underlying growth accounting fit the data set and, therefore, to what extent the common use of value added is valid for productivity measurement. Particularly, the objective is to examine the direction and size of the bias in TFP estimates when allowing for both imperfect competition and adjustments in capacity utilisation. To do so, parametric estimates of TFP growth from a baseline model based on a gross output specification of the production function[19] are presented and compared with those obtained from the growth accounting approach.

### 3.5.1 Theoretical Framework

The analysis proceeds by assuming the existence of an aggregate industry production function in which gross output ($Q_{it}$) depends on the services of primary inputs, capital ($K'_{it}$) and labour ($L'_{it}$), on intermediate inputs ($M_{it}$) and on the state of technology ($A_{it}$).

[19] We extensively tried an alternative approach to obtain TFP growth estimates based on a Total Revenue model in which output prices were endogenised through a demand equation. However, the results were

(3.19) $Q_{it} = A_{it} F(L^s, K^s, M)_{it}$

As seen in Chapter 2, one can express capital services as the function of the capital stock, $K_{it}$, and its degree of utilisation, $Z_{it}$. Additionally, labour services can be decomposed in terms of number of employees, $N_{it}$, the number of hours worked, $H_{it}$, and the effort of each worker, $E_{it}$. Formally, input services can be expressed as follows: $K^s_{it}=Z_{it}K_{it}$, and $L^s_{it}=N_{it}H_{it}E_{it}=L_{it}E_{it}$.

Expression (3.19) is differentiated with respect to time, allowing for different production function parameters across industries.

(3.20) $\Delta \ln Q_{it} = \Delta \ln A_{it} + \varepsilon_{it}^{Q,L} \Delta \ln L_{it} + \varepsilon_{it}^{Q,K} \Delta \ln K_{it} + \varepsilon_{it}^{Q,M} \Delta \ln M_{it} + \delta_{it} \Delta \ln CU_{it}$

where $\Delta \ln CU_{it} = \varepsilon_{it}^{Q,Z} \Delta \ln Z_{it} + \varepsilon_{it}^{Q,E} \Delta \ln E_{it}$, is a weighted average of the unobserved variation in capital utilisation and effort.

Additionally, the TFP growth parameter, $\Delta lnA_{it}$, is modelled by a combination of an intercept, capturing sector specific effects, time dummies and a random error term:

(3.21) $\Delta \ln A_{it} = \eta_i + \rho_t + \nu_{it}$

unsatisfactory. The outline of the theoretical model and some empirical results are briefly presented in the where $\eta_i$ varies across industries but is constant over time, $\varrho_t$ is constant across industries but varies over time, and $v_{it}$ is a random error with mean zero. The common shocks ($\varrho_t$), included to allow for changes in TFP growth over the sample period, is a set of three shift dummies (one for 1973-79, one for 1980-89, and one for 1990-97).

A challenge in estimating expression (3.20) is to relate the unobservable $\Delta lnCU_{it}$ to observable variables. Notice that if this effect is present and it is not considered, the estimated TFP growth will be contaminated by the cyclical utilisation of inputs[20]. In order to proxy capacity utilisation this chapter takes a different approach to previous studies[21]. Particularly, data on deviations from the hours trend for each industry is used to construct the cyclical utilisation index. For each industry, we fit the following equation:

(3.22) $\ln H_{it} = \ln H_{i0} + \lambda_i t$

In which, $H_{it}$ is the annual average of hours worked per person engaged in the industry $i$ in time $t$. The trend ($t$) would stand for the normal utilisation rate while deviations from that trend would represent over and under-utilisation of the inputs used. From these deviations from the hours trend, an index of capacity of utilisation for each industry is constructed, in the following way:

Technical Appendix C.2.

[20] Mendis and Muellbauer (1984), among others, have pointed out that the published UK data on labour and capital contain short-term cyclical variations in over and under-utilisation that can be easily misinterpreted as long-term improvements.

[21] Different proxies for the unobserved changes in utilisation have been used in past studies, among them energy use, material inputs and hours worked (see Muellbauer 1986; Cameron 2003 and Malley *et al.* 2003).

$$(3.23)\quad CU_{it} = \frac{\ln(H_{it})}{\ln(\hat{H}_{it})} = \frac{Actual}{Fitted}$$

From this basis and after assuming constant returns to scale, the baseline equation in terms of gross output becomes:

$$(3.24)\quad \Delta\ln(Q/K)_{it} = \eta_i + \rho_t + \varepsilon_{it}^{Q,L}\Delta\ln(L/K)_{it} + \varepsilon_{it}^{Q,M}\Delta\ln(M/K)_{it} + \delta_{it}\Delta\ln CU_{it} + v_{it}$$

The analysis proceeds assuming that producers operate under imperfect competition in output markets charging a price, $P_{it}$, that is a mark up, $\mu_{it}$, over marginal cost. However, they act as price-takers in input markets when choosing their factor inputs so as to maximise profit (or minimise cost). Therefore, producers take the price of all $J$ inputs, $P_{it}^J$, as given by competitive markets.

The first-order conditions for cost minimisation imply that producers set the value of a factor's marginal product equal to a mark-up over the factor's input price. That is:

$$(3.25)\quad P_{it}\frac{\partial Q_{it}}{\partial J_{it}} = \mu_{it}P_{it}^J$$

Using equation (3.25), one can write each output elasticity as the product of the mark-up multiplied by the ratio of total expenditure in each input to total revenue.

$$(3.26)\quad \varepsilon_{it}^{Q,J} = \mu_{it} \frac{P_{it}^{J} J_{it}}{P_{it} Q_{it}} = \mu_{it} s_{it}^{J}$$

The shares, $s^{J}_{it}$, are total cost of each input divided by total revenue.

Substituting the input elasticities into (3.25) and rearranging one gets an equation similar to Hall's (1988) econometric model, although allowing for variations in capacity utilisation. The resulting equation allows one to simultaneously estimate price-cost margins and the impact of adjustments in capacity utilisation on TFP growth.

$$(3.27)\quad \Delta \ln(Q/K)_{it} = \eta_i + \rho_t + \mu_{it}[s_{it}^{L} \Delta \ln(L/K)_{it} + s_{it}^{M} \Delta \ln(M/K)_{it}] + \delta_{it} \Delta \ln CU_{it} + \nu_{it}$$

To simplify notation, let $\Delta \ln FC_{it} = [s_{it}^{L} \Delta \ln(L/K)_{it} + s_{it}^{M} \Delta \ln(M/K)_{it}]$ then equation (3.27) becomes[22]:

$$(3.28)\quad \Delta \ln(Q/K)_{it} = \eta_i + \rho_t + \mu_{it} \Delta \ln FC_{it} + \delta_{it} \Delta \ln CU_{it} + \nu_{it}$$

### 3.5.2 Econometric Issues

Before turning to the empirical results there are a number of issues to discuss relating to the estimation of equation (3.28). First, this model is based on the assumption of stationarity of all variables included in the regression. If this assumption fails one might be dealing with a spurious relationship. To ensure all variables entering equation (3.27) are stationary, the individual series are tested for unit roots. Among the various tests proposed in the literature the Im, Pesaran and Shin (1997), IPS, panel unit root test is performed here[23]. The IPS *t*-bar test is based on an average of the individual industry Augmented Dickey Fuller (ADF) tests while allowing for heterogeneous coefficients under the alternative hypothesis and different serial correlation patterns across groups. Under the null hypothesis all industry groups exhibit a unit root while under the alternative this is not true for some[24].

Table B.2 in the Statistical Appendix B.2 presents the results of the panel unit root tests allowing for an intercept, along with the critical values for the variables of interest. Following the procedure suggested by Im *et al.* (1997) and, applying the *t*-bar test to the variables in first differences, test statistics are obtained above the critical value for rejecting the hypothesis of the presence of a unit root. This is based on an ADF regression of 1 lag and a DF (Dickey Fuller) regression. Therefore, the rejection of the null hypothesis implies that the data series are stationary in first differences and consequently, traditional estimation methods can be used to estimate the relationship between them as suggested by equation (3.28). The only exception is the growth rate of the capital stock, a variable that is required to test the degree of scale economies.

Second, equation (3.28) can be estimated in various ways, depending on how one considers the composite error term and addresses potential simultaneity and omitted variable

[22] For empirical purpose, discrete growth rates replace continuous ones and the index of input growth (FC) is a Törnqvist one, where the weights are the arithmetic average of the shares in year (t) and (t-1) respectively.

[23] The power of the panel unit root test is substantially greater than the test for a single time series in the sense that the failure to reject a unit root occurs less frequently.

[24] A more detailed discussion of the test can be found in Baltagi and Kao (2000).

problems[25]. In the results to be presented the individual industry equations are estimated as a system using the seemingly unrelated regression (SUR) approach. This allows for the possibility that the residuals of the individual industry equation are contemporaneously correlated, for instance due to common macro shocks. In fact, for the different specifications presented in Table 3.5 the LM test developed by Breusch and Pagan (1980) leads to the rejection of the hypothesis of a diagonal variance-covariance matrix at 10% level of significance or higher, confirming the appropriateness of SUR estimation. Finally, the weighted factor contribution term is potentially endogenous in equation (3.26), so the system is additionally estimated using 3SLS to account for the simultaneity problem. Following Klette and Griliches (1996)[26], changes in the number of employees and capital stock were used as instruments[27].

### 3.5.3 Empirical Results

Table 3.5 reports the results obtained from estimating the production function in equation (3.26) excluding and including the capacity utilisation term respectively. The first two columns report the non-instrumented (SUR) results, while the last two present the instrumented results by 3SLS. Although not reported, all regressions include time dummies and industry specific intercepts, which appear highly significant.

[25] See Griliches and Mairesse (1998) for a comprehensive review of this problem.
[26] According to the Klette and Griliches (1996: p. 354), "it seems likely that the number of employees is less responsive to short-term changes in productivity, as compared to man-hours and materials in the production function".
[27] Lagged values were also tried as instruments. However, the problem with this set of instruments is that there was not much identifying power in past changes for current changes. In this case, the instrumental variable estimates may be more biased (Nelson and Starz 1990).

**Table 3.5**
**Parametric Results from the Model in Equation (3.26)**

| | SUR | 3SLS | SUR | 3SLS | SUR |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Constrained model** | | | | | |
| Δln(FC) | 1.124‡ | 1.125‡ | 1.085‡ | 1.089‡ | 1.068‡ |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| Δln(CU) | | | 5.352‡ | 5.308‡ | 4.603‡ |
| | | | (0.85) | (0.85) | (0.92) |
| ΔlnK | | | | | -0.143 |
| | | | | | (0.89) |
| LL | 564.93 | 564.94 | 570.11 | 570.14 | 571.35 |
| $H_0$: $\eta_i = \eta$ | 44.78 | 44.72 | 43.53 | 43.25 | 45.52 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| BP | 49.62 | | 42.12 | | 29.63 |
| | [0.007] | | [0.042] | | [0.381] |
| Hausman Test | $\chi^2(4)=0.57$ | | $\chi^2(5)=0.93$ | | |
| | [0.966] | | [0.968] | | |
| **Less Constrained Model** | | | | | |
| $\Delta\ln(FC_{FBT})$ | 0.909‡ | 0.949‡ | 0.891‡ | 0.912‡ | 0.900‡ |
| | (0.094) | (0.096) | (0.096) | (0.098) | (0.098) |
| $\Delta\ln(FC_{TL})$ | 0.940‡ | 0.936‡ | 0.912‡ | 0.915‡ | 0.913‡ |
| | (0.053) | (0.054) | (0.049) | (0.049) | (0.049) |
| $\Delta\ln(FC_{WWP})$ | 1.150‡ | 1.148‡ | 1.110‡ | 1.105‡ | 1.108‡ |
| | (0.040) | (0.049) | (0.050) | (0.050) | (0.050) |
| $\Delta\ln(FC_{PPP})$ | 1.281‡ | 1.273‡ | 1.336‡ | 1.334‡ | 1.342‡ |
| | (0.105) | (0.106) | (0.102) | (0.104) | (0.101) |
| $\Delta\ln(FC_{CH})$ | 1.002‡ | 1.007‡ | 0.966‡ | 0.975‡ | 0.973‡ |
| | (0.050) | (0.051) | (0.056) | (0.057) | (0.057) |
| $\Delta\ln(FC_{NMM})$ | 1.247‡ | 1.251‡ | 1.210‡ | 1.213‡ | 1.202‡ |
| | (0.060) | (0.060) | (0.055) | (0.055) | (0.057) |
| $\Delta\ln(FC_{BFM})$ | 1.161‡ | 1.161‡ | 1.091‡ | 1.091‡ | 1.093‡ |
| | (0.051) | (0.051) | (0.052) | (0.053) | (0.051) |
| $\Delta\ln(FC_{MOT})$ | 1.171‡ | 1.162‡ | 1.047‡ | 1.070‡ | 1.060‡ |
| | (0.068) | (0.070) | (0.068) | (0.071) | (0.070) |
| Δln(CU) | | | 5.246‡ | 5.161‡ | 5.014‡ |
| | | | (0.878) | (0.929) | (0.945) |
| ΔlnK | | | | | -0.722 |
| | | | | | (0.086) |
| LL | 576.20 | 576.01 | 580.77 | 580.72 | 580.66 |
| $H_0$: $\eta_i = \eta$ | 49.88 | 48.98 | 51.29 | 50.29 | 49.68 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| $H_0$: $\mu_i = \mu$ | 31.13 | 29.07 | 28.42 | 26.79 | 26.70 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| BP | 52.67 | | 40.44 | | 25.73 |
| | [0.003] | | [0.060] | | [0.588] |
| Hausman Test | $\chi^2(11)=15.69$ | | $\chi^2(12)=17.23$ | | |
| | [0.153] | | [0.141] | | |

*Notes*: Standard errors are in parenthesis and probabilities in brackets. Number of observations is 27 (time periods) by 8 (industries) = 216. Sample period covers 1971-1997. The time dummies included were the following: $D_{7379}$ is the dummy for 1973-79, $D_{8089}$ that for 1980-89 and $D_{9097}$ that for 1990-97.

‡ significant at 1% level or better

LL: Log likelihood, BP: Breusch and Pagan (1980) Lagrange multiplier test for independent equations.

In the top panel of Table 3.5 a special case of equation (3.26) is estimated, where the mark-up is constrained to be the same across industries ($\mu_i = \mu$). In estimating equation (3.26) one assumes that mark-ups are constant over time. For all specifications and estimation methods the average mark-up is significantly different from 1 (see Appendix C.1, Tables C.1 and C.2), indicative of the presence of imperfect competition in the UK manufacturing sector.

In the lower panel of Table 3.5, a more general model is considered, in which the mark-up ($\mu_i$) is allowed to vary across industries. On the basis of a Wald test the model with $\mu_i$ allowed to vary across industries is preferable in all specifications. From this panel, the non-instrumented results are highlighted. A Hausman specification test is carried out to indicate if SUR estimation is an appropriate method for estimating equation (3.26). Under the null hypothesis that the right hand side variables in (3.26) are exogenous, non-instrumented regression (SUR) is efficient and consistent. Only SUR is not consistent under the alternative hypothesis. The tests indicate that the null hypothesis is not rejected at high levels of significance. Additionally, in this type of analysis different authors refer to the fact that the set of instruments may not be completely exogenous and therefore may be correlated with the error term[28].

Therefore, the results are discussed on the basis of the SUR estimates presented in columns (1) and (3) of the lower panel of Table 3.5, in which the capacity utilisation term is excluded and included from the regression respectively. The null hypothesis that the capacity

[28] The use of instruments that are relatively weak or/ and potentially correlated with the error term may be more biased than the non-instrumented results.

utilisation rate term is the same across industries is not rejected on the basis of a Wald test ($\chi^2(7) = 7.75$, p=0.355).

Overall, the point estimates show that most manufacturing industries have average mark-ups greater than one, with the exception of the food and textile industries[29] when capacity utilisation is excluded from the regression. The average mark up estimate is 1.108. In addition, individual tests in those industries where the mark-up point estimate is greater than one reject the restriction of perfect competition (the hypothesis of $\mu_i = 1$), except in the chemical industry (see Appendix C.1, Table C.1). Ordered according to market power, the industries with (statistically) significant mark-ups are the paper industry (PPP), the non-metallic mineral industry (NMM), the machinery industry (MOT), the basic metal industry (BFM), and the wood industry (WWP)[30].

However, the most striking aspect of these results is that when capacity utilisation is included in the regression the significance of the mark-ups diminishes considerably. In this case, the average mark-up estimate is 1.070. On the basis of individual tests (see Appendix C.1, Table C.2) mark-ups appear significantly greater than one (at 5% level) for the PPP, NMM, WWP and BM industries. This is perhaps not too surprising if one considers that mark-ups are found to be procyclical (Small 1997). Nevertheless, the results suggest the presence of significant differences in the level of competition within UK manufacturing. The Wald test rejects the restriction that the average mark-ups are the same in all industries ($\chi^2(7) = 33.08$, p=0.000).

[29] The negative mark-up for textiles is not surprising, as this is an industry that has made losses at some time in the period (Small 1997).

*Relaxing the Assumption of Constant Returns to Scale*

As noted in Chapter 2, the econometric approach allows one to estimate the joint hypothesis of perfect competition and constant returns to scale. In what follows the assumption of constant returns is relaxed. The intention here is not one of obtaining estimates of the degree of returns to scale, as it is to be able to see if the findings about the mark-ups are affected. In order to relax the constant returns assumption the production function is assumed to be homogeneous of degree $(1+\lambda)$, where $\lambda$ is a convenient measure of the extent to which the production function differs from constant returns to scale. Using this, one obtains the following expression to be estimated:

$$(3.29)\quad \Delta \ln(Q/K)_{it} = \eta_i + \rho_t + \mu_i \Delta \ln FC_{it} + \delta_i \Delta \ln CU_{it} + \lambda_i \Delta \ln K_{it} + \nu_{it}$$

From column (5) in Table 3.5 it can be appreciated that the point estimate of the parameter $\lambda$ is equal to -0.722 (s.e. = 0.086). This result suggests decreasing returns to scale, however the parameter is statistically insignificant[31]. Additionally, the point estimates of the mark-up $(\mu_i)$ have the same sign, similar size and significance than those obtained assuming constant returns to scale (columns 1-4). These results imply that the estimates of the mark up and the cyclical adjustment coefficient are robust to the relaxation of the constant returns assumption. In addition, no evidence against constant returns to scale was found. The finding of constant returns in UK manufacturing is nothing new as seen in Chapter 2. Results obtained within the primal approach tend to imply constant returns to scale in the

[30]The same results are obtained for the 3SLS regression presented in the second column.

[31] When the parameter $\lambda$ was allowed to vary between industries, we obtained rather imprecise estimates of returns to scale.

UK manufacturing industry (see Lynde and Richmond 1993; Haskel *et al.* 1995 and Oulton 2000).

*Bias in the Traditional Solow Residual*

Table 3.6 presents the implied average TFP growth rates estimated using both the parametric and non-parametric techniques, for different industry groups and over different periods. The parametric estimates presented are those based on the results presented in the lower panel of Table 3.5, when SUR is applied and capacity utilisation adjustments are taken into account. On the other hand, the non-parametric estimates are those based on the accounting approach from a gross output measure of output, reported in Table 3.2. The main interest is to compare both results in order to examine the direction and magnitude of the bias in the productivity residual.

First, the TFP growth estimates under the two approaches are rather different in magnitude. It is for the period 1973-79 that the growth accounting approach leads, in general, to significant downward biases in the estimates of UK manufacturing productivity growth. For the periods 1980-89 and 1990-97, however, the accounting TFP growth rates are, on average, upward biased. Overall, the industries for which the results differ more significantly are the Mineral (NMM), the Paper (PPP) and Metal (BFM) industries, those for which mark-ups were significantly different from one. From Table 3.6, one can also observe that the differences between the two approaches are reduced for the Food and Textile industries, for which the hypothesis of perfect competition could not be rejected in all specifications.

**Table 3.6**
**Parametric vs. Non-Parametric Gross Output based TFP Growth Estimates**
Averages of annual rates of change (in percentage terms)

| Industry | Parametric Estimates | | | Growth Accounting estimates | | |
|---|---|---|---|---|---|---|
| | 1973-79 | 1980-89 | 1990-97 | 1973-79 | 1980-89 | 1990-97 |
| FBT | -1.40 | 0.07 | 0.43 | -1.18 | 0.16 | 0.26 |
| TL | 0.01 | 1.52 | 1.53 | -0.31 | 1.80 | 1.43 |
| WWP | -0.41 | 0.70 | 0.01 | -1.59 | 0.77 | 0.63 |
| PPP | -1.88 | 1.08 | -0.03 | -2.28 | 0.89 | 0.29 |
| CH | 0.75 | 1.49 | 1.39 | 0.45 | 1.64 | 1.46 |
| NMM | -2.20 | 0.52 | 0.40 | -2.81 | 0.38 | -0.60 |
| BFM | -0.87 | 2.53 | 1.40 | -1.46 | 2.74 | 1.68 |
| MOT | 0.22 | 1.68 | 2.96 | -0.14 | 2.06 | 2.98 |
| Mean | -0.72 | 1.20 | 1.01 | -1.16 | 1.31 | 1.02 |
| St. Dev. | 1.05 | 0.77 | 1.01 | 1.11 | 0.90 | 1.10 |

*Source*: Results from Table 3.2 and Table 3.5.

Second, it can be observed that the degree of disparity across industries in terms of productivity growth rates is generally more accentuated under the growth accounting results. Third, although the magnitudes of the results presented in both tables are rather different, the trends followed by the industries over the sample period are quite similar. For the growth accounting approach, the manufacturing industries recovered during the 1980s from negative growth rates achieved in the previous decade, but growth rates slow down again in the 1990s, the exception being the Food and the Machinery industry. For the parametric results these trends are also observed, except in less degree for the textile industry. Nevertheless, the recovery experienced in the 1980s is not as spectacular as implied by the growth accounting approach.

*Comparison with Previous Studies*

In Chapter 2, it was stated that most of the studies testing for the assumptions underlying the growth accounting framework found that they are not valid. Strong evidence was found that neither the assumption of perfect competition nor the assumption of instantaneous input adjustment could be sustained in the context of the UK manufacturing industry. Overall, the majority of UK based studies reported in Chapter 2 found that the bias in the Solow residual is positive for the period early 1970s to mid 1990s. The results here confirm these findings (Oliveira Martins *et al.* 1996 and Cameron 2003).

**Table 3.7**
**Average Estimated Bias for Selected Periods**
(Averages of annual rates in percentage terms)

| Study | Solow Residual | Adjusted TFP | Bias |
|---|---|---|---|
| | (1) | (2) | (2)-(1) |
| **1973-79** | | | |
| Cameron (2003)[1] | 0.15 | 1.88 | 1.73 |
| Author | -1.16 | -0.72 | 0.44 |
| **1979-90** | | | |
| Cameron (2003)[1] | 3.03 | 2.75 | -0.28 |
| Author | 1.31 | 1.20 | -0.11 |
| **1970-87** | | | |
| Maley *et al.* (2003) | 0.95 | 0.50 | -0.45 |
| Author | 1.21 | 0.45 | -0.76 |

*Note*: (1) The Adjusted TFP growth rate in Cameron (2003) is that referred as "Trends" in Table 6 (p. 134).

In Table 3.7 the average estimated bias for selected periods found in the present research is compared with that from other related studies. As can be noticed the sign of the bias found here coincides with that found in other studies. The sign represents to what extent the Solow residual over-estimates (negative sign) or under-estimates (positive sign) the growth rate of TFP. The sign is positive for the period 1973 to 1979, while it is negative for the period 1979-1990. In Chapter 2, attention was directed at the negative bias estimate found by Malley *et al.* (2003). In Table 3.7 it can be observed that the results obtained here also find a negative sign of the bias for that particular period, 1970 to 1987.

**Table 3.8**
**Decomposition of Output Growth in UK Manufacturing**
Averages of annual rates in percentage terms

| | Gross output | Labour | Capital | Interm. Inputs | Capacity Utilisation | TFP Growth |
|---|---|---|---|---|---|---|
| **1970-1997** | | | | | | |
| Growth Accounting | 0.39 | -0.61 | 0.13 | 0.34 | | 0.53 |
| Parametric | 0.39 | -0.65 | 0.01 | 0.41 | -0.01 | 0.64 |
| **1973-79** | | | | | | |
| Growth Accounting | -1.28 | -0.63 | 0.28 | 0.24 | | -1.16 |
| Parametric | -1.28 | -0.67 | 0.12 | 0.31 | -0.32 | -0.72 |
| **1980-89** | | | | | | |
| Growth Accounting | 1.68 | -0.66 | 0.04 | 0.85 | | 1.31 |
| Parametric | 1.68 | -0.70 | -0.06 | 0.97 | 0.25 | 1.22 |
| **1990-97** | | | | | | |
| Growth Accounting | 1.04 | -0.32 | -0.07 | 0.42 | | 1.02 |
| Parametric | 1.04 | -0.34 | -0.14 | 0.41 | 0.10 | 1.01 |

*Source*: Results from Table 3.2 and Table 3.5.

Table 3.8 compares the decomposition of output growth for different time periods from the growth accounting and the parametric approaches respectively. It is for the period 1973 to 1979 for which the disparities between both approaches become more evident. Particularly, it is precisely for this period for which the capacity utilisation term has its greatest impact. Nevertheless, the capacity utilisation term has little impact on the decomposition of output growth for the entire period.

## 3.6. CONCLUSIONS

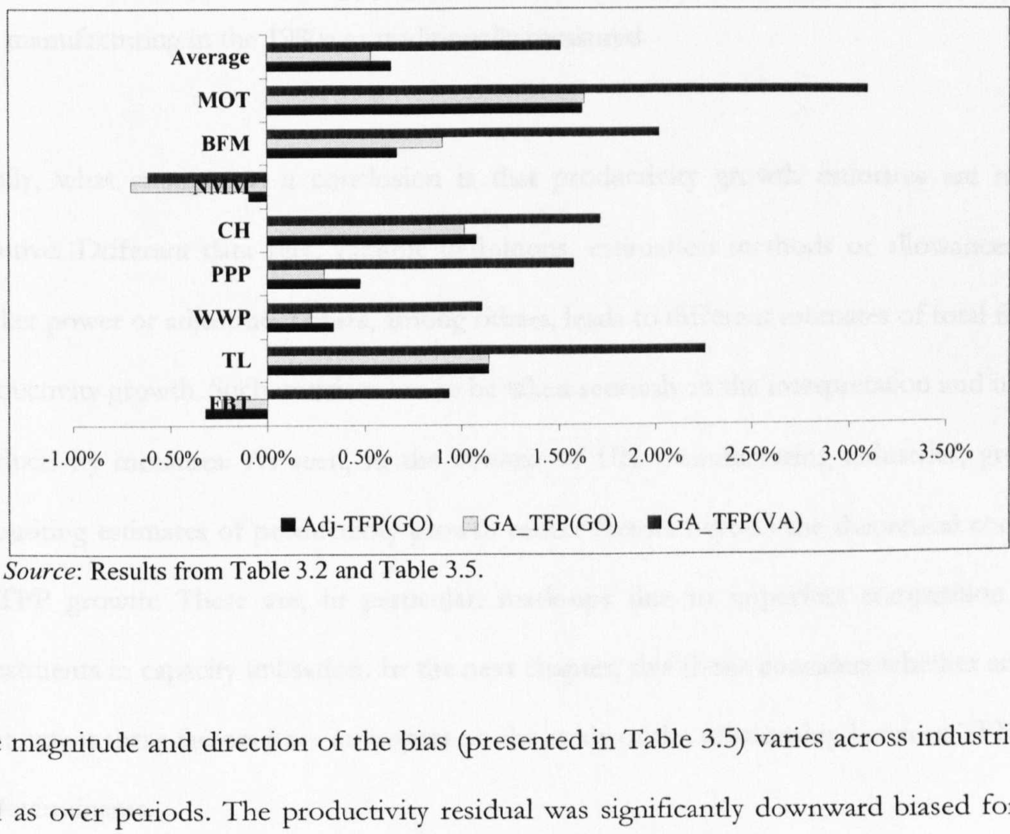
The objective of this chapter was to examine the bias in measuring productivity growth using the traditional growth accounting framework in the context of UK manufacturing. Emphasis was placed upon both alternative measures of the change in real output and different estimation techniques. First, a number of alternative indicators of output growth were considered on theoretical and empirical grounds. It was argued that gross output was the superior concept of real output to employ for the measurement of productivity growth. The common practice of using single deflated value added as an output measure was considered to bring considerable measurement bias. The reason is that intermediate input prices and output prices do not grow at the same rate, and the assumption of perfect competition cannot be sustained for all industries. In the latter case, the use of any value added concept suffers from an omitted variable bias.

Second, the econometric approach to productivity measurement was argued to be the preferred estimation technique for productivity measurement on theoretical grounds. Although not free of problems, the econometric approach allows one to test for the presence of imperfect competition as well as to correct for changes in capacity utilisation due to adjustment costs. The results showed that the assumption of perfect competition could not be sustained for all manufacturing industries, and that variation in capacity utilisation was statistically significant. Particularly, significant mark-ups were found for the non-metallic mineral industry (NMM), the paper industry (PPP), the wood industry (WWP), and the basic metal industry (BFM). When the assumptions of perfect competition or long run equilibrium can no longer be sustained, the traditional growth accounting approach leads to a biased estimate of factor productivity growth.

Figure 3.1 summarises the impact of different output concepts and estimation methods on the average TFP growth estimates for the different industries considered over the period 1970 to 1997. While gross output based TFP measures are presented in terms of parametric and non-parametric techniques (Adj-TFP(GO) and GA_TFP(GO), respectively), the single value added based TFP rates are those from the growth accounting approach

(GA_TFP(VA))[32]. The difference in magnitude between these estimates is considerable, especially with respect to TFP growth rates based on alternative output concepts. In terms of estimation techniques, parametric and non-parametric gross output TFP rates differ to a greater degree in those industries for which mark-ups were found significantly greater than one.

**Figure 3.1**
**TFP Growth Rates 1970-1997**




*Source*: Results from Table 3.2 and Table 3.5.

The magnitude and direction of the bias (presented in Table 3.5) varies across industries as well as over periods. The productivity residual was significantly downward biased for the period 1973-79. However, for the periods 1980-89 and 1990-97, the growth accounting approach led, in general, to significant upward biases in the estimates of UK manufacturing TFP growth. The growth accounting estimates indicate that the average UK manufacturing

[32] The parametric estimates are those based on the results reported in the lower panel of Table 3.5, when SUR is applied and capacity utilisation adjustments are taken into account. On the other hand, the non-parametric estimates are those based on the accounting approach, reported in Table 3.2.

TFP growth fell at an average annual rate of 1.16 per cent between 1973-79, but rose at an average annual rate of 1.31 per cent between 1980-89. In contrast, the parametric estimates indicate that the UK manufacturing industries experienced average annual rates for these periods of –0.72% and 1.20% respectively. These parametric results imply that the recovery experienced in the 1980s was not as spectacular as implied by the growth accounting estimates. These results are consistent with those of other quantitative studies, based on rather different methodologies, which have queried the apparent strength of TFP growth in UK manufacturing in the 1980s as traditionally measured.

Finally, what emerges as a conclusion is that productivity growth estimates are highly sensitive. Different data sets, variable definitions, estimation methods or allowances for market power or adjustment costs, among others, leads to different estimates of total factor productivity growth. Such criticism has to be taken seriously in the interpretation and use of productivity measures. As seen, in the context of UK manufacturing industries, growth accounting estimates of productivity growth reflect factors beyond the theoretical concept of TFP growth. These are, in particular, mark-ups due to imperfect competition and adjustments in capacity utilisation. In the next chapter, this thesis considers whether and to what extent these factors have an impact on the study of the relationship between TFP and its determinants.

# CHAPTER 4 –

## THE IMPACT OF RESEARCH AND DEVELOPMENT SPILLOVERS ON UK MANUFACTURING TFP

*"The UK's strongest innovative industries are global leaders, but too many of our sectors are significantly lagging behind international investment levels in R&D. In 2000, the Government started to tackle this, through introducing tax incentives for R&D among smaller technology-based firms. This year, the Government has widened these fiscal reforms to encompass all UK-based business R&D."*

DTI and HMT (2002: p. 6)

## 4.1 INTRODUCTION

Advances in the state of knowledge through technological change tend to be the primary determinant of productivity growth over long periods of time. Since research and development (R&D) investment directly contributes to knowledge accumulation, R&D activities are a potentially important source of productivity gains. R&D capital improves the quality or reduces the average production costs of existing goods and services or simply extends the range of intermediate inputs or final goods available to other economic agents. Indeed, a large number of empirical studies, at different levels, come to the conclusion that R&D is a major source of economic growth[1]. Quoting Coe and Helpman (1995: p. 860) there exists "*convincing empirical evidence that cumulative domestic R&D is an important determinant of productivity.*"

A distinctive characteristic of R&D activities is that benefits are not completely captured by R&D investors. The unappropriated benefits, referred to as R&D spillovers, provide a source of new knowledge and thereby potential productivity gains to spillover receivers. These spillovers must be taken into account when assessing the impact of R&D on sectoral

[1] Classic references in this literature include Griliches (1980, 1992) and Griliches and Lichtenberg (1984).

productivity. Griliches (1992) reviews the basic model of R&D spillovers and comments on the empirical evidence for their existence and magnitude[2]. Though the contribution of R&D spillovers to productivity growth has been acknowledged a long time ago, it is only recently that the empirical measure of the magnitude and the direction of such effects has become a major point in the research agenda on the economics of innovation.

The recent revival of new growth theory has emphasised the contribution of international transmission of new technologies across national borders to economic growth and productivity (Grossman and Helpman 1991). With international trade, foreign direct investment, and international information diffusion, it can be expected that R&D spillovers extend beyond national boundaries, at least in open economies. The mechanics of this engine and the power of spillovers have been under empirical scrutiny by many important scholars[3]. International R&D externalities imply that productivity growth depends, not only on domestic spillovers, but additionally on the R&D activities undertaken in other economies.

A priori, the "convincing empirical evidence" pointed out by Coe and Helpman (1995) can be criticised on the grounds of the results obtained in previous chapters. This refers to the problem of measurement and definitions of total factor productivity. In this regard, most of these studies are based on growth accounting measures of productivity obtained from production functions in which only labour and capital are included as inputs. This implies the use of value added as a measure of real output and, therefore, a potential source of bias when certain restrictive conditions are not met. An even more relevant criticism is based on

[2] Other more recent surveys may be found in Nadiri (1993), Mohnen (1996) and Cameron (1999).

the possible bias deriving from the use of the growth accounting framework to obtain productivity measures. When its underlying assumptions cannot be sustained, the use of the growth accounting Solow residual produces biases that can alter the relationship between productivity and its main determinants, in particular R&D efforts (Atella and Quintieri 2001).

Chapter 3 revealed that in the context of UK manufacturing industries, growth accounting provides biased estimates of TFP growth. This is because some of its underlying assumptions could not be sustained. These are perfect competition and instantaneous input adjustment. Moreover, beyond concerns regarding the biases of the Solow residual, theory suggests that it might be very revealing to study the role of knowledge and the presence of market power in an integrated approach.

The objectives of this chapter are twofold. On one hand, it seeks to study the long-term relationship between R&D efforts and productivity following on the results obtained in Chapter 3. Additionally, it assesses empirically the importance of domestic and foreign R&D spillovers for productivity in UK manufacturing industries. It combines an analysis at a sectoral level with the original approach from Coe and Helpman (1995). More specifically, data for the eight UK manufacturing industries considered in the previous chapter are used to explain the long run impact on factor productivity of R&D activities by the sector itself, by other UK manufacturing sectors and by foreign sectors. This allows one to answer whether externalities are important in the process of economic growth and whether R&D spillovers are national or international in scope.

[3] See for example Coe and Helpman (1995) and Berstein and Mohnen (1998), among others.

Additionally, while some attention has been paid to the impact of R&D activities upon productivity in the context of static econometric models[4], the dynamic evidence is more limited, the exceptions being Frantzen (1998), Cameron (2002), Los and Verspagen (2000) and Guellec and Pottelsberghe (2001). However, where dynamic models are required, which will be the rule with non-stationary series (and the series under study are no exception), standard pooled models are not simply inefficient but may also be highly inconsistent (Pesaran and Smith 1995).

A contribution of the present study is to provide additional insights on the relationship between productive knowledge and productivity in UK manufacturing sectors employing a dynamic heterogeneous error correction (ECM) panel model. Specifically, the ECM statistical framework is attractive in that is compatible with long run equilibrium behaviour and the concept of cointegration. Moreover, the ECM in the panel data setting can be estimated by using the Pooled Mean Group (PMG) estimator (Pesaran *et al.* 1999). This allows short-term adjustments and convergence speeds to vary across industries and imposes cross-industry homogeneity restrictions on the long run coefficients. There are indeed good reasons to believe in common long run coefficients across UK manufacturing sectors, given that they have access to common technologies and have intensive intra-trade. Conversely, there is no reason to assume that the speed of convergence to the steady state or the dynamics should be the same across industries.

[4] Quoting Harris (1995: p. 5), "*long-run models are often termed 'static models', but there is no necessity actually to achieve equilibrium at any point in time... All that is required is that economic forces move the*

The rest of this chapter is organised as follows. The next section describes previous UK-based studies on the impact of productive knowledge upon productivity. Section 4.3 describes the empirical model relating productivity to the innovation and spillovers variables. Section 4.4 gives an overview of the data and characteristics of the sectors under consideration. The main empirical findings are presented in section 4.5. More precisely, some econometric issues are put forward with respect to the stationarity of the series and the econometric estimation method. The econometric results are presented along with comparisons with those results reported in related empirical studies. Finally, section 4.6 offers some concluding remarks.

## 4.2 PREVIOUS STUDIES ON PRODUCTIVE KNOWLEDGE IN RELATION TO FACTOR PRODUCTIVITY

The literature on the impact of productive knowledge on factor productivity and the presence of spillovers is large and diverse in terms of approaches followed and questions addressed. As Sakurai *et al.* (1996) point out, comparisons across different studies may be misleading or meaningless, given that studies not only differ in the data and methodologies used but also in terms of measurement. In spite of this cautious note, the majority of studies in this tradition found that R&D spending (measured in a variety of ways) contributed significantly to productivity growth. In this regard, Nadiri (1993) indicates that, for industry data, the estimated elasticity of output with respect to R&D is usually found to be between 0.10 and 0.30, while rates of return to R&D range between 20 and 40 per cent.

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*system toward the equilibrium defined by the long-run relationship posited...Thus, what matters is the idea of a steady-state relationship between variables which are evolving over time."*

**Table 4.1**
**Empirical Studies on the Impact of R&D on UK Productivity**

| *Study* | *Database* | *Model* | *Direct Effect* | *Weights* | *Domestic Spillovers* | *Foreign Spillovers* |
|---|---|---|---|---|---|---|
| ***1. Primal Approach*** | | | | | | |
| ***Cross-Sectional Studies*** | | | | | | |
| *Sterlacchini (1989)* | 15 ind. 1945-83 | ΔTFP, IR | 0.12-0.2 [2] | I/O flows<br>Innovation flows | 0.09-0.12 [2]<br>0.15-0.35 [2] | |
| *Wakelin (2001)* | 170 firms 1988-92 | LP, IR | 0.27 [2] | Innovation flows | 0.00 | |
| ***Time Series Studies*** | | | | | | |
| *Cameron & Muellbauer (1996)* | Manuf. 1962-92 | ΔTFP, RD | 0.15-0.37 [1] | | | |
| *O'Mahony & Wagner (1996)* | Manuf. 1973-89 | ΔLP, IR | 0.00 [2] | | | |
| *Cameron (2003)* | Manuf. 1960-95 | TFP, RD | 0.29 [1] | | | |
| ***Panel Data Studies*** | | | | | | |
| *Geroski (1991)* | 79 ind. 1976-79 | ΔLP, I | 0.015 [3] | Innovation flows | 0.00 | |
| *Coe & Helpman (1995)* | 22 Ec. 1970-91 | TFP, RD | 0.234 [1] | Bilateral trade flows | | 0.06-0.08 [1] |
| *Cameron (1999)* | 19 ind. 1972-92 | TFP, RD | 0.237 [1] | | | |
| *McVicar (2002)* | 7 ind. 1973-92 | TFP, RD | 0.015 [1] | FDI<br>Bilateral trade flows | <br>0.076 [1] | 0.00<br>-0.015 [1] |
| ***2. Dual Approach*** | | | | | | |
| *Nadiri & Kim (1996)* | G-7 Ec. 1964-91 | C, RD | 0.142 [2] | Bilateral trade flows | | 0.061 [2] |
| *Hubert & Pain (2001)* | 15 ind. 1983-92 | ΔL, RD | 0.029 [1] | FDI<br>Bilateral trade flows | <br>0.032 [1] | 0.008 [1]<br>0.003 [1] |

*Notes*: Estimates derived from data on ind.: industry level; Manuf.: total manufacturing; Ec.: country level; TFP: total factor productivity; LP: labour productivity; L: labour demand; C: total costs; IR: R&D intensity; RD: R&D capital stock; I: innovation variables other than R&D. 1: output elasticity; 2: rate of return; 3: coefficient estimate.
*Source*: Author.

Although most empirical work on the relationship between knowledge and productivity has been for the United States, Table 4.1 summarises the results of a number of studies for the UK economy. Despite the shortcomings and differences in approach, the majority of the selected studies tend to find a strong and enduring link between own R&D activities and output, or productivity. Indeed, the average estimated elasticity of R&D stock on output (performed on the basis of the estimates in Table 4.1, fourth column) is about 0.17, with a lower bound of 0.02 and an upper bound of 0.37. Moreover, the estimated rate of return to R&D lies between 0.12 and 0.27.

Less extensive is the literature dealing with national and international spillovers in the UK context. Results are mixed depending on the weights considered to obtain the inter-industry and foreign knowledge capital stocks, with the balance in favour of recognising their existence. Nevertheless, when significant, the estimates presented in Table 4.1 suggest that international spillovers contribute to productivity growth significantly less than domestic inter-industry spillovers. Consequently, these results imply that R&D spillovers for the UK economy are primarily intra-national in scope.

Since Griliches' (1979) article, there is a clear conceptual distinction between rent or "pecuniary" spillovers and knowledge spillovers. The formers arise because the prices of intermediate inputs are not fully adjusted for quality improvements resulting from R&D investments in other industries or countries. For example, quoting Los and Verspagen (2000: p. 130), "*a new personal computer that can perform certain calculations twice as fast as the existing ones, will often be sold at a price between once and twice the price of the existing machines. As an immediate consequence, the price per efficiency unit has fallen, and the productivity of the firms or industries using the new computer will rise.*" Part of the effect of rent spillovers is in fact due to mis-measurement: if prices could accurately reflect quality improvements, productivity growth could be attributed more precisely to its original source. Studies estimating the impact on productivity of the so-called indirect R&D embodied in traded inputs (e.g. Coe and Helpman 1995) generally concentrate on this interpretation of spillovers.

The second type of R&D externality is knowledge spillover that can be defined as the potential benefits for a given industry due to the research efforts of other industries. This kind of spillovers is related to the diffusion and imperfect appropriability of the knowledge associated with an innovation, which partly posses the characteristics of a public good (non-rival and non-excludable[5]). Due to this property the benefits of R&D spread beyond the limits of the original performer, contributing to the innovation process of other industries or countries. Knowledge spillovers are generally characterised by the transfer of technology that may occur via different channels: foreign direct investment, foreign technology payments[6] and international R&D collaboration, among others. Since these knowledge spillover channels are often associated with an economic transaction, the extent to which they also reflect some rent spillover is not so obvious.

Certainly, if the distinction between the two spillover concepts is clear from the analytical point of view, it appears more ambiguous in practice. The ambiguity is due to the fact that it is difficult to dissociate empirically rent spillovers from knowledge spillovers. Rent spillovers are approximated through economic transactions, which may also be associated to –or imply- some knowledge transfers. Additionally, quoting Cincera and van Pottelsberghe (2001: p. 2) "*the two types of R&D spillovers might not be combined but their respective*

[5] Non-rivalry means that the costs required to reproduce an innovation once it is made is negligible with respect to the original investment involved to discover it so that the technology can be seen as a public good. Partial excludability means that the owner of an innovation cannot exclude others from obtaining a part of the benefits free of charge.
[6] Foreign technology payments include royalties, licensing fees and patent sales.

*profiles across industries might be similar. Therefore, since each type of R&D spillover is estimated under a common econometric procedure, serious collinearity bias might emerge.*" It is due to these arguments that the present study relies on a broader concept of R&D spillover, instead of attempting to distinguish rent- from knowledge spillovers.

Another important issue in this literature is the distinction between the private (or "own", "direct") and the social (or "indirect", "external") rate of return to R&D. The former relates to the benefits that can be appropriated by the original R&D performer. The latter refers to the total benefits from research activities, i.e. the returns that revert to the industry or sector in which the R&D performer is located in or to society at large. The basic methodology used to evaluate social returns to R&D consists in estimating a production function –i.e., the primal approach- or a cost function, which incorporates one or more variables proxying an outside (or external) R&D capital stock. The key issue is then to determine how this outside R&D capital stock (the pool of external knowledge) has to be aggregated.

In the literature on R&D spillovers a variety of different weights have been used to obtain a measure of the aggregated external R&D stock (see Mohnen 1996, for a review). A first group of studies analyses the influences of R&D spillovers by treating them as an unweighted sum of R&D of all other firms, industries or countries (Berstein 1988 and Levin 1988). A second group treats the R&D spillover variable as a weighted sum of all external R&D (Coe and Helpman 1995; Sakurai *et al.* 1996). This second approach can be additionally subdivided according to the proximity measure used to construct the weights. This proximity can be based on the inter-industry flows of goods and services, capital goods, R&D personnel, patents, innovations, citations or R&D co-operation agreements.

Another set of measures of proximity is the distance between position vectors in different spaces (Bernstein 1997), such as patent classes, qualifications of R&D personnel, lines of business or types of R&D. In the present study, inter-industry spillovers are estimated using R&D expenditures, input-output statistics and bilateral import transactions.

## 4.3 THE PRODUCTION FUNCTION FRAMEWORK AND THE MEASUREMENT OF R&D CAPITAL STOCK

This section aims at reviewing the production function framework as a model to study the relationship between productivity and knowledge capital. Changes in TFP can be explained by many factors: innovative activities or productive knowledge, scale economies, changes in the quality of labour and capital, organisational change, etc. Among these underlying factors, this study focuses on the role of productive knowledge, proxied by the R&D capital stock, and R&D embodied in products purchased as inputs into production in explaining industry's TFP. Particular attention is paid to the empirical measurement of knowledge capital and R&D spillovers.

### 4.3.1 The Model

The model used for the analysis of the role of productive knowledge is built on the traditional production function approach[7] (Griliches 1980), where a measure of innovative

[7] It should be noted that, besides the "primal" approach, another way to study the contribution of R&D has followed in the literature. This refers to the "dual" approach, which usually rests on a representation of technology by a cost function and from which a system of factor demand equations is then estimated. Among others, Mohnen *et al.* (1986), Bernstein and Nadiri (1991) and Nadiri and Kim (1996) have implemented the dual approach.

effort is included as one of the production factors[8]. Unlike most of the empirical evidence on the contribution of innovative activity to productivity, this study does not rely on non-parametric measures of TFP derived from the traditional approach suggested by Solow (1957). According to this methodology, measures of TFP are based on assumptions that are difficult to accept as maintained hypotheses, particularly perfect competition and long run equilibrium. However, the evidence in Chapter 3 suggested the importance of the role of market power and of accounting for deviations from long run equilibrium in measuring productivity. Certainly, if the hypotheses maintained by the growth accounting approach are not satisfied the use of the "Solow residual" as a proxy of technical change can lead to misleading interpretations of the role played by productivity and its ultimate determinants.

To formulate the relationship between TFP and cumulative productive knowledge, this study proceeds by assuming the existence of an aggregate industry production function as that considered in Chapter 3. This function is represented by a conventional Cobb Douglas production function, where gross output ($Q_{it}$) is the result of a combination of two separable functions. These are the technical progress function, $A_{it}$, and a traditional input function, $F_{it}(.)$, which depends on the services of primary inputs, capital ($K^s$) and labour ($L^s$), and on intermediate inputs ($M$).

(4.1) $$Q_{it} = A_{it}F(L^s, K^s, M)_{it}$$

As seen in Chapter 3, one can express capital services as the function of the capital stock, $K_{it}$, and its degree of utilisation, $Z_{it}$. Additionally, labour services can be decomposed in

[8] See Cuneo and Mairesse (1984), Jaffe (1986), Griliches and Mairesse (1984), Griliches (1986, 1995),

terms of number of employees, $N_{it}$, the number of hours worked, $H_{it}$, and the effort of each worker, $E_{it}$. In this way, equation (4.1) can be re-written as:

$$(4.2) \qquad Q_{it} = A_{it} F(L_s, K_s, M)_{it} = A_{it} (L_{it} E_{it})^{\varepsilon_{QL}} (K_{it} Z_{it})^{\varepsilon_{QK}} M_{it}^{\varepsilon_{QM}}$$

Following Basu and Fernald (1997), the level of capacity utilisation ($CU_{it}$) can be considered a function of the non-observed intensity with which labour and capital are used, namely labour effort, $E_{it}$, and capital utilisation, $Z_{it}$. As stated in previous chapters due to short run fixities of capital and because of labour hoarding, producers do not vary inputs in the short run proportionately with outputs, leading to cyclical movements in capacity utilisation and measured TFP.

$$(4.3) \qquad CU_{it} = G(Z_{it}, E_{it}) = E_{it}^{\varepsilon_{QL}} Z_{it}^{\varepsilon_{QK}}$$

Substituting expression (4.2) and (4.3) into (4.1) and re-arranging gives:

$$(4.4) \quad Q_{it} = A_{it} F(L_{it}, K_{it}, M_{it}) G(Z_{it}, E_{it}) = A_{it} (L_{it} E_{it})^{\varepsilon_{QL}} (K_{it} Z_{it})^{\varepsilon_{QK}} M_{it}^{\varepsilon_{QM}} = A_{it} L_{it}^{\varepsilon_{QL}} K_{it}^{\varepsilon_{QK}} M_{it}^{\varepsilon_{QM}} (CU)_{it}^{\zeta}$$

The specification (4.4) has the feature that capacity utilisation is fully utilized (100%) when $CU = 1$, the value that is achieved in the steady state[9].

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and Hall and Mairesse (1995), among others.

[9] The parameter $\delta$ in equation (4.4) is the elasticity of capacity utilisation with respect to the business cycle (see Harrigan 1999). In the steady state $CU^{*}=1$, therefore $lnCU^{*}= 0$, independently of the value of $\delta$.

Regarding equation (4.4) one can establish three important differences with respect to the traditional approach to the study of the contribution of productive knowledge to productivity. Firstly, this research focuses on the use of gross output instead of the commonly used value added as a measure of real output[10]. Secondly, while most of the empirical evidence in this tradition has been conducted assuming that industries are at their potential production level at any moment in time, this study argues that producers adjust toward their potential level through successive short run or temporary disequilibria ($CU_{it} \neq 1$). Quoting Bernstein and Mohnen (1998: p. 317), "*mistakenly assuming that producers are at their long run desired* ... [input demand levels] *can lead to significant biases in measured productivity growth rates and biases in accounting for the various determinants of productivity growth.*" Finally, the analysis proceeds without assuming perfect competition in output markets, or in other words, without imposing the relationship between production elasticities and income shares as in the growth accounting approach.

Taking logs in (4.4), and after assuming constant returns to scale[11] in the traditional input function $F_{it}(\cdot)$, one can rearrange to yield (where lower case letters denote the variables in terms of physical capital stock):

$$\text{(4.5)} \qquad \ln q_{it} = \ln A_{it} + \varepsilon_i^{Q,L} \ln l_{it} + \varepsilon_i^{Q,M} \ln m_{it} + \zeta_i \ln CU_{it}$$

[10] There is an extensive literature that shows the inadequacy and the resulting biases of using value added for productivity measurement (see Basu and Fernald 1997).
[11] The results in Chapter 3 showed that the assumption of constant returns to scale could not be rejected in the context of the UK manufacturing industries.

In addition, the TFP parameter, $lnA_{it}$, is modelled by a combination of a sector specific intercept, allowing disembodied productivity to vary across sectors, a time trend ($\lambda$, the rate of disembodied technical change), and cumulative productive knowledge ($R_{it}$):

$$(4.6) \quad \ln A_{it} = \eta_i + \lambda_i t + \xi_i \ln R_{it} + v_{it}$$

The subscripts $i$ and $t$ denote the industry and the period (year) respectively. Additionally, $v_{it}$ is a white noise residual and $\xi$ represents the output elasticity with respect to productive knowledge.

Combining equation (4.5) and (4.6) one can obtain the long run (stationary) form of the model[12], which is represented as follows[13]:

$$(4.7) \quad \ln q_{it} = \eta_i + \lambda_i t + \varepsilon^{Q,L} \ln l_{it} + \varepsilon^{Q,M} \ln m_{it} + \delta_i \ln CU_{it} + \xi_i \ln R_{it} + v_{it}$$

Although equation (4.7) is usually considered suitable for estimation, some problems arise from the application of standard regression techniques. These difficulties occur when unit roots are present in the data (and the series under examination are no exception). When dealing with non-stationary data, equilibrium is synonymous with the concept of cointegration (Engle and Granger 1987). Failure to establish cointegration often leads to spurious regressions which do not reflect long run economic relationships but, rather,

[12] Note that by construction, the capacity utilisation measure, $CU$, has a mean or steady state value of one (see Table B.3 in the statistical Appendix B.3).

[13] The alternative approach followed by most of the empirical evidence would be to use TFP as the dependent variable, which involves the implicit assumption of perfect competition. This amounts to

reflect the common trends contained in most non-stationary series. For this reason, there is a need to use the appropriate modelling procedure. Detrending is not appropriate and simply differencing the variables is not a solution since this removes any information about the long run.

An alternative procedure for obtaining meaningful estimates of the long run elasticities of TFP with respect to the innovative variables is to estimate the corresponding error correction formulation (ECM) to equation (4.7). The ECM statistical framework is attractive in that it is closely bound up with the concept of cointegration, thus providing a useful and meaningful link between the long run and short run approach to econometric modelling, with disequilibrium as a process of adjustment to the long run model.

Thus, the basic equation to be estimated, adapted from (4.7), is the following error correction model, that allows one to separate short-term from long-term effects:

$$\begin{aligned}\Delta \ln q_{it} &= \alpha_{li}\Delta \ln l_{it} + \alpha_{mi}\Delta \ln m_{it} + \alpha_{ci}\Delta \ln CU_{it} + \alpha_{ri}\Delta \ln R_{it} + \theta_i \ln q_{i(t-1)} + \\ &+ \beta_{li} \ln l_{i(t-1)} + \beta_{mi} \ln m_{i(t-1)} + \beta_{ci} \ln CU_{i(t-1)} + \beta_{ri} \ln R_{i(t-1)} + \eta_i + \lambda_i t + v_{it}\end{aligned} \tag{4.8}$$

In equation (4.8), the long run elasticity of output with respect to, say productive knowledge (R) in industry $i$, is $(-\beta_{ri}/\theta_i)$.

There are two immediate practical challenges to implementing an equation like (4.7) or (4.8) : there are neither direct measures of the capacity utilisation term nor observable measures

inferring the output elasticities (as the input revenue shares) from the data, which in this study we prefer to of the productive knowledge stock. In order to proxy capacity utilisation[14], data on deviations from the hours trend for each industry are used to construct the respective indices as in the previous chapter. On the other hand, following previous literature (see Keller 1998), the present study models $R_{it}$ as a function of the own industry R&D stock, based on the sum of past R&D spending, and the domestic and foreign embodied R&D stock.

### 4.3.2 Empirical Measurement of Productive Knowledge, Inter-industry and International R&D Spillovers

*Innovation Variables*

Comprehensive attempts to describe the technological performance of countries, industries or firms have usually relied on a variety of partial indicators of innovative effort (R&D expenditures, patents, royalties or innovation surveys, among others). While there is no single, perfect measure of innovative effort or productive knowledge, following previous studies this study argues that an appropriate indicator of successful innovations, and of increases in the stock of knowledge, is an increase in knowledge capital through new investment in R&D[15, 16].

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avoid.

[14] A more refined treatment of capacity utilisation would define capacity as the minimum of the short run average cost curve, however the data required for such an adjustment is not available. See Morrison (1999).

[15] Industries perform R&D to design new or better products that will provide more value per unit of resources used, or new process which will reduce the resource requirements of existing products (Griliches and Lichtemberg 1984). To the extent that TFP measures are appropriate indicators of technological progress, R&D activities may contribute to expanding or shifting the production possibility frontier in R&D-conducting industries. At the same time, some industries that might be less R&D intensive can obtain large productivity benefits simply by acquiring quality improved inputs or capital goods into their production process (i.e. embodied R&D).

[16] Criticisms to the wide use of R&D spending are present in the literature. Pavitt and Patel (1988) argue that expenditures on R&D may be an inadequate measure of both the inputs into and the outputs into the innovative process. R&D expenditure is an input measure, much of which will not result in innovative output. Sterlacchini (1989) points out that R&D expenditure do not represent satisfactory indicator of

As any other capital stock variable, the construction of the R&D stock is not devoid of problems such as the choice of an appropriate depreciation rate, lag structure, base value and deflators. Although, the approach followed in this research on the construction of the R&D stock is discussed at length in Appendix A.1, some comments may be in place. In the present study, the R&D or knowledge capital stock is computed using the well-known perpetual inventory method. This method assumes that the current state of knowledge is a result of present and past R&D expenditures discounted by a certain rate of depreciation (see Data Appendix A.1).

Two other renowned issues encountered when estimating the contribution of R&D remained to be mentioned. The first problem is the "double counting" of R&D. This double counting arises since conventional inputs generally include the components of R&D expenditures. As shown by Schankerman (1981) and Mairesse and Hall (1996), this double counting reflects itself in downward estimates of R&D elasticities and rates of returns[17]. As a consequence, when the input factors are not cleaned of their R&D components, the rate of return to R&D has to be interpreted as an excess rate. The second issue is related to the way current and past values of R&D investments have to be deflated when measuring the R&D capital. Some authors have paid attention to this issue by constructing 'compound'

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technological change as they account primarily for patterns of production (or performance) rather than patterns of use (or diffusion) of technological innovation among industries.

[17] Quoting Mairesse and Hall (1996: p. 5), *"Conceptually, the value added, labor, and capital measures used to estimate [the productivity equation] should be purged of the contribution of R&D materials, physical capital used in R&D laboratories, and R&D personnel, since these inputs do not produce current output, but are used to increase the stock of R&D capital. If this is not done, the cross section estimates [...] will not necessarily be incorrect, but the measured R&D coefficient will be some kind of 'excess' elasticity of output to R&D rather than a total elasticity, i.e. the incremental productivity of R&D rather than a total elasticity."*

and 'two digit level' price indexes[18], but in general, there seems to be no substantial differences in the results according to whether these price indexes or the GDP deflator are used.

*Inter-industry Spillovers*

Modelling the economic effects of R&D spilling over from one industry to another raises two empirical issues. The first concerns the more general question of how to measure spillovers and to interpret their existing measures. The second is related to the specification of the transmission mechanism. The methodology on constructing domestic embodied R&D indicators followed in this study builds on the seminal work of Terleckyj (1974) which used input-output data to measure inter-sectoral flows of technologies. This type of technology flow indicator focuses on R&D embodied in products purchased by an industry. The concept of "R&D embodiment" relies on the fact that market commodity flows among industries can be regarded as the channel for the transfer of the technology developed by supplying industries.

In contrast to other previous work which directly uses input-output tables to capture R&D in purchased products, the current R&D embodiment indicators have been formulated on the basis of a Leontief inverse, and more precisely, on the basis of the output multipliers[19], taking into account the cumulative nature of inter-industrial R&D flows. The merit of the

[18] Bernstein (1986) has constructed for Canada a Divisia price index that incorporates the prices of different components of R&D, while Cameron (1996) has considered Divisia price indices for the UK business enterprise R&D.

[19] These output multipliers (Miller and Blair 1985: p. 328) "*are less than or equal to traditional Leontief multipliers defined by final demand*". While the use of the Leontief multipliers cannot avoid the double counting of the R&D embodiment of industry *i* by the extend of increase in industry *i*'s output during the propagation, the use of such adjusted multipliers enables to exactly define total R&D embodiments of industry *i* by the simple sum of direct R&D and indirect R&D embodied in the purchased products.

Leontief inverse model is that enables the measurement of second-round R&D gains for a specific industry of R&D performed by industries elsewhere[20]. Such multiplier effects in R&D embodiment estimates can be important.

To obtain a proxy for domestic (intranational) inter-industry spillovers, a weighted measure of real domestic inter-industry R&D expenditures, $IB_{it}$, is first computed:

$$IB_{it} = \sum_{j \neq i} \omega_{ji} B_{jt} \quad , j \neq i \tag{4.9}$$

Here, $B_{jt}$ is the real R&D spending of industry $j$ and $\omega_{ij}$ is the $(j, i)$ element of the output-to-output Leontief inverse. This is cumulated into a stock in the same way that for the direct R&D stock in order to obtain the proxy for the domestic inter-industry spillovers, $IRD_{it}$.

*International R&D Spillovers*

It has already been mentioned that within the literature on R&D spillovers, international R&D spillovers seem to be of increasing interest, with a number of recent studies exploring this dimension. Nevertheless, results are mixed depending on the country and/or the transfer channel considered, with the balance tending to tilt towards the recognition of their existence. However, there is not agreement on their direction or actual magnitude. For example, Coe and Helpman (1995) and Bernstein and Mohnen (1998) find strong and significant evidence of inter-country spillovers, while van Pottelsberghe and Lichtenberg (2001) find that small countries benefit more from R&D performed overseas than large

[20] The structure of the output-to-output Leontief inverse is shown in Appendix A.1 in Table A.2. The

ones. Recently, however, Coe and Helpman's (1995) results have come to under some criticism. Keller (1998) provides evidence that foreign R&D stocks weighted by randomly generated trade matrices perform nearly as well as regressors as the true foreign R&D stocks. This finding questions whether any of Coe and Helpman's results can be interpreted as indicating a link between knowledge flows and imports. On the other hand, Kao *et al.* (1999) applying panel cointegration methods to Coe and Helpman's estimation conclude that the evidence of the relationship between imports and research spillovers is weak.

In the present research, the contribution of foreign R&D to the domestic knowledge stock in each sector is modelled by utilising bilateral import shares as weights as in many preceding empirical studies (Coe and Helpman 1995)[21] alongside the import transaction matrix from the UK 1990 Input-Output Tables (Keller 2002). The focus is on the indirect benefits emanating from the import of goods and services proceeding from the same and other industries that have been developed by trade partners. Let $m_{ik}$ be the bilateral import share from country $k$ for industry $i$ and $a_{ij}$ denote the import share of the $j$ intermediate input that go to the $i$ industry. The pool of foreign R&D, denoted by $FRD_{it}$, is defined as:

$$(4.10)\quad FRD_{it} = \sum_{j}\sum_{k} \alpha_{ij} m_{ik} RD_{it}^{k}\,,\ \forall i.$$

where $RD^{k}_{i}$ is the stock of capital R&D in the $i$ industry in country $k$.

industry raw data matrix is aggregated up to the 8*8 industry classification used in this study.

[21] Although informative, there exist clearly limitations to this approach. The assumption that the spillover of R&D stock is proportional to import flows is a strong one. Other channels of technology transmission

Since the interest in the present research lies not only in the impact of performed R&D but also in that embodied R&D acquired from the purchased of domestic and imported intermediate inputs, an expression for TFP analogous to (4.6) can be written as:

$$(4.11) \qquad \ln A_{it} = \eta_i + \lambda t + \xi_{RD} \ln RD_{it} + \xi_{IRD} \ln IRD_{it} + \xi_{FRD} \ln FRD_{it} + v_{it}$$

Equation (4.11) allows one to answer whether and to what extent embodied R&D from other industries or from abroad can affect productivity in the user industries. In this expression productive knowledge ($R_{it}$) represented in equation (4.6) is a function of cumulative R&D in the industry itself (denoted $RD_{it}$) and R&D in other industries and trade partners (denoted $IRD_{it}$ and $FRD_{it}$, respectively).

## 4.4 CHARACTERISATION OF SECTORS AND DATA

This section discusses briefly some features of the data and characteristics of the eight manufacturing sectors considered[22]. Data sources from the main variables are the same ones considered in Chapter 3. However, for the purposes of the analysis, input data on labour, physical capital stock and intermediate inputs have been adjusted for R&D double counting. Summary statistics of the data are presented in Table B.3 in Appendix B.3.

as foreign direct investment, licenses, trade in high-tech products and co-operation in research and exchange of information might be important as well.

[22] These industries are: (1) FBT Food, beverages, and tobacco; (2) TL Textiles and leather; (3) WWP Wood and wood products; (4) PPP Paper, paper products and printing; (5) CH Chemicals, man-made fibres, and rubber and plastic products; (6) NMM Non-metallic mineral products; (7) BFM Basic metal and fabricated metal products; and (8) MOT Machinery, optical and transport equipment.

### 4.4.1 Data

The present empirical analysis is conducted on a panel of the 8 two-digit UK manufacturing industries considered in Chapter 3 over the period 1970-1997. For these industries measures of direct R&D stocks, indirect domestic R&D stocks, and foreign R&D stocks are constructed combining data on R&D expenditures, input-output transactions and bilateral trade data. The trade partners considered are: Canada, France, Germany, Ireland, Italy, Japan, Netherlands, Spain, and United States; which represent to a great degree the most important source of imports for the UK. In addition, this data set encompasses most of the world's innovative activity, as measured by R&D, during this period. For instance, the R&D conducted in the sample accounted for at least 91% of the OECD business R&D in the manufacturing sector in the year 1995.

Following Schankerman (1981) data on labour, physical capital stock and intermediate inputs have been adjusted for R&D double counting. In Appendix A.1 details about data sources and the construction of variables for estimation purposes are provided.

### 4.4.2 Industry Characterisation

In Table 4.2 some features of the data for the eight manufacturing industries are highlighted. The first column of the table shows the gross R&D intensity –i.e. the ratio of real R&D investment to real gross output- by industry averaged over the period 1970-1997. These industry-specific figures regarding gross R&D intensity reflect to a large extent the degree of technological opportunity associated with each sector. On average, the UK manufacturing sectors devoted 1.2% of gross output to research activities, with industries like Chemicals and Machinery devoting 3.27% and 4.37% respectively. However, relatively little R&D was conducted in the wood, paper and textile industries.

**Table 4.2**
**Sectoral Statistics in 1997 (1970 = 1.0)**

| *Industry* | *Symbol* | *R&D Intensity*+ | *Sectoral R&D Stock* | *Domestic Embodied R&D* | *Foreign R&D Stock* |
|---|---|---|---|---|---|
| | | (%) | $RD_{97}/RD_{70}$ | $IRD_{97}/IRD_{70}$ | $FRD_{97}/FRD_{70}$ |
| *Food, Beverages & Tobacco* | FBT | 0.28 | 1.14 | 1.43 | 1.72 |
| *Textile & Leather* | TL | 0.26 | 0.17 | 1.52 | 1.71 |
| *Wood and Wood Products* | WWP | 0.10 | 0.61 | 1.27 | 1.68 |
| *Paper and Paper Products* | PPP | 0.14 | 0.88 | 1.42 | 1.73 |
| *Chemicals, man-made fibres, rubber & plastic products* | CH | 3.27 | 4.10 | 1.07 | 1.78 |
| *Other Non-Metallic Mineral Products* | NMM | 0.52 | 0.47 | 1.34 | 1.66 |
| *Manufacture of Basic Metals & Fabricated Metal Products* | BFM | 0.47 | 0.62 | 1.33 | 1.66 |
| *Machinery, Optical Equipment & Transport Equipment* | MOT | 4.37 | 1.22 | 1.66 | 1.65 |
| **Average** | | 1.20 | 1.15 | 1.38 | 1.70 |

*Sources:* R&D Data are from ANBERD (OECD). Other data are from the Census of Production (ONS), UK 1990 input-output data (OECD) and bilateral trade (OECD).
+: Ratio of real R&D investment over gross output. Yearly average in percentage (%) terms.

Although on average the sectoral R&D stock experienced an increase of about 15% over the sample period, this performance was not uniform across the several industries. Between 1970 and 1997 the sectoral R&D stocks increased only for the food, the machinery industry and, above all, for the chemical industry while decreasing for other industries, especially for the textiles. On the other hand, the indirect domestic R&D stock increased substantially everywhere, with a relatively more homogeneous pattern. Additionally, changes over time in the foreign R&D stock were somewhat more pronounced although very similar across industries, with an average increased of 70 per cent.

## 4.5 EMPIRICAL FINDINGS

The major findings are presented in this section. However, before turning to the results some econometric issues must be discussed. Particularly, this section summarises the non-stationary panel data tests for unit roots and cointegration[23] together with the econometric estimation methods in the context of dynamic heterogeneous panel models that are used in this chapter.

### 4.5.1 Econometric Issues

*Panel Unit Root and Cointegration Tests*

The main purpose of the present chapter is to estimate the long run relationship between productivity and domestic plus foreign R&D capital stock in the UK manufacturing sectors. If all the variables in the model are stationary, then traditional estimation methods can be used to estimate the relationship between them. If, however, at least one of the series is determined to be non-stationary then the long run elasticities in equation (4.7) cannot be consistently estimated unless the series are cointegrated, otherwise there exists the risk of estimating a spurious regression[24]. Therefore, the first step in determining a potentially

[23] The analysis of unit roots and cointegration in panel data has been fruitful area of study in recent years, with Levin and Lin (1992; 1993) and Quah (1994) being the seminal contributions. See Banerjee (1999) and Maddala and Wu (1999) for a survey.

[24] If cointegration can not be accepted then one encounters the problem of estimating a spurious regression. As discussed in Granger and Newbold (1974) a spurious regression of two independent non-

cointegrated relationship is to test whether the variables involved are stationary or non-stationary, i.e. whether individual series contain unit roots.

Among the various tests proposed in the literature, the Im, Pesaran and Shin (1997) (IPS) panel unit root test is suitable here. The power of the panel unit root tests is substantially greater than the test for a single time series in the sense that the failure to reject a unit root occurs much less frequently. The IPS $t$-bar test is based on an average of the individual industry augmented Dickey Fuller (ADF) tests while allowing for heterogeneous coefficients under the alternative hypothesis and different serial correlation patterns across groups. Under the null hypothesis all groups exhibit a unit root while under the alternative this is not the case for some $i$. A more detailed discussion of the test can be found in Baltagi and Kao (2000). Table B.4 in Appendix B.4 presents the results of the unit-root tests[25]. Following the procedure suggested by Im *et al.* (1997) and applying the $t$-bar test to the variables in levels one obtains test statistics below the critical value to reject the hypothesis of a unit-root, based on an ADF regression with one and two lags. Therefore, the null of non-stationarity cannot be rejected at the 1 per cent level, suggesting that all variables in levels are generated by a non-stationary stochastic process. Furthermore, Table B.5 reports that the $t$-bar test can reject the null of unit root for the first difference variables, except for the intra-industry R&D capital stock.

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stationary series will tend to show a significant relationship when none exists. This problem generally increases with the sample size. In the absence of a cointegration relationship, the specification is spurious. A spurious regression has the following characteristics: (a) estimates are not consistent and converge to random variables, not constant; (b) $t$- and $F$- statistics do not have standard distribution, so the usual statistical inference is invalid; (c) $R^2$ may not tend to 0. Thus caution is suggested when interpreting results from spurious estimated regressions.

[25] In this case, the input variables are adjusted for R&D double counting.

While a number of cointegration tests are documented in the time series literature, there are few cointegration tests developed in panel data. Here, the cointegration tests proposed by Kao (1999); Pedroni (1995) and Pedroni (1999) are used to test whether a long run relationship exists in the estimated panel equations. The first two panel cointegration tests assume that the cointegrating vector (slope coefficients) is the same across industries, whereas Pedroni's (1999) test allows for heterogeneous slope coefficients. The null hypothesis for the panel cointegration tests of Kao (1999) and Pedroni (1995; 1999) is that the estimated equations are not cointegrated.

Table B.6 in Appendix B.4 reports cointegration test results using the "homogeneous" panel cointegration tests of Kao (1999) and Pedroni (1995), assuming slope coefficients being the same across all units. Kao (1999) presents two types of cointegration tests in panel data, the Dickey-Fuller (DF) and augmented Dickey-Fuller (ADF) types. Building on the assumption that the regressors are strictly exogenous, Pedroni (1995), on the other hand, provides a pooled Phillips and Perron-type test. The residuals obtained from the static fixed effect or long run cointegrating equation presented in the next section (Table 4.3) are used to test whether the estimated equation is cointegrated or not. For the models without trend and common trend the null of cointegration is rejected at 10% level or higher, with the exception of the $DF_{tp}$ test statistic. On the other hand, for the model with industry specific time trends all test statistics are significant, so that the null of no cointegration is strongly rejected. Therefore, the cointegration relationship among variables for all equations is strongly supported.

On the other hand, the Pedroni (1999) tests allow for heterogeneity among individual members of the panel, including heterogeneity in both the long run cointegrating vectors and the dynamics. In these tests, the null hypothesis is that for each industry of the panel the variables involved are not cointegrated and the alternative that for each member of the panel there exists a single cointegrating vector. Moreover, this vector need not be the same in all cases. Pedroni (1999) proposes seven tests. Of these tests, four are based on pooling along the within dimension (panel statistics), and three are based on pooling along the between-dimension (group mean statistics). Both cases present the panel version of the Phillips and Perron $\rho$ and $t$-statistics, as well as an ADF-type test.

The results obtained with Pedroni's (1999) heterogeneous panel cointegration tests are reported in Table B.7 in Appendix B.4. For the model with industry specific time trends almost all test statistics reject the null of no cointegration, the exception being the panel-$v$, the panel-$\rho$ and the group-$\rho$ statistics. However, in small panels ($T$ = 20), Pedroni (1997) shows, that in terms of power, the group-*ADF* statistic generally performs best, followed by the panel-ADF statistic, while the panel-$v$ and the group-$\rho$ statistics do poorly.

*Econometric Estimation Method*

The empirical analysis of the ECM in equation (4.8) above generally involves a system of $NT$ equations ($N$ industries and $T$ time observations) that can be examined in different ways. The choice of the econometric approach partially depends upon the size of $N$ and $T$ and the quality of data across these two dimensions. In the type of data set this study considers, $T$ is sufficiently large to allow individual industry estimation. Nevertheless, one may still be able to exploit the cross-section dimension of the data to some extent. As static models are rarely adequate for typical time series, dynamic models are usually more appropriate. The small $T$ problems with dynamic panels[26] are not relevant here as the fixed-effects problem from the initial conditions declines rapidly as $T$ rises. But instead, there are profound problems that result from heterogeneity in the model parameters that emerge as soon as a lagged dependent variable is introduced (Pesaran and Smith 1995).

The primary difference between the various panel data models is the degree to which they impose homogeneity across the industries with respect to variances, short or long-run regression slope coefficients and intercepts. In this section four specifications are considered according to the dimensions of the panel: the Mean Group (MG), the PMG (Pesaran *et al.* 1997), the seemingly unrelated regression equation (SUR) and the Dynamic Fixed Effect model (DFE). The four models are nested within the specification (4.8) with the restriction either on the dynamic specification or the homogeneity of error variances and/ or the equality of short or long run slope coefficients across the industries.

The most restrictive procedure is the dynamic fixed-effect (DFE). Instrumental variables (e.g. Arellano and Bond 1991; Arellano and Bover 1995) are generally applied to overcome the usual small-sample downward lagged dependent variable bias (see Nickell 1981). However, Pesaran and Smith (1995) show that, unlike in static models, pooled dynamic heterogeneous models generate estimates that are inconsistent even in large samples. The DFE specification generally imposes homogeneity of all slope coefficients, allowing only the intercepts to vary across industries. In other words, DFE imposes $(N-1)(2k + 2)$ restrictions on the unrestricted model in equation (4.8): i.e. $k$ long-run coefficients, $k$ short-

[26] Arellano and Bond (1991).

run coefficients plus the convergence coefficient and the common variance. The validity of DFE, in particular, depends critically on the assumptions of common technology and common convergence parameter that in turn requires both common technological change and input factor growth across industries.[27] Pesaran and Smith (1995) suggest that, under slope heterogeneity, the convergence estimates are affected by a heterogeneity bias.

The least restrictive procedure is the MG. This imposes no homogeneity and is calculated as the mean (across the individual groups) estimates of the long run, the short run and adjustment coefficients (e.g. Evans 1997; Lee *et al.* 1997). In particular, there are $N(2k + 3)$ parameters to be estimated: each equation has $2k$ coefficients on the exogenous regressors, an intercept, a coefficient on the lagged dependent variable and a variance. The small-sample downward bias in the coefficient of the lagged dependent variable remains. Moreover, while consistent, this estimator is likely to be inefficient in small group samples, as is the case here, where any industry outlier could severely influence the averages of the industry coefficients.

The intermediate choices between imposing homogeneity on all slope coefficients (DFE) and imposing no restrictions (MG) are the Seemingly Unrelated Regression (SUR) approach and the pooled mean group (PMG). On one hand, the Zellner's SUR method, which is a form of feasible GLS, imposes homogeneity on the long-run coefficients and the speed of

[27] Instrumental variable estimators suggested by Arellano and Bond (1991) are particularly suited for dealing with dynamic panel data when $N$ is large and $T$ relatively small. As shown by Nickell (1981) the downward lagged dependent variable bias depends on $1/T$ and it is less of a concern when $T$ is large and of the same order of magnitude of $N$. In this latter case, heterogeneity of individuals (industries) is a more serious problem and imposing homogeneity of all (short and long-run) parameters risk leading to inconsistent results (see Lee *et al.* 1997).

convergence while allows the short run coefficients to differ across industries. The SUR approach requires the estimation of $(k+1)(N+1)$ coefficients plus $\frac{1}{2}N(N+1)$ elements of the covariance matrix. On the other hand, the PMG allows short-run coefficients, the speed of adjustment and error variances to differ across industries, but imposes homogeneity on long-run coefficients. In other words, the PMG imposes $(N-1)k$ restrictions on the unrestricted model shown in equation (4.8).

Given the access to common technologies, and the intense trade relations between manufacturing industries, the assumption of common long-run production function parameters is reasonable. By contrast, it might be more difficult to assume homogeneity of speed of convergence, as in the SUR approach[28] and, short-term dynamics as in the dynamic fixed effects specification. Under the long-run slope homogeneity the PMG estimator increases the efficiency of the estimates with respect to mean group estimators (Pesaran *et al.* 1999). Formally, conditional on the existence of a convergence to a steady state path, the long-run homogeneity hypothesis permits the direct identification of the parameters of factors affecting the steady state path of output per capital ($\beta_i / \phi_i = \theta_i$, see below). In other words, with the PMG procedure, the following restricted version of equation (4.8) is estimated on pooled cross-industry time-series data:

[28] SUR is generally concerned with linear cross-equation restrictions, whereas common long-run coefficients and idiosyncratic speed of adjustment in equation (4.12) above imply non-linear restrictions across different industry equations.

$$\Delta\ln q_{i,t} = -\phi_i\left(\ln q_{i,t-1} - \theta_l \ln l_{i,t-1} - \theta_m \ln m_{i,t-1} - \theta_c \ln CU_{i,t-1} - \theta_{rd} \ln RD_{i,t-1} - \theta_{ird} \ln IRD_{i,t-1} - \theta_{frd} \ln FRD_{i,t-1} - \lambda_i t - \theta_{0,i}\right)$$
$$+ b_{l,i}\Delta\ln l_{i,t} + b_{m,i}\Delta\ln m_{i,t} + b_{c,i}\Delta\ln CU_{i,t} + b_{rd,i}\Delta\ln RD_{i,t} + b_{ird,i}\Delta\ln IRD_{i,t} + b_{frd,i}\Delta\ln FRD_{i,t} + \varepsilon_{i,t} \quad (4.12)$$

The hypothesis of homogeneity of the long-run parameters cannot be assumed *a priori* and is tested empirically in all specifications. In particular, in the next section, the Hausman test (Hausman 1978) is used for this purpose: under the null hypothesis, the difference in the estimated coefficients between the MG and the PMG are not significantly different and PMG is more efficient. Nevertheless, if the homogeneity assumption is not valid, then pooling the cross-section information might still have some merits since it yields to more efficient estimates than running independent regressions for each group and then computing an average of the estimated coefficients, the MG estimator. Moreover, when $N$ is small as is the case here, the PMG estimator is less sensitive to outliers since it weights the individual unrestricted country coefficients according to their precision (see Pesaran *et al.* (1999) for a more detailed discussion).

### 4.5.2 Econometric Results

The first results presented are based on the commonly used static equation (4.13), in which an identical form of the long run production function is assumed for all industries. As such a model misses the dynamics of the linkages between the variables, its purpose is to just look for simple, static relationships. The pooled OLS estimates with heteroskedastic consistent standard errors are reported in Table 4.3 (industry fixed effects are included but not reported, although these are highly significant in all regressions). These results are reported partly to illustrate how misleading they may be.

$$(4.13)\quad \ln q_{it} = \eta_i + \lambda t + \varepsilon^{Q,L}\ln l + \varepsilon^{M,L}\ln m + \delta \ln CU_{it} + \xi_{rd}\ln RD_{it} + \xi_{ird}\ln IRD_{it} + \xi_{frd}\ln FRD_{it} + v_{it}$$

The estimates of equation (4.13) are reported for three alternative cases: first (column 1), the time trend is excluded from the regression, which is the form most commonly used in these studies; second, a common trend across industries is assumed; and finally (column 3), specific industry time trends are allowed. In general, for the first two regressions the estimated coefficients are similar, with the expected sign and statistically significant. Nevertheless, the size of the coefficient on the labour elasticity is greater than expected, according to the average labour revenue share. In particular, the impact of domestic R&D upon productivity is positive and significant and, inter-industry and foreign R&D spillovers appear also positive and statistically significant.

In column 3, a specific time trend for each industry is allowed, which is the option used in the PMG estimator. Moreover, the null hypothesis of a common trend is rejected ($F(6,194) = 9.06$, [Prob. = 0.000]). In general, although the point estimates are rather different, the coefficient estimates keep the sign and significance, except for the impact of own domestic R&D efforts. Nevertheless, the distribution of the estimators of the cointegrating vector provided by such static regression is generally non-normal (Kao *et al.* 1999) and so inference cannot be drawn about the significance of the individual parameters by using standard "*t*" test.

**Table 4.3**
**UK Sectoral TFP Static Regressions**

*(Dependent variable $ln(q)_{it}$)*

| | | Regression number | | |
|---|---|---|---|---|
| | | 1 | 2 | 3 |
| **Variable** | | **OLS** | **OLS** | **OLS** |
| **Labour per capital** | $ln(l)_t$ | 0.427*** | 0.415*** | 0.397*** |
| | | (0.064) | (0.067) | (0.047) |
| **Intermediates per capital** | $ln(m)_t$ | 0.663*** | 0.673*** | 0.519*** |
| | | (0.059) | (0.061) | (0.038) |
| **Capacity utilisation** | $ln(CU)_t$ | 4.546** | 4.230*** | 8.618*** |
| | | (1.934) | (2.013) | (1.169) |
| **Own domestic R&D** | $lnRD_t$ | 0.083*** | 0.082*** | 0.027 |
| | | (0.029) | (0.029) | (0.088) |
| **Domestic intra-industry R&D** | $lnIRD_t$ | 0.570*** | 0.588*** | 0.408*** |
| | | (0.165) | (0.167) | (0.108) |
| **Foreign R&D** | $lnFRD_t$ | 0.185*** | 0.224*** | 0.209*** |
| | | (0.045) | (0.067) | (0.034) |
| **Time trend** | $t$ | | -0.002 | 0.000 |
| | | | (0.003) | (0.002) |
| **Industry specific dummies** | | √ | √ | √ |
| **Robust Std. Err.** | | √ | √ | √ |
| **$R^2$** | | 0.978 | 0.978 | 0.994 |
| **s.e.** | | 0.061 | 0.061 | 0.031 |
| **Log Likelihood** | | 304.36 | 304.62 | 458.77 |
| **No. of obs.** | | 216 | 216 | 216 |
| **Significance FE** | | F(7,202)=60.22 | F(7,201)=49.68 | F(7,194)=145.3 |
| | | [0.00] | [0.00] | [0.00] |

*Notes:* Sample period is 1971-1997, 8 sectors. Industry-specific dummies are included. Dependent variable is ln(Y/K). Heteroskedasticity-Consistent Standard errors are given in parentheses under the estimates. *** and ** denotes statistical significance at the 1% and 5% level, respectively.

*Estimation of the Heterogeneous Dynamic Panel*

The investigation of the data properties in the previous section implies that an estimation of equation (4.12) can provide reliable inferences about the long and short-term influences of the R&D efforts upon productivity. Deviations from the long run relationship are possible in the short run. There are various reasons for such deviations, including adjustment costs.

Table 4.4 reports the results from the dynamic heterogeneous panel estimation of the empirical specification provided by equation (4.12) for 8 UK manufacturing sectors. A common autoregressive distributed lag (ARDL) model is estimated for each industry where the lag length is selected to be 1 for all variables.

As discussed above, results are also likely to vary significantly with respect to the estimation method- *i.e.* from the least restrictive, but potentially not efficient MG, to the PMG[29], SUR and to the most restrictive DFE, which only allows intercepts to vary across industries. Table 4.4 and Table 4.5 report results using these four approaches to specifications without and with an industry-specific linear time trend respectively. Although the reported "pooled" time trend is non-significant, in the industry specific regressions this is significant for five of the eight industries considered. Additionally, the equation with the linear time trend appears to be more robust to the different specifications. Therefore, from now on, the comments on the results are based on those obtained in Table 4.5 in which the industry specific time trend is included. This allows for different rates of disembodied technical change across industries in the long run.

The next step is to test for homogeneity in the speed of convergence and short-term dynamics, *i.e.* from PMG to the DFE model. The latter yield a much lower speed of convergence due to a downward bias in dynamic heterogeneous panel data. Moreover, restricting the short-term dynamics affects the sign and significance of the long-run coefficients. The DFE is also sensitive to panels with small groups and seems overly

[29] This is implemented in a GAUSS procedure, downloadable as JASA.EXE, made available at Hashem Pesaran's website. This software is used in estimation, being grateful to the authors for making it available.

restrictive. In both cases, moving from MG to PMG (*i.e.* imposing long-run homogeneity to all but the time trend) reduces the standard errors. Moreover, it reduces significantly the measured speed of convergence, with impact on the size and the statistical significance (but not the sign) of the estimated long-run coefficients.

In what follows, the homogeneity of the long run parameters in the model is tested. Pesaran, Shin and Smith argue that in panels, omitted group specific factors or measurement errors are likely to severely bias the individual industry estimates. This may explain why is a commonplace in empirical panels to report a failure of the poolability test. Nevertheless, the individual Hausman test does not reject poolability of the long run parameter. This means that the efficient estimates of the common long run parameters are given by the PMG method. The inefficient MG estimates differ from the PMG estimates but are also much worse determined, reflecting the inefficiency of the MG for this dataset.

Moreover, if the focus of the analysis is on the average (across industries) elasticities, then the PMG estimates are probably preferable to the MG estimates on the grounds of their better precision and the fact that they are less sensitive to outlier estimates, especially in small group samples. Under the assumption that the long-run elasticities are identical across industries but allowing the short run elasticities to vary (PMG), there is significant support for the hypothesis that own R&D stock and intra-industry R&D capital stock are linked to productivity in the UK manufacturing industry.

**Table 4.4**
**Alternative Estimates of the ARDL Model without Time-Trend**

| *Dependent variable: Δ log q* | Without time trend | | | | |
|---|---|---|---|---|---|
| | **Mean Group (MG)** | **Pooled Mean Group (PMG)** | **h-test** | **SUR** | **Dynamic Fixed Effect** |
| **Convergence Coefficient** | | | | | |
| ***log q*** | -0.748 *** (0.14) | -0.286 ** (0.13)) | | -0.128 *** (0.03) | -0.094 *** (0.03) |
| **Long-Run Coefficients** | | | | | |
| ***log m*** | 0.321* (0.17) | 0.645 *** (0.05) | 4.16 | 0.356 * (0.20) | 0.296 (0.24) |
| ***log l*** | 0.449 *** (0.15) | 0.343 *** (0.05) | 0.58 | 0.703 *** (0.16) | 0.656 *** (0.19) |
| ***log CU*** | 13.161 *** (3.74) | 3.687 ** (1.76) | 8.27 | -3.241 (8.02) | -5.044 (9.20) |
| ***log RD*** | 0.039 (0.27) | 0.081 * (0.05) | 0.02 | 0.303 *** (0.07) | 0.282 *** (0.10) |
| ***log IRD*** | 0.526 (0.39) | 0.622 *** (0.16) | 0.08 | 2.327 *** (0.36) | 2.498 *** (0.60) |
| ***log FRD*** | -0.001 (0.07) | -0.123 ** (0.06) | 32.3 | -0.237 (0.17) | -0.266 (0.19) |
| **Short Run Coefficients** | | | | | |
| ***Δ log m*** | 0.508 *** (0.13) | 0.571 *** (0.12) | | 0.539 *** (0.03) | 0.625 *** (0.05) |
| ***Δ log l*** | 0.259 ** (0.11) | 0.224 *** (0.08) | | 0.212 *** (0.05) | 0.259 *** (0.08) |
| ***Δ log CU*** | 6.808 *** (1.98) | 4.944 *** (1.44) | | 5.112 *** (1.28) | 3.554 *** (1.85) |
| ***Δ log RD*** | -0.553 (0.37) | -0.422 *** (0.17) | | -0.278 (0.14) | -0.356 *** (0.17) |
| ***Δ log IRD*** | -0.225 (0.64) | -0.687 (0.44) | | -0.645 *** (0.26)) | -0.290 (0.43) |
| ***Δ log FRD*** | -0.012 (0.05) | -0.017 (0.02) | | -0.010 (0.04) | -0.048 (0.02) |
| No. of industries | 8 | 8 | | 8 | 8 |
| No. of obs. | 216 | 216 | | 216 | 216 |
| Log Likelihood | 659.9 | 576.4 | | 596.9 | 510.8 |

*Notes:* All equations include a constant industry-specific term. Standard errors are in brackets. The standard errors of the SUR long run estimated coefficients are calculated from the estimated variance-covariance matrix of the respective parameter estimates (see Greene 2000: p. 297-300). The rest of long run estimated standard errors are given by the JASA program.

*: significant at 10 % level; ** at 5% level; *** at 1 % level. The Joint Hausman test statistic is indeterminate if the difference between the variance-covariance matrices of the MG and PMG estimators is not positive definite (see Pesaran *et al.* (1999) for more details). The unrestricted short run coefficient estimates are the MG estimates under the restriction of long run homogeneity.

## Table 4.5
## Alternative Estimates of the ARDL Model with Time-Trend

| ***Dependent variable:* Δ *log q*** | **With time trend** | | | | |
|---|---|---|---|---|---|
| | **Mean Group (MG)** | **Pooled Mean Group (PMG)** | **h-test** | **SUR** | **Dynamic Fixed Effect** |
| **Convergence Coefficient** | | | | | |
| ***log q*** | -0.820 *** | -0.464 *** | | -0.476 *** | -0.093 *** |
| | (0.14) | (0.08) | | (0.05) | (0.03) |
| **Long-Run Coefficients** | | | | | |
| ***log m*** | 0.443 ** | 0.642 *** | 1.34 | 0.530 *** | 0.322 |
| | (0.18) | (0.06) | | (0.05) | (0.22) |
| ***log l*** | 0.315 * | 0.231 *** | 0.23 | 0.379 *** | 0.621 *** |
| | (0.19) | (0.07) | | (0.06) | (0.18) |
| ***log CU*** | 13.447 *** | 8.918 *** | 1.59 | 5.605 *** | -6.400 |
| | (4.01) | (1.78) | | (1.97) | (10.24) |
| ***log RD*** | 0.310 | 0.331 *** | 0.00 | 0.315 ** | 0.281 *** |
| | (0.39) | (0.11) | | (0.13) | (0.10) |
| ***log IRD*** | 0.421 | 0.942 *** | 1.87 | 1.078 *** | 2.553 *** |
| | (0.41) | (0.14) | | (0.16) | (0.62) |
| ***log FRD*** | -0.008 | -0.048 | 2.40 | 0.009 | -0.162 |
| | (0.06) | (0.05) | | (0.07) | (0.24) |
| **Time trend** | -0.002 | -0.003 | | -0.001 | -0.001 |
| | (0.01) | (0.00) | | (0.00) | (0.00) |
| **Short Run Coefficients** | | | | | |
| Δ ***log m*** | 0.553 *** | 0.602 *** | | 0.563 *** | 0.626 *** |
| | (0.13) | (0.08) | | (0.03) | (0.04) |
| Δ ***log l*** | 0.205 ** | 0.236 *** | | 0.268 *** | 0.260 *** |
| | (0.11) | (0.06) | | (0.05) | (0.05) |
| Δ ***log CU*** | 7.460 *** | 4.045 *** | | 3.844 *** | 3.506 ** |
| | (1.98) | (0.81) | | (1.11) | (1.32) |
| Δ ***log RD*** | -0.396 | -0.305 | | -0.133 | -0.342 ** |
| | (0.37) | (0.26) | | (0.13) | (0.16) |
| Δ ***log IRD*** | -0.142 | -0.963 *** | | -1.060 *** | -0.283 |
| | (0.64) | (0.31) | | (0.26) | (0.24) |
| Δ ***log FRD*** | -0.009 | -0.009 | | 0.016 | -0.041 |
| | (0.05) | (0.01) | | (0.04) | (0.04) |
| No. of industries | 8 | 8 | | 8 | 8 |
| No. of obs. | 216 | 216 | | 216 | 216 |
| Log Likelihood | 667.5 | 597.8 | | 630.8 | 510.9 |

*Notes:* All equations include a constant industry-specific term. Standard errors are in brackets. The standard errors of the SUR long run estimated coefficients are calculated from the estimated variance-covariance matrix of the respective parameter estimates (see Greene 2000: p. 297-300). The rest of long run estimated standard errors are given by the JASA program.

*: significant at 10 % level; ** at 5% level; *** at 1 % level. The Joint Hausman test statistic is indeterminate if the difference between the variance-covariance matrices of the MG and PMG estimators is not positive definite (see Pesaran *et al.* (1999) for more details). The unrestricted short run coefficient estimates are the MG estimates under the restriction of long run homogeneity.

SUR estimates are reported alongside PMG estimates in Table 4.5. The difference between both methods depends on distinct assumptions on the speed of adjustment and cross-section correlation of the errors terms. While SUR imposes homogeneity on the speed of adjustment, the PMG allows for idiosyncratic convergence coefficients, which imply imposing non-linear restrictions across the industry equations (not possible in SUR). The PMG estimates of the speed of convergence coefficient differ considerably across industries, with these varying from (-0.762) in the paper industry to (-0.078) in the basic metal industry. These differences give support to the PMG estimates.

Additionally, SUR estimation is appropriate on the assumption of contemporaneous correlation of disturbances. In fact, the Breusch-Pagan LM test based on equations with homogenous speed of convergence coefficients establishes the presence of non-diagonal error covariance matrices confirming the appropriate of SUR estimation under the homogeneity convergence restriction. PMG, on the other hand, assumes that the error term is independently distributed across *t* and *i*, although variances may be heterogeneous across industries. The cross-sectional independence assumption of the error term is rather strong and restrictive. For example, it is not hard to imagine shocks that affect all industries at the same time. However, this assumption is standard in the dynamic panel literature.

Despite these comments, the point estimates under both approaches appear quite similar in terms of size, sign and significance, although the PMG estimates seem economically more plausible. This analysis relies on the appropriateness of the PMG to comment the results, on the basis of the existence of different convergence coefficients across industries. The PMG estimates indicate that the long run elasticities of output with respect to inputs are close to the respective average revenue shares. Additionally, the long run impact of own R&D efforts on productivity is positive and significant.

The impact of intra-manufacturing R&D upon productivity is positive and significant. This effect is robust to specification changes. The results suggest that, at least internally, there is evidence that the UK manufacturing social rate of return to R&D is higher than the private rate of return at industry level. Conversely, the estimated effect on TFP of the foreign R&D stock variable is negative, although not significant at standard levels. This insignificant effect is consistent across the majority of the alternative specifications estimated as a test of robustness. The only exception to this is when a static model is estimated, what it is indicative that the dynamic clearly matters. Possible explanations for this finding are given in the next section.

It could be argued that, in small industry samples, one individual industry could significantly affect the estimated parameters, even when the Hausman tests do not reject the assumption of common long run coefficients. A sensitivity analysis was thus performed on the preferred specification (corresponding to PMG estimates with specific time trends reported in Table 4.5) in order to asses the robustness of the results to variations of industry coverage, by eliminating one industry at a time and re-running the PMG estimation procedure. Figures C.1 to C.4 in Appendix C.3 report the results of the sensitivity analysis on the long run coefficients of labour, intermediate inputs, own R&D and inter-industry R&D spillovers. Taking into account the width of the confidence intervals, these estimates seem stable to the exclusion of industries from the sample. Point estimates remain in the bound of the confidence intervals of the baseline estimate ("Main" in Figures C.1 to C.4 in Appendix C.3).

Table 4.6 reports the estimated long run elasticities of output with respect to the input factors (intermediate inputs and labour) and to the own R&D capital stock. The estimated long-run elasticity of own R&D is 0.331. Such elasticity is in line with estimates reported in the literature (see Table 4.1), although it is in the high range.

**Table 4.6**
**PMG Long Run Input Elasticities**

| | *Intermediate inputs* | *Labour* | *Own domestic R&D* |
|---|---|---|---|
| **Coefficient** | 0.642 | 0.231 | 0.331 |
| **Std. Err.** | (0.06) | (0.07) | (0.11) |

*Source*: Coefficient estimates and standard errors from Table 4.5

On the other hand, the PMG short-run coefficients are not restricted to be the same across industries, so there is no pooled estimate for each coefficient. Nevertheless, one can still analyse the average short run effect by considering the mean of the corresponding coefficients across industries, which is reported in Table 4.7.

It was found that the average short-run relationship between own sectoral R&D and productivity is negative, although non-significant. In particular, the industries for which the short run coefficient was found positive were the wood and machinery, optical and transport equipment industries, while being found negative for the others, particularly, for the chemical industry.

**Table 4.7**
**PMG Short Run Growth Effects**

| *Industry* | *RD* | *IRD* |
|---|---|---|
| **FBT** | -0.365 | -0.732 |
| **TL** | -0.621 | -1.775 |
| **WPP** | 1.268 | -1.051 |
| **PPP** | -0.510 | -1.821 |
| **CH** | -1.179 | -1.050 |
| **NMM** | -0.659 | -1.128 |
| **BFM** | -0.435 | 0.852 |
| **MOT** | 0.062 | -0.994 |
| **Average** | -0.305 | -0.963 |

*Source:* Results from Table 4.5

Due to the way in which R&D stocks are defined, the short run impact of R&D on productivity growth mainly reflects the effect of R&D investment costs at the beginning of the period upon changes in current output and productivity. In the short run, it seems plausible to assume that investments in R&D do not lead necessarily to successful innovations and that industries may finance large parts of their R&D expenditures by setting higher prices. This is particularly true for industries, like chemicals, where innovation processes tend to be product orientated instead of process orientated. In this case, additionally, downstream industries will be faced with higher prices for their inputs. Thus negative externalities may occur, as is found in the results presented in Table 4.7. Only in markets with strong competition and relatively weak product differentiation, industries could arguably decide to let R&D costs erode their profit margins, expecting that their R&D projects will yield them future profits.

A few further remarks on the econometric procedure are in order: The coefficients on the lagged dependent variables are subject to the familiar small sample (small *T*) downward bias (as seen in Chapter 3 one would expect at least short run elasticities to differ from average revenue shares, indicating the presence of mark-ups). Since this downward bias is in the same direction for each group, averaging or pooling does not remove the bias. Kiviet and Phillips (1993) have proposed a procedure to remove this bias, which applies to the short run coefficients. Since the long run coefficients are non-linear transformations of the short run coefficients such bias corrections can leave the long run coefficients biased. We are not aware of any procedure in the literature that has resolved this problem.

*Comments on Results and Comparisons with Previous Studies*

Robust evidence was found of a positive and significant link between industry's R&D effort and productivity. Particularly, the long run output elasticity with respect to own sectoral R&D was estimated to be 0.331. Such elasticity is in line with previous studies. Nadiri (1993), for instance, reports elasticities at the industry level of 0.06 to 0.42, while Cameron (1999), in a more comparable set up, finds an elasticity of 0.24 for the UK manufacturing sector.

One of the main questions in the introduction was the relative importance of domestic versus foreign spillovers (is domestic or international R&D the driving force behind UK manufacturing productivity growth?). The results reported above suggest that domestic spillovers seem to overwhelm foreign spillovers. The finding that domestic spillovers are important confirms results found in related studies (see for instance, Sterlacchini 1989; Keller 1997 and McVicar 2002). Nadiri's (1993) overview reports findings for the domestic spillover elasticities ranging from 0.10 to 0.26.

One of the striking features of the reported results, however, is the frequency with which foreign spillovers are estimated to have a negative impact on innovative output, though in many cases the coefficients are not significant at standard levels. This effect is consistent across the majority of alternative specifications as a test of robustness. However, this result of negative or no significant impact of foreign spillovers upon productivity is not at odds with findings from other related studies (e.g. Aitken and Harrison 1999; Branstetter 2001 and McVicar 2002).

Branstetter (2001) encounters negative and non-significant foreign technology spillovers and provides three potential explanations for this finding. The first explanation points out at data inaccuracies, which shouldn't be discarded. An alternative argument, supported as well by Mohnen (1996), is that this finding is an artefact of the data, driven by multicollinearity problems between the various R&D measures combined with a low number of observations. In fact, the domestic and foreign spillover terms are highly correlated with one another. Because there is little independence variation in the two series, regressions could in principle, produce coefficients with the "wrong sign", as it often happens in the case of severe multicollinearity.

Finally, the third argument, and most intuitively appealing, refers to the dominance of a negative competition effect over any positive technological spillovers. In this sense, Aitken and Harrison (1999) describe how a market stealing effect might force domestic firms to reduce output in response to competition from the technological superior foreign sector. This in turn could drive domestic firms further up their average cost curves[30] and hence

[30] This would be the case if average cost curves were downward sloping due to substantial fixed costs.

lower the productivity of these firms. If this decline in the productivity of domestic firms is large enough, net domestic productivity can decline despite the technology transfer from foreign firms. This could threaten or even interrupt the growth of national economies.[31]

## 4.6 CONCLUSIONS

Following on the results in Chapter 3, the purpose of this chapter was to consider the influence of different methodological and measurement issues on studying the relationship between productive knowledge and TFP. More specifically, the stress was placed upon the long-run relationship between innovative efforts and productivity and the nature of the R&D spillovers accruing to the panel of eight UK manufacturing industries over the period 1970 to 1997.

The outlines of the production function framework necessary to perform this study were summarized in section 4.3. In contrast to other empirical studies in this tradition, this study focused on gross output as measure of real output and allowed for imperfect competition and temporary disequilibria. In particular, an ECM was adopted for estimating the long-run parameters in a pooled framework. As mentioned, the ECM statistical framework is attractive in that is closely bound up with the concept of cointegration, thus providing a useful and meaningful link between the long run and the short run approach to econometric modelling when series are non-stationary. In fact, panel tests for order of integration reveal that the core variables are non-stationary. Thus for estimation to be valid,

[31] See Jaffe (1986) and Mohnen (1996) for different arguments on the possibility of negative externalities on productivity as a result of R&D activities.

the data must also satisfy tests for the existence of long-run relationships. The tests for cointegration using Kao's and Pedroni's residual based panel unit root tests showed evidence for the existence of cointegrating relationships in the panel members. Another advantage of the ECM framework in the panel data setting is that it can be estimated by using the PMG estimator, which allows short-term adjustments and convergence speeds to vary across industries, and imposes cross-industry homogeneity restrictions on the long run. This restricted poolability was tested for by individual Hausman tests, which couldn't reject pooling of the long run coefficients.

The results of the empirical analysis indicated that there is a positive and significant link between industry's R&D activities and productivity in the long run. Particularly, the estimated long run output elasticity with respect to own R&D is 0.331. In addition, robust evidence was found of positive and significant domestic cross-industry R&D spillovers. These results certainly support the view that private R&D has public good aspects and that the private marginal product of investment in R&D may be considerably lower than the social marginal product at the industry level. The presence of spillover effects means that the market will tend to under-invest in innovation. This provides a rationale for Government intervention to sharpen incentives for firms to increase the level of privately funded R&D.

On the other hand, the results showed that international spillovers do not significantly contribute to TFP in UK manufacturing sectors. This finding suggests that R&D externalities are primarily an intranational phenomenon, which may serve as a warning against under-estimating the importance of domestic technological efforts and over estimating the potential contribution of international spillovers.

Finally, despite the concerns about measurement bias in TFP estimates, the results presented above are consistent with those from other quantitative studies using different methodologies. In other words, adjusting TFP estimates for the presence of capacity utilisation adjustments and imperfect competition does not affect qualitatively the results found in related studies with respect to the relationship between UK Manufacturing TFP and R&D efforts.

# Chapter 5 –

# International comparisons of productivity performance in manufacturing industries

*"Productivity is a fundamental yardstick of economic performance...we are not as productive as our major partners and the extent of our under-performance is very substantial...tackling it must be a central priority"*

HM Treasury (1998: p. 28)

## 5.1 INTRODUCTION

Recent studies of international productivity comparisons[1] draw attention to the significance of the UK productivity gap in manufacturing relative to other industrialized countries. Particularly, latest evidence from O'Mahony and de Boer (2002) indicates that the UK differential in terms of TFP in manufacturing in 1999 is of the order of 10% and 21% compared with France and Germany respectively, and 43% with respect to the US. As documented by Maddison (1991), Broadberry (1997) and Crafts (2002), among others, this productivity gap is not a recent phenomenon; it has been a persistent feature of British industry, opening up with the US at the beginning of the 20th century, and with Europe during the 1970s.

Following Harrigan's (1999: p. 268) argument, one possibility for the existence and reported size of the productivity gap is the fact that *"this is the result of a mismatch between the theory of productivity comparisons and the technological and measurement process which generate the data."* In this regard, measurement errors and/or restrictive assumptions underlying traditional methods of productivity measurement may cause biases that can alter the size and direction of the measured productivity gap differential.

[1] See for instance O'Mahony (1999), HM Treasury (2000), O'Mahony and de Boer (2002) and Malley *et al.* (2003).

While previous findings on international productivity differentials have largely been in terms of labour productivity measures, comparisons based on total factor productivity (TFP) are less frequent[2]. Additionally, most of earlier studies have been restricted to aggregate productivity analysis based on value added as a measure of real output (van Ark 1993; O'Mahony 1999), instead of gross output. As emphasized in previous chapters the use of value added may constitute a potential source of bias when certain conditions are not met. One of the primary interests in this chapter is to analyse the sensitiveness of the magnitude of the UK's productivity gap in manufacturing to different measures of productivity. To this end, the chapter reviews some previous attempts along these lines and provides comparative estimates of relative productivity in terms of both alternative productivity and output concepts.

The second aim of this chapter is to provide new estimates of growth performance and levels of productivity at sectoral level and compare them with earlier findings. In essence, there are two objectives. First, the present research aims to provide a detailed evaluation of productivity performance for the major branches of UK manufacturing relative to other industrialized countries. The reason for this is that the aggregate analysis of productivity performance may hide significant differences in trends across sectors (see Bernard and Jones 1996).

[2] Exceptions to this are provided by O'Mahony (1999), O'Mahony and de Boer (2002) and Malley *et al.* (2003), who all study Britain's relative productivity performance. Their studies are discussed in the next section.

Second, keeping track on the main theme of this thesis, this chapter pays particular attention to the impact of different measurement issues on the analysis of international productivity comparisons. In Chapter 3 it was found that the traditional accounting framework leads to biased estimates of TFP growth in UK manufacturing industries. This is due to the presence of mark-ups and adjustment in capacity utilisation. This section takes the analysis a step further. The objective here is to determine whether and to what extent adjusting for measurement bias has an impact on the size and direction of the productivity gap as traditionally measured.

To these ends, in the present chapter, a panel regression is conducted in which imperfect competition; returns to scale and adjustments for capacity utilisation are allowed. The resulting parametric estimates of TFP growth are then compared to those derived from the traditional accounting framework. The new estimates of sectoral TFP are important because not only do they cover an important range of countries and industries, but also they use recent data and try to improve, if not overcome, some of the data and index number problems of previous work. However, it has to be emphasized that the coverage and depth of analysis in this chapter is necessarily constrained by the availability, accuracy and international comparability of economic statistics.

The rest of the chapter is organized as follows. The next section reviews some of the studies that consider Britain's productivity position in manufacturing in an international perspective. Section 5.3 briefly describes the data and industry characteristics. Section 5.4 outlines the basic concepts and traditional methods of measurement used to quantify comparative productivity differentials. This section also analyses the sensitivity of the productivity gap in manufacturing to measurement issues. Section 5.5 presents sectoral measures of TFP. Section 5.6 sets out the econometric approach used to implement the adjustments in traditional measures of TFP to allow for imperfect competition, scale economies and adjustments for capacity utilisation. Additionally, this section reports the result of this estimation. Section 5.7 discusses the implication of these results. Finally, section 5.8 draws conclusions and discusses the relevance of the results.

## 5.2 PREVIOUS STUDIES ON RELATIVE PRODUCTIVITY PERFORMANCE IN UK MANUFACTURING

In recent years there has been renewed interest in international comparisons of factor productivity. The literature on this topic is considerable and diverse in terms of approaches followed, breadth of coverage, levels of detail and questions addressed. Table 5.1 gives an overview of studies that consider Britain's relative productivity position in manufacturing in an international perspective[3]. Despite the diversity in approaches, these studies coincide in recognising the laggard position of British manufacturing performance relative to other industrialized countries. The earliest comparative studies were mainly based on the UK industry compared to the US[4]. However, the productivity gap that had emerged between the UK and other European countries during the post-war period, received increasing attention during the 1980s in studies by the NIESR, among others[5].

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[3] See Kravis (1976) and Islam (1995) for other surveys of international comparisons of productivity.
[4] See Broadberry and Crafts (1990) and Broadberry (1994) for a detailed analysis of the various Anglo-American cross-country comparisons.
[5] For comparisons between the UK and Germany see Smith *et al.* (1982), O'Mahony and Wagner (1996) and Broadberry (1997), among others. For comparisons between France and UK see van Ark (1990).

The earliest comparisons of Britain's productivity during the 1940's and 1950's, including those of Rostas[6] (1948) and Maddison (1952), were frequently made by comparing physical quantities of output. As the number of product varieties in manufacturing increased these comparisons based on physical quantities became less feasible. This led to a shift in methodology from physical quantity comparisons to converting output to a common unit using currency conversion factors. Since then, two different approaches have been used to compute currency conversion factors specific to manufacturing output. One approach, "the industry-of-origin approach", is based on computing unit value ratios (UVRs) using data on output and prices at the industry level. In this line, Smith *et al.* (1982) compared British, German and American output and productivity by constructing UVRs using census data on net output and prices for a large number of individual industries. Later studies largely replicated and refined this method.

The second approach to calculating currency conversion factors is "the expenditure approach". This approach uses data on the comparative levels of prices of disaggregated final expenditures. For several reasons[7] it is considered less desirable for sectoral international productivity comparisons than the former approach. Some scholars, for instance Malley *et al.* (2003), have used the aggregate expenditure purchasing parities (PPPs) for total GDP as proxies for manufacturing output price ratios. This is considered an inferior method, as it does not take account of differences in price levels across industries (see Pilat and Prasada Rao 1996, van Ark 1996 and Harrigan 1999). Others have attempted

[6] Rostas (1948) also included a comparison with Germany and, though based on much smaller samples with some other countries including the Netherlands. For an up-date of the Germany versus UK comparison of Rostas, see Broadberry and Fremdling (1990).
[7] See van Ark (1996) and O'Mahony (1996) for an elaborate discussion of the relative merits of different deflators.

to refine these proxies by computing weighted averages of disaggregated expenditure PPPs specific to manufactured categories. For instance, Prais (1981) uses disaggregated PPPs to compare manufacturing output in Germany, UK and the US in the 1970s. Roy (1982) and Roy (1987) did much the same for a wider set of countries in 1975 and 1989. Hooper and Larin (1989) improve this methodology by "peeling off" indirect taxes and trade and transportation margins from the expenditure PPPs for the ten major industrialised countries. All these adjustments represent an improvement over the use of unadjusted expenditure PPPs. However, they also make the expenditure PPPs increasingly sensitive to the procedure used and the quality of data.

As can be observed from Table 5.1, most of these studies base their findings on measures of labour productivity (e.g. Maddison 1952 and Pilat 1996, among others). These partial productivity measures can be misleading indicators of technological differences. This is because they may be positively influenced by the availability of other factors of production[8] (see Hulten 2000). Less extensive, however, is the empirical literature dealing with TFP, which is considered a preferable measure of technological differences –provided that the measures control for market power, scale and cyclical effects. Studies that consider TFP[9] call attention to the fact that the impact of generally lower capital intensity in British industry is to considerably reduce the UK's productivity differential with respect to other industrialised countries when measured by TFP.

[8] The major problem with the use of partial productivity measures is that they also incorporate the effects of factor substitution. As Harris and Trainor (1997: p. 485) point out "*the factor-price ratio between capital and labour services have been falling in UK manufacturing for a good deal of the last quarter century, and thus much of the gain in labour productivity has been achieved through 'capital deepening' rather than 'capital-widening'.*"
[9] O'Mahony and Wagner (1995), O'Mahony (1999), Harrigan (1999) and Malley *et al.* (2003)

**Table 5.1**
**Empirical Studies on British Manufacturing Relative Productivity Performance**

| Author | Benchmark Year(s) | Country Coverage | Industry Coverage | Productivity Concept | Output Concept |
|---|---|---|---|---|---|
| ***Industry of Origin Approach*** | | (1) | | (2) | (3) |
| *Rostas (1948)* | 1935-39 | UK/US | 31 industries | LP | GO |
| *Maddison (1952)* | 1935 | UK/US<br>CD/US | 34 products | LP | GO |
| *Smith et al. (1982)* | 1967/68 | US/UK<br>GY/UK | 87 industries<br>69 industries | LP | VA |
| *van Ark (1990)* | 1984 | NT/UK<br>FR/UK | 16 industries<br>14 industries | LP<br>LP | VA<br>VA |
| *O'Mahony (1992)* | 1987 | GY/UK | 14 industries | LP | VA |
| *van Ark (1992)* | 1987 | UK/US | 16 industries<br>Manufacturing | LP<br>TFP | VA<br>VA |
| *O'Mahony & Wagner (1995)* | 1979-89 | UK/GY | 30 industries | TFP | VA |
| *Pilat (1996)* | 1987 | AU, FR, GY, IT, JP, NT, SW, UK, US. | 36 industries | LP | VA |
| *van-Ark (1996)* | 1970-1994 | FR, GY, JP, UK, US | 6 Industries | LP | VA |
| *Broadberry (1997)* | 1950-1990 | US, UK, GY | 70 Industries | LP<br>TFP | VA<br>VA |
| *O'Mahony (1999)* | 1950-95 | FR, GY, JP, UK, US | 40 Industries | LP<br>TFP | VA<br>VA |
| *O'Mahony & de Boer (2002)* | 1950-99 | FR, GY, UK, US. | 47 Industries | LP<br>TFP | VA<br>VA |
| ***Expenditure Approach*** | | | | | |
| *Prais (1981)* | 1950-80 | US, UK, GY | Manufacturing | LP | VA |
| *Roy (1982)* | 1973, 1980 | US, UK, JP, IT, GY, FR, BG, NT | 11 Industries | LP | VA |
| *Roy (1987)* | 1980 | 44 countries | 7 Industries | LP | VA |
| *Hooper & Larin (1989)* | 1960-89 | 10 countries | Manufacturing | LP | VA |
| *Hooper (1996)* | 1975-90 | US, UK, JP, IT, GY, FR, CD | 7 Industries | LP | VA |
| *Harrigan (1999)* | 1980-89 | US, UK, JP, IT, GY, FI, NW, CD | 8 Industries | TFP | VA |
| *Malley et al. (2003)* | 1971-95 | FR, GY, IT, JP, UK, US. | 13 industries | TFP | GO |

*Notes:* (1) Country Coverage: AU: Australia, BG: Belgium, CD: Canada, FI: Finland, FR: France, GY: Germany, IT: Italy, JP: Japan, NT: Netherlands, NW: Norway, SW: Sweden, UK: United Kingdom, US: United States.
(2) Productivity Concepts: LP: Labour Productivity; TFP: Total Factor Productivity.
(3) Output Concepts: GO: Gross Output; VA: Value Added.
*Sources*: Author

Another critical issue in the literature is the output concept used for sectoral productivity comparisons. While real gross output is the most theoretically appealing concept for output[10] in productivity analysis at the industry level, value added is, however, the concept used in the great majority of empirical productivity studies[11]. The studies of Rostas (1948), Maddison (1952) and, more recently, the studies by Craft and Mills[12] (2001) and Malley *et al.* (2003) are some of the few examples that use gross output for studying Britain's relative productivity performance in an international context[13].

Finally, growth accounting exercises are traditionally used to measure international differences in productivity. As mentioned previously, the assumptions underlying the accounting approach can potentially bias the magnitude of the productivity differential if they are not correct. Few researchers, however, "correct" the standard productivity measures to account at least for the presence of imperfect competition, returns to scale and/ or adjustments in factor utilisation. The exceptions to this are the studies by Harrigan (1999), Crafts and Mills (2001) and Malley *et al.* (2003), which make use of econometric techniques to estimate productivity differentials. Overall these studies conclude that these biases are important and vary substantially over time, but tend not to impact heavily on the estimate of the British productivity gap.

[10] As mentioned in previous chapters, the use of gross output has, among others; analytical advantages in that intermediate inputs can be treated symmetrically with inputs of capital and labour services in measuring productivity.
[11] See, for instance, van Ark (1990, 1992 and 1996).
[12] The study by Crafts and Mills (2001) considers growth rates instead of levels through estimating a cost function.
[13] Other studies that use gross output for international comparisons are Jorgenson, Kuroda and Nishimizu (1987), Jorgenson and Kuroda (1990), and Cameron (2000). These studies refer to productivity comparisons between US and Japan.

The main difference between the present study and that of Harrigan (1999) is that here gross output instead of value added is used to obtain adjusted TFP measures. This research differs from the study of Crafts and Mills (2001) in several aspects. First, the main focus here is on eight manufacturing industries, while Crafts and Mills base their results on the aggregate manufacturing sector. Second, they compare productivity growth rates for Germany and UK based on the dual approach. This study, conversely, provides estimates of growth performance and levels of productivity for the G7 countries based on the primal approach to productivity measurement.

In Chapter 2, the main differences between the present research and the study by Malley *et al.* (2003) were established. To repeat, first, the data source for gross output and intermediate inputs is different. Malley and co-authors obtain their data from the national input-output model databases provided by the Inforum Group at the University of Maryland[14] whereas this study uses OECD STAN data[15]. Second, the proxy for capacity utilisation is also different. Malley's *et al.* study employs data on raw materials and energy inputs to proxy the capacity utilisation parameter while this study uses deviation from the hours trend. Third, the sample period in Malley's *et al.* study is curtailed for some of the countries in the analysis. For instance, in the case of UK the period for which data is available is 1970-1987. This chapter, on the other hand, extends the period of analysis until 1998.

[14] See the technical note by Wilson and Mead (1998), which is available from http://www.gla.ac.uk/economics/TFP. In this technical note the main caveats of the database are discussed. In particular, the main problems come from the fact that Input-Output Tables are not available for every year and country. Therefore, extrapolation methods have to be employed to obtain estimates of the missing series.

[15] The OECD STAN database is mainly based on national accounts data of individual OECD country members. The use of national accounts has the advantage that its components are harmonised across countries on the basis of the International System of National Accounts.

# 5.3 DATA AND CHARACTERISATION OF UK SECTORS RELATIVE TO THE G7-AVERAGE

This section discusses briefly some features of the data and characteristics of the British manufacturing sectors relative to their principal competitors.

## 5.3.1 Data

In order to compute the various measures of productivity the present chapter uses data on eight two-digit manufacturing industries and on the manufacturing sector as an aggregate of the G7 economies over the period 1970-1998. The countries are: Canada, France, Germany, Italy, Japan, UK, and the US. In contrast to previous chapters and due to international comparability issues, the main data set used to construct these series is the OECD STAN-2002 database[16]. This was updated for missing series from other OECD databases (e.g. ISDB, STAN-1998) and O'Mahony and de Boer (2002). Data, however, was not always complete for every country-industry. Particularly, data for Germany is available only up until 1996 and it refers to the former Western Germany. Data limitations in the case of Japan for the capital stock did not allow one to obtain a TFP series for the wood and basic metal industries.

In the present chapter productivity measures are provided both in terms of levels and growth rates. Particularly, international comparisons of productivity levels require three main components, namely comparable information on output, comparable information on

[16] See Appendix A.2 for a detailed analysis of the data and data sources.

factor inputs and currency conversion factors in order to translate output and factor inputs expressed in national currencies into a common currency. The latter is not required when growth rates of productivity are computed. Appendix A.2 provides a more detail analysis about the data and data sources.

Table B.8 in the Statistical Appendix B.5 provides summary statistics of the main variables for the UK manufacturing industries derived from the OECD-STAN dataset. These statistics are presented for different subperiods to compare them with those derived from the UK Census of Production presented in Table B.1. For the period 1970-1997 one observes that the main variables from both data sources grow at very similar rates. Major differences are, however, found with respect to the labour share in gross output, which is considerably higher in the OECD-STAN database.[17]

Nevertheless, these averages seem to hide different growth patterns for some of the variables over the different subperiods when comparing both data sets. In general, real gross output and labour show both similar average growth rates and similar patterns over the different subperiods. However, major differences are found with respect to the growth rates of the physical capital stock and intermediate inputs. Therefore, part of the discrepancies in TFP growth rates for UK manufacturing industries found in this chapter and those obtained in Chapter 3 are due to the different datasets, particularly to data on physical capital stocks and real intermediate inputs.

[17] The impact of a higher share of labour in revenues is to increase the contribution of labour to output growth.

### 5.3.2 Characteristics of British Manufacturing Sectors Relative to the G7-Average

In Table 5.2 some features of the data for the UK manufacturing industries relative to the G7 average are highlighted. In particular, the information in Table 5.2 contains the relative difference on average growth rates for output and input factors between the UK industries and the average of the G7 economies during 1970 to 1998.

**Table 5.2**
**Differences in Average Annual Growth Rates - UK vs. G7-Average (1970-1998)ǂ**

| *Industry* | *Symbol* | *1* | *2* | *3* | *4* | *5* |
|---|---|---|---|---|---|---|
| | | $\Delta\ln\left(\frac{Q^{UK}}{Q^{G7}}\right)$ | $\Delta\ln\left(\frac{K^{UK}}{K^{G7}}\right)$ | $\Delta\ln\left(\frac{L^{UK}}{L^{G7}}\right)$ | $\Delta\ln\left(\frac{M^{UK}}{M^{G7}}\right)$ | 1-3 |
| *Food, Beverages & Tobacco* | FBT | -1.97 | -1.67 | -1.28 | -2.67 | -0.69 |
| *Textile & Leather* | TL | -1.75 | -2.49 | -0.92 | -2.01 | -0.83 |
| *Wood & Wood Products* | WWP | -2.34 | -3.23 | 0.24 | -2.78 | -2.58 |
| *Paper & Paper Products* | PPP | -0.70 | -1.55 | -1.07 | -0.77 | 0.37 |
| *Chemicals, man-made fibres, rubber & plastic products* | CH | 0.05 | -1.59 | -1.10 | 0.22 | 1.15 |
| *Other Non-Metallic Mineral Products* | NMM | -1.27 | 1.32 | -1.93 | -1.13 | 0.66 |
| *Manufacture of Basic Metals & Fabricated Metal Products* | BFM | -2.29 | -2.52 | -2.47 | -2.50 | 0.18 |
| *Machinery, Optical Equipment & Transport Equipment* | MOT | -1.29 | -2.40 | -2.03 | -0.89 | 0.75 |
| **Average** | | -1.45 | -1.77 | -1.32 | -1.57 | -0.13 |
| **Std. Dev.** | | 0.77 | 1.29 | 0.78 | 1.02 | |

*Sources:* Data are from STAN database and O'Mahony and de Boer (2002). See Data Appendix A.2 for further detail.

*Notes:* ǂ Yearly average in percentage (%) terms.

*Q* represents gross output, *K* is the physical capital stock, *L* is labour measured as hours per man, and *M* refers to intermediate inputs.

Over the period considered, real output (measured in terms of real gross output) in the British industries grew at lower rates than the output of the G7 average, except in the chemical industry. Additionally, lower rates than British competitors were also found with respect to the labour input. However, significant differences can be observed in growth dynamics between industry groups. The last column of Table 5.2 shows relative differences in gross output based labour productivity as the difference between column 1 and column 3. The UK achieved higher labour productivity growth rates than the G7 average in the paper, chemical, minerals, basic metals and machinery industries. On the other hand, capital stock was the variable that had relatively lower rates in comparison with the G7 average.

## 5.4 SENSITIVITY OF THE UK PRODUCTIVITY GAP IN MANUFACTURING TO MEASUREMENT ISSUES

Different productivity concepts are often used without sufficient clarity about the specific concept that is being employed and its correct interpretation. Broadly, productivity concepts can be classified as partial factor productivity (relating a measure of real output to a single measure of real input) or multifactor productivity (relating a measure of output to a bundle of inputs). As can be observed from above, international comparisons have been habitually made in terms of labour productivity, which may be a misleading indicator of technological differences as it may be positively influenced by other factors of production, as intermediate inputs or capital stock (see Hulten 2000).

Another distinction of particular relevance at the industry level is between productivity concepts that relate gross output to one or several inputs and those which use the value added concept to capture movements of real output. Empirically, as seen in previous chapters, the choice of concepts matters. As pointed out by Dollar and Wolff (1993) "*the value added concept creates a problem for productivity studies since intermediate inputs are transferred from a "source" of output to an explanation of output growth*". Contrary to value added, gross output allows a symmetrical treatment of intermediate inputs and primary inputs (labour and capital). Despite the theoretical recognition of gross output as the relevant output concept for productivity analysis, value added is still the concept used in the great majority of international productivity comparisons (Dollar and Wolff 1993; van Ark and Pilat 1993), exceptions being the works of Jorgenson (1995) and his co-authors.

The aim of this section is to analyse the sensitiveness of the measure of the productivity gap in British manufacturing to different concepts of productivity. To this end, the section provides estimates of relative labour and total factor productivity for manufacturing based on both value added and gross output, respectively. These estimates are calculated from the data described above on output, factor inputs and currency conversion factors and use the traditional growth accounting framework.

First, the relative labour productivity index is defined according to equation (5.1) and (5.2) depending on the output concept used, value added[18] ($V_t$) or gross output ($Q_t$), respectively.

$$(5.1) \quad LP^{V}_{t_{AB}} = \left(\frac{V_t^{A(\$)}}{L_t^A}\right)\left(\frac{L_t^B}{V_t^{B(\$)}}\right)$$

$$(5.2) \quad LP^{Q}_{t_{AB}} = \left(\frac{Q_t^{A(\$)}}{L_t^A}\right)\left(\frac{L_t^B}{Q_t^{B(\$)}}\right)$$

[18] Two main approaches can be distinguished to convert value added in national currencies into a common currency. These are single deflation and double deflation. In the single deflation procedure, the currency conversion factor based on relative prices of gross output is used to convert value added. In the double deflation approach outputs and intermediate inputs are converted separately.

On the other hand, following much of the literature on productivity comparisons, the relative TFP index presented is that derived by Caves *et al.* (1982), which compares, for any two countries and for a particular industry, how much output the industry of each country can produce given a weighted measure of input factors. An advantage of the multilateral TFP index used is that is superlative (i.e. it is exact[19] for the flexible translog functional form) and it is transitive, so that the choice of the base country is unimportant. The TFP index requires the assumption of constant returns to scale in production and perfect competition through this section. The index is presented, respectively, in terms of value added, equation (5.3), and gross output, equation (5.4).

$$(5.3) \qquad TFP^{V}_{t_{AB}} = \frac{V_t^A}{V_t^B}\left(\frac{\bar{L}}{L_t^A}\right)^{\bar{\sigma}_A}\left(\frac{\bar{K}}{K_t^A}\right)^{1-\bar{\sigma}_A}\left(\frac{L_t^B}{\bar{L}}\right)^{\bar{\sigma}_B}\left(\frac{K_t^B}{\bar{K}}\right)^{1-\bar{\sigma}_B}$$

$$(5.4) \qquad TFP^{Q}_{t_{AB}} = \frac{Q_t^A}{Q_t^B}\left(\frac{\bar{L}}{L_t^A}\right)^{\sigma_A}\left(\frac{\bar{K}}{K_t^A}\right)^{1-\sigma_A-\theta_A}\left(\frac{\bar{M}}{M_t^A}\right)^{\theta_A}\left(\frac{L_t^B}{\bar{L}}\right)^{\sigma_B}\left(\frac{K_t^B}{\bar{K}}\right)^{1-\sigma_B-\theta_B}\left(\frac{M_t^B}{\bar{M}}\right)^{\theta_B}$$

where a bar denotes the geometric mean over all the observations in the sample. The variable $\sigma_c = (s_c + \bar{s})/2$ is the average of the labour share in country $c$ ($s_c$) and the geometric mean labour share ($\bar{s}$). Additionally, the variable $\theta_c = (m_c + \bar{m})/2$ is the average of the intermediate input share in country $c$ ($m_c$) and the geometric mean of the intermediate input share ($\bar{m}$)

[19] An index number is said to be exact for a particular functional form if it equals the Fisher ideal index for that functional form, i.e. it is equal to the geometric mean of the Paasche and Laspeyres index. An index is said to be superlative if it is exact for a flexible functional form such as the translog (Diewert 1976).

**Table 5.3**
**Productivity Estimates for Alternative Output Concepts**
Total Manufacturing, 1995

| Country | LP(VA) | r | LP(GO) | R | TFP(VA) | r | TFP(GO) | r |
|---|---|---|---|---|---|---|---|---|
| **US** | 100 | 1 | 100 | 1 | 100 | 1 | 100 | 1 |
| **JP** | 84.0 | 4 | 82.0 | 5 | 65.4 | 5 | 85.9 | 5 |
| **GY** | 87.3 | 3 | 89.7 | 3 | 83.2 | 2 | 93.6 | 2 |
| **FR** | 95.3 | 2 | 96.6 | 2 | 82.8 | 3 | 93.4 | 3 |
| **IT** | 72.3 | 5 | 61.1 | 7 | 52.8 | 7 | 74.5 | 7 |
| **UK** | 64.1 | 7 | 63.5 | 6 | 67.8 | 4 | 87.0 | 4 |
| **CD** | 65.0 | 6 | 83.1 | 4 | 61.9 | 6 | 84.5 | 6 |
| **Std Dev.** | 14.31 | | 15.14 | | 16.05 | | 8.21 | |

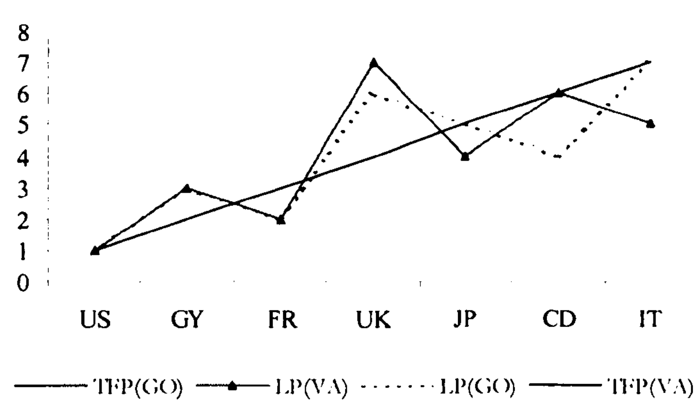
*Note:* r refers to the rank position of each country relative to the total

Notwithstanding the number of factors affecting productivity measurement it is, nonetheless, of importance to assess the sensitivity of the results obtained through adopting different productivity concepts. Table 5.3 reports relative productivity estimates in 1995 for manufacturing in terms of labour and total factor productivity respectively for alternative output concepts. The country of comparison is the US, which is set equal to 100. Additionally, ordinal information contained in the indices is summarized in the form of ranks. Independently of the productivity concept used, the United States clearly stands out as the productivity leader in manufacturing in 1995[20]. The UK's manufacturing relative position, on the other hand, changes considerably depending on the productivity concept used. While UK is ranked the least productive in terms of LP(VA), with a productivity gap of 35% with respect to the US, its relative productivity position is improved in terms of TFP. As already pointed out by other studies (O'Mahony 1999), the relatively low levels of labour productivity in UK manufacturing are partially caused by less capital-intensive production.

[20] To the extent that the countries' business cycles are not synchronized, relative TFP may change due to changes in relative capacity utilisation.

Not only the relative position of some of these countries varies with the productivity concept used, but the size of the productivity gap changes considerably too. In the case of the UK manufacturing sector, for instance, the productivity differential with respect to the leader by 1995 is estimated of the order of 32% in terms of TFP(VA) while is reduced to only 13% in terms of TFP(GO). Overall, one can observe that TFP(GO) reports smaller productivity differentials than the rest of the productivity estimates presented. Nevertheless, despite the apparent closeness in gross output based productivity levels, one must consider that, as noted in Chapter 2, the TFP growth rates based on gross output will be lower than those based on value added. In other words, the speed by which the gap with respect to the leader is reducing or broadening will be lower in terms of gross output based productivity measures. Additionally, gross output based TFP tends to show a less marked variation across countries than the other productivity estimates.

**Figure 5.1**
**Comparisons of Manufacturing Productivity Concepts**
Data relative to 1995



On the other hand, Figure 5.1 considers the question of how alternative productivity concepts affect the ranking of the G7 economies according to their performance in manufacturing. In the horizontal axis of Figure 5.1, countries have been arrayed in order of their TFP(GO) levels. Thus, while the line corresponding to TFP(GO) is continuously increasing by definition, changes in the sign of the slope for other productivity estimate represent a change in the ranking of countries. Some countries, and this is the case for the UK, sharply change their position from one data set to the other. While TFP(GO) and TFP(VA) overlap in Figure 5.1, it is worth mentioning that in terms of magnitudes the distance to the leader is reduced, on average, by half when gross output[21] is used.

**Table 5.4**
**Spearman's Rank Correlation Coefficients**

| | **LP(VA)** | **LP(GO)** | **TFP(VA)** |
|---|---|---|---|
| **LP(GO)** | .8214*<br>[0.023] | | |
| **TFP(VA)** | 0.7143<br>[0.071] | .8214*<br>[0.023] | |
| **TFP(GO)** | 0.7143<br>[0.071] | .8214*<br>[0.023] | 1.00**<br>[0 .000] |

*Notes:* The Table reports Spearman rank correlation coefficients
* Significant at 5% level.
** Significant at 1% level.

[21] Note that, in particular, for the year 1995 currency conversion factors for gross output, intermediate inputs and value added are assumed to be the same, and equal to the UVR used for output. The lack of reliable information on international price data on intermediate goods makes the double deflation approach not practicable here.

One way of formalizing the closeness of these various rankings presented in Table 5.3 is to compute rank correlation. The results in Table 5.4 suggest that the ranking provided by the commonly used LP(VA) is only significantly (rank) correlated with the ranking provided by LP(GO) at the 5% level of significance. Additionally, LP(GO), a measure of labour productivity rarely used, appears to be significantly correlated with the rankings provided by the other different measures at 5% significance level. Not surprising the null hypothesis of independence of the two rankings provided by TFP(VA) and TFP(GO) is rejected.

## 5.5 THE UK'S RELATIVE PRODUCTIVITY PERFORMANCE IN MANUFACTURING INDUSTRIES: A GROWTH ACCOUNTING APPROACH

Aggregate patterns of manufacturing convergence and relative decline may be represented by similar movements at a more disaggregated level or may hide diverging trends. This section considers the empirical evidence on UK's productivity performance at sectoral level relative to some of its major and most influential competitors. The growth accounting framework is used throughout this section as a method of describing and benchmarking productivity performance based on gross output, both in terms of levels and in terms of growth rates.

### 5.5.1. Sectoral TFP Levels

This section aims to examine the patterns that emerge from the sectoral gross output based TFP level data. Moreover it seeks to identify those sectors which in relation to productivity performance in other countries have represented the engines of the British industry over the past three decades. To this end Table 5.5 shows how the level of TFP in terms of gross output has evolved for several manufacturing industries in a comparative context. The figures relate to the level of TFP on three intermediate dates (i.e. 1975, 1985 and 1995).

**Table 5.5**
**Total Factor Productivity Levels, Relative to US level (US=100)**

| | | Industry | | | | | | | | (1) |
|---|---|---|---|---|---|---|---|---|---|---|
| **Country** | **Year** | **FBT** | **TL** | **WWP** | **PPP** | **CH** | **NMM** | **BFM** | **MOT** | **MAN** |
| **CD** | **1995** | 84 | 93 | 92 | 83 | 81 | 86 | 84 | 86 | 85 |
| | **1985** | 87 | 96 | 89 | 86 | 86 | 96 | 90 | 86 | 89 |
| | **1975** | 90 | 98 | 85 | 81 | 87 | 97 | 88 | 79 | 88 |
| **FR** | **1995** | 84 | 96 | 95 | 105 | 94 | 105 | 98 | 85 | 93 |
| | **1985** | 88 | 103 | 96 | 99 | 94 | 114 | 103 | 86 | 97 |
| | **1975** | 94 | 109 | 107 | 92 | 92 | 110 | 93 | 78 | 94 |
| **GY** | **1995** | 96 | 97 | 88 | 82 | 102 | 97 | 109 | 96 | 94 |
| | **1985** | 101 | 103 | 81 | 74 | 105 | 101 | 111 | 107 | 99 |
| | **1975** | 101 | 111 | 88 | 69 | 100 | 95 | 107 | 97 | 96 |
| **IT** | **1995** | 77 | 73 | 69 | 79 | 75 | 70 | 75 | 73 | 74 |
| | **1985** | 79 | 73 | 60 | 71 | 95 | 73 | 76 | 74 | 78 |
| | **1975** | 80 | 79 | 56 | 54 | 101 | 66 | 63 | 69 | 76 |
| **JP** | **1995** | 74 | 77 | n/a | 82 | 87 | n/a | 89 | 95 | 86 |
| | **1985** | 86 | 90 | n/a | 80 | 99 | n/a | 93 | 95 | 90 |
| | **1975** | 97 | 100 | n/a | 78 | 104 | n/a | 86 | 79 | 86 |
| **UK** | **1995** | 85 | 89 | 80 | 95 | 92 | 96 | 87 | 87 | 87 |
| | **1985** | 84 | 94 | 71 | 79 | 91 | 99 | 88 | 80 | 86 |
| | **1975** | 83 | 98 | 80 | 76 | 86 | 96 | 77 | 77 | 82 |

*Note:* See Data Appendix A.2
(1) MAN denotes Total Manufacturing

Although the US stands out as the clear leader in productivity in total manufacturing for the period considered; it does not lead in some of the manufacturing subsectors, rather Germany and France do. In fact, by 1985, Germany and France had even higher productivity levels than the US in the manufacture of textiles (TL), non-metallic mineral products (NMM) and basic metals (BFM); and Germany was also ahead in food (FBT), chemicals (CH) and machinery (MOT). However, the trend by which these countries were catching up with the US stagnated or even began to diverge in the 1990's. Overall, it can be observed that most of the countries were closer to the US in 1985 than in 1995, the exception being the UK, which continued converging to US values, at least until 1995, and closed the gap with Germany and France in many industries. Particularly, by 1995, the productivity gap in the British chemical, mineral and paper industries with respect to the best country performer was of order of 8-10% (in terms of gross output based TFP measures).

From Table 5.5 one can conclude that over the period 1970 to 1998, British industries were, on average, ranked amongst the laggards in terms of TFP levels in the context of the G7 economies, with an average differential over 15%[22]. However, their relative position improved over time. Particularly, by 1995, the best British industry performers in relative terms were the food and paper industries, which were ranked in third position within the G7 economies, while the worst performers were the textile, basic metals and wood industries, which were ranked in fifth position.

### 5.5.2 Sectoral TFP Growth Rates

This section turns now to describe the patterns of TFP growth rates using standard methods of growth accounting. The advantage of computing growth rates of TFP is that it does not require the time series data for different countries to be converted to a common

[22] Italian sectors were, on average, the least productive in relative terms over the period considered.

currency. Table 5.6 shows the average annual growth rates of TFP for the manufacturing industries for the individual countries over the sample period 1970-1990 and 1990-1998, respectively. The first observation is that productivity growth rates do not exceed 2% per annum, thus the speed by which these industries tend to converge (or diverge) towards the productivity leader (in case a pattern of catching-up exists) is relatively very low.

**Table 5.6**
**Annual Average TFP(GO) Growth Rates of Manufacturing Industries**

| Industry | FBT | TL | WWP | PPP | CH | NMM | BFM | MOT | Average | Std. Dev. | MAN |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Country** | *Growth rates of TFP(GO), 1970-90 (in % terms)* | | | | | | | | (1) | (1) | |
| **CD** | 0.12 | 1.15 | 0.56 | 0.01 | 0.55 | 0.61 | 0.16 | 0.89 | 0.51 | 0.40 | 0.51 |
| **FR** | -0.13 | 0.82 | 1.28 | 0.45 | 0.90 | 1.05 | 0.75 | 1.05 | 0.77 | 0.44 | 0.67 |
| **GY** | 0.22 | 0.85 | 0.32 | 0.71 | 0.94 | 0.95 | 0.94 | 0.77 | 0.71 | 0.29 | 0.77 |
| **IT** | 0.23 | 0.87 | 1.45 | 1.41 | -0.71 | 1.88 | 0.81 | 0.28 | 0.78 | 0.83 | 0.58 |
| **JP** | -0.84 | 0.41 | n/a | -0.50 | 0.02 | n/a | 0.18 | 1.25 | 0.08 | 0.73 | 0.44 |
| **UK** | 0.62 | 1.03 | -0.11 | 0.99 | 1.16 | 0.74 | 1.08 | 1.28 | 0.85 | 0.44 | 1.04 |
| **US** | 0.20 | 1.20 | 0.67 | 0.17 | 0.64 | 0.63 | 0.21 | 0.56 | 0.54 | 0.35 | 0.61 |
| **Average** | 0.06 | 0.91 | 0.70 | 0.46 | 0.50 | 0.98 | 0.59 | 0.87 | | | 0.66 |
| **Std. Dev.** | 0.45 | 0.27 | 0.59 | 0.64 | 0.65 | 0.48 | 0.39 | 0.36 | | | 0.20 |
| **Country** | *Growth rates of TFP(GO), 1990-98 (in % terms)* | | | | | | | | | | |
| **CD** | 0.07 | -0.14 | -0.53 | -0.45 | 0.94 | 1.07 | 0.75 | 0.91 | 0.33 | 0.66 | 0.62 |
| **FR** | -0.05 | 0.39 | 0.22 | -0.05 | 0.70 | -0.02 | 0.21 | 1.28 | 0.34 | 0.46 | 0.66 |
| **GY(2)** | -0.94 | -0.89 | -1.40 | -1.15 | 1.36 | -1.26 | -0.26 | 0.13 | -0.55 | 0.93 | 0.34 |
| **IT** | -0.23 | 0.49 | 1.06 | -0.02 | 0.58 | -0.19 | 0.73 | -0.12 | 0.29 | 0.49 | 0.33 |
| **JP** | -0.76 | -1.32 | n/a | -0.83 | -0.21 | n/a | -0.31 | 0.22 | -0.54 | 0.54 | 0.06 |
| **UK** | 0.21 | 0.07 | -0.13 | 0.02 | 0.96 | 0.32 | 0.37 | 0.81 | 0.33 | 0.38 | 0.56 |
| **US** | -0.26 | 0.62 | -1.05 | -0.64 | 0.31 | 0.81 | 0.87 | 1.76 | 0.30 | 0.91 | 0.91 |
| **Average** | -0.28 | -0.11 | -0.31 | -0.45 | 0.66 | 0.12 | 0.34 | 0.71 | | | 0.50 |
| **Std. Dev.** | 0.43 | 0.74 | 0.89 | 0.46 | 0.51 | 0.83 | 0.48 | 0.68 | | | 0.28 |

*Notes:* (1) Average & standard deviation excludes total manufacturing
(2)Germany refers to Western Germany, and growth rates are calculated for the period 1990-96

Second, significant differences in growth dynamics can be observed between industry groups. Overall, the industries that, on average, grew at lower rates over both periods were the food and paper industries. On the other hand, the machinery industry (an ICT producing industry) was amongst the industries with higher productivity growth rates, particularly during the last decade. With respect to differences in growth dynamics across countries, the results show that UK manufacturing industries performed better than the average of the G7 countries over the two first decades, except in the case of the wood industry. Japan, on the other hand, performed poorly, except for the machinery industry, which was the driving force behind productivity growth in the Japanese manufacturing sector.

The second panel of Table 5.6 shows a significant decline in productivity growth rates over the last decade (1990-1998), experienced by most of the industries considered. Despite this slowdown, TFP in the British manufacturing industries continued growing at rates above the G7-average. The figures reveal that the markedly greater slowdown in other countries, particularly in Germany, and Japan, rather than an acceleration in UK productivity growth rates, explains the relative better performance in British industry in recent years. It is worth mentioning that this last period brings two opposite country experiences. On the one hand, the decline of Japan, and on the other, the resurgence of the US. Total manufacturing productivity growth rates accelerated significantly in the US during the last decade, boosted principally by the machinery (MOT) industry.

# 5.6 ECONOMETRIC ESTIMATION OF TFP GROWTH DIFFERENCES

The results presented in the previous section were based on standard neoclassical methods of growth accounting. Although the growth accounting methodology serves as the framework for TFP computation, there is always the concern that the actual conditions of an economy may be different from the neoclassical assumptions. In fact, the results in Chapter 3 showed that the conditions of the UK manufacturing industries differ from those postulated by the growth accounting approach. In particular, evidence was found of the importance of the role of market power and adjustments in capacity utilisation. As pointed out by Crafts and Mills (2001: p.1), "*in standard growth accounting comparisons these problems are either assumed away or, for the purpose of benchmarking, taken to impart equal bias in each case.*" Thus, in order to correct for the potential bias this section describes a methodology for calculating productivity growth rate differences by econometric estimation of country-industry gross output production functions. In developing the analytical framework this section follows the methodology highlighted in previous chapters and initially advocated by Hall (1988) and extended by Harrigan (1999), among others. The difference with respect to previous chapters is that here a three dimensional panel is considered. The dimensions are: industry, country and time, respectively.

## 5.6.1 The Model

Using a homogeneous production function one can represent actual output for a particular industry (*i*) in country (*c*) in year (*t*) in the following way:

$$(5.5) \quad Q_{ict} = A_{ict} F(L^s, K^s, M)_{ict}$$

where $Q_t$ denotes gross output[23], $A_t$ represents the industry's level of technology in a particular country and, $L^s_t$, $K^s_t$, $M_t$ stands for labour and capital services and intermediate inputs, respectively. The function $F$ will be assumed to be homogeneous of degree $(1+\lambda)$ in total inputs. Thus, $\lambda=0$ will correspond to constant returns to scale.

As seen in previous chapters, one can express input services as follows: $K^s_t=Z_tK_t$, and $L^s_t=N_tH_tE_t=L_tE_t$. In this way, capital services can be represented as the function of the capital stock, $K_t$, and its degree of utilisation, $Z_t$. Additionally, labour services can be decomposed in terms of number of employees, $N_t$, the number of hours worked, $H_t$, and the effort of each worker, $E_t$.

Equation (5.5) is logarithmically differentiated with respect to time. Rearranging and expressing the result in discrete time one obtains the following expression:

$$(5.6) \quad \Delta \ln Q_{ict} = \Delta \ln A_{ict} + \frac{\partial F_{ict}}{\partial L_{ict}} \frac{L_{ict}}{F_{ict}} \Delta \ln L_{ict} + \frac{\partial F_{ict}}{\partial K_{ict}} \frac{K_{ict}}{F_{ict}} \Delta \ln K_{ict} + \frac{\partial F_{ict}}{\partial M_{ict}} \frac{M_{ict}}{F_{ict}} \Delta \ln M_{ict} + \delta_{ict} \Delta \ln CU_{ict}$$

where $CU_t=G(Z_t, E_t)$, represents the level of capacity utilisation, which is defined as a function of the intensity with which input factors are used in the production process. This variable is not observed by the econometrician.

[23] For easy of exposition country and industry subscripts are reported only when strictly necessary

A challenge in estimating expression (5.6), as mentioned in other chapters, is to relate the unobservable $\Delta lnCU_t$ to observable variables. Notice that if this effect is present and it is not considered, estimated technological growth would be biased by the cyclical utilisation of inputs. Following the same methodology as in previous chapters, data on deviation from the hours trend for each national industry is used to construct the cyclical utilisation index.

Additionally, market imperfection in the output market is accommodated. The analysis proceeds assuming that producers charge a price, $P_t$, which is a mark up, $\mu_t$, over marginal cost. Nevertheless, they act as price-takers in input markets when choosing their factor inputs so as to maximise profit (or minimise cost). In this regard, producers take the price of all $J$ inputs, $P_t^J$, as given by competitive markets.

The first-order conditions for cost minimisation imply that the value of a factor's marginal product is set equal to a mark-up over the factor's input price. That is:

$$(5.7) \quad \frac{\partial F_{ict}}{\partial J_{ict}} \frac{J_{ict}}{F_{ict}} = \left( \frac{P_{ict}}{MC_{ict}} \right) \frac{P_{ict}^J J_{ict}}{P_{ict} Q_{ict}} = \mu_{ict} s_{ict}^J$$

where: $P_t$ and $P_t^J$ are the output and input prices respectively; $MC_t$ is marginal cost, $\mu_t = P_t/MC_t$ is the mark up ratio and $s_{it}^J$ are the input revenue shares. Equation (5.7) means that the ratio of the input payment to output valued at marginal cost measures the elasticity of output with respect to this input. In other words, the shares, $s_t$, are an exact measure of the elasticity when marginal price and cost are equal ($\mu_t = 1$) but underestimates it when the marginal cost falls short of price.

Combining equation (5.6) and (5.7) and rearranging after applying Euler's theorem[24], one obtains an equation similar to Hall's (1988) econometric model, although allowing for variations in capacity utilisation[25].

$$(5.8)\quad \Delta\ln(Q/K)_{ict} = \beta_{ic} + \mu_{ic}[s^{L}_{ict}\Delta\ln(L/K)_{ict} + s^{M}_{ict}\Delta\ln(M/K)_{ict}] + \lambda_{ic}\Delta\ln(K)_{ict} + \delta_{ic}\Delta\ln CU_{ict} + \upsilon_{ict}$$

The resulting equation (5.8) permits one to simultaneously estimate price-cost margins (μ) alongside returns to scale (1+λ). The parameter λ is a convenient measure of the extent to which the industry production function differs from constant returns to scale.

To simplify notation, let $\Delta\ln FC_{ict} = [s^{L}_{ict}\Delta\ln(L/K)_{ict} + s^{M}_{ict}\Delta\ln(M/K)_{ict}]$ then equation (5.8) becomes[26]:

$$(5.9)\quad \Delta\ln(Q/K)_{ict} = \Delta\ln A_{ict} + \mu_{ic}\Delta\ln FC_{ict} + \lambda_{ic}\Delta\ln K_{ict} + \delta_{ic}\Delta\ln CU_{ict}$$

As mentioned above, productivity differences between industries and across countries tend to be highly persistent over time. In equation (5.9) the term $\Delta lnA_{i,t}$ represents the national

[24] Note that since the output elasticities of factors J sum up to the scale elasticity (Euler's Theorem) one can compute the capital elasticity as the following difference: $\frac{\partial F}{\partial K}\frac{K}{F} = 1 + \lambda - \mu s^{L} - \mu s^{M}$. This relation is very useful as it avoids the problematic computation of the shadow value of capital.

[25] The mark up, the capacity utilisation and scale coefficients are considered as average parameters.

[26] For empirical purpose, discrete growth rates replace continuous ones and the index of input growth (FC) is a Törnqvist one, where the weights are the arithmetic average of the shares in year (t) and (t-1) respectively.

industry's productivity growth rate, which will be represented by an error component structure in the following way:

$$(5.10)\quad \Delta \ln A_{ict} = \beta_{ic} + v_{ict}$$

where the term $\beta_{ic}$, represents the average growth rate of productivity for a particular industry in a particular location. On the other hand, the term $v_{ict}$ is an idiosyncratic disturbance to industry *i* in nation *c* at time *t*, assumed to be an independent identically distributed normal random variable.

Finally, inserting equation (5.10) into equation (5.9) one obtains the equation to be estimated:

$$(5.11)\quad \Delta \ln(Q/K)_{ict} = \beta_{ic} + \mu_{ic}\Delta \ln FC_{ict} + \lambda_{ic}\Delta \ln(K)_{ict} + \delta_i \Delta \ln CU_{ict} + v_{ict}$$

### 5.6.2 Econometric Issues

Before turning to the results, there are a number of issues to discuss relating to equation (5.11). First, based on the results obtained in Chapter 3, it is in principle sensible to assume that there may be important differences between industries in each country. However, it is assumed that the production structure of the same industry is very likely to be similar in a set of industrialized countries. Therefore, parameters estimated are assumed to be the same across industries in different countries[27] except for the estimated TFP growth rates, which, in principle, are allowed to vary across sectors and countries.

Second, this model is based on the assumptions of stationarity of all the variables included in the regression. Failing such an assumption one might be dealing with spurious regressions. Unit root test are performed on the individual series to ensure all variables entering equation (5.11) are stationary. Among the various tests proposed in the literature, the Im, Pesaran and Shin (1997), IPS, panel unit root test is suitable here. The IPS $t$-bar test is based on an average of the individual country industry Dickey Fuller (ADF) tests while allowing for heterogeneous coefficients under the alternative hypothesis and different serial correlation patterns across groups. Under the null hypothesis, all groups exhibit a unit root while under the alternative this is not true for some.

Table B.9 in the Statistical Appendix B.6 presents the results of the panel unit root tests allowing for an intercept. Applying by industry the $t$-bar test to the variables in first differences, test statistics are obtained above the critical value to reject the hypothesis of the presence of a unit root. These tests are based on an ADF regression of 1 lag and a DF regression. Therefore, the rejection of the null hypothesis implies that the data series are stationary and consequently, traditional estimation methods can be used to estimate the relationship between them.

[27] The mark-up, the capacity utilisation and the scale coefficients are assumed to be constant across countries but allowed to vary across industries. This is achieved using slope dummy variables for each industry.

As mentioned in previous chapters, equation (5.11) can be estimated in various ways depending on how one considers the error term and addresses potential correlation between the right hand side variables and the composite error term due to simultaneity and/or omitted variable problems. The appropriate solution to the potential correlation problem is to use an instrumental variable estimator. The difficulty, however, is the lack of appropriate instruments in this kind of regressions (as shown in other studies, see Griliches and Mairesse 1998). In fact, Basu and Fernald (1997) find that using OLS does not greatly affect the result The estimated parameters of (5.11) are thus non-instrumented[28].

Finally, an issue in estimating equation (5.11) is the possibility of serial correlation and heteroskedasticity in the residuals. A preliminary regression of equation (5.11) by OLS (results not reported) suggests the non-existence of serial correlation in the residuals. The Baltagi autocorrelation LM test for panel data predicts a $\chi^2(1)$ statistic for the null of no serial correlation of 0.124 with a probability value of 0.724, and the Durbin-Watson statistic for panel data is 1.90. However, pre-testing the null of a constant variance rejects the assumption of homoskedasticity. Assuming homoskedasticity disturbances when heteroskedasticity is present will still result in consistent estimates of the regression coefficients, but these estimates will not be efficient. In particular, the modified Wald test for groupwise heteroskedasticity ($H_0$: $\sigma^2_{ic} = \sigma^2$, $\forall\ ic$) predicts a $\chi^2(54)$ statistic of 1597.99 with a probability value of 0.000. On the basis of this test the analysis proceeds by estimating the regression allowing for heteroskedasticity in the residuals[29].

[28] They should be interpreted with caution, as they may not be consistent estimates of the structural parameters due to the simultaneity problem.
[29] In addition, the Breuch and Pagan LM test for cross-sectional correlation cannot reject the null of spatial independence of the residuals. The $\chi^2(1431)$ statistic reports a value of 1461.61 with probability value of 0.281.

In the cases of heteroskedastic panels one has two possibilities to proceed: (a) making assumptions about the precise form of heteroskedasticity and estimating the model again with GLS; or (b) using a covariance matrix estimator that is robust against heteroskedasticity of unknown form. The results presented in this chapter are based on the first approach. Nevertheless, point estimates under both approaches were very similar, although standard errors were slightly higher under the second approach, but in no case changing the significance of the coefficients. In particular, the Kmenta/CHTA correction for panel heteroskedasticity is used, i.e. Panel Weighted Least Squares (PWLS). This estimator is a form of GLS although it applies the finite sample normalisation adjustment to the estimated variances. The analysis starts by estimating equation (5.11) via OLS and generating residuals, which are then used to estimate the error variances. The estimated variances are then used to weight every observation in a particular unit "*ic*", and OLS is run again on the weighted data[30].

### 5.6.3 Empirical Results

Table 5.7 reports estimates of three variants of equation (5.11). The estimator in each case is PWLS as discussed above. Model 1 is the unrestricted equation, while Model 2 imposes constant returns to scale. Model 3 imposes restriction across countries on the TFP growth term at the industry level and, finally, Model 4 is the constant returns restricted version of Model 3.

[30] This is roughly analogous to "robust" standard error in a panel context.

**Table 5.7**
**Estimates of Equation (5.11)**

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | |
|---|---|---|---|---|---|---|---|---|
| | **Coeff.** | **Std. Err.** | **Coeff.** | **Std. Err.** | **Coeff.** | **Std. Err.** | **Coeff.** | **Std.** |
| **Mark-up** | | | | | | | | |
| **FBT** | 1.015*** | (0.030) | 1.035*** | (0.030) | 0.998*** | (0.028) | 1.032*** | (0.028) |
| **TL** | 1.136*** | (0.023) | 1.136*** | (0.023) | 1.141*** | (0.022) | 1.141*** | (0.022) |
| **WWP** | 1.081*** | (0.019) | 1.091*** | (0.018) | 1.082*** | (0.018) | 1.086*** | (0.016) |
| **PPP** | 1.118*** | (0.028) | 1.131*** | (0.022) | 1.113*** | (0.027) | 1.135*** | (0.021) |
| **CH** | 1.052*** | (0.019) | 1.057*** | (0.019) | 1.052*** | (0.019) | 1.060*** | (0.019) |
| **NMM** | 1.210*** | (0.040) | 1.209*** | (0.040) | 1.189*** | (0.039) | 1.186*** | (0.038) |
| **BFM** | 1.081*** | (0.024) | 1.088*** | (0.023) | 1.078*** | (0.024) | 1.089*** | (0.023) |
| **MOT** | 1.166*** | (0.021) | 1.173*** | (0.021) | 1.160*** | (0.021) | 1.166*** | (0.021) |
| **Returns to scale** | | | | | | | | |
| **FBT** | -0.132** | (0.054) | | | -0.167*** | (0.038) | | |
| **TL** | 0.006 | (0.048) | | | -0.010 | (0.036) | | |
| **WWP** | -0.030 | (0.024) | | | -0.008 | (0.021) | | |
| **PPP** | -0.029 | (0.036) | | | -0.042 | (0.034) | | |
| **CH** | -0.094* | (0.055) | | | -0.110** | (0.050) | | |
| **NMM** | -0.002 | (0.048) | | | 0.015 | (0.046) | | |
| **BFM** | -0.062 | (0.050) | | | -0.067 | (0.041) | | |
| **MOT** | -0.073* | (0.043) | | | -0.063 | (0.038) | | |
| **Capacity Utilisation** | | | | | | | | |
| **FBT** | -0.819 | (0.519) | -0.683 | (0.525) | -0.824 | (0.514) | -0.639 | (0.527) |
| **TL** | -1.750*** | (0.429) | -1.751*** | (0.424) | -1.785*** | (0.422) | -1.771*** | (0.422) |
| **WWP** | -0.431 | (0.653) | -0.476 | (0.648) | -0.410 | (0.645) | -0.449 | (0.642) |
| **PPP** | 1.571** | (0.689) | 1.501** | (0.677) | 1.598** | (0.687) | 1.463** | (0.676) |
| **CH** | 2.010*** | (0.734) | 2.195*** | (0.739) | 2.051*** | (0.736) | 2.259*** | (0.744) |
| **NMM** | -0.557 | (0.925) | -0.518 | (0.914) | -0.231 | (0.907) | -0.215 | (0.906) |
| **BFM** | 1.172** | (0.543) | 1.248** | (0.543) | 1.188** | (0.540) | 1.256** | (0.544) |
| **MOT** | -0.033 | (0.578) | 0.080 | (0.569) | 0.075 | (0.577) | 0.181 | (0.576) |
| **Industry Productivity Growth Rates in % (averages)** | (1) | | (1) | | | | | |
| **FBT** | 0.361** | (0.002) | 0.019 | (0.001) | 0.509*** | (0.001) | 0.160** | (0.001) |
| **TL** | 0.826*** | (0.001) | 0.830*** | (0.001) | 0.899*** | (0.001) | 0.897*** | (0.001) |
| **WWP** | 0.546*** | (0.002) | 0.462*** | (0.001) | 0.423*** | (0.001) | 0.406*** | (0.001) |
| **PPP** | 0.575*** | (0.002) | 0.490*** | (0.001) | 0.521*** | (0.002) | 0.402*** | (0.001) |
| **CH** | 0.805*** | (0.002) | 0.569*** | (0.001) | 1.005*** | (0.002) | 0.751*** | (0.001) |
| **NMM** | 1.042*** | (0.002) | 1.039*** | (0.002) | 0.957*** | (0.002) | 0.976*** | (0.001) |
| **BFM** | 0.772*** | (0.001) | 0.671*** | (0.001) | 0.755*** | (0.001) | 0.668*** | (0.001) |
| **MOT** | 1.244*** | (0.002) | 0.975*** | (0.001) | 1.240*** | (0.002) | 1.016*** | (0.001) |
| Adj $R^2$ | 0.947 | | 0.947 | | 0.947 | | 0.946 | |
| N. Obs | 1488 | | 1488 | | 1488 | | 1488 | |
| RMSE | 0.013 | | 0.013 | | 0.013 | | 0.013 | |
| LL | 4356.4 | | 4347.2 | | 4330.3 | | 4311.1 | |
| $H_o$: $\beta_{ic}=$ | 7.06 | [0.000] | 8.48 | [0.000] | 4.15 | [0.000](2) | 11.31 | [0.000](2) |

*Notes*: Standard errors are in parenthesis and probabilities in brackets. Number of observations is 28 time periods (except for Germany), by 8 industries (except for Japan), by 7 countries.
(1) Averages within industries across countries from point estimates. (2) $H_o$: $\beta_i = 0$.
* significant at 10% level, ** at 5% level and *** at 1% level.

The unrestricted model allows for two sources of industry productivity growth differences: differences in the scale of production within industry and industry-country differences in productivity growth rates. The imposition of constant returns to scale ($\lambda$ = 0) in Model 2 means that any differences in productivity growth will be attributed to industry-country specific growth rates. In fact, the test of the null hypothesis of $\lambda_i = 0$ for all industries cannot be rejected at the 5% level of significance on the basis of an F-test, F(8, 1410)=1.96. On the other hand, the assumption of equal TFP growth rates for industry $i$ across countries ($H_0$: $\beta_{ic} = \beta_i$) cannot be rejected (Model 1 to Model 3, and Model 2 to Model 4). In other words, the results suggest that average differences in productivity growth rates within an industry across the G7 economies are not statistically significant.

As can be verified in Table 5.7, the coefficient estimates confirm the presence of positive and statistically significant mark-ups, except for the FBT industries, where the 95% confidence interval of the estimate of $\mu$ includes 1 in any of the models analysed. In Chapter 3, it was also found that the assumption of perfect competition could not be rejected in the context of the British food industry. Industries with higher mark-ups are the non-metallic mineral industry followed by the machinery industry. In prior studies, estimates for mark-ups obtained within the primal framework vary in size, but all of them point toward the existence of market power (Hall 1988, 1990). The crucial factor when estimating mark-ups appears to be the definition of output.[31] Regardless of the output concept used in prior studies, mark-up estimates presented in this research are in general both more homogeneous across industries and lower, mostly ranging between 1.1 and being well below 1.3 for every industry.

[31] In Chapter 3 it was shown that the use of value added data biases results upwards. In fact, estimates obtained with gross output data are generally lower than those obtained with value added data.

In Chapter 2, it was shown that high mark-ups are associated with increasing returns to scale. In fact, mark-ups and returns to scale are economically related such $\mu(TR/TC)=(1+\lambda)$[32]. However, in this case the results suggest that deviation from constant returns to scale is individually non significant for all the considered industries, except for the FBT industry which appears to show significant decreasing returns to scale, although its mark-up is not significantly different from 1. As far as economies of scale is concerned, the finding of constant returns is nothing new (Burnside 1996; Burnside *et al.* 1995; Haskel *et al.* 1995). Results obtained within the primal approach are mixed. Some estimates imply high increasing returns to scale (Hall 1990), while others find only moderate economies of scale (Bartelsman *et al.* 1994), constant (Burnside 1996; Burnside *et al.* 1995) or even decreasing returns (Basu and Fernald 1997).

The capacity utilisation term, on the other hand, appears significant for 4 of the industries considered. Similar to what we found in Chapter 3, correcting measures of input for cyclical changes in capacity utilisation has a significant impact on estimates of the mark-ups and returns to scale. When capacity utilisation is included in the regression the significance and sizes of the mark-up diminishes. The same applies to the estimates of the returns to scale.

## 5.7 DISCUSSION

The interest in this section is multiple. Based on the results derived in previous sections, the first objective is to examine the direction and size of the bias in the productivity residual by

[32] TR and TC stand for total revenues and total costs respectively.

using the traditional growth accounting approach. The second goal is to study whether adjusting for bias materially affects international comparisons of TFP over time. Finally, the results reported here are compared with those from other recent studies.

### 5.7.1 Bias in Traditional TFP Estimates

Table 5.8 presents the implied average gross output based TFP rates using both the parametric and non-parametric techniques for different industry groups and countries over the period 1970-1998. Particularly, the parametric estimates are those based on the results reported in the last column of Table 5.7, corresponding to the estimation of Model 4. On the other hand, the non-parametric estimates are those based on the accounting approach outlined in section 5.5.

Are traditional growth accounting measures of TFP growth seriously biased? The results presented in Table 5.8 suggest that the growth accounting TFP rates estimates, which are not corrected for biases resulting from imperfect competition and adjustments in capacity utilisation are a poor guide to the "adjusted" TFP. The latter are obtained when those biases have been removed and they may be thought of as a better measure of the contribution of innovation to productivity growth. Overall, for the period 1970 to 1998, the sign of the bias is positive, in the sense that growth accounting estimates underestimate true average TFP growth rates, the only exception being for the wood industry. The size of the bias changes across industries and countries. For the case of UK the average estimated bias is equal to 0.17, which is very similar to the averaged estimated 0.11 found in Chapter 3 (see Table 3.8). The major differences between both approaches are found for Japan and Germany. Additionally, the industry for which the results differ most is the textile industry.

**Table 5.8**
**Parametric vs. Non-Parametric Gross Output-Based TFP Growth Estimates**
1970-1998 (in % terms)

| | FBT | TL | WWP | PPP | CH | NMM | BFM | MOT | Average | Std. Dev. | MAN |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***Growth rates of TFP(GO) - Growth Accounting*** | | | | | | | | (1) | (1) | |
| **CD** | 0.11 | 0.78 | 0.25 | -0.12 | 0.66 | 0.74 | 0.33 | 0.90 | 0.46 | 0.37 | 0.54 |
| **FR** | -0.11 | 0.70 | 0.98 | 0.31 | 0.84 | 0.75 | 0.60 | 1.12 | 0.65 | 0.39 | 0.67 |
| **GY** | -0.05 | 0.45 | -0.08 | 0.28 | 1.03 | 0.44 | 0.67 | 0.63 | 0.42 | 0.37 | 0.67 |
| **IT** | 0.10 | 0.76 | 1.34 | 1.00 | -0.34 | 1.29 | 0.79 | 0.17 | 0.64 | 0.60 | 0.51 |
| **JP** | -0.82 | -0.09 | n/a | -0.60 | -0.05 | n/a | 0.04 | 0.95 | -0.09 | 0.61 | 0.33 |
| **UK** | 0.50 | 0.76 | -0.12 | 0.72 | 1.10 | 0.62 | 0.87 | 1.15 | 0.70 | 0.40 | 0.90 |
| **US** | 0.07 | 1.04 | 0.18 | -0.06 | 0.55 | 0.68 | 0.40 | 0.90 | 0.47 | 0.40 | 0.70 |
| **Average** | -0.03 | 0.63 | 0.43 | 0.22 | 0.54 | 0.75 | 0.53 | 0.83 | 0.50 | 0.56 | 0.62 |
| **UK-Avg.** | 0.53 | 0.13 | -0.54 | 0.50 | 0.56 | -0.13 | 0.35 | 0.32 | 0.20 | | 0.28 |
| **Std. Dev.** | 0.40 | 0.36 | 0.60 | 0.54 | 0.55 | 0.29 | 0.29 | 0.34 | | | |
| | ***Growth rates of TFP(GO) - Parametric results*** | | | | | | | | | | |
| **CD** | 0.26 | 0.95 | 0.26 | 0.02 | 0.85 | 0.53 | 0.39 | 0.91 | 0.52 | 0.35 | 0.58 |
| **FR** | 0.09 | 1.20 | 0.77 | 0.14 | 1.06 | 1.00 | 0.69 | 1.39 | 0.79 | 0.47 | 0.79 |
| **GY(2)** | 0.18 | 0.89 | 0.25 | 0.57 | 1.08 | 0.90 | 0.97 | 0.94 | 0.72 | 0.34 | 0.78 |
| **IT** | 0.26 | 0.84 | 1.14 | 1.25 | -0.08 | 1.50 | 0.82 | 0.27 | 0.75 | 0.55 | 0.55 |
| **JP** | -0.58 | 0.40 | n/a | 0.07 | 0.28 | n/a | 0.42 | 1.30 | 0.32 | 0.61 | 0.67 |
| **UK** | 0.72 | 0.87 | -0.10 | 0.79 | 1.29 | 1.23 | 0.97 | 1.19 | 0.87 | 0.44 | 1.00 |
| **US** | 0.18 | 1.13 | 0.11 | -0.03 | 0.78 | 0.69 | 0.41 | 1.10 | 0.55 | 0.45 | 0.76 |
| **Average** | 0.16 | 0.90 | 0.41 | 0.40 | 0.75 | 0.98 | 0.67 | 1.02 | 0.66 | 0.72 | 0.73 |
| **UK-Avg.** | 0.56 | -0.03 | -0.50 | 0.39 | 0.54 | 0.25 | 0.31 | 0.18 | 0.21 | | 0.27 |
| **Std. Dev.** | 0.38 | 0.26 | 0.46 | 0.48 | 0.49 | 0.35 | 0.26 | 0.37 | | | |
| | **Bias: Parametric –Growth Accounting** | | | | | | | | | | |
| **CD** | 0.16 | 0.16 | 0.01 | 0.14 | 0.19 | -0.21 | 0.06 | 0.02 | 0.06 | | 0.03 |
| **FR** | 0.20 | 0.50 | -0.20 | -0.16 | 0.22 | 0.25 | 0.09 | 0.28 | 0.15 | | 0.12 |
| **GY(2)** | 0.23 | 0.44 | 0.33 | 0.29 | 0.04 | 0.47 | 0.31 | 0.31 | 0.30 | | 0.11 |
| **IT** | 0.16 | 0.08 | -0.20 | 0.25 | 0.26 | 0.21 | 0.03 | 0.10 | 0.11 | | 0.05 |
| **JP** | 0.24 | 0.48 | n/a | 0.67 | 0.33 | n/a | 0.38 | 0.35 | 0.41 | | 0.34 |
| **UK** | 0.21 | 0.11 | 0.02 | 0.07 | 0.18 | 0.61 | 0.10 | 0.05 | 0.17 | | 0.10 |
| **US** | 0.11 | 0.10 | -0.07 | 0.03 | 0.24 | 0.01 | 0.01 | 0.20 | 0.08 | | 0.07 |
| **Average** | 0.19 | 0.27 | -0.02 | 0.18 | 0.21 | 0.22 | 0.14 | 0.19 | | | |

*Source:* Results from Table 5.6 and Table 5.7.
*Note:* (1) Average & standard deviation excludes total manufacturing
(2) Germany refers to Western Germany, and growth rates are calculated for the period 1990-96

Although the magnitudes of the results presented in the first two panels of Table 5.8 are rather different, similar patterns across industries over the sample period emerge. In particular, the industry with lowest productivity growth rates is the food industry, while the machinery industry is the one experiencing fastest growth rates under both approaches.

Does adjusting for bias affect comparisons between British and the G7 average TFP growth rates? The results presented in Table 5.8 suggest that with respect to the performance of the British industries, both approaches conclude that overall UK manufacturing industries experienced higher rates than the G7 average, with very few exceptions. Major differences between both approaches are found for the mineral industry, followed by the textile and machinery industry (industries with high estimated mark-ups).

Does adjusting for bias affect the size and direction of the British productivity gap with respect to the TFP performance of the G7 countries? To answer this question Table 5.9 presents the estimated bias of the UK relative productivity gap. The bias is obtained as the difference between the gross output based TFP levels in 1995 obtained from adjusting for imperfect competition and capacity utilisation and the TFP levels from the accounting approach outlined in section 5.5.

For Total Manufacturing, the estimated bias is negative for the US and Canada and positive otherwise. A negative bias means that relative TFP levels estimates from the growth accounting approach are larger than the "adjusted TFP" levels. At sectoral level, the sign of the bias is positive and its size of the order of 5% in both directions. Larger biases are found for the mineral, paper and the textile industries. Across countries major differences are estimated with respect to Italy (with an average bias of 8%), Germany, and Japan (with an average bias of 5%).

**Table 5.9**
**Bias of UK Relative TFP Gap**

| | US | JP | GY | FR | IT | CD | Average |
|---|---|---|---|---|---|---|---|
| **MAN** | -1.5 | 5.7 | 0.2 | 1.6 | 7.2 | -0.4 | 2.1 |
| **FBT** | -1.6 | 1.2 | -1.4 | 0.7 | 1.5 | -1.2 | -0.1 |
| **TL** | -6.5 | 2.6 | -9.4 | -0.1 | 6.5 | -9.5 | -2.8 |
| **WWP** | -1.5 | n/a | -1.8 | 2.3 | 7.1 | -1.9 | 0.8 |
| **PPP** | 0.0 | 10.3 | 8.5 | -2.6 | 7.6 | 8.3 | 5.3 |
| **CH** | 0.1 | 5.4 | -0.9 | -0.1 | 5.9 | 1.6 | 2.0 |
| **NMM** | 4.4 | n/a | 10.1 | 8.6 | 17.5 | 9.5 | 10.0 |
| **BFM** | 1.0 | 9.6 | -3.0 | 2.9 | 8.3 | 1.6 | 3.4 |
| **MOT** | -1.3 | 2.5 | -11.7 | 4.4 | 8.7 | -2.5 | 0.0 |
| **Average** | -0.7 | 5.3 | -1.2 | 2.0 | 7.9 | 0.7 | |

*Note*: The bias is calculated as the difference between the TFP level in 1995 obtained from the results presented in Table 5.7 and the TFP level from the growth accounting approach in Table 5.5.

Overall, these estimates imply that it is important to be concerned about biases in traditional estimates of TFP, particularly at the sectoral level. Although for total manufacturing the average bias of the productivity gap is estimated of the order of 2.5 percentage points, there are some industries for which this bias is even above 10 percentage points.

### 5.7.2. Comparison with Previous Studies

As mentioned in the introduction to this chapter, there has been much recent interest in comparing the UK's performance in terms of productivity levels with that of other industrialized economies. This is reflected in the studies by O'Mahony (1999), O'Mahony and de Boer (2002) and Malley *et al.* (2003). The first two studies are based on growth accounting and use value added as a measure of output. The latter uses gross output and adjust for the presence of imperfect competition and capacity utilisation. But how do these other estimates of relative UK TFP for manufacturing compare with those reported here? Table 5.10 compares relative TFP levels derived from previous sections with those reported by others. All data refer to 1995, with the exception of the data reported by Malley *et al.* (2003), which refers to 1994. For ease of comparison, the indices of Table 5.10 have been rebased so the UK's TFP level is set equal to 100.

**Table 5.10**
**UK Manufacturing Productivity Gap: Comparisons with Previous Studies**

| Studies | TFP Measure | US | JP | GY | FR | IT | UK | CD |
|---|---|---|---|---|---|---|---|---|
| *Author* | Adjusted GO-TFP | 113 | 104 | 108 | 109 | 93 | 100 | 97 |
| *Author* | Solow(GO) | 115 | 99 | 108 | 107 | 86 | 100 | 97 |
| *Author* | Solow(VA) | 147 | 96 | 123 | 122 | 78 | 100 | 91 |
| *Malley et al. (2003)* | Adjusted GO-TFP | 136 | | 112 | 113 | | 100 | |
| *O'Mahony(1999)* | Solow(VA) | 142 | 116 | 108 | 103 | | 100 | |
| *O'Mahony(2002)* | Solow(VA) | 143 | | 121 | 110 | | 100 | |

*Notes*: Malley *et al.* (2003) data refers to 1994

Although our approach is closest to the Malley *et al.* (2003) study our results differ to some degree. Major differences with Malley's results refer to the estimated gap with respect to the US. In fact, their result is called into question. Focusing on the differential with the US: Malley's productivity gap of 36% implies that, at average gross output based TFP growth rates of 1% and 0.76% for UK and the US respectively, it will take 128 years for the UK to catch-up with the US levels in manufacturing. On the other hand, the reported O'Mahony's gap of 42% implies that at value added based TFP growth rates[33] of 1.85% and 1.21% for UK and US respectively, it will take just 55 years to converge to the US levels. Therefore, the differences between both studies are quite considerable, although the reported gap

[33] These growth rates are the ones reported in O'Mahony (1999) for value added based TFP for the period 1973-1996.

looks similar. The results reported here are more in line with the estimates by O'Mahony (1999), in the sense that they imply a 51-year span to attain the US levels in manufacturing (given constant rates of growth).

The preferred estimates here (those adjusted for market power and variations in capacity utilisation) confirm the finding of these previous studies that UK manufacturing faces a significant productivity lag in terms of TFP. Additionally, in agreement with other studies, the analysis concludes that adjusting for biases does not impact heavily on the British productivity gap for the manufacturing sector in aggregate. In particular, the results obtained in the present study suggest that the gap in terms of gross output based TFP with respect to the US is of the order of 13%, with respect to Germany and France of 8-9%, and of 4% with respect to Japan.

## 5.8 CONCLUSIONS

The purpose of this chapter was to revisit the well-documented productivity gap in manufacturing between the UK and its most direct and influential competitors. To this end, new estimates of growth performance and levels of productivity were provided for the aggregate manufacturing sector and for a set of eight manufacturing industries over the period 1970-1998. Particularly, the stress of the present study was placed upon the sensitivity of the size and direction of the productivity differential to measurement issues and restrictive assumptions.

First of all, the results showed that the British productivity gap in total manufacturing is particularly sensitive to different productivity concepts. Not only the relative position of the UK manufacturing sector with respect to the performance of other countries varies with the productivity concept used, but also the size of the reported productivity differential changes considerably too.

Growth accounting productivity estimates were presented together with parametric estimates. The problem with growth accounting estimates is that they may not be an accurate measure of the true TFP since they ignore the role of market power, scale economies and adjustments in capacity utilisation. In fact, the econometric results presented in this chapter suggest that some of the assumptions underlying the growth accounting approach are not sustainable. Particularly, the results confirm the presence of positive and statistically significant mark-ups for all industries considered, except for the food industry, and the significance of the capacity utilisation term. However, the assumption of constant returns to scale could not be rejected.

Taking into account these results, "adjusted" TFP estimates were presented, which are obtained when those biases have been removed and which might be thought of as more accurate measures of the underlying technological change. These estimates permitted the study of the bias and its impact on the UK's productivity differential. The results presented in this chapter showed that the magnitude and direction of the bias varies across industries as well as across countries. Nevertheless, the sign of the bias was on average positive, in the sense that traditional growth accounting productivity estimates are significantly downward biased for the period 1970-98. This result confirmed the findings obtained in Chapter 3 for the UK economy.

Overall, these results suggested that is important to be concerned about biases in traditional estimates of TFP but, mainly, at sectoral level. Although for total manufacturing the average bias of the productivity gap was found of the order of 2.5 percentage points, there are some industries for which this bias was even greater to 10 percentage points. This implies that adjusting for biases does not impact greatly on the British productivity gap at the aggregate manufacturing level but it does at a more disaggregated level.

Despite the concern about biases, the results showed that, although there are British success stories (such as chemicals, minerals and paper and printing industries), the productivity gap still remains significant. Moreover, although the productivity gap has been reduced over time (until 1995), the productivity of the UK still trails behind that in the US, France and Germany and to a lesser extent Japan, almost regardless of the sector.

Finally and supporting the results encountered in Chapter 3 what emerges as a conclusion is that productivity growth estimates are highly sensitive. However, despite the sensitivity of productivity measures, one must be cautious about the use of the standard accounting approach to benchmark productivity performance and study differences in productivity across countries. Such criticism must be taken seriously in the interpretation and use of productivity measures as representations of the theoretical concept of TFP.

# CHAPTER 6 –
# SUMMARY AND CONCLUSIONS

## 6.1 SUMMARY OF FINDINGS

The main objectives of this study were threefold. First, this thesis was concerned with the sensitivity of UK manufacturing TFP growth estimates to different methodological and measurement issues. Particular stress was placed upon alternative output concepts –gross output vs. value added- and estimation methods –growth accounting vs. econometrics. The second purpose was to examine how taking into account these issues might influence estimates of the relationship between TFP and R&D efforts. Finally, the third main goal was to address how these measurement and methodological concerns might affect the measurement of the size and direction of the UK productivity gap. Each of these objectives was addressed respectively in a separate empirical chapter.

Before addressing each of these objectives, Chapter 2 provided the framework that leads to the questions addressed in the thesis. This chapter considered some of the issues related to the conceptualisation, interpretation and measurement of TFP growth. A review of the growth accounting framework was presented in addition to insights into methodological extensions that relax its underlying assumptions. This chapter also reviewed recent empirical studies on UK TFP growth measurement. The literature review revealed that TFP growth estimates are very sensitive to different assumptions. Significant evidence was found that some of the assumptions underlying the growth accounting approach to measuring TFP growth in UK manufacturing industries could not be sustained. These are, specifically, the assumptions of perfect competition and instantaneous input adjustment. The evidence with respect to returns to scale was, however, inconclusive. Additionally, productivity measures were found to be highly sensitive to the output concept employed. This chapter concluded that there is a need for a comprehensive and integrated framework that takes into account these measurement issues in three areas of productivity analysis: the measurement of TFP growth rates, the analysis of TFP and its determinants and finally, international productivity comparisons.

The purpose of Chapter 3 was to examine the sensitivity of TFP growth estimates to different methodological and measurement issues in the context of UK manufacturing industries over the period 1970-1997. Emphasis was placed upon both alternative concepts of real output and estimation techniques. First, it was argued that gross output was the superior concept of real output to employ for the measurement of productivity growth, while the common practice of using single deflated value added accounted for considerable measurement bias. Second, the econometric approach to productivity measurement showed that the assumption of perfect competition couldn't be sustained for all manufacturing industries and that adjustment in capacity utilisation was statistically significant. Significant mark-ups were found in the non-metallic mineral industry, the paper industry, the wood industry and the basic metal industry.

The empirical results suggested that the traditional growth accounting approach leads to a biased estimate of UK manufacturing TFP growth. In line with previous studies, the productivity residual was found to be significantly downward biased for the period 1973-1979. On the other hand, for the periods 1980-1989 and 1990-1997 the growth accounting approach leads, in general, to significant upward biases in the estimates of UK manufacturing TFP growth. These parametric results suggest that the recovery in TFP growth rates experienced by the British manufacturing industries in the 1980s was not as spectacular as implied by the growth accounting estimates.

Building on the results obtained in Chapter 3, the purpose of Chapter 4 was to study the impact of productive knowledge upon industry's TFP. The emphasis in this analysis was placed upon the long-run relationship between innovative efforts and productivity and the nature of the R&D spillovers accruing to a panel of eight UK manufacturing industries over the period 1970 to 1997. In contrast to other empirical studies in the literature, the analysis in Chapter 4 focused on gross output and allowed for imperfect competition and temporary disequilibria. In particular, an ECM was adopted for estimating the long-run parameters in a pooled framework.

The results of the empirical analysis in Chapter 4 supported the findings found in related studies using different methodologies. The results showed the existence of a positive and significant link between industry's R&D activities and productivity in the long run. In addition, robust evidence was found of positive and significant domestic R&D spillovers. Interestingly, the results also indicated that international spillovers do not contribute significantly to TFP in UK manufacturing sectors. The findings therefore suggest that controlling for measurement bias, although important, does not affect markedly the estimated relationship between TFP and R&D activities.

The purpose of Chapter 5 was to provide new evidence on the productivity gap in manufacturing between the UK and other industrialized countries. Particularly, the stress was placed upon the sensitivity of the size and direction of the productivity differential to measurement issues and restrictive assumptions. To this end, new estimates of growth performance and levels of productivity were provided for the aggregate manufacturing sector and for the set of eight manufacturing industries over the period 1970-1998. Additionally, the study extended existing research by providing new growth accounting productivity estimates together with parametric estimates.

The results obtained in Chapter 5 support the proposition that the British productivity gap in total manufacturing is particularly sensitive to different productivity concepts. Not only the relative position of the UK manufacturing sector with respect to the performance of other countries varies with the productivity and output concepts used, but also the size of the reported productivity differential changes considerably too. Additionally, the results indicated that the bias in traditional TFP estimates does not impact greatly on the British productivity gap at the aggregate manufacturing level but does so at a more disaggregated level. Finally, despite concerns about biases, the results obtained showed that the productivity of UK manufacturing still trails behind that achieved in the US, France, Germany and to a less extent Japan, almost regardless of the sector.

## 6.2 SUGGESTIONS FOR FUTURE RESEARCH

A number of ways could be recommended to improve and extend the empirical analysis developed in previous chapters. First, while the focus of this thesis has been the manufacturing sector, the analysis of service industries would be of particular importance for future research. The service sector now represents the largest part of the UK economy in terms of contribution to GDP and employment[1]. However, work looking at the productivity of the service sector is sparse relative to that undertaken on the production industries (the exceptions being the works by O'Mahony *et al.* 1998 and O'Mahony 1999). This is partly due to data availability and in part due to measurement issues.

With the data available, traditional productivity measurement methods have proved inadequate for analysing service industries. The primary initial difficulty in measuring productivity in service sectors involves the appropriate definition and measurement of output and prices (Griliches 1992). Recent approaches to productivity measurement at the firm level could serve as a starting point to develop new methodologies to measure productivity in contexts where price deflators are not available. The basic idea would therefore be to augment the production function with the demand side and, thereby endogenise prices (see the works by Griliches and Klette 1996 and Ornaghi 2003).

Related to the problem of measuring real output in service industries there is the further problem of how to capture quality improvements in both manufacturing goods and services. Hedonic methods have been considered as the best way to address this problem although their use is still uncommon. However, it is insufficient to limit quality adjustment to measures of output, as measures of inputs need equal consideration. While this thesis did not attempt to treat the issue of quality adjustment in productivity measurement, further assessments to build quality changes directly into the model are likely to provide important insights into the analysis.

[1] See Julius and Butler (1998), and Julius (1999) for a series of stylised facts about the UK service sector between 1970-97.

In addition, more attention needs to be devoted to the understanding of the extent to which R&D spillovers take place and the channels of their transmission. First, questions about composition issues may be raised, since different types of R&D may have varying potential for generating spillovers. This is the case when comparing public and private R&D, or basic and applied R&D. Second, it would be interesting to examine the role of different channels of transmission of R&D spillovers (e.g. R&D spillovers embodied in capital goods vs. non-capital goods)[2]. Finally, the analysis of Chapter 4 could be extended by considering the service industry. This industry has the reputation of doing little research but benefiting extensively from outside knowledge –i.e., the knowledge generated by manufacturing industries.

## 6.3 CONCLUDING REMARKS

If we recognise that productivity growth is the key to sustained economic growth, the measurement and analysis of productivity represents an area of great importance to economists and policy makers alike. The accurate measurement of productivity growth plays an important role in providing the information economists need to improve policy recommendations and for policy makers to make well-founded decisions. However, despite its importance, the interpretation and measurement of productivity is still a matter of ongoing debate.

[2] Capital goods are considered to have a higher content of technological improvement than non-capital goods. Hence, they are major potential carriers of R&D spillovers embodied in trade flows (Xu and Wang 1999).

This thesis has considered some of the issues related to the conceptualisation, measurement and interpretation of TFP and its determinants in the context of UK manufacturing industries during the last three decades. The research performed through this thesis has been empirical and comparative in its nature and concern. Two main features have distinguished the analysis from the existing body of empirical literature in the context of the measurement and analysis of UK productivity and its determinants. First, greater emphasis was placed on some of the main measurement issues that are traditionally ignored in conventional TFP estimates based on growth accounting. Particular attention has been paid to the use of gross output and the allowance for the role of market power and adjustments in capacity utilisation in measuring TFP. Second, several dimensions of the literature, which are usually studied independently have been analysed within a given integrated empirical framework.

What has emerged as a conclusion is that productivity estimates are highly sensitive and that the degree of sensitivity is greater at higher levels of disaggregation. Given this sensitivity of productivity measures, one must be cautious about the use of the standard growth accounting approach to benchmark productivity performance, to analyse the relationship between productivity and its determinants and, finally, to study differences in productivity across countries and industries.

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# APPENDICES

## A DATA APPENDIX

### A.1 Data Definitions and Data Sources for Chapter 3 and Chapter 4

**Gross Output**: An annual series of nominal gross output is published in the Census of Production from 1970. It is defined as sales and work done plus the increase during the year of stock of work in progress and goods on hand for sale. Up to and including 1979, the Census is classified in accordance with the 1968 SIC; in subsequent years, it is classified in accordance with the 1980 SIC until 1993, when it is published according to a 1992 SIC. Data prior to 1979 and 1993 were reclassified in terms of 1992 SIC. Additionally, following the Oulton and O'Mahony (1994) methodology, gross output figures were adjusted for stock appreciation.

The producer price indices for home sales classified by 1992 SIC, published in various issues of The Annual Abstract of Statistics, were used to deflate nominal gross output. Their use as deflators is not devoid of problems due to the fact that producer price indices reflect only home sales. A "domestic price bias" may arise if domestic price indices diverge from unobserved export prices (Cameron 2003), and its importance will vary according to the industry's share of exports in total sales. Although data were not adjusted for this possible bias, Stoneman and Francis (1994) and Cameron (2003) noted the problem and attempted to correct for it using different approaches. Stoneman and Francis (1994) conclude that the producer price index and the export price series differ little from each other in manufacturing. On the other hand, Cameron (2003) finds that the domestic price bias is significant when using value added as measure of output, although of limited magnitude.

**Value Added**: The Annual Census of Production publishes since 1973 an annual series of nominal value added at factor cost. This is defined as gross output minus purchases, plus increases during the year in stocks of materials, stores and fuel, minus the cost of industrial and non-industrial services received.

Prior to 1973 payments for non-industrial services (NIS) were not published, so these are estimated for 1970-1972 using the following technique. The ratio of NIS to gross output was first calculated in 1973. This ratio then is applied to the gross output of 1970 to 1972 to get an estimate of NIS for these years. Thus, the ratio of NIS to gross output is kept constant over the period (1970-73). With the estimates of payments for NIS we are able to get an estimate for the value-added series for 1970-1972. Additionally, adjustments for stock appreciation and reclassifications to 1992-SIC are also conducted.

To get the single deflated value added (SDVA) index[1], nominal value-added was deflated by the producer price index of manufacturing products (home sales). The "domestic price bias" referred previously applies also here.

**Intermediate Inputs:** These are obtained as the difference between nominal gross output and nominal value added, after adjustment for stock appreciation and reclassification to SIC-1992. However, there is no official intermediate price index to deflate nominal

[1] Refer to Chapter 3 on the discussion about the problems in deflating value added.

intermediate input. As manufacturing industries are their own largest consumers, the intermediate inputs price index deflator is obtained as a weighted combination of the producer price index deflator (home sales) for the whole manufacturing sector and the price index of materials and fuel purchased by the corresponding industry. On average, 80% of intermediate inputs consumed in manufacturing come from other manufacturing industries while 20% come from outside. Therefore, the respective weights are: 0.80 and 0.20, which were assumed to be constant over the 1970-1997 period.

A point that deserves special mention when defining the variables in Chapter 4 is the convenience of adjusting the input factors for double counting (Schankerman 1981). An estimate of material and equipment expenditures on R&D has been subtracted from the nominal figures on intermediate inputs to avoid the expensing bias. Particularly, this estimate is constructed using the percentage of material and equipment expenditure on R&D over total expenditure on R&D (see Table A.1), for 1985 data (ONS), under the assumption that this share behaves stable over the sample period.

**Labour Input:** The labour input refers to the number of annual hours worked in manufacturing, which are computed as numbers employed times the annual average of hours worked. The number of persons engaged is from the Census of Production. The annual average of hours worked in manufacturing are from (O'Mahony 1999) and several issues of the Employment Gazette.

Employees engaged on R&D (sourced by the OECD, ANRSE data set) have been subtracted for the total number of persons engaged in each industry in the analysis performed in Chapter 4.

**Physical Capital Input:** Data for manufacturing industries classified by 1992-SIC at 1995 prices were supplied directly by the Office of National Statistics.

In Chapter 4 the physical capital stock is corrected for double counting. An estimate of the capital R&D stock has been obtained from data on capital expenditure on R&D, and then subtracted from the physical capital stock. Particularly, this estimate is constructed using the percentage of capital expenditure on R&D over total expenditure on R&D (Table A.1), for 1985 data (ONS). It is assumed that this share behaves stable over the sample period.

**Table A.1**
**Percentage of Capital and Materials Expenditure over Total Expenditures on R&D**
(Data for 1985)

| | FBT | TL | WPP | PPP | CH | NMM | BFM | MOT |
|---|---|---|---|---|---|---|---|---|
| % of capital expenditure on R&D over total expenditure on R&D | 16.2 | 10.0 | 3.4 | 9.6 | 14.3 | 9.9 | 10.8 | 7.9 |
| % of materials & equipment expenditure on R&D over total expenditure on R&D | 13.4 | 14.3 | 9.1 | 14.8 | 12.2 | 15.6 | 17.2 | 26.5 |

*Source:* Data supplied by the ONS.

**Stock of R&D:** The measure of domestic productive knowledge is based on data of UK R&D expenditure from the OECD data set (ANBERD). These data have been transformed in real terms using the UK GDP deflator (1995=100). To construct the stock of R&D for the industry, a perpetual inventory method is followed like the commonly used for the physical capital (see Hall and Mairesse 1995). This method specifies the capital for each period as the sum of the capital of the previous period minus the depreciated capital and plus the investment of the previous period. Thus, the equation defining R&D capital stock is the following:

(A.1.) $$RD_t = (1-\delta)RD_{t-1} + B_{t-1}$$

Where $RD_t$ is the period capital stock and $B_t$ is real R&D expenditures during the period. Our base assumptions are those most frequently used in this type of estimation. We assume a depreciation rate[2] ($\delta$) of 10 percent (Cameron 1996), a pre-sample growth rate ($g$) of the industry average growth rate in real R&D expenditures during the overall period[3], and we start the perpetual inventory method with the earliest year of R&D data available. The knowledge capital at the beginning of the first year is defined by the following equation:

(A.2) $$RD_0 = B_0/(g+\delta)$$

**Inter-Industry R&D Stock:** Particularly, following Scherer (1982) and Cameron (1996) a technology flows matrix based upon the 1990 UK input-output table of intermediate goods (the 'Leontief inverse') is constructed to weight the real BERD expenditures of the other industries. Say that one has a (8*8) matrix $\Omega$ of the proportion of intermediate goods produced by 8 industries ($j$ =1...8) and sold to the same 8 industries ($i$ = 1...8). Then a

[2] Changes in the rate of depreciation do not generally alter the results substantially (see, for instance, Coe and Helpman 1995).

[3] The pre-sample growth rate is approximately the mean growth rate for the industry, which we observe during the whole period considered. In any case, the precise choice of growth rates affects only the initial stock and declines its importance as time passes, unlike the choice of depreciation rate

typical element of the matrix $w_{ji}$ represents the proportion of the intermediate goods purchased by industry $i$ that are produced by industry $j$. The diagonal of the matrix is set to 0 (since the effect of R&D within each industry is captured separately).

The resulting (8*8) matrix $\Omega$ (Table A.2) is then multiply by the (8*1) vector $B$, which contains the real BERD spending of each of the 8 industries. This gives a (8*1) vector $\Omega B$ in which each element is the amount of BERD imported from other industries by industry $i$. This can be cumulated into a stock in the same way as for BERD in each industry to give a capital stock of used-BERD industries ($i$ =1...8). This stock is represented by $IRD_{ir}$

**Table A.2**
**Input-Output Relations (%, p.a.)**

| | FBT | TL | WPP | PPP | CH | NMM | BFM | MOT |
|---|---|---|---|---|---|---|---|---|
| **FBT** | | 0.58 | 0.08 | 0.21 | 0.79 | 0.11 | 0.28 | 0.74 |
| **TL** | 0.21 | | 1.13 | 0.50 | 0.92 | 0.25 | 0.22 | 1.99 |
| **WPP** | 0.55 | 0.26 | | 1.07 | 0.85 | 0.43 | 1.83 | 4.45 |
| **PPP** | 6.19 | 1.45 | 0.72 | | 3.62 | 0.90 | 1.47 | 6.63 |
| **CH** | 4.96 | 1.97 | 1.19 | 1.94 | | 0.76 | 2.41 | 9.81 |
| **NMM** | 3.46 | 0.29 | 0.63 | 0.28 | 1.83 | | 2.86 | 7.81 |
| **BFM** | 4.86 | 0.40 | 1.63 | 0.81 | 4.22 | 0.73 | | 28.24 |
| **MOT** | 0.57 | 0.16 | 0.11 | 0.31 | 0.73 | 0.33 | 1.12 | |

*Source:* Author's calculation form (1990) input-output table.

**Foreign R&D Stock:** The foreign research and development capital stock is a bilateral import-share weighted average of the domestic research and development capital stocks of each country's trading partners. The R&D expenditure data for the trading partners was collected from the ANBERD (OECD) database. To calculate the R&D stock, nominal expenditures were deflated by the respective country GDP deflator (1995=100) and converted to constant price sterling flows using 1995 PPP exchange rates. R&D stocks for each industry and country were calculated from these expenditures following equations (A.1) and (A.2). The bilateral import shares were calculated for each year from 1970-1997 based on the data from the STAN bilateral Trade Database, provided by the OECD. This is available for Canada, Denmark, France, Germany, Ireland, Italy, Japan, The Netherlands, Spain and The United States. The available length of time series is 1970 to 1997.

## A.2 Data Description for Chapter 5

The main data for Chapter 5 are obtained from the OECD Structural Analysis (STAN) database. This database, which is largely based on national accounts of individuals OECD member states, provides a comprehensive tool for analysing industrial performance across countries using the ISIC Rev. 3 Industry classification. The use of national accounts for the purpose of international comparisons has the advantage that its components are harmonised across countries on the basis of the International System of National Accounts.

International comparisons of productivity levels require three main components, namely comparable information on output, comparable information on factor inputs and currency conversion factors in order to translate output and factor inputs expressed in national currencies into a common currency.

**Currency Conversion Factors:** One of the most serious limitations in attempting to estimate relative productivity levels is the lack of adequate data on internationally comparable prices. The individual country data sets contain price indexes for inputs and outputs which are normalized in some particular year. As an example consider the price of output. For the countries considered, the data set records the price of output in each country as 1 in 1995. However, it would be incorrect to assume that the relative output price across countries is 1 in 1995. Therefore, one needs to know the relative industry output prices across countries for at least one year. The lack of this information implies that output will be measured in different units. A similar argument holds for each input.

This study uses the UVR for 1987 employed by Pilat (1996) and extrapolated to 1995, except for Italy, which is not included in this study. Following van Ark (1996) these UVRs are extrapolated[4] for each industry (*i*) with the industry specific *national price indexes* obtained from the OECD[5], as represented in equation (A.3):

(A.3) $$UVR_{it}^{AB} = UVR_{i0}^{AB} \frac{P_{it}^{A} / P_{i0}^{A}}{P_{it}^{B} / P_{i0}^{B}}$$

with superscripts refer to country A and B, and "*i*" refers to the industry.

The extrapolated UVR for year 1995 are then used to convert the real output for year 1995 expressed in its own currency to a common currency (US$).

[4] van Ark and Pilat (1993) used the same methodology to extrapolate their 1987 UVRs for Germany and Japan to 1990.

[5] The reliability of this extrapolation procedure is affected by the differences in data and methodology used to construct the UVRs and the national price indices respectively.

(A.4) $$Q_{i95}^{A(\$)} = \frac{Q_{i95}^{A(A)}}{UVR_{i95}^{AB}}$$

In the case of Italy, output was converted to US$ using the specific output price ratios (based on the expenditure PPPs adjusted for net taxes and subsidies and, for import and export prices) provided by Hooper (1996). These are additionally extrapolated to 1995 using the above procedure.

**Real Output:** Through Chapter 5, two output concepts are used for comparison purposes. These are gross output and value added.

a) *Gross Output*[6]*:* The nominal gross output data by sector was obtained from the STAN database. The industry-specific producer price indices, obtained from the Historical Indicators ISIC (OECD), were used to deflate nominal gross output. Finally, data in real terms (in 1995 prices) was converted into dollar terms using the updated Pilat (1996) UVR for individual industries.

b) *Value Added:* Real value added data by sector was obtained from the STAN database. The data series in real terms were converted into dollar terms using the updated Pilat (1996) UVR for individual industries. In principle, different conversion factors should be used for gross output and intermediate inputs (double

[6] Gross output is the preferred measure for productivity analysis at lower levels of aggregation, but the problem of double counting remains at higher levels. It seems that at the level of analysis proposed in this study, the benefits of using gross output are bigger than the potential disadvantages (see also OECD 2001).

deflation approach) to obtain a measure of real value added in a common currency[7]. However, the lack of reliable information on international price data on intermediate goods makes this option not practicable.

**Intermediate Inputs:** Nominal intermediate inputs were obtained as the difference between nominal gross output and nominal value added. As there is no official price deflator for intermediate inputs at sectoral level, real intermediates inputs in national currencies are obtained using the Divisia definition of real value added, in other words, using the implicit deflator used by the OECD database to construct the real value added. In this sense:

$$\text{(A.5)} \qquad \frac{d\ln V_t}{dt} = \frac{1}{1-s_M}\left[\frac{d\ln Q_t}{dt} - s_M\frac{d\ln M_t}{dt}\right]$$

Expression (A.5) is the Divisia definition of value added discussed by Sims (1969) (that is, in growth rates in continuous time)[8].

Finally, to obtain intermediate inputs into a common currency, due to the problems highlighted above on international prices on intermediate good, specific conversion factors for gross output are applied to real intermediate inputs.

[7] There is also some doubt as to the validity of international price data on intermediate goods outside the agriculture sector and relatively "heroic" assumptions such as the application of the "law of one price" to such products have to be made (Roy 1987).

[8] In practice we use the discrete Törqvist index (the geometric mean of the two estimates) as a good first approximation to the desired figure.

**Labour:** The labour input refers to the number of annual hours worked in manufacturing calculated on the basis of employment (from industry employment figures in the STAN dataset) and the annual average of hours worked (STAN and O'Mahony and de Boer 2002, for missing series) at the sectoral level. In the case of Italy, annual average hours worked for total manufacturing are applied at the sectoral level.

**Capital Stock:** International comparisons of levels of TFP require that an industry conversion factor is also needed to translate capital into a common currency. In principle, these can be derived from official PPPs for investment by converting investment series to a common currency and then calculating capital stock in a common currency.

In this study, capital stock data for UK, US, France and Germany come from O'Mahony and de Boer (2002). This data was originally in constant 1996 US$, and was rebased to 1995 using investment specific PPPs from the OECD. Capital stock data for Italy, Japan and Canada come from the OECD (STAN database) and are converted to a common currency on the basis of PPPs for investment derived from the OECD.

## A.3 Industry Concordance

Tracking the different industry groups over time proved to be difficult because of the change in the system of the Standard Industrial Classification (SIC) in 1980 and in 1992. The concordance used is based upon Oulton and O'Mahony (1994), Cameron (1996) and author's calculations. The data set in Chapter 3 and Chapter 4, composed of 8 manufacturing industry groups, was reclassified to SIC 1992, as shown in Table A.3. However, it was not always possible to obtain a perfect concordance between SIC 1968, SIC 1980 and SIC 1992.

**Table A.3**
**Industry Concordance**

| | SIC 1968 | SIC1980 | SIC 1992 |
|---|---|---|---|
| Food, Beverages & Tobacco (FBT) | III | 41+42 | 15+16 |
| Textile & Leather (TL) | XIII+XIV+XV-411 + 492 | 43+44+45 | 17+18+19 |
| Wood and Wood Products (WWP) | XVII-472/3/4 | 46-467 | 20 |
| Paper and Paper Products (PPP) | XVIII | 47 | 21+22 |
| Chemicals, man-made Fibres, Rubber & Plastic Products (CH) | V- (0.2*271(3)) + 411+ 491 + 496 | 25+26+48 | 24 |
| Other Non-Metallic Mineral Products (NMM) | XVI | 24 | 26 |
| Manufacture of Basic Metals & Fabricated Metal Products (BFM) | VI + XII | 22 + 31 | 27 + 28 |
| Machinery, Optical Equipment & Transport Equipment (MOT) | VII + VIII + IX + X + XI | 32/3/4/5/6 + 37 | 29 + 30/1/2/3/4 /5 |

# B STATISTICAL APPENDIX

## B.1 Summary - Chapter 3

**Table B.1**
**Summary Statistics on Variables in First Differences (%, p.a.)**
Average eight industry groups

| | | 1970-97 | | 1973-79 | | 1980-89 | | 1990-97 | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Name** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** |
| Gross Output [a] | $\Delta lnQ$ | 0.39 | 6.82 | -0.14 | 7.93 | 0.73 | 6.07 | 0.28 | 7.63 |
| Single Deflated Value Added [a] | $\Delta lnV$ | 0.07 | 7.66 | -1.61 | 7.76 | 0.51 | 8.28 | 0.17 | 7.20 |
| Divisia Value Added [a] | $\Delta lnV^d$ | 0.14 | 8.72 | -3.91 | 10.35 | 1.60 | 6.99 | 1.17 | 9.23 |
| Labour [a] | $\Delta lnL$ | -2.54 | 5.22 | -2.10 | 4.02 | -3.17 | 4.88 | -2.21 | 7.14 |
| Capital [a] | $\Delta lnK$ | 0.61 | 2.46 | 2.25 | 1.34 | -0.03 | 2.32 | -0.84 | 2.33 |
| Intermediate Inputs [a] | $\Delta lnM$ | 0.62 | 7.67 | 2.10 | 9.39 | 0.37 | 6.82 | -0.20 | 7.65 |
| Capacity Utilisation | $\Delta lnCU$ | -0.01 | 0.18 | -0.06 | 0.21 | 0.04 | 0.16 | 0.00 | 0.19 |
| Labour share in gross output [b] | $s^L$ | 22.32 | 5.31 | 22.67 | 5.78 | 22.29 | 5.46 | 21.92 | 4.57 |
| Intermediate inputs share in gross output [b] | $s^M$ | 63.31 | 7.19 | 62.82 | 8.14 | 63.93 | 6.89 | 64.16 | 5.91 |
| Labour share in Value Added [b] | $\hat{s}$ | 63.21 | 9.72 | 64.57 | 10.51 | 64.43 | 10.22 | 62.17 | 8.22 |

*Sources:* See Data Appendix A.1
*Notes:* [a] Annual growth rates.
[b] The averaged shares are measured by the following Törnqvist index: $\bar{s}^J = (1/2)[s^J(t) + s^J(t-1)]$.

## B.2 Panel Unit Root Tests – Chapter 3

**Table B.2**
**Panel Unit Root Test for Variables in First Differences**
(Intercept included)$^+$

| Variables | No-lags | 1 lag |
|---|---|---|
| | *t-bar* | *t-bar* |
| $\Delta ln(Q/K)$ | -4.754*** | -3.877*** |
| $\Delta ln(FC)$ | -4.865*** | -3.545*** |
| $\Delta ln(CU)$ | -5.921*** | -4.322*** |
| $\Delta ln(K)$ | -1.709 | -1.999* |
| *Critical values t-bar (Im et al.)* | 1% | -2.18 |
| | 5% | -1.99 |
| | 10% | -1.88 |

$^+$ *, ** and *** denote statistical significance at the 10% level, the 5% level, and the 1% level, respectively.

## B.3 Summary Statistics - Chapter 4

**Table B.3**
**Summary Statistics of Variables in Levels**
(Data adjusted by R&D double counting)

| | Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Ratio output to capital | *ln(Q/K)* | 224 | 0.024 | 0.414 | -0.710 | 1.149 |
| Ratio labour to capital | *ln(L/K)* | 224 | -3.519 | 0.515 | -4.469 | -1.948 |
| Ratio Intermediates to capital | *ln(M/K)* | 224 | -0.427 | 0.374 | -1.127 | 0.343 |
| Capacity Utilisation | *ln(CU)* | 224 | 0.000 | 0.002 | -0.006 | 0.006 |
| Direct R&D | *ln(RD)* | 224 | 7.425 | 1.800 | 4.100 | 10.712 |
| Intra-industry R&D | *ln(IRD)* | 224 | 6.257 | 1.103 | 4.775 | 8.384 |
| Foreign R&D | *ln(FRD)* | 224 | 9.993 | 0.960 | 8.528 | 11.963 |
| Labour Share | $S_l$ | 224 | 0.224 | 0.056 | 0.104 | 0.324 |
| Intermediates Share | $S_m$ | 224 | 0.635 | 0.071 | 0.492 | 0.786 |

*Sources:* See Data Appendix A.1

## B.4 Panel Unit Root and Cointegration Tests – Chapter 4

**Table B.4**
**Panel Unit Root Test for Variables in Levels**
(Time-trend and intercept included)†

| Variables | 1 lag | 2 lags |
|---|---|---|
| | t-bar | t-bar |
| *ln(Q/K)* | -2.045 | -2.098 |
| *ln(L/K)* | -1.075 | -1.192 |
| *ln(M/K)* | -2.328 | -2.492 |
| *ln(CU)* | -2.719** | -2.450 |
| *ln(RD)* | -2.021 | -2.166 |
| *ln(IRD)* | -1.135 | -1.502 |
| *ln(FRD)* | -2.646** | -2.102 |
| Critical values t-bar (Im et al.) | 1% | -2.79 |
| | 5% | -2.60 |
| | 10% | -2.51 |

† *, ** and *** denote statistical significance at the 10% level, the 5% level, and the 1% level, respectively.

**Table B.5**
**Panel Unit Root Test for Variables in First Differences**
(Intercept Included)$^{+}$

| **Variables** | **No-lags** | **1 lag** |
|---|---|---|
| | *t-bar* | *t-bar* |
| $\Delta ln(Q/K)$ | $-4.770^{***}$ | $-4.330^{***}$ |
| $\Delta ln(L/K)$ | $-4.241^{***}$ | $-3.375^{***}$ |
| $\Delta ln(M/K)$ | $-4.921^{***}$ | $-4.480^{***}$ |
| $\Delta ln(CU)$ | $-5.921^{***}$ | $-5.428^{***}$ |
| $\Delta ln(RD)$ | $-2.127^{**}$ | $-1.927^{*}$ |
| $\Delta ln(IRD)$ | -1.029 | -1.320 |
| $\Delta ln(FRD)$ | $-5.790^{***}$ | $-5.962^{***}$ |
| *Critical values t-bar (Im et al.)* | 1% | -2.18 |
| | 5% | -1.99 |
| | 10% | -1.88 |

*Note*: $^{+\,*}$, $^{**}$ and $^{***}$ denote statistical significance at the 10% level, the 5% level, and the 1% level, respectively.

**Table B.6**
**Cointegration Tests Based on Results from Table 4.3**

| | **No trend** | | **Common trend** | | **Different trends** | |
|---|---|---|---|---|---|---|
| | ***Test*** | ***Prob*** | ***Test*** | ***Prob*** | ***Test*** | ***Prob*** |
| **Kao (1999)**[1] | | | | | | |
| **$DF_{\rho}$*** | -3.348 | 0.000 | -3.711 | 0.000 | -14.298 | 0.000 |
| **$DF_{t\rho}$*** | -1.091 | 0.138 | -1.205 | 0.114 | -5.535 | 0.000 |
| **ADF** | -1.356 | 0.088 | -1.362 | 0.087 | -6.032 | 0.000 |
| **Pedroni (1995)**[2] | | | | | | |
| **PC1** | -6.064 | 0.000 | -6.293 | 0.000 | -25.007 | 0.000 |
| **PC2** | -5.951 | 0.000 | -6.175 | 0.000 | -24.540 | 0.000 |

***Note:*** All tests are left-hand side, i.e. large negative values are used to reject the null of no cointegration.

1: The DF tests are analogous to the parametric Dickey-Fuller test for non-stationary time series. Particularly, $DF_{\rho}^{*}$ and $DF_{t\rho}^{*}$ statistics are based upon endogenous regressors. The ADF test is analogous to the parametric Augmented Dickey Fuller test for non-stationary time series.

2: PC1 and PC2 are the non-parametric Phillips-Perron tests.

**Table B.7**
**Pedroni's (1999) Cointegration tests for Heterogeneous Panels**

| | No trend | Different trends |
|---|---|---|
| **Panel v-stat.** | 0.225 | -0.370 |
| **Panel ρ-stat.** | 1.185 | 1.421 |
| **Panel ρρ-stat.** | -1.349 | -2.000* |
| **Panel ADF-stat.** | -1.642* | -1.651* |
| | | |
| **Group ρ-stat.** | 1.899 | 2.026 |
| **Group ρρ-stat.** | -1.600 | -2.428* |
| **Group ADF-stat.** | -2.608* | -2.494* |

*Note:* The cointegration tests reject the null hypothesis of no cointegration above the value −1.64 (10% probability threshold). One exception is the panel v-static which diverges to positive infinite under the alternative hypothesis, so rejection of the null requires values larger than 1.64. The calculations of the panel statistics were carried out in RATS 4.2 using an algorithm provided by Pedroni. The number of lag truncations used in the calculation of all Pedroni statistics is 2.

## B.5 Summary Statistics - Chapter 5

**Table B.8**
**Summary Statistics on UK Data in First Differences (%, p.a.)**
Average eight industry groups

| | | 1970-98 | | 1973-79 | | 1980-89 | | 1990-97 | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Name** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** |
| Gross Output [a] | $\Delta lnQ$ | 0.39 | 6.59 | 0.21 | 8.12 | 0.65 | 6.30 | 0.28 | 6.38 |
| Labour [a] | $\Delta lnL$ | -2.37 | 4.16 | -1.94 | 3.32 | -2.76 | 4.51 | -2.11 | 4.80 |
| Capital [a] | $\Delta lnK$ | 0.75 | 3.15 | 1.00 | 2.19 | 0.48 | 4.16 | 0.49 | 2.60 |
| Intermediate Inputs [a] | $\Delta lnM$ | 0.50 | 8.55 | 0.13 | 10.78 | 0.77 | 7.70 | 0.69 | 8.60 |
| Capacity Utilisation | $\Delta lnCU$ | -0.01 | 0.18 | -0.06 | 0.21 | 0.03 | 0.15 | 0.02 | 0.17 |
| Labour share in gross output | $s^L$ | 27.62 | 5.51 | 27.04 | 6.39 | 27.93 | 5.52 | 27.57 | 4.55 |
| Intermediate inputs share in gross output | $s^M$ | 61.81 | 5.21 | 62.89 | 5.61 | 61.82 | 5.43 | 61.04 | 4.46 |

*Sources:* See Data Appendix A.2
*Notes:* [a] Annual growth rates.

## B.6 Panel Unit Root Tests – Chapter 5

**Table B.9**
**Panel Unit Root Test for Variables in First Differences**
(Intercept Included)

| | *t-bar* | | | |
|---|---|---|---|---|
| **Variables** | ***Δln(Q/K)*** | ***Δln(FC)*** | ***Δln(K)*** | ***Δln(CU)*** |
| **No-lags** | | | | |
| FBT | -4.524 | -4.484 | -2.328 | -4.388 |
| TL | -4.240 | -4.348 | -2.870 | -4.647 |
| WWP | -4.178 | -4.199 | -2.700 | -4.991 |
| PPP | -4.102 | -4.141 | -3.537 | -4.318 |
| CH | -5.068 | -5.003 | -2.188 | -4.513 |
| NMM | -3.996 | -3.905 | -2.316 | -4.810 |
| BFM | -4.135 | -4.138 | -2.827 | -5.349 |
| MOT | -3.995 | -3.909 | -2.375 | -4.486 |
| **1-lag** | | | | |
| FBT | -4.361 | -4.297 | -2.246 | -4.505 |
| TL | -4.245 | -4.386 | -3.023 | -4.512 |
| WWP | -4.026 | -4.101 | -2.763 | -4.512 |
| PPP | -3.776 | -3.854 | -3.371 | -4.195 |
| CH | -5.101 | -5.113 | -2.187 | -4.427 |
| NMM | -4.021 | -4.082 | -2.476 | -4.410 |
| BFM | -3.960 | -3.872 | -2.789 | -5.155 |
| MOT | -3.995 | -3.909 | -2.375 | -4.486 |
| ***Critical Values of t-bar (Im et al. 1997)*** | | | | |
| | **cv10** | **cv5** | **cv1** | |
| | -1.950 | -2.080 | -2.320 | |

*Source*: See Appendix Data A.2.

# C TECHNICAL APPENDIX

## C.1 Significance of Mark-ups – Chapter 3

Table C.1
Adjustment for Imperfect Competition

| Industry | SUR | $H_0$: $\mu_i$= 1 | 3SLS | $H_0$: $\mu_i$= 1 |
|---|---|---|---|---|
| Constrained Model | 1.124 | 22.45 | 1.125 | 22.37 |
| | (0.026) | [0.000] | (0.026) | [0.000] |
| FBT | 0.909 | 0.94 | 0.949 | 0.34 |
| | (0.094) | [0.333] | (0.096) | [0.559] |
| TL | 0.940 | 1.25 | 0.936 | 1.42 |
| | (0.053) | [0.263] | (0.054) | [0.234] |
| WWP | 1.150 | 9.35 | 1.148 | 9.15 |
| | (0.040) | [0.002] | (0.049) | [0.002] |
| PPP | 1.281 | 7.21 | 1.273 | 6.62 |
| | (0.105) | [0.007] | (0.106) | [0.010] |
| CH | 1.002 | 0.00 | 1.007 | 0.02 |
| | (0.050) | [0.969] | (0.051) | [0.891] |
| NMM | 1.247 | 17.22 | 1.251 | 17.57 |
| | (0.060) | [0.000] | (0.060) | [0.000] |
| BFM | 1.161 | 9.87 | 1.161 | 9.81 |
| | (0.051) | [0.001] | (0.051) | [0.002] |
| MOT | 1.171 | 6.32 | 1.162 | 6.32 |
| | (0.068) | [0.012] | (0.070) | [0.020] |

Table C.2
Adjustments for Imperfect Competition and Capacity Utilisation

| Industry | SUR | $H_0$: $\mu_i$= 1 | 3SLS | $H_0$: $\mu_i$= 1 |
|---|---|---|---|---|
| Constrained Model | 1.085 | 11.67 | 1.089 | 12.43 |
| | (0.025) | [0.000] | (0.025) | [0.000] |
| FBT | 0.891 | 0.23 | 0.912 | 0.80 |
| | (0.096) | [0.394] | (0.098) | [0.372] |
| TL | 0.912 | 3.66 | 0.915 | 2.98 |
| | (0.049) | [0.056] | (0.049) | [0.08] |
| WWP | 1.110 | 4.87 | 1.105 | 4.33 |
| | (0.050) | [0.027] | (0.050) | [0.039] |
| PPP | 1.336 | 11.49 | 1.334 | 10.39 |
| | (0.102) | [0.001] | (0.104) | [0.001] |
| CH | 0.966 | 2.70 | 0.975 | 0.20 |
| | (0.056) | [0.100] | (0.057) | [0.658] |
| NMM | 1.210 | 12.14 | 1.213 | 14.82 |
| | (0.055) | [0.000] | (0.055) | [0.000] |
| BFM | 1.091 | 4.47 | 1.091 | 3.03 |
| | (0.052) | [0.034] | (0.053) | [0.082] |
| MOT | 1.047 | 1.59 | 1.070 | 0.99 |
| | (0.068) | [0.207] | (0.071) | [0.319] |

## C.2 Total Revenues Model –An Alternative Approach to Measure TFP Growth

### C.2.1. The Model

The theoretical model developed here is an industry equilibrium model with profit-maximizing firms in a context of imperfect competition. It is assumed that the industry's revenue $R_{it}= P_{it}Q_{it}$ is observable, but not its real gross output $Q_{it}$. Changes in total revenues are the result of demand and supply shocks. The latter are identified as changes in Total Factor Productivity (TFP), which is sought to be identified.

The technology is assumed to be represented by a production function:

(C.1) $$Q_{it} = A_{it}F_{it}(L,K,M)$$

which is a function of capital services ($K$), labour services ($L$), intermediate inputs ($M$), and the state of technology ($A_{it}$).

Additionally, output demand is represented by the inverse demand function $P_{it}=D^{-1}(Q_{it}, \Phi_{it})$, where $\Phi$ is a vector of shift variables that reflect demand shocks. Particularly, the functional form specified for the inverse demand function can be summarised as follows:

(C.2) $$P_{it} = \Phi_{it}(NDI, RPI, IP, REP, BERD, IR)Q_{it}^{\gamma} = \left[ \frac{(\prod_{h \in \Theta} \phi_h^{\beta_h})^{-1/\gamma}}{Q_{it}} \right]^{-\gamma}$$

where $\gamma$ represents the inverse of the demand elasticity and $h$ indexes the components of the vector demand determinants. This specification allows demand-shift variables to be incorporated in the producers' pricing decisions. The arguments of the demand function contained in $\Phi$ are assumed to be nominal national disposable income (NDI), the retail price index (RPI), the price of imports (IP), the relative export prices for manufactured goods (REP), the expenditure in business enterprise R&D (BERD) and the interest rate (IR).

The Total Revenue Function adopts the following form, being the product of the demand and supply curves:

(C.3) $$R_{it} = P_{it}Q_{it} = \Phi_{it}(NDI, RPI, IP, REP, BERD, IR)Q_{it}^{1+\gamma} = \Phi_{it}Q_{it}^{1+\gamma}$$

Differentiating the total revenue function ($R_{it}$) with respect to time, after inserting the production function (C.1), one obtains:

(C.4) $$\begin{aligned} \frac{dR_{it}}{dt} &= \frac{d\Phi_{it}}{dt}\frac{R_{it}}{\Phi_{it}} + (1+\gamma)\frac{dA_{it}}{dt}\frac{R_{it}}{A_{it}} + (1+\gamma)\frac{dF_{it}()}{dt}\frac{R_{it}}{F_{it}()} \\ \frac{dF_{it}()}{dt} &= \frac{\partial F_{it}}{\partial K_{it}}\frac{dK_{it}}{dt} + \frac{\partial F_{it}}{\partial L_{it}}\frac{dL_{it}}{dt} + \frac{\partial F_{it}}{\partial M_{it}}\frac{dM_{it}}{dt} \end{aligned}$$

Additionally, market imperfection in the output market is accommodated. The analysis proceeds assuming that producers charge a price, $P_t$, which is a mark up over marginal cost. Nevertheless, they act as price-takers in input markets when choosing their factor inputs so as to maximise profit (or minimise cost). In this regard, producers take the price of all $J$ inputs, $P_t^J$, as given by competitive markets.

The first-order conditions of the producer optimisation problem imply that the value of a factor's marginal product is set equal to a mark-up over the factor's input price. That is:

$$\text{(C.5)} \qquad \frac{\partial F_{it}}{\partial J_{it}}\frac{J_{it}}{F_{it}} = \left(\frac{P_{it}}{MC_{it}}\right)\frac{P_{it}^J J_{it}}{P_{it}Q_{it}} = \frac{1}{1+\Omega\gamma}s_{it}^J$$

where: $P_t$ and $P_t^J$ are the output and input prices respectively; $MC_t$ is marginal cost, $1/(1+\Omega\gamma)=P_t/MC_t$ is the mark up ratio and $s_{it}^J$ are the input revenue shares. Additionally, $\gamma$ is the inverse of the price elasticity of demand while $\Omega$ measures the responses in the industry output to changes in the firm production, showing the degree of market power existing at the industry level ($\Omega$ [0,1]). In the monopoly case $\Omega$ should be equal to 1, while in the perfect competition case should be equal to 0.

Using (C.5) and expressing the result in discrete time one obtains the following equation to be estimated:

$$\text{(C.6)} \quad \Delta\ln R_{it} = (1+\gamma)\Delta\ln A_{it} + \beta_h\Delta\ln\Phi^h{}_{it} + \frac{(1+\gamma)}{(1+\Omega\gamma)}\left[s_{it}^l\Delta\ln L_{it} + s_{it}^k\Delta\ln K_{it} + s_{it}^m\Delta\ln M_{it}\right]$$

Using Euler's theorem, one can re-arrange equation (C.6) in the following way:

$$\text{(C.7)} \qquad \begin{aligned} \Delta \ln R_{it} &= (1+\gamma)\Delta \ln A_{it} + \beta_h \Delta \ln \Phi^h{}_{it} + \\ &\frac{(1+\gamma)}{(1+\Omega\gamma)}\left[s^l_{it}\Delta \ln\left(L/K\right)_{it} + s^m_{it}\Delta \ln\left(M/K\right)_{it}\right] + (1+\gamma)(1+\lambda)\Delta \ln K_{it} \end{aligned}$$

The parameter λ measures the extent to which the production function differs from constant returns to scale. Under the assumption of constant returns to scale in production (λ = 0), one is able to identify the parameters of the equation.

### C.2.2 Empirical Analysis

The OLS estimates of different versions of the revenue equations (C.4) and (C.7) are presented in Table C.3. Some of the arguments of the demand function contained in Φ are omitted because appear non-significant in the different regressions. In particular, these are expenditures on R&D, nominal income and, the relative export price index on manufactured goods. The long run interest rate, instead of the short run, appears significant in some of the regressions.

In column (1) a version of equation (C.4) is estimated. The coefficients of the production factors are the interaction between one plus the inverse elasticity of demand (1+γ) times the input elasticities. The results suggest the presence of increasing returns to scale, otherwise implying an implausible positive demand elasticity. Using the point estimates, one obtains that (1+γ)(1+λ)=1.174. Therefore, for negative values of γ, this implies positive values of λ, and by implication, increasing returns to scale in production. The drawback of these results is that without identifying the value of the inverse elasticity of demand, one is unable to identify the average growth rate of TFP.

The equation estimated in column (2), a version of equation (C.7) is estimated. In this case, the results are consistent with those obtained in column (1). The point estimates imply that $(1+\gamma)(1+\lambda)=1.174$. Once again, an identification problem arises.

**Table C.3**
**Results from a Revenue Function (1971-1996)**
Dependent variable ($\Delta$lnR) – Total Manufacturing

| | (1) | (2) | (3) |
|---|---|---|---|
| **Constant** $(1+\gamma)\Delta lnA_{it}$ | $0.014^{*}$ (1.86) | 0.014 (1.86) | 0.010 (1.89) |
| $\Delta ln$(RPI) | $0.727^{***}$ (10.38) | $0.727^{***}$ (10.38) | $0.749^{***}$ (9.84) |
| $\Delta ln$(IR) | $-0.066^{*}$ (-1.99) | -0.066 (-1.99) | |
| $\Delta ln$(IP) | $0.240^{***}$ (5.74) | $0.240^{***}$ (5.74) | $0.196^{***}$ (5.21) |
| $\Delta ln$(L) | $0.443^{***}$ (3.506) | | |
| $\Delta ln$(K) | 0.072 (0.38) | $1.174^{***}$ (7.14) | $1.056^{***}$ (6.51) |
| $\Delta ln$(M) | $0.659^{***}$ (6.39) | | |
| $\Delta ln$(L/K) | | $0.443^{***}$ (3.27) | |
| $\Delta ln$(M/K) | | $0.659^{***}$ (7.62) | |
| $s_l\Delta ln$(L/K)+$s_m\Delta ln$(M/K) | | | $1.186^{***}$ (12.27) |
| D_90 | $-0.03^{**}$ (-2.26) | $-0.03^{**}$ (-2.26) | $-0.04^{***}$ (-3.11) |
| $R^2$ | 0.969 | 0.969 | 0.961 |
| DW | 2.36 | 2.36 | 1.68 |

*Source:* Data from the Census of Production and ONS.
*Notes*: t-values in parenthesis.

Finally, in column (3), equation (C.7) is estimated. In this case, we have made use of the first order conditions of the optimisation problem, in which elasticities are equated to the shares of inputs in revenue times the inverse of the mark-up, the latter being estimated. From the results one can infer the relationship between total revenues and total cost. Particularly:

$$(1+\lambda)=(P/MC)*(TC/TR)$$

$$1.056= 1.186* (TC/TR)$$

Therefore, total revenues are greater that total cost. Additionally, for negative values of $y$, the results imply positive values of $\lambda$ and also positive mark ups. The drawback, once again, is that without identifying the value of the inverse elasticity of demand, one is unable to identify the average growth rate of TFP[9].

[9] Although not shown, an equation endogenising labour and intermediate inputs have been run, however the results are non-satisfactory. There exist some problems of correlation between the different coefficients apart from non-stationarity.

## C.3 Sensitivity of Long-Run Coefficients to Reduction of Industry Coverage – Chapter 4

(Pooled Mean Group estimates)

**Figure C.1**
**Coefficient of log(M/K)**

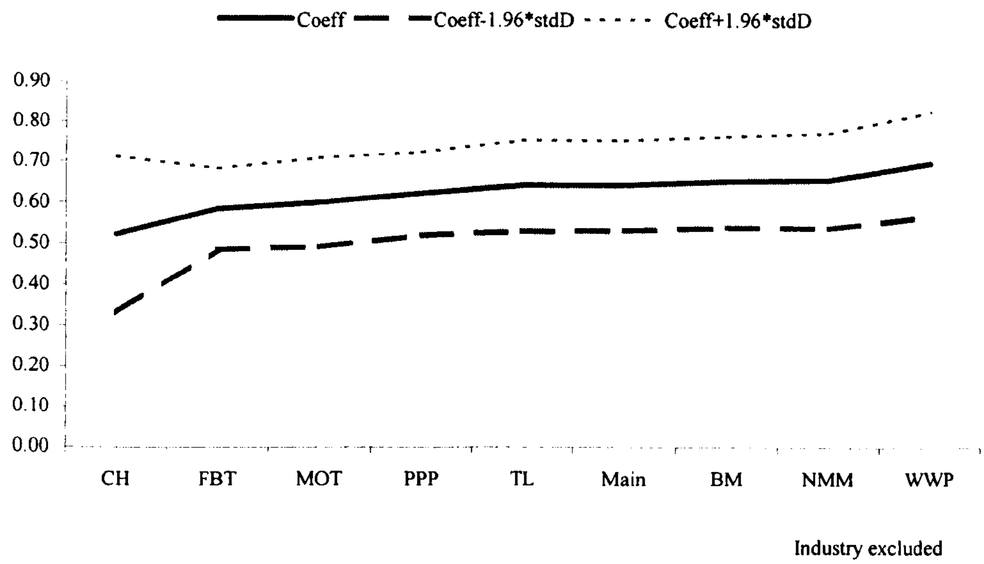



**Figure C.2**
**Coefficient of log(L/K)**

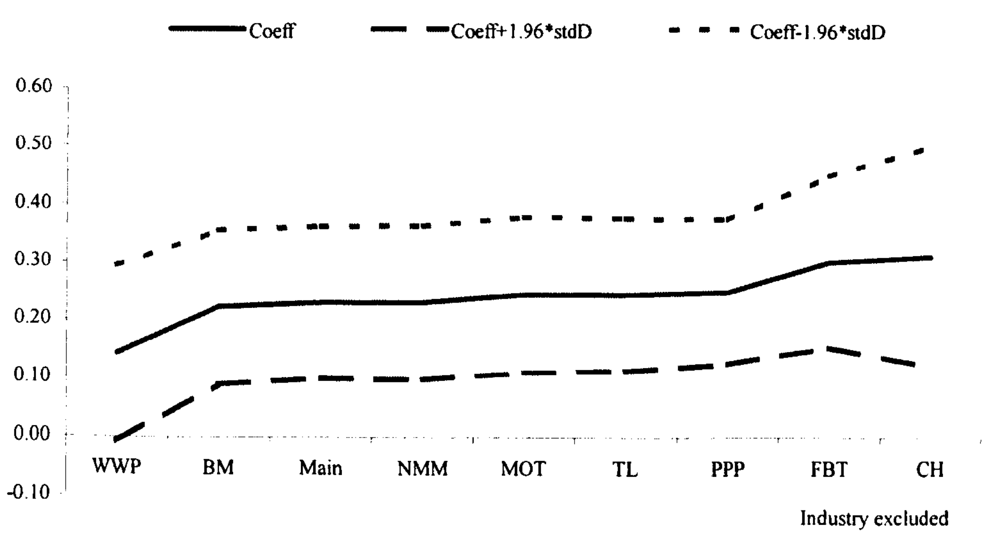


**Figure C.3**
**Coefficient of log(RD)**

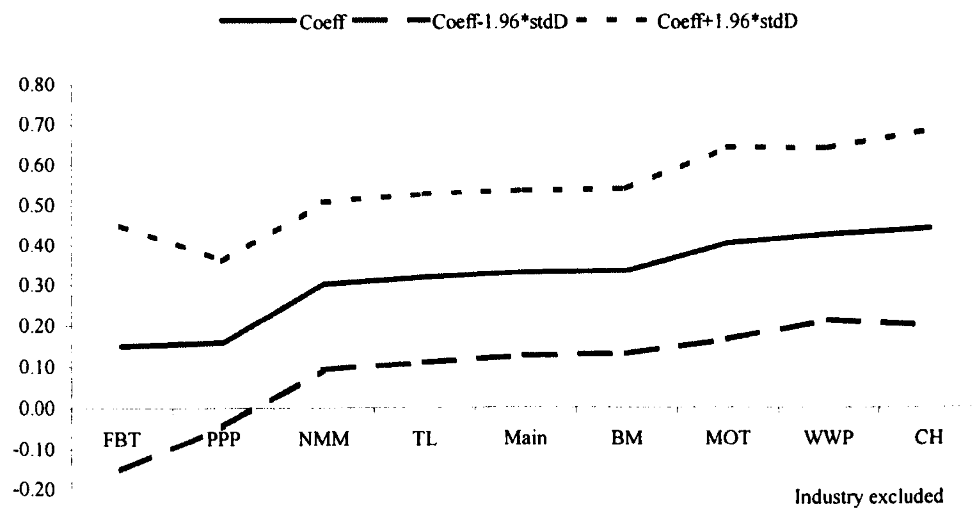
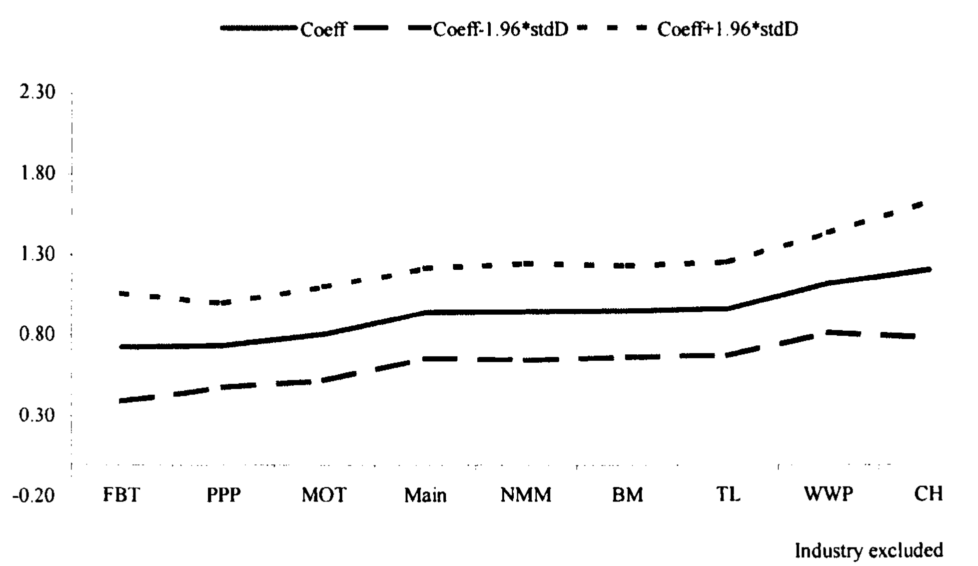



**Figure C.4**
**Coefficient of log(IRD)**




*Note:* Coefficient estimates and standard error bands according to PMG (95% confidence interval around coefficient estimates) when excluding one industry at a time from the sample. The coefficient estimates are arranged in increasing order.
"Main" indicates the baseline estimation (cf. Table 4.5, Chapter 4).