

***Technological change and growth dynamics: an
analysis of UK industries***

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*To Elisa, my niece.
I wish for you a life as happy as the one I had in Oxford.*



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Mara

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Abstract

In this work we investigate the sources and growth effects of technological innovation in UK industries over the years 1966-1993. Our main finding is that technological activities are always beneficial to labour productivity growth and normally also beneficial to employment growth. Moreover, it is possible to aggregate industries into fairly stable technological clusters, and the main sources of innovation change broadly in accordance with the technological characterisation of the industry. We also analyse the effect of inter-industry demand transmissions on employment share dynamics, and find that these effects are generally important. However, demand expansions in customer industries do not always imply expanding employment shares in supplying industries, and we did not find any evident linkage between the sign of the demand effect and the technological characterisation of industries. Testing the models developed to fit observed changes in labour productivity and employment shares over the periods 1974-79 and 1979-91, we find that growth dynamics over the period 1974-79 have been more related to technological change than over the period 1979-91. In particular, pure capital deepening has been one of the main engines of growth over the period 1979-91.

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General Introduction

This work is an empirical investigation of the sources and growth effects of technological innovation in UK industries over the years 1966-1993. It is now widely recognised that technological change is one of the main determinants of growth in modern economies. The analysis of its determinants at the industry level is of special interest for two main reasons. First, the aggregate effect of technological change on growth is the result of complex growth dynamics at the industry level. In particular, productivity, value added and employment dynamics at the industry level determine the whole economy productivity performance. Second, inter-industry differences seem to play a major role in explaining the innovative performance of firms. The investigation of industry dynamics can thus enhance our understanding of the functioning of the economic system in a way that more aggregate analysis is unable to do.

We will concentrate in particular on the effects of technological innovation on labour productivity and employment growth. While it is commonly recognised that labour productivity growth and technological innovation are positively related¹, there is more uncertainty on the employment effects of technological innovation. One of the purposes of this work is to investigate whether the employment effects of technological innovation may depend upon, and vary with, the technological characterisation of industries.

A major element of novelty of this analysis is that it is based on all industrial groups of the UK economy; thus it includes all industries operating in the service sector. The vast majority (if not the totality) of empirical studies we looked at during this work refer to the manufacturing sector only. The main reason for this is the availability of

data. The types of data commonly used for this sort of analysis² are in fact extremely difficult to collect for service industries. They are normally available over limited time periods and serious doubts can be raised on their accuracy, especially for the less recent time periods. On the other hand, service industries account for a substantial share of overall employment³, and some of them have also undergone major technological modifications⁴. It is thus certainly of interest to have at least some indications of the effects of technological innovation on the growth dynamics of service industries. We have therefore chosen to give up some degree of accuracy in the analysis in favour of a more extended industry coverage. Moreover, although we recognise that the quality of the data we use may not be very accurate, and that some statistical ingenuity has been necessary to cope with disaggregation and missing data problems, they are still the best data we were able to get.

We began this work with the expectation of finding a substantial role of technological innovation in explaining observed growth patterns at the industry level. In particular, we were expecting that innovating industries would show high value added and employment share growth, while low technology ones would show decline in both value added and employment share. While these expectations are broadly confirmed by our empirical analysis, some of our results in Chapter 3 and the analysis of Owen (1999) point to the substantial relevance of two economic and political changes that occurred in the UK during the period analysed.

The UK entered the Common Market in 1973, and most UK industries faced an immediate disadvantage with respect to their European counterparts. According to

¹ In fact labour productivity changes are often interpreted as evidence of technological change.

² Especially all the indicators of technological activity, in particular R&D expenditures, number of Patents, Number of Scientists and Engineers.

³ To give an idea of the magnitude, in 1991 one group of service industries accounted for 44% of total employment in the UK.

Owen (1999), part of the difficulties were due to general organisational problems, part to the fact that the UK had special trade treaties with their ex-colonies, but for the most part to the fact that UK industries had to enter markets in which other industries were already operating. Some UK industries⁵ had also a technological disadvantage with respect to their competitors, but overall competitiveness problems were not due to technological conditions. Up to 1979 the government made massive interventions to support declining industries and especially employment. In 1979, with the first Thatcher government, the policy guidelines changed drastically and the UK economy underwent massive restructuring. This included downsizing and closure of plants, strong reduction of government intervention to support production, and a general modernisation of the organisational and technical aspects of production. The year 1979 also marks the beginning of a recessionary phase of the business cycle in the UK economy.

Owen (1999)⁶ gives a detailed analysis of the changes intervened from the late 1960s to the early 1990s in some manufacturing and service industries.

The slowdown in growth of the Steel industry started in the early 1960s, due to the end of post-war reconstruction and to the emerging of the Japanese steel industry as a very strong competitor. The industry was nationalised in 1967 and in 1971 a massive investment plan started to copy the Japanese model of big plants. However, problems of over-manning and obsolete capital stocks soon started to emerge. As reported by Owen “The over-manning issue was of particular urgency since the UK economy had moved into recession in 1974 and steel demand was falling at an alarming rate. The recession was a worldwide phenomenon, caused in part by the doubling of oil prices

⁴ This is the case, for example, of financial services.

⁵ Noticeably Electronics and Engineering, although the competitors were US and Japanese firms.

by the OPEC, and it hit the steel industry with exceptional force. Britain was not the only country where steel producers were expanding their capacity, and much of the new plants came on stream in the second half of the 1970s, just as the world economy was slowing down. To make matters worse for British Steel, entry into the Common Market was exposing the industry to serious import competition for the first time”.

Towards the end of the 1970s the need to reduce the industry and cut employment starts to be recognised. When the Thatcher government entered office in May 1979, the immediate priority was to halt British Steel’s losses. Plant closures, and wage and employment reductions started. Following Owen “The rehabilitation of British Steel during the 1980s was not simply a matter of closing plants and cutting costs. There was also a greater emphasis on product development and marketing. ...As quality improved, relationships with important domestic customers, such as the car-makers, were rebuilt, and British Steel recovered some of the ground that had been lost to imports. At the same time, a more aggressive export policy was pursued in Continental Europe.”

In 1988 the industry was privatised again; in that year British Steel had 52000 employees, compared with 142000 at the start of the decade.

A similar pattern was followed by the Engineering Industry⁷, which overcame the difficulties of the 1970s by specialising in niche markets with sophisticated and high technology products.

The downsizing of the Electronics industry was caused by the strong advances of United States and Japanese firms. UK Electronic industries had in the 1940s a technological capability comparable to that of the United States. Also, the government

⁶ Most of what follows is taken directly from Owen (1999).

⁷ Although the industry was not nationalised.

directly or indirectly financed most of their early research. During the years 1974-79 there was an increase in R&D activities to keep pace with the competition from the United States and Japan. However, in 1979 the Thatcher government stopped to support fully the industry, and it was decided to concentrate competition in specific areas of the market and cut other R&D activities. Moreover, agreements with Japanese companies to use their technology were established.

Unsuccessful competition with other European industries and lack of specialisation were at the origin of the difficulties of the Textile industry. As reported by Owen “At the end of the 1990s, after three decades of restructuring, the British textile industry was drastically reduced in size, and the mistakes made during the merger mania of the 1960s had been largely reversed. Although the contraction in employment was certain to continue as more production was shifted overseas, what was left of the industry was better equipped to compete in the world market.”

As to the Paper industry, the difficulties it experienced were mainly due to delayed modernisation⁸. Technical advance and increased competition made possible the recovery of the industry.

The historical evolution of Motors, Aerospace and Chemical industries follow a broadly similar pattern of sudden exposure to European competition and eventual recovery by specialisation in niche markets. Exceptions are Aerospace, for which governmental support was fundamental to its survival and recovery, and Chemical (especially Pharmaceutical) industries, which based their success on technological innovation.

⁸ Due to, in Owen's opinion, slowly growing domestic demand, protectionist practices of the government, and late entering of the common market.

Thus, while technological factors have indeed been important for the growth performance of some industries, their suitability to explain growth dynamics for other industries is at best limited.

The thesis is organised in three chapters. The first two chapters are more closely concerned with the supply side effects of technological innovations, while the third chapter examines demand effects, in particular inter-industry demand transmission effects. The thesis is essentially an empirical study and does not normally develop original methodologies. Chapter 1 is based on broadly standard production function models. Chapter 2 heavily relies on an investment model proposed by Nickell and Nicolitsas (1997). Chapter 3 is a partial exception. Drawing on a supply model proposed by Harrigan (1997), we attempt to develop an original framework to analyse inter-industry demand transmission.

The first chapter focuses on the effects of internal (or in-house) innovative activities on labour productivity and employment shares growth. First, we describe the dataset used for the study. Then, we proceed to make a technological classification of industries, ranging from *technology producer* to *low technology*, on the basis of some indicators of innovative activity. Next, we propose a decomposition of aggregate labour productivity growth in its sectoral components. We find that the contribution of each sector to aggregate labour productivity growth is determined by the weighted growth rates of its labour productivity and employment share. In accordance with the evidence reported in other works, we get that within industry growth is generally the most important factor for aggregate productivity growth. However, for two industrial groups of the service sector, the main engine of growth is between industry growth. We also show that this decomposition, usual in studies analysing growth dynamics at

the industry level, may be not invariant to the level of aggregation of the data. Finally, we present a first set of estimation results from production function and employment shares models in order to determine the effects of internal innovative activities on labour productivity and employment shares growth at the industry level.

In the second chapter, we concentrate on the effects of external innovative activities on employment shares and labour productivity growth. In particular, we focus on the possibility for firms to acquire technology via investment in new machines, and on the spillover effects. We first determine the causality linkage between R&D expenditures and investment. Next, we proceed to estimate an investment model⁹ that explicitly relates investment expenditures to total factor productivity and inter and intra industry R&D expenditures. Then, we investigate the presence and importance of pure spillover effects at the industry level. Finally, on the basis of the results obtained in the first and second chapter, we proceed to determine the overall impact of internal and external sources of innovation on labour productivity and employment shares growth. One of the most interesting results from this chapter is that technology embodied in capital is a significant source of technological improvement, and its relative importance with respect to internal innovative activities depends on the technological characterisation of the industries.

In the third and last chapter we concentrate on changes in employment shares generated by inter-industry demand transmissions and on the “technological” interpretation of the observed historical changes in labour productivity and employment shares at the industry level. In fact, it is possible that the employment share of one industry changes not because of technological change in the industry but because of demand expansion in its customers industries. We first propose and

estimate a demand-supply model in order to determine how the value added and employment share of a supplying industry j , not experiencing technological change, vary as a consequence of technologically induced changes in demand of its customer industries. Next, we link the models and the results obtained in chapters 1, 2 and 3 to compare the fitted values from our models with the actual ones and determine the technological causes of success and failures in industries performance. The final results broadly confirm the expectations we had at the beginning¹⁰ and also provide an accurate description of the changes intervened in the UK industrial structure. However, for the reasons presented before, technological change seems to have played only a secondary role in shaping industrial evolution over the period 1979-91. A general summary of the results obtained concludes the thesis.

⁹ Originally proposed by Nickell and Nicolitsas (1997).

¹⁰ I.e. more innovating industries have a better growth performance, both in terms of labour productivity and employment shares, than less innovating industries.

Chapter 1: Employment, Productivity and the internal sources of innovation: an analysis of the UK industries

Introduction

A wide body of both theoretical and empirical work has pointed to the importance of intersectoral and international flows of innovations in determining the productivity performance of each industry¹¹. Recent empirical evidence suggests that, for some industries, externally acquired technology and spillover effects have a more profound impact on productivity growth than the knowledge generated by internal R&D activities. Moreover, a definite technological structure seems to be common to the majority of developed countries. That is, some firms are heavily engaged in the discovery and production of new knowledge while others rely on externally acquired innovations to improve their productivity performance. Obviously, a complete description of an economic system involves many firms in an intermediate position with respect to the two main categories described here. Anyway, it is not part of our concern to pursue a study of the determinants and exploitation of innovations at the firm level. We rather consider the industry level for our analysis of innovative behaviour, particularly because inter-industry differences seem to play a major role in explaining the innovative performance of firms¹².

The aim of this chapter is to analyse the impact of internal innovative activities on employment and labour productivity growth in UK industries over the period 1966-1993.

¹¹ See, among the others, Griliches (1979), Scherer (1982), Geroski (1994).

We begin here the analysis of the impact of technological change on employment. It is in principle possible to decompose the global effect of technological change on employment into two separate effects. First, there is the “factor saving” effect. As a first approximation, improvements in productivity imply that it is possible to produce the same amount of output using less input. As a consequence, employment might be negatively affected by technological improvements. Second, there is the “demand expansion” effect. As far as technological improvements are reflected in price reductions or in the creation of new and better products, successfully innovating firms will face an expansion in their demand. There is thus room for potentially increasing employment. The global effect of technological change on employment depends on the relative strength of the two effects mentioned above. In this chapter we will concentrate on the effects of internal innovative activities on employment at the industry level. Our aim is to study if the sign and significance of the effect vary from industry to industry, and if they depend on the technological characterisation of the industry.

The chapter is organised in six sections. In the first section, we review the theoretical background and methodologies for studying the effects of technological change, focusing in particular on spillover effects and the relative importance of internal and external sources of innovation. In section 2, we describe the dataset used in this study. In the third section, we present a technological classification of industries according to two indicators of internally generated and externally acquired technology. In the fourth section, we present some stylised facts about the growth patterns of GDP, Employment and Productivity at the whole economy level over the years 1966-1993.

¹² See Scherer (1984), Levin and Reiss (1984), Acs and Audretsch (1987), Geroski (1990), Geroski (1994).

We will then analyse the evolution of the sectoral contribution to aggregate labour productivity over selected time periods, by decomposing the aggregate into its industry's components. In the fifth section, we present the econometric models used to determine the impact on employment and labour productivity of internal sources of innovations. The discussion of results and conclusions complete the Chapter.

I.1 Background and methodology

Since the discovery of the “Solow residual”, explaining up to 80 per cent of output growth, many theoretical and empirical studies have addressed the analysis of the determinants and effects of technological change at the micro and macro level. Technological change is now recognised as an endogenous process determined by, and determining, the characteristics of the economic system.

In general, theoretical macro models of growth explicitly formalise a sector producing knowledge whose inputs are some measure of innovative effort, usually R&D expenditures¹³. The output of this sector affects the standard inputs of production through learning by doing effects and labour skills improvements.

At the micro level, empirical studies of firms' innovative behaviour have mainly investigated the relationship between firm size and innovative efforts or between input and output measures of innovation¹⁴.

One of the striking results common to most studies is that innovative behaviour at the firm level seems to be highly dependent on industry specific characteristics. These

¹³ On the macro models of growth see Barro and Sala-i -Martin (1995), Romer (1996) and Cameron (1997).

¹⁴ See, among the others, Acs and Audretsch (1987), Scherer (1984), Geroski (1990) and (1994), Griliches (1979) and Schmalenssee and Willig (1989) for a good synthesis.

industry characteristics have been classified under three main headings: product market demand, technological opportunity and appropriability conditions.

In simple words, product market demand is important because it is usually easier to sell in large and growing markets than in stagnating ones¹⁵. Moreover, the price elasticity of demand plays a major role in determining the eventual gains from innovations. This is true when innovations cause prices to fall, usually process innovations, and when they cause prices to increase, usually via product innovations at an early stage in their diffusion.

Technological opportunity and appropriability conditions refer even more closely to the technological environment and characteristics. According to Geroski (1994) “technological opportunity is the term usually used to describe the conditions that determine the number and kinds of inventions and innovations that it is feasible to produce given the existing knowledge base”. Dosi (1990) defines the knowledge base as “the set of information inputs, knowledge and capabilities that inventors draw on when looking for innovative solutions”. As such, the term technological opportunity covers a wide variety of factors shaping the general possibilities of development.

Appropriability conditions determine the extent to which innovating firms are able to appropriate the economic benefits of own innovations. It is not clear if more appropriability actually enhances innovative efforts, because general spillover effects may more than offset the loss¹⁶. But definitely appropriability conditions differ among industries and different too are the strategies firms adopt to maintain their innovative

¹⁵ More rigorous arguments refer to the fixed investment necessary to engage in R&D activity and to the spillover effects among technologically competing firms.

¹⁶ See Griliches (1979).

advantage¹⁷. Unfortunately, this biases the efficiency of patent count data as indicators of innovative success.

In view of these findings and of the interplay between demand and supply forces¹⁸ determining innovative efforts, it is clearly of some interest to analyse the technological structure at the industry level. As mentioned before, we will concentrate in particular on the *modus innovandi* and on the contribution to overall economic growth of the various industries. A few preliminary choices are necessary in order to be able to carry out an empirical study. The first is how to represent production at the industry level. Next, the measure of productivity to be used has to be chosen. Finally, it has to be determined what measures technological progress.

The standard way to represent production at the industry level is through a production function, namely a relation linking industry's output and inputs. Gomulka (1990) defines the industry technology as "the collection of all the firm-specific technology sets, each of which contains the production techniques of one firm in the industry". Nelson (1989) pointed out the conceptual difficulties of growth accounting when analysing big changes in technology¹⁹. However, we do not know of other specifications available to describe the productive process at the industry level. As such, we will follow the standard approach and use a production function, in a Cobb-Douglas specification with constant returns to scale. One of its interpretations is that it

¹⁷ See Cohen and Levin (1989).

¹⁸ See Dosi (1990).

¹⁹ According to Nelson (1990) "First there is the question of how to specify the function relating output to inputs and technology, or one relating costs to factor prices and technology, ignoring the issue of aggregation. Second, a difficult identification problem arises if one tries to estimate both the elasticity of substitution and the sensitivity of innovation to factor prices. Third, recognition that beneath industry

is the production process of the representative neoclassical firm. Otherwise, it may be thought as some sort of average of the production techniques used by the firms in the industry.

Two measures of productivity are traditionally used to study the economic impact of technological change. The first one is the growth rate of *total factor productivity*. In its more general definition, given by Geroski (1990) “to identify total factor productivity growth in any industry i at time t , one needs to subtract an appropriately weighted sum of the rates of growth of inputs from the rate of growth of output”. The weights normally used are based on the shares of capital and labour in output²⁰. The definition of total factor productivity corresponds closely to the concept of separability of movements along the production function and movements from the production function. The second measure is the growth rate of *labour productivity*, that is the growth rate of the value of output per head eventually corrected for changes in labour utilisation²¹. As noted by Kendrick (1991) “Partial productivity ratios reflect factor substitutions in response to technological developments and changes in factor prices, as well as changes in productive efficiency”. Which measure of productivity to use is mainly related to the definition of technological progress. In this work, we have decided to take labour productivity as a measure of productivity for the following reasons. First, we believe that investments in technologically advanced capital goods are one of the most important sources of technological improvements. It is easier, and more theoretically sound, to analyse the technological content of capital goods on the basis of labour productivity growth rather than total factor productivity growth. Then,

level aggregation lies considerable inter-firm variation raises some interesting questions about how industry level functions should be interpreted”.

²⁰ For a complete discussion see Cameron (1996).

²¹ The average number of hours worked is the usual proxy for labour utilisation.

as noted by Nelson (1989) “almost any change in technique contains at least a modicum of technological change, if that term is meant to connote a change in the things firms know how to do reliably and profitably.”

²⁰ For a complete discussion see Cameron (1996).

²¹ The average number of hours worked is the usual proxy for labour utilisation.

as noted by Nelson (1989) “almost any change in technique contains at least a modicum of technological change, if that term is meant to connote a change in the things firms know how to do reliably”. Finally, theoretical models show that²², if the production process is characterised by constant returns to scale and an approximately constant capital-to-output ratio, the growth rate of labour productivity is a good proxy for the effects of technological change on output growth even in a standard neoclassical framework.

We are now left with the problem of measuring technology. Unfortunately, technological indicators are quite often selected more on the basis of data availability than of theoretical considerations²³. Research and development expenditures and the number of patents are amongst the most frequently used indicators of technological change²⁴. However, their explanatory power presents a number of shortcomings²⁵. First, R&D expenditures are input measures in the production process of new knowledge. The discovery of innovations is a highly uncertain and time-consuming process. This means, on the one hand, that not everything spent on R&D generates technological progress²⁶. Moreover, the conditions of technological opportunity may affect the efficacy of the process of search for novelty. On the other hand, current technological improvements are probably the cumulative result of R&D expenditures made in the past. As such, it is important to take into account the lagged and

²² See Gomulka (1990) and Geroski (1994).

²³ OECD and the European Commission are among the international organisations most concerned with the development of technological indicators on internationally comparable basis.

²⁴ Others include the number of scientists and engineers engaged in R&D activities, bibliometric indicators, the decomposition of R&D expenditures into basic research, applied research and development, and the composition of R&D expenditures by financial sources.

²⁵ A wide body of literature is concerned with the relationship between R&D expenditures and number of patents and their efficacy as indicators of technological change. See among the others Pavitt (1982), Griliches (1984), Evenson (1991), Verspagen (1991), Geroski (1994).

incremental characteristics of the R&D process. One additional problem is that R&D expenditures do not reflect innovative efforts that are generated outside formalised research structures²⁷.

Patent data are output measures of the innovating process. But, as noted earlier, the propensity to patent depends on the industry appropriability conditions. As reported by Cohen and Levin (1989), there is empirical evidence that, while the appropriability issue is seriously considered when starting an R&D project, patents are regarded as a necessary incentive for innovation in only a few industries. In most cases, firms prefer to rely on investment in complementary assets (such as marketing, customer services) or on the inherent cost of imitation or, again, on the advantage of specific know-how to prevent early stage imitation. Likewise, international differences in the legal regulation to grant patents, secrecy conditions and selection mechanisms seriously affect the power of patent count data as indicators of technological change.

Moreover, both R&D expenditures and the number of patents are indicators of internal innovative efforts (or internally generated technological change) only. They do not measure “acquired” improvements in productivity due to the use of technologically improved capital goods.

To get a complete specification of the industrial technological status it is necessary to take into account the inter-industry flows of innovations. There are three main channels of inter-industry diffusion of innovations: purchases of technologically improved capital goods, purchases of technologically improved intermediate goods and spillover effect. According to Griliches (1979) “spillover effect is the effect of

²⁶ It may be argued that even unsuccessful R&D has a positive effect on technological change, by enhancing the general pool of knowledge through spillover effects.

outside knowledge capital - outside the firm or industry in question - on the within industry productivity. The level of productivity achieved by one firm or industry depends not only on its own research efforts but also on the level and size of the pool of general knowledge accessible to it". At a theoretical level it is possible to distinguish among knowledge spillovers, rent spillovers and the technological flows embodied in capital and intermediate goods²⁸. Knowledge spillovers represent the free contribution of own R&D efforts to the general pool of knowledge. They arise because the economic benefits of new knowledge or new technology cannot be entirely appropriated by the firm that develops them. Rent spillovers arise when suppliers firms are unable to raise prices proportionally to quality improvements of their products. Supplied firms (or consumers) will then gain free benefits from outside innovation. Finally, new technology can be bought by purchasing technologically advanced intermediate and capital goods. Clearly, such a distinction is possible at a theoretical level only²⁹. Empirically, the role of technologically improved capital goods in labour productivity growth has been analysed taking some normalised measure of gross capital formation as an indirect indicator of the introduction of innovations embodied in capital goods³⁰.

The technological content of capital goods is usually proxied by the weighted average of suppliers R&D expenditures, using as weights the input-output coefficients of investment purchases. Other possible approaches go through the specification of an

²⁷ See Geroski (1994).

²⁸ See Verspagen (1996) and (1997), and Papacostantinou, Sakurai, Wyckoff (1996).

²⁹ In particular, Griliches and Lichtenberg (1984) point to the difficulties of constructing a price deflator that takes into account "costless" quality improvements.

³⁰ See Pianta (1995) for an empirical analysis, and Papacostantinou, Sakurai, Wyckoff (1996) for a theoretical discussion.

investment function and the analysis of the effects of own and suppliers R&D expenditures on investment³¹.

Technologically induced quality changes in intermediate products are, again, usually proxied by the weighted average of suppliers R&D expenditures, using as weights the input-output coefficients of intermediate materials purchases³².

As to the spillover effect measurement, it follows one of two main approaches: the first one is based on R&D expenditures, the second one is based on patent data.

In the first approach, total factor productivity is the productivity measure and the spillover effect is given by a weighted sum of outside R&D expenditures³³. The weights used are usually derived on the basis of input-output tables, or on the purchases of capital and intermediate inputs or, again, according to some definition of distance as from official industrial classification schemes. More rarely, they have been estimated econometrically³⁴.

The second approach uses specific datasets with information about the source and first user of a certain patented innovation³⁵. The productivity measure is labour productivity and the spillover effect is proxied by the number of innovations used by industry. The impact of outside innovations on productivity is estimated econometrically. In other specifications, the spillover effect is again proxied by the weighted sum of outside R&D expenditures. The weights are computed on the basis of the innovation flows derived from the patent data. This approach certainly has provided most valuable information about the intersectoral flows of technology. Nevertheless, it has some limitations. First, all the problems discussed earlier about

³¹ See Nickell and Nicolitsas (1997).

³² See Greenhalgh and Gregory (1997).

³³ See e.g. Griliches (1979); Papacostantinou, Sakurai, Wyckoff (1996); and Nickell and Nicolitsas (1997).

³⁴ See Srinivasan (1996).

the use of patent data obviously apply. Then, specific surveys are often necessary in order to collect the information needed. This means that the results may possibly present a sample selection bias and that international comparisons are very difficult. Moreover, data are not usually available for intertemporal comparisons.

We will adopt here the following approach: first, we will use as technological indicators of in-house innovative activities both R&D expenditures, patent data and the number of scientists and engineers normalised by the labour force. In this way, we hope to compensate the various data shortcomings described above. Then, we will classify and analyse our industries in terms of internally generated and externally acquired technology. We will initially use data on investment as a proxy for externally acquired technology. Due to data limitations, we will not consider the role played by technologically improved intermediate goods. Next, we will decompose aggregate productivity growth in its sectoral components and analyse the contribution of each industry to aggregate productivity growth over selected time periods. Finally, we will analyse the impact of the internal sources of innovations on employment and labour productivity.

I.2 The data

In order to perform our analysis, we had to create a specific dataset. It covers all industries (manufacturing and non-manufacturing) of the UK economy and contains annual data from 1966 to 1993³⁶. We choose an (ideal) industrial disaggregation at the

³⁵ See Robson, Townsend and Pavitt (1988), Geroski (1994) and Verspagen (1997).

³⁶ The data for the number of patents are available from 1969 only.

2-digit level. We have not been able to exactly achieve this level of disaggregation because between 1966 and 1993 there have been three changes in the UK official standard industrial classification (SIC). These classifications are known as SIC 1968, SIC 1980, and SIC 1992. While the correspondence between SIC 1968 and SIC 1980 is fairly good, the SIC 1992 presents major changes with respect to the previous ones. Changes in the classification and the lack of more disaggregated data have prevented an exact 2-digit classification, and we have been obliged to aggregate some of the industries. The dataset is thus based on the following industrial sectors:

Table I.1: Industrial sectors composing the database

		2-digit SIC80 class
Group 1	Agriculture	01, 02, 03
Group 2	Extractive	11, 12, 13, 21, 23
Group 3	Non Metallic	24
Group 4	Metal and Mechanical	22, 31, 32, 33
Group 5	Electrical and Instruments	34, 37
Group 6	Food, Drink and Tobacco	41, 42
Group 7	Textile, Leather and Clothing	43, 44, 45
Group 8	Timber and Wood	46
Group 9	Paper	47
Group 10	Chemicals, Transport, MNES	14, 15, 25, 26, 35, 36, 48, 49
Group 11	Constructions	50
Group 12	Electricity, Gas and Water	16, 17
Group 13	Distribution, Hotels, Repairs	6
Group 14	Transport and Communications	7
Group 15	Financial, Education, Health and Other services	8, 9

In the 2-digit Standard Industrial Classification 1980 our groups are thus composed of the following industries:

Group 1: Agriculture and Horticulture, Forestry, Fishing

Group 2: Coal Extraction and Manufacture of Solid Fuels, Coke Ovens, Extraction of Mineral Oil and Natural Gas, Extraction and Preparation of Metalliferous Ores, Extraction of Minerals not elsewhere specified

Group 3: Manufacture of non-metallic Mineral Products

Group 4: Metal Manufacturing, Manufacture of Metal Goods not elsewhere specified, Mechanical Engineering, Manufacture of Office Machinery and Data Processing Equipment

Group 5: Electrical and Electronic Engineering, Instrument Engineering

Group 6: Food, Drink and Tobacco Manufacturing Industries

Group 7: Textile industry, Manufacture of Leather and Leather Goods, Footwear and Clothing industries

Group 8: Timber and Wooden Furniture industries

Group 9: Manufacture of Paper and Paper products; Printing and Publishing

Group 10: Mineral Oil Processing, Nuclear Fuel Production, Chemical industry, Production of man-made Fibres, Manufacture of Motor Vehicles and Parts thereof, Manufacture of Other Transport Equipment, Processing of Rubber and Plastics, Other Manufacturing industries

Group 11: Construction

Group 12: Production and Distribution of Electricity, Gas and Other Forms of Energy, Water Supply industry

Group 13: Wholesale Distribution, Dealing in Scrap and Waste Materials, Commission Agents, Retail Distribution, Hotels and Catering, Repair of Consumer Goods and Vehicles

Group 14: Railways, Other Inland Transport, Sea Transport, Air Transport, Supporting Services to Transport, Miscellaneous Transport Services and Storage not elsewhere specified, Postal Services and Telecommunications

Group 15: Banking and Finance, Insurance, except for compulsory social security, Business Services, Renting of Movables, Owning and Dealing in Real Estate, Public Administration, National Defence and Compulsory Social Security, Sanitary Services, Education, Research and Development, Medical and other Health Services: Veterinary Services, Other Services Provided to the General Public, Recreational Services and Other Cultural Services, Personal Services, Domestic Services

To better understand how the groups' composition arose, let us take the example of group 4. The SIC 1980 two-digit classes 22 (Metal manufacturing) and 31 (Manufacture of metal goods n.e.s.) were aggregated because both comprise parts of the same SIC 1968 three digit class (for example class 313, Iron castings, etc.). Similarly, for group 10, the SIC 1968 494 class (Toys, games, children's carriages, and sports equipment) is comprised in both the SIC 1980 36 (Manufacture of other transport equipment) and 49 (Other manufacturing industries) classes, that were therefore aggregated. For each group we collected the following variables: Expenditures on Research and Development, Weekly Hours worked, Domestic Price Deflator, Investment, Capital Stock, Number of patents, Number of Scientists and Engineers engaged in research activities, Employment, Value Added. Moreover, we get the aggregate (whole economy) GDP and Employment series.

The dataset is the result of a work of matching and co-ordination of different data sources. We collected data from various CSO publications³⁷, from the OECD International Sectoral Database (ISDB) and from the Labour Force Survey (LFS).

The patent data we use here are those granted by the US Patent Office to UK firms or to multinationals whose main centre of activity is in the UK³⁸. By doing so, we miss out on patents by foreign multinationals who locate their innovations in the UK, while we include innovations patented by parent companies located outside the UK. This bias might be partially avoided using the information on the location of the inventor appearing on the patent sheet³⁹. However, as reported by Jaffe et al. (1993), even this adjustment does not completely guarantee against improper patents attributions. In particular, employees of multinational corporations may decide on the assignement of the patent to the head company or to a parent company, preventing an exact localisation matching⁴⁰. Principally because of the impressive amount of work that this adjustment would have asked, we decided on the patent attribution based on the multinational main country of activity. Patents were attributed to industries according to the main sector of activity of the owner firm⁴¹.

We deflated R&D expenditures with a price index developed in Cameron (1996).

According to Cameron (1996), wages and salaries are the largest components of R&D

³⁷ Annual Abstract of Statistics, Blue book of United Kingdom National accounts, Business Monitor, Census of Production, Economic Trends, Employment Gazette, Monthly Digest of Statistics, Statistics of Science and Technology.

³⁸ We choose these data for two reasons. First, it seems that the US Patent Office has a reliable selection procedure to process the patent applications. Thus, our data should include only fairly relevant inventions. Second, the patent right applies in the country where the patent has been granted only. Given that the US is the largest developed market, our data should be good indicators of the firms innovative success.

³⁹ This information has been used by Jaffe et al. (1993) and Bloom and Van Reenen (2000).

⁴⁰ Cfr. Jaffe et al. (1993), footnote 13, pag. 585.

⁴¹ To get the data at the industry level, we first found the SIC firms' codes, and then aggregated the data according to the needed classification. The databases we used to get the SIC firms' codes are: Exstat, Extel - Company Research, Key British Enterprises and the UNITSIC codes from the SPRU database user manual.

costs (around 47%). As such, it is advisable to use a specific price index for R&D expenditures taking into account this predominance of labour costs. The use of a general deflator, like the GNP deflator, would in fact overestimate the real level of R&D expenditures. Cameron (1996) computes Divisia indices of the cost of R&D between 1970 and 1992 for seven broad sectors of UK manufacturing. We have extended these data to cover our whole period of observation and range of industries.

While the inclusion of data for the service sector is a major element of novelty of the dataset, it also poses a number of difficulties. In terms of the series used in this work, gathering data for service sectors' R&D expenditures has been particularly problematic. In fact, it is only since 1981 that these data have been collected on regular basis. For the years before 1981, only rough and incomplete data are at best available. To solve this problem we decided to investigate possible econometric relationships among sectors, and to use these relationships to provide backward estimates of the missed values⁴². More generally, it is well known that the quality of economic data referring to the service sector is quite often lacking. This is both because the sector comprises many small economic activities (e.g. retail sales) that are difficult to monitor, and because of conceptual difficulties at evaluating services not sold on the market. For example, the output of the public sector is generally evaluated on the basis of labour and capital costs, because of the difficulty at obtaining reliable market prices for the services it provides. Poor quality data may also be expected for those services that have been privatised in the recent past and are now under the control of regulators, such as telecommunications and air and road transports. In these cases, the data will not generally support the empirical regularities predicted by

economic theory under the assumption of perfect competition, and fluctuations and inconsistencies may be expected following the various steps of implementation of the privatisation process.

Unfortunately, there are no agreed upon statistical procedures to solve these problems, likely to affect the robustness of the econometric estimates shown here. As such, we decided to rely on the data as the best possible available ones, while pointing out and discussing each occurrence in which there is strong suspicion that these problems may be biasing the empirical results. Overall, we had to use some statistical ingenuity to cope with disaggregation and missing data problems. Despite this, we judge the dataset's informative content overall reliable.

I.3 The industrial technological classification

We begin in this section the analysis of the technological characterisation of industries. Our target is to classify industries for being mainly producers or users of innovation. An industry is a technology producer if most of its innovative activities are performed in-house, while is a technology user if it relies most on technology acquired from other industries. We have used both the Capital to Output and Capital to Labour ratios as indicators of the degree of externally acquired technology. The final classification does not show significant changes with respect to the two measures. As an indicator of internally generated technology, we have computed an index based on the principal component analysis of R&D expenditures, number of scientists and engineers, and number of patents. More specifically, to compute this indicator we have first normalised by year all the above variables. Next, we computed

⁴² See the data appendix to this chapter for a detailed description of the procedures used.

for each variable the average by sector over the whole time period. Finally, we took the first principal component of the averages (explaining 72.2% of the total variance, see Table I.3) and computed the indicator of internally generated technology by year and sector by multiplying the values of R&D expenditures, number of scientists and engineers and number of patents by the respective coefficients of the principal component (Table I.4).

Tables I.2 to I.4 show the correlation coefficients and the results of the principal component analysis. From the correlation matrix we see that there is significant positive correlation between R&D expenditures and the number of patents, and between R&D expenditures and the number of scientists and engineers.

Table I.2: Correlation Matrix

		<i>Number of patents</i>	<i>R&D Expenditures</i>	<i>Number of Scientists and Engineers</i>
<i>Correlation</i>	<i>Number of patents</i>	1.000	.652**	.464
	<i>R&D Expenditures</i>	.652**	1.000	.626*
	<i>Number of Scientists and Engineers</i>	.464	.626*	1.000
<i>Sig. (1-tailed)</i>	<i>Number of patents</i>		.004	.041
	<i>R&D Expenditures</i>	.004		.006
	<i>Number of Scientists and Engineers</i>	.041	.006	

** Correlation is significant at the 1% significance level (1-tailed)
 *Correlation is significant at the 5% significance level (1-tailed)

Table I.3: Total Variance Explained

	<i>Initial Eigenvalues</i>		
<i>Component</i>	<i>Total</i>	<i>Percentage of Variance Explained</i>	<i>Cumulative Percentage of Variance Explained</i>
1	2.165	72.172	72.172
2	.536	17.880	90.051
3	.298	9.949	100.000

Extraction Method: Principal Component Analysis.

Table I.4: Component Matrix

	<i>First Principal Component</i>
<i>Number of patents</i>	.829
<i>R&D Expenditures</i>	.902
<i>Number of Scientists and Engineers</i>	.815

Extraction Method: Principal Component Analysis.

The correlation between number of patents and number of scientists and engineers is high but not significant. This fact confirms the observations made in Section 1 about the different explanatory power of each of these variables.

We have identified four typologies of industries according to the indicators of internally generated and externally acquired technology: *technology producer*, *technology user and producer*, *technology user* and *low technology* industries. *Technology producer* industries are all industries for which the indicator of internally generated technology is high and the level of capital intensity is medium or low. This class comprises groups 4, 5, 10, 11, 12, and 15.

Technology user and producer industries (groups 2 and 6) have a medium level of both the index of internally generated technology and capital intensity.

Technology user industries have a low level of the index of internally generated technology and a medium to high level of capital intensity. These are groups 1, 3, 9, and 14.

Finally, *low technology* industries (groups 7, 8, and 13) have a low value of both the index of internally generated technology and capital intensity.

Whenever the index of internally generated technology and capital intensity were discordant, we have decided the attribution to the class on the basis of the first index.

The classification is fairly stable over the period analysed. In particular, while there is evidence of changes in the relative position of some groups in each typology, we do not find changes in the overall class composition. As a first approximation, this result may be explained in terms of a high degree of path dependency in the industrial technological structure and of absence of big changes in the technological fundamentals over the years 1966-1993. That is, during these years technological progress has been more in the direction of incremental improvements rather than radical changes in the methods of production. Certainly, more complete analysis are necessary in order to prove these findings.

Note that our classification roughly resembles the ones presented in Robson, Townsend and Pavitt (1988), and Geroski (1994), based on survey data about production and use of technological innovations; and the one in Buxton and Clokie (1992) based on the classification of industries according to the R&D to Sales ratio.

I.4 GDP, Employment and Labour Productivity

In this section, we start investigating the observed growth patterns of GDP, Employment and Labour Productivity⁴³. We analyse in particular the extent to which each industrial group contributes to the growth of aggregate labour productivity. We

will then look at how the relative shares of employment and productivity determine such contributions. Our scheme of analysis is based on the causality flow running from technological improvements to changes in production and employment. Roughly speaking, we can think of an ordering of the effects of technological change in the following sequence. First, labour productivity increases, so employment per unit of output falls. Then output expands both because the increase in labour productivity reduces costs and hence output prices and because technological change generates improved goods. Then, as noted before, the global outcome on employment will depend on the relative strength of the factor substitution and demand expansion effects.

Graphs A.1 to A.6 in Appendix I.A show, respectively, the levels and growth rates of GDP, aggregate employment and labour productivity over the period 1966-1993.

Over the whole period aggregate labour productivity has had a 54% increase. GDP has increased by 40% and aggregate employment⁴⁴ has decreased by 11%. Anyway, while there is evidence of a decreasing trend in aggregate employment, it must be taken into account that the series shows a strongly cyclical pattern. In particular, the year 1993 seems to mark a recessive phase. The figures for 1991, when one cycle completed, are 47% growth for labour productivity, 44% growth for GDP and 5% decrease for employment.

We can identify three cycles in the pattern of aggregate employment. The first one goes from 1966 to 1974 and shows employment decreasing by 3% in 1970 and 1971 before approximately going back to its 1966 level in 1974. The second one goes from

⁴³ In this and what follow we will consider Labour Productivity adjusted for the number of hours worked. However, excluding the correction for the number of hours worked does not change significantly the results.

⁴⁴ The employment measure we consider here is in terms of number of hours worked or men-hours.

1974 to 1979 and shows employment decreasing by 3% in one year (in 1975) as an effect of the first oil shock. The third one goes from 1979 to 1991 and includes the big depression caused by the second oil shock (employment fell by 11% between 1979 and 1983) and the expansion in the late eighties.

Labour productivity follows a generally increasing trend except for the two negative peaks in 1974 and 1991, corresponding to the years of maximum employment expansion.

We decompose aggregate labour productivity growth in its sectoral components according to the following formula. Let x_t indicate aggregate labour productivity and x_{it} and λ_{it} the, respectively, labour productivity and employment share of industry i ($i = 1, \dots, 15$). The change between an initial year $t = 0$ and a final year $t = T$ of aggregate labour productivity is then given by:

$${}_0\Delta_T x = \sum_i (\lambda_{iT} x_{iT} - \lambda_{i0} x_{i0}) = \sum_i [\lambda_{iT} (x_{iT} - x_{i0}) + (\lambda_{iT} - \lambda_{i0}) x_{i0}] \quad [1]$$

The sectoral contribution to aggregate productivity growth is thus determined by two components. The first one, $\lambda_{iT}^*(x_{iT} - x_{i0})$, is the change in labour productivity multiplied by the employment share in the final year. The second one, $x_{i0}^*(\lambda_{iT} - \lambda_{i0})$, is the change in employment share multiplied by the level of productivity in the initial year. The first component is normally referred to as the ‘within effect’, representing the contribution made by productivity growth within individual sectors⁴⁵. The second term is the ‘between effect’, representing the contribution made by the reallocation of production factors between sectors with different levels of productivity.

It is worth noting that the between effect, $\sum_i (\lambda_{iT} - \lambda_{i0}) x_{i0}$, can be rewritten as⁴⁶:

⁴⁵ Cfr. Cameron et al. (2000).

⁴⁶ Being $\sum_i \lambda_{iT} = \sum_i \lambda_{i0} = 1$.

$$\sum_i (\lambda_{iT} - \lambda_{i0}) * x_{i0} = \sum_i (\lambda_{iT} - \lambda_{i0}) * (x_{i0} - \bar{x}_0) + (\lambda_{iT} - \lambda_{i0}) * \bar{x}_0 \quad [2]$$

where $\bar{x}_0$ is the average level of labour productivity in the initial year. The second term of equation [2] is a pure employment share growth effect, positive for increasing employment shares and negative for decreasing employment shares. The first term in equation [2] links changes in employment shares to the productivity position of the industry in the initial year. Interestingly, this term is positive whenever both factors are of the same sign. Thus both employment share expansion of industries whose productivity in the initial year is above average, and employment share contraction of industries whose productivity in the initial year is below average, are potentially beneficial to aggregate productivity growth⁴⁷. However, for decreasing employment shares the pure employment share growth effect is likely to dominate, causing an overall negative contribution to aggregate growth of between-industry productivity growth. We will refer to the first term of equation [2] as “productivity adjusted changes in employment shares”.

The decomposition of aggregate productivity growth in its sectoral components is not unique⁴⁸, depending in particular on the structure of weights adopted. In order to check for its robustness, we have repeated the analysis with the opposite weight structure, i.e. employment share in the initial year and final year level of productivity. The results obtained are robust with respect to the weight structure adopted.

The percentage contribution of each industry to aggregate labour productivity growth, and its determinants (i.e. productivity adjusted changes in employment shares and labour productivity growth), for the periods 1966-1993, 1966-1991 and 1966-1974,

⁴⁷ The reason for this is that we are considering movements in employment shares. Thus if industries with below average labour productivity decrease their employment shares, then the employment shares of industries with labour productivity on or above average must be increasing.

1974-1979, 1979-1991 are reported in Tables I.5 to I.9, while Table I.10 reports, for the same time periods, the contribution by technological group.

Some interesting results emerge. First, between 1966 and 1993 all industries except group 13 (Distribution, Hotels and Repairs) have experienced increases in labour productivity. Second, while for most industries and at the aggregate level positive contributions are essentially due to within-industry productivity growth, for groups 13 and 15 the opposite is true. Despite the use of data at different levels of aggregation⁴⁹, this result is in accordance and qualifies the evidence reported in other empirical studies. Cameron et al. (2000), for example, find for UK manufacturing industries over the years 1970 to 1992 a preponderant importance of within-industry productivity growth as compared to sectoral shifts of resources⁵⁰. Our results confirm this finding, but also show that for some service industries between-industry growth is the main determinant of their contribution to aggregate productivity growth. Third, on average, productivity grows faster in those industries whose initial productivity levels are lower than average. This suggests the existence of catching up phenomena at the industry level.

⁴⁸ Cfr. Gregory and Greenhalgh (1996).

⁴⁹ The decomposition in equation [1] may not be invariant to the level of aggregation of the data, cfr. Appendix I.B.

⁵⁰ Within-industry growth is found to account for as much as 97% of total manufacturing labour productivity growth, cfr. Cameron et al. (2000).

Table I.5: 1966-1993 sectoral contribution to aggregate labour productivity growth

	% Contribution $[(\lambda_{i,T}x_{i,T}-\lambda_{i,0}x_{i,0})/\Delta_Tx_i]*100$	Within effect	Between effect	Productivity adjusted L share effect	Pure L share growth effect	% Growth Employment Shares $[(\lambda_{i,T}-\lambda_{i,0})/\lambda_{i,0}]*100$	Share Employment 1993 $\lambda_{i,T}$	Level of Labour Productivity 1966 $x_{i,0}$	% Growth Labour Productivity $[(x_{i,T}-x_{i,0})/x_{i,0}]*100$	% Value Added	% Growth Employment	% Deviation from average labour productivity 1966
TOTAL	100	78.7	21.3	17.2	4.1			239	54	40	-11	
GR1	2.3	3.8	-1.5	1.2	-2.7	-56	0.01	132	32	64	-61	-45
GR2	1.5	6.3	-4.8	-0.6	-4.2	-84	0.005	275	667	12	-85	15
GR3	-0.9	0.8	-1.7	-0.4	-1.3	-51	0.01	304	48	-36	-57	27
GR4	-1.2	5.4	-6.6	1.7	-8.3	-49	0.05	189	78	-19	-55	-21
GR5	3.2	4.8	-1.6	1.2	-2.8	-39	0.03	139	186	55	-46	-42
GR6	2.6	4.6	-2	-0.03	-1.9	-34	0.02	242	119	28	-41	1
GR7	-0.6	1.6	-2.3	2.9	-5.2	-61	0.02	104	114	-26	-66	-56
GR8	-0.27	0.3	-0.5	0.04	-0.6	-28	0.01	221	20	-24	-36	-7
GR9	2.7	3.7	-1	-0.1	-0.9	-19	0.02	272	90	36	-28	14
GR10	4	10.4	-6.4	-1.1	-5.3	-40	0.05	291	106	10	-46	22
GR11	2.7	9.5	-6.7	-0.7	-6	-46	0.04	266	122	5	-53	11
GR12	838	9.8	-1.1	0.3	-1.4	-45	0.01	180	777	323	-52	-25
GR13	8.2	-0.2	8.3	0.8	7.6	26	0.21	262	-0.47	11	12	10
GR14	13.5	15.3	-1.7	0.4	-2.1	-16	0.06	191	170	101	-26	-20
GR15	53.5	2.6	50.8	11.5	39.3	99	0.46	309	3	80	76	29

Table I.6: 1966-1991 sectoral contribution to aggregate labour productivity growth

	% Contribution $[(\lambda_{i,T}x_{i,T}-\lambda_{i,0}x_{i,0})/\Delta_Tx_i]*100$	Within effect	Between effect	Productivity adjusted L share effect	Pure L share growth effect	% Growth Employment Shares $[(\lambda_{i,T}-\lambda_{i,0})/\lambda_{i,0}]*100$	Share Employment 1991 $\lambda_{i,T}$	Level of Labour Productivity 1966 $x_{i,0}$	% Growth Labour Productivity $[(x_{i,T}-x_{i,0})/x_{i,0}]*100$	% Growth Value Added	% Growth Employment	% Deviation from average labour productivity 1966
TOTAL	100	76.7	23.3	18.4	4.9			239	47	44	-5	
GR1	2.6	4.2	-1.6	1.3	-2.9	-53	0.01	132	294	76	-55	-45
GR2	4.2	8.4	-4.2	-0.6	-3.7	-65	0.01	275	365	56	-66	15
GR3	-0.8	0.7	-1.6	-0.3	-1.2	-43	0.01	304	35	-27	-46	27
GR4	0.5	7.6	-7.1	1.8	-8.9	-46	0.05	189	92	-1	-49	-21
GR5	3	4.7	-1.7	1.2	-2.9	-35	0.03	139	149	55	-38	-42
GR6	3.1	4.7	-1.6	-0.02	-1.6	-25	0.02	242	96	40	-28	1
GR7	-0.3	2.2	-2.5	3.3	-5.8	-60	0.02	104	131	-12	-62	-56
GR8	-0.2	0.2	-0.4	0.03	-0.4	-18	0.01	221	9	-15	-22	-7
GR9	2	3.1	-1.1	-0.1	-1	-19	0.02	272	66	28	-23	14
GR10	1.1	7.2	6	-1.1	-5	-33	0.05	291	58	0.9	-36	22
GR11	2.6	9.2	-6.6	-0.7	-6	-40	0.04	266	94	10	-43	11
GR12	8.6	9.7	-1.1	-0.4	-1.5	-42	0.01	180	637	307	-45	-25
GR13	5.3	-2.7	8	0.7	7.3	22	0.20	262	-6	9	16	10
GR14	12.2	14.2	-2	0.5	-2.5	-17	0.06	191	141	91	-21	-20
GR15	56.2	3.2	53	12	41	91	0.44	309	3	87	82	29

Table I.7: 1966-1974 sectoral contribution to aggregate labour productivity growth

	% Contribution $[(\lambda_{i,T}x_{i,T}-\lambda_{i,0}x_{i,0})/\Delta_Tx_i]*100$	Within effect	Between effect	Productivity adjusted L share effect	Pure L share growth effect	% Growth Employment Shares $[(\lambda_{i,T}-\lambda_{i,0})/\lambda_{i,0}]*100$	Share Employment 1974 $\lambda_{i,T}$	Level of Labour Productivity 1966 $x_{i,0}$	% Growth Labour Productivity $[(x_{i,T}-x_{i,0})/x_{i,0}]*100$	% Growth Value Added	% Growth Employment	% Deviation from average labour productivity 1966
TOTAL	100	79.3	20.7	16.5	4.2			239	15	12	-3	
GR1	2.8	5.9	-3.1	2.5	-5.6	-31	0.02	132	86	24	-33	-45
GR2	-0.2	8.7	-8.9	-1.2	-7.7	-41	0.02	275	69	-4	-43	15
GR3	3.3	4.3	-1	0.2	-0.8	-8.3	0.01	304	39	23	-11	27
GR4	16.1	20.6	-4.5	1.2	-5.7	-8.9	0.09	189	45	28	-12	-21
GR5	6.8	6.8	-0.02	0.01	-0.03	-0.1	0.04	139	43	39	-3	-42
GR6	10.5	10.3	0.2	0	0.2	0.9	0.03	242	47	44	-2	1
GR7	4.5	6.5	-2	2.5	-4.5	-14.3	0.04	104	55	28	-17	-56
GR8	0.8	0.7	0.04	0	0.04	0.5	0.01	221	10	7	-3	-7
GR9	3.4	4.1	-0.7	-0.1	-0.6	-3.8	0.03	272	22	14	-7	14
GR10	4.8	5.1	-0.3	-0.1	-0.2	-0.5	0.08	291	8	4	-4	22
GR11	3.4	12.8	-9.5	-1	-8.5	-17.6	0.06	266	29	3	-20	11
GR12	1.1	2.5	-1.4	0.5	-1.8	-16	0.01	180	34	9	-19	-25
GR13	-12.8	-14.5	1.7	0.2	1.5	1.4	0.17	262	-12	-14	-2	10
GR14	15.6	17.4	-1.8	0.4	-2.2	-4.5	0.07	191	46	35	-7	-20
GR15	39.9	-12	51.9	11.8	40.1	27	0.29	309	-5	17	23	29

Table I.8: 1974-1979 sectoral contribution to aggregate labour productivity growth

	% Contribution $[(\lambda_{i,T}x_{i,T}-\lambda_{i,0}x_{i,0})/\Delta_Tx_i]*100$	Within effect	Between effect	Productivit y adjusted L share effect	Pure L share growth effect	% Growth Employment Shares $[(\lambda_{i,T}-\lambda_{i,0})/\lambda_{i,0}]*100$	Share Employment 1979 $\lambda_{i,T}$	Level of Labour Productivity 1974 $x_{i,0}$	% Growth Labour Productivity $[(x_{i,T}-x_{i,0})/x_{i,0}]*100$	% Growth Value Added	% Growth Employment	% Deviation from average labour productivity 1974
TOTAL	100	97.5	2.5	1.6	0.9			276	6	5	-0.80	
GR1	0.5	3.7	-3.2	0.4	-3.6	-12	0.02	246	15	1	-13	-11
GR2	32	32.2	-0.4	-0.2	-0.2	-0.8	0.02	463	72	70	-2	68
GR3	-8	-3.2	-4.8	-1.7	-3.2	-15	0.01	421	-12	-25	-16	53
GR4	-16	-1.2	-14.4	0.1	-14.5	-10.3	0.08	274	-1	-12	-11	-0.5
GR5	-1.7	3.3	-4.9	1.9	-6.8	-10.4	0.04	199	8	-4	-11	-27.7
GR6	-4.7	0.1	-5.7	-1.3	-4.5	-8.4	0.03	356	2	-8	-9	29.3
GR7	-5.1	0.8	-5.9	4.1	-10	-15	0.04	162	2	-14	-16	-41.3
GR8	-1.5	0.1	-1.6	0.2	-1.8	-9.6	0.01	243	1	-10	-10	-11.8
GR9	-3.2	0.4	-3.7	-0.6	-3	-7.7	0.02	333	1	-8	-8	20.8
GR10	-16	10.8	-5.1	0.6	-4.5	-3.7	0.07	315	-8	-12	-4	14.2
GR11	-0.17	7.1	-7.3	-1.4	-5.9	-6	0.06	342	6	-1	-7	24.2
GR12	19	19	-0.2	0.02	-0.2	-0.8	0.01	241	93	90	-2	-12.5
GR13	9.5	-2.5	11.9	-2.3	14.3	5.4	0.18	231	-1	3	4	-16.3
GR14	10.2	11.9	-1.7	-0.02	-1.6	-1.4	0.07	279	10	8	-2	1.1
GR15	85.1	35.7	49.3	3	46.4	10	0.32	293	7	16	9	6.4

Table I.9: 1979-1991 sectoral contribution to aggregate labour productivity growth

	% Contribution $[(\lambda_{iT}x_{iT}-\lambda_{i0}x_{i0})/\Delta_Tx_i]*100$	Within effect	Between effect	Productivit y adjusted L share effect	Pure L share growth effect	% Growth Employment Shares $[(\lambda_{iT}-\lambda_{i0})/\lambda_{i0}]*100$	Share Employment 1991 λ_{iT}	Level of Labour Productivity 1979 x_{i0}	% Growth Labour Productivity $[(x_{iT}-x_{i0})/x_{i0}]*100$	% Growth Value Added	% Growth Employment	% Deviation from average labour productivity 1979
TOTAL	100	94.7	5.3	-2.5	7.8			293	21	22	-0.90	
GR1	3	4.6	-1.6	0.1	-1.7	-23	0.01	284	83	40	-23	-3.2
GR2	-0.6	7.3	-7.9	-5	-2.9	-39	0.01	799	60	-4	-40	172
GR3	-1.2	0.5	1.7	-0.4	-1.3	-27	0.01	372	10	-20	-27	26.8
GR4	-3.8	7.3	-11.1	0.9	-12	-34	0.05	272	34	-12	-35	-7.4
GR5	2.1	5.4	-3.2	1.2	-4.4	-27	0.03	215	61	17	-28	-26.8
GR6	1	4.1	-3.1	-0.6	-2.5	-18	0.02	362	31	5	-19	23.4
GR7	-1.8	2.2	-4	3.1	-7.1	-45	0.02	166	46	-21	-45	-43.5
GR8	-0.4	-0.1	-0.4	0.1	-0.5	-10	0.01	245	-1	-12	-10	-16.6
GR9	2.6	3.6	-1	-0.1	-0.9	-9	0.02	336	34	21	-9	14.7
GR10	3.6	13.1	-9.6	0.1	-9.7	-30	0.05	289	59	10	-30	-1.4
GR11	2.9	10.2	-7.3	-1.4	-5.9	-23	0.04	364	42	8	-24	24
GR12	10.1	13.2	-3.1	-1.2	-2	-30	0.01	467	184	96	-31	59
GR13	14.2	5.5	8.7	-2.5	11.2	14	0.20	228	8	22	13	-22
GR14	10.8	14.6	-3.8	-0.2	-3.6	-11	0.06	308	49	31	-12	4.9
GR15	57.6	3	54.6	3.4	51.2	36	0.44	313	1	37	35	6.7

Table I.10: Technological Groups’ contribution to aggregate productivity growth

		<i>% Contribution to aggregate productivity change</i>	<i>Average by industry</i>
1966-1993			
	<i>Technology Producer</i>	70.9	11.8
	<i>Technology User and Producer</i>	4.1	2.1
	<i>Technology User</i>	17.7	4.4
	<i>Low technology</i>	7.3	2.4
1966-1991			
	<i>Technology Producer</i>	72.1	12
	<i>Technology User and Producer</i>	7.3	9.6
	<i>Technology User</i>	15.9	4
	<i>Low technology</i>	4.8	1.6
1966-1974			
	<i>Technology Producer</i>	72	12
	<i>Technology User and Producer</i>	10.3	5.2
	<i>Technology User</i>	25.1	6.3
	<i>Low technology</i>	-7.5	-2.5
1974-1979			
	<i>Technology Producer</i>	70.6	11.7
	<i>Technology User and Producer</i>	27.1	13.6
	<i>Technology User</i>	-0.6	-0.1
	<i>Low technology</i>	2.9	0.9
1979-1991			
	<i>Technology Producer</i>	72.5	12.1
	<i>Technology User and Producer</i>	0.4	0.18
	<i>Technology User</i>	15.1	3.8
	<i>Low technology</i>	12	4

Over the period 1966-1991, *technology producer* industries have contributed to 72% of aggregate productivity growth. Their contribution is broadly stable over all the periods analysed and highest across all technological groups. A significant part of the contribution of *technology producer* industries is due to group 15 (Finance, Public Administration, Education, Health and Other services), that alone contributes to about 56% of aggregate productivity growth. In general, groups 14 (Transports, Postal services and Telecommunications) and 15 are the major contributors to aggregate productivity growth, jointly determining more than 65% of aggregate productivity

growth⁵¹. For the period 1974-79, in particular, the contribution of the two groups adds to more than 95%. The contribution of group 15 ranges from a minimum of 40% over the period 1966-74 to a maximum of 85% over the period 1974-79. The contribution of group 14 is more stable and ranges from a minimum of 10.2% over the period 1974-79 to a maximum of 15.6% over the period 1966-74.

Interestingly, the two most important contributions to aggregate productivity growth result from very different sources. First, while the contribution of group 14 is broadly constant over all the periods analysed, the one of group 15 shows an impressive peak for the period 1974-79. Next, with reference to the period 1966-91, the results show that the positive contribution of group 14 is largely due to within-industry productivity growth. As for other groups, productivity adjusted employment share reductions have given a positive contribution to growth⁵², but this effect has been more than compensated by the (negative) pure employment share growth effect.

Overall, the positive contribution of group 14 may be largely ascribed to labour productivity improvements and, to a much lesser extent, to restructuring.

The positive contribution of group 15, instead, is largely due to between-industry growth, accounting for around 94% of the group contribution. This has arisen from both positive pure employment share growth and productivity adjusted employment share effects⁵³. The scarce relevance of within-industry growth is due to the relatively poor labour productivity performance of the group. Labour productivity growth of group 15 is in fact almost negligible and well below average during this period.

⁵¹ For the subperiods 1974-79 and 1979-91 the contributions of groups 12 and 13 were also substantial, sometimes above that of group 14. However, while the contribution of group 14 is consistently high, those of groups 12 and 13 show high variability over sub-periods.

⁵² The productivity of group 14 in 1966 was below average.

⁵³ The productivity of group 15 in 1966 was above average.

Given that Banking and Finance are the two sectors in the UK most often reported to have experienced massive technological change, it is of interest to analyse at a more disaggregated level the contribution of group 15. Also, it would be interesting to identify the factors behind the peak in the contribution of the group in 1974-79. Data are available to investigate separately the contribution of Division 8 (SIC 1980), Banking, Finance, Insurance, Business Services and Leasing, and Division 9 (SIC 1980), Other Services.

Tables A.1 to A.5 in Appendix I.A show the results of the decomposition over the periods 1966-93, 1966-91, 1966-74, 1974-79, and 1979-91 for the two Divisions.

The results show that, since the mid-1970s, the contribution of group 15 is mainly determined by changes taking place in Division 8 (Banking, Finance, Insurance, Business Services and Leasing). The relatively slight contribution of Division 9 is due to the modest dynamics of within-industry growth, almost nihil for the sub-periods 1974-79 and 1979-91. The productivity contribution of Division 8 is essentially the result of between-industry growth. The growth of Division 8 labour productivity is in fact overall negative, although its level remains constantly above average. Only in 1974-79 within-industry growth in Division 8 becomes positive, actually surpassing the between-industry component. This pattern explains the peak in the positive contribution of group 15 observed over the years 1974-79.

The productivity performance of Division 8, and of group 15 as a whole, is at odds with its technological characterisation as a *technology producer* industry, and the sustained growth rate of employment per hour (+86% over the period 1966-1991). However, a number of qualifications apply. As to the adjustments in Division 9, it must be noted that output in the public sector is evaluated on the basis of its costs, made mainly of employment costs. It is thus hardly surprising that the Division shows

very limited labour productivity growth. The contribution pattern of Division 8 is more puzzling, although not economically illogical once it is taken into account that the productivity level of the Division is well above the economy average and in fact the highest among UK industries. It might thus have been profitable to expand employment even with declining productivity growth, with the slowdown in employment growth occurring in 1974 once the productivity level had reached a relative minimum. However, data problems might also be the cause of the contribution pattern of Division 8. The data for 1966 might in fact overestimate the productivity level, thus causing overall negative productivity growth rates.

Also, a number of studies⁵⁴ have recently pointed how not quality adjusting price indices for information and communication technology products may seriously underestimate the output of ITC-producing and ITC-using industries. The internationally observed productivity slowdown in the output of banking, insurance and health care services seems indeed to be the result of price indices measurement problems, and similar considerations might also apply to the UK.

The contribution of the other technological groups shows a high degree of variability. It ranges from 0.4% in 1979-1991 to 27% in 1974-1979 for *technology user and producer* industries; from -0.6% in 1974-1979 to 25.1% in 1966-1974 for *technology user* industries; and from -7.4% in 1966-1974 to 12% in 1979-1991 for *low technology* industries.

The average contribution by industry however remains broadly in accordance with the technological classification, with *technology producer* industries normally contributing most and *low technology* industry least. However, with the exception of

⁵⁴ See, for example, Schreyer (1998).

the period 1974-79, the growth contribution of *technology user* industries is normally higher than that of *technology user and producer*.

Overall, the period 1974-1979 seems to have been particularly difficult for the UK economy. The rate of growth of aggregate labour productivity is at its lowest level (+6%), with 9 groups only giving a positive contribution (1, 2, 12, 13, 14, and 15).

Labour productivity growth at the industry level is also modest, although still positive for the majority of industries. With the exception of groups 13 and 15, positive contributions to aggregate labour productivity growth are determined by within-industry growth. Among these, groups 1 and 12 show a positive productivity adjusted employment share effect, indicating a beneficial productivity growth counterpart to employment reductions. For groups 2 and 14, instead, the productivity adjusted employment share effect is negative, reducing the extent of their positive contribution.

The period 1979-91 is a time of recovery for the UK. Labour productivity and value added grow at a more sustained level than in 1974-79 (the implied five years average growth rates are, respectively, 8.5% and 9%), with employment decreasing at approximately the same rate than in 1974-79⁵⁵. Substantial employment reallocation from manufacturing industries to groups 13 (Distribution, Hotels, Repairs) and 15 (Financial, Education, Health and Other services) has however taken place: manufacturing industries reduce their employment more than in 1974-79, and their overall limited effect on aggregate employment is due to the noticeable employment absorption capacity of groups 13 and 15. Most industries contribute positively to aggregate productivity growth, with substantial contributions coming from groups 12, 13, 14, and 15.

⁵⁵ Note however that the average decrease by year is lower than in 1974-79. On the other hand, the average over a longer time span may hide significant fluctuations.

As before, within-industry growth is predominant for all industries except groups 13 and 15.

Our analysis leads to the following conclusions:

- 1) Service industries have accounted for most of the aggregate productivity growth in the UK. Among them is predominant the importance of between-industry growth. This result is however exclusively due to groups 13 and 15. If these were excluded from the analysis, within-industry growth would predominate also across service industries.
- 2) Some of our results are compatible with an interpretation in terms of technological catching-up at the industry level. Going beyond the scope of this work, we will not pursue further the analysis of this issue. This result must thus be considered as highly preliminary.
- 3) The relation between labour productivity and employment changes differs among industries and over time periods. In general, increases in labour productivity are associated with decreases in employment in manufacturing industries, while demand expansion effects seems to dominate in service industries.

1.5 Internal sources of innovation, labour productivity and employment: the econometric models

We have seen in section 4 that the sectoral contribution to aggregate productivity growth depends on the joint effect of changes in productivity and changes in employment shares. In this section, we start investigating the direction and the intensity of the effect of internal sources of innovation on labour productivity and employment shares growth. Our general scheme of analysis attributes changes in

productivity to internal innovative efforts (R&D expenditures, Patents, Number of scientists and engineers) and externally acquired technology (investment in technologically advanced capital goods). Changes in technology and output determine the global impact of technological change on employment.

The first general model we estimate relates, for each group, the growth rate of labour productivity to the growth rate of the capital to labour ratio and the growth rate of R&D expenditures, Number of scientists and engineers, and Number of patents. It is derived by a Cobb-Douglas production function with constant returns to scale. Let Y , K , and L be respectively value added, capital stock and employment. Let A indicate the effect of technology. A Cobb-Douglas production function with constant returns to scale has the following specification:

$$Y_t = A_t * L_t^\alpha * K_t^{1-\alpha} \quad [3]$$

By taking logs and differentiating get:

$$\Delta \ln(Y/L)_t = \Delta \ln A_t + \alpha * \Delta \ln(K/L)_t \quad [4]$$

The model we estimate is:

$$\Delta \ln(Y/L)_{it} = \alpha_i + \beta_i * \Delta \ln(K/L)_{it} + \Theta_{1i}(L)(\Delta \ln(R \& D)_{it}) + \Theta_{2i}(L)(\Delta \ln(Sci)_{it}) + \Theta_{3i}(L)(\Delta \ln(Pat)_{it}) + \varepsilon_{it} \quad [5]$$

where $i = 1, \dots, 15$ is the group indicator⁵⁶.

Compared to the specifications normally found in the literature, equation [5] may, at first sight, appear rather unconventional. First, because contemporaneous lags of the various technological variables are in principle included. Next, because R&D expenditures are entered in first difference form. The first issue is in fact only

⁵⁶ Note that the technological variables are implicitly normalised in that they are expressed as first differences of log.

apparent, because the empirical selection of the model never brought to including more than one type of technological variable⁵⁷. As to R&D expenditures, standard approaches would consider either the elasticity of productivity to the R&D capital stock, or the rate of return (marginal productivity) of R&D expenditures⁵⁸. In the first case, equation [5] would be specified in level terms and should include a measure of the R&D capital stock. In the second case, the first differences structure of the equation would be kept, but the current flow of R&D expenditures, normalised by value added, should replace R&D first differences. The specification adopted here largely corresponds to analysing the elasticity of productivity growth to changes in the R&D capital stock, with the depreciation rate of R&D determined by the data. We choose this approach essentially because the construction of an R&D capital stock would have meant losing already scarce degrees of freedom. It has also the advantage of not imposing further theoretical restrictions related to the determination of an industry level R&D depreciation rate. Also, we tried various specifications of equation [5] before selecting the form presented here⁵⁹. Although not completely satisfactory,⁶⁰ the specification presented is the best econometric one we could get.

The second general model relates, for each group, the growth rate of the sectoral share of employment to the growth rate of the sectoral share of capital and the growth rate of R&D expenditures, Number of scientists and engineers, and Number of patents. It is derived from Cobb-Douglas constant returns to scale production functions at the

⁵⁷ Cfr. Tables C.1 to C.15 in Appendix I.C.

⁵⁸ Cfr. Mairesse and Saissenou (1991) for a survey of studies investigating the relationship between R&D and productivity at the firm level.

⁵⁹ Not imposing constant returns to scale, using as explanatory variables the levels and the 3-years centred moving average of the index of internally generated technology; and using the 3-years centred moving average of the above technological variables.

⁶⁰ We have not been able to get significant estimates for all groups.

industry and whole economy level. Let l , w , p , k , and a be, respectively, the whole economy values for the natural logarithm of employment, the wage level, the general price level, the capital stock, and technology. The same variables with the subscript i indicate industry values. Assume that the labour share, α , varies very little across industries, so that $\alpha_i \cong \alpha$.⁶¹ Transformation of a Cobb-Douglas production function at the industry level gives the following relation for sectoral employment:

$$l_{ii} = \frac{\alpha}{1-\alpha} + \frac{a_{ii}}{\alpha-1} + k_{ii} + \frac{1}{\alpha-1} * (w_{ii} - p_{ii}) \quad [6]$$

Similarly, transformation of a Cobb-Douglas production function at the whole economy level gives the following relation for whole economy employment:

$$l_i = \frac{\alpha}{1-\alpha} + \frac{a_i}{\alpha-1} + k_i + \frac{1}{\alpha-1} * (w_i - p_i) \quad [7]$$

Using the equilibrium relations between marginal productivities and marginal costs of the factors of production, it is possible to express industry prices as:

$$p_{ii} = p_i + (a_i - a_{ii}) + \alpha \cdot (w_{ii} - w_i) + (1-\alpha) \cdot (c_{ii} - c_i) \quad [8]$$

where c_i is the marginal cost of capital at the industry and whole economy level, and α is the whole economy labour share of production.

Assuming that the marginal cost of capital is equal across industries, substituting equation [8] in equation [6], and subtracting equation [7] from equation [6] gives:

$$l_{ii} - l_i = \gamma_0 + \gamma_1 \cdot (k_{ii} - k_i) + \gamma_2 \cdot (w_{ii} - w_i) + \gamma_3 \cdot (a_{ii} - a_i) \quad [9]$$

where γ_0 is a constant added to pick up effects not considered here, γ_1 is theoretically equal to 1, γ_2 and γ_3 are transformations of the parameter α . In first differences equation [9] becomes:

⁶¹ This is an indeed very strong assumption, made in order to get a simple final empirical model. For labour shares substantially differing across industries, the final equation [9] should include terms for the

$$\Delta(l_i - l)_i = \gamma_0 + \gamma_1 \Delta(k_i - k)_i + \gamma_2 \Delta(w_i - w)_i + \gamma_3 \Delta(a_i - a)_i \quad [10]$$

On the assumption that nominal wage differentials grow at a constant rate (hence their effect is picked up by the constants), we express equation [10] for estimation purposes as:

$$\Delta \ln(L_i/L)_i = \alpha_i + \beta_i * \Delta \ln(K_i/K)_i + \Phi_{1i}(L) (\Delta \ln(R \& D_i/R \& D)_i) + \Phi_{2i}(L) (\Delta \ln(Sci_i/Sci)_i) + \Phi_{3i}(L) (\Delta \ln(Pat_i/Pat)_i) + \gamma_i \Delta \ln H_i + \varepsilon_{ii} \quad [11]$$

where $i = 1, \dots, 15$ is the group indicator and H are average hours worked. The assumption of constant nominal wage differentials growth is clearly very restrictive. It avoids however to tackle the problem of endogeneity between wages and employment when performing empirical estimates. If this hypothesis were not maintained, the only reliable way to manage the endogeneity issue would have been to estimate a structural system determining wages. This task, however, goes beyond the scope of this work. Therefore, we choose to apply this hypothesis, but we warn that it is a very rough approximation. The growth rate of H is added to the equation to control for cyclical changes in capacity utilisation. As for equation [5], changes in technology have been expressed as a function of lagged and actual growth rates of the technological variables.

I.5.1 Estimation procedure

Equations [5] and [11] have been estimated by OLS over the period 1966-93. Before estimating the models we took care to avoid spurious regression problems. On the one hand, taking first differences in logs eliminate this problem for $I(1)$ series. On the other hand, the analysis of the residuals' correlation structure does not show signs of

industry's real wage, cost of capital, and technical progress. Estimating rather than imposing the value

significant autocorrelation. The number of lags for each technological variable has been determined on the basis of a sort of ‘general to specific’ method. A first estimation round was carried on including normally 3 or, only exceptionally, 4 lags of the variables⁶². Not significant variables were iteratively excluded, starting from the higher lag, up to reach either a minimal one-lag specification, or a specification including only significant variables. The variables were also separately tested, at various lags, to decide, on the basis of the significance level and the overall performance of the model, which ones gave the better fit. Two admittedly arbitrary conditions have been imposed. First, significant but wrongly signed technological variables have been dropped from the production function model. We assumed that, given the parsimonious specification adopted, wrongly signed variables were most likely reflecting specification problems rather than being evidence of theoretically inconsistent effects. The most appropriate solution would have clearly been to proceed to the re-specification of the model. The lack of longer time series and the serious difficulties at eventually gather other consistent industry level data made us decide for this ‘shortcut’. Next, at least one technological variable, even if not significant, has always been retained in the specification. Note however that this condition is effective for only 6 groups in the production function models and for 4 groups in the employment share models. Moreover, the chosen final specifications had to pass the usual specification tests⁶³.

The estimation procedure adopted, while allowing the parameters underlying the model to be data determined, might in principle pose a number of problems. Griliches and Mairesse (1995) discuss at length the issue of endogeneity of production and

for α reduces to some extent the bias induced by this approximation.

⁶² This is because longer lags would have implied losing too many degrees of freedom.

production factors for panel data based production function estimates. In this respect, the estimates presented here are less likely to show substantial biases both because the production function model is estimated in first differences⁶⁴, and because data aggregation reduces the relevance of the issue. Besides, the authors show that correcting for endogeneity is not costs free, and may induce other serious specification problems. Mairesse and Sassenou (1991) note that the estimation of time series production functions is likely to suffer of two general specification problems⁶⁵. First, the coefficients may be biased because of the difficulty at adequately specifying the number of lags occurring in the relationship between productivity and its factors. Next, especially for estimates based on one-lag first differences, biases may arise due to the omission of variables reflecting short-term adjustments to business cycle fluctuations, such as hours of work and capacity utilisation. The first observation is certainly relevant for the estimates presented here, constrained by the relatively short length of the time series available. As to the second observation, we controlled for fluctuations in the number of hours worked by explicitly adding this variable in equation [11], and by considering men hours labour productivity and employment in equation [5]. More specific to the approach adopted here are the issues of collinearity among explanatory technological variables, and of the exogeneity assumption regarding the contemporaneous changes of technological variables and productivity⁶⁶. As to the collinearity issue, its relevance is limited to at most 3 employment share group- models⁶⁷. The model selection procedure never identified more than one type of technological variable significant in the production function models, while this

⁶³ Normality, serial correlation, heteroskedasticity, linear form.

⁶⁴ Cfr. Griliches and Mairesse (1995) pag. 12.

⁶⁵ Cfr. Mairesse and Sassenou (1991) pag. 15.

⁶⁶ I am grateful to Gavin Cameron and John Van Reenen for having pointed out these problems.

⁶⁷ Cfr. Tables C.1 to C.15 in appendix I.C.

happened for 7 groups in the employment shares models, but with different technological variables included at the same lag in only three cases. The exogeneity issue is more pervasive and might in fact explain the low explanatory power of R&D expenditures as compared to the percentage of scientists and engineers in the production function models. The data however do not show any significant correlation between labour productivity and percentage of scientists and engineers⁶⁸. Moreover, we took care to exclude scientists and engineers from employment when computing labour productivity. Overall, while recognising that richer and more complex specifications could certainly add to the informative content of the estimates, we regard the results obtained as overall robust.

I.5.2 Estimation results

Tables C.1 to C.15 in Appendix I.C show details of the estimation results. Two general results emerge. First, the intensity of the effect of internal innovative activities varies greatly from industry to industry. A substantial degree of variability is also present in the lag structure of the "internal innovative activities" variables. Second, while the effect of these variables on labour productivity is always positive, the one on employment shares is positive for some industries and negative for others.

For both the production function and employment models, we have computed the average long run value of the estimated coefficients by technological group. For each industry, we have first determined the long run effect of the independent variables, summing together the technological ones. Then, we have computed the average effect

⁶⁸ Correlation values between productivity and number of scientists and engineers' growth are in fact quite low, reaching a maximum of 0.5 (in absolute value) for group 6, and being less than 0.3 for 13

for each technological group by taking a weighted average of the long run coefficients, using employment shares as weights. Table I.11 shows the average effect of changes in the capital to labour ratio and in the technological variables over labour productivity for the four technological groups. The average lag structure is reported too.

Some of our estimates are certainly affected by general specification problems. Moreover, robust inferences can not be drawn on the lag structure because we are strongly bounded by the length of our time series. Nevertheless, one can conclude that the general indications coming from the estimation results hold and are reinforced by the technological classification that we get with different methodologies. As expected, the effect of internal technological activities on labour productivity growth is strongest in *technology producer* industries. Confirming our previous classification, *technology user and producer*, *technology user* and *low technology* industries follow. Changes in the capital to labour ratio are important sources of productivity changes for almost all technological groups⁶⁹. Their effect is biggest, on average, in *technology user* industries and lowest in *technology producer* ones.

groups.

⁶⁹ Technology producers industries are the exception. Anyway this result is due to the strong weight attached to the negative contribution of group 15 for which we did not get good econometric estimates.

Table I.11: Average effects of capital to labour ratio and technological variables growth on labour productivity growth

<i>Groups</i>	$\Delta \ln(K/L)$	<i>Technological variables</i>	<i>Number of lags of the technological variables</i>
4	-0.29	0.14	3.00
5	0.69	0.11	1.00
10	0.84	0.24	3.00
11	0.37	0.08	1.00
12	0.93	0.32	2.00
15	-0.25	0.01	1.00
<i>Average technology producer*</i>	0.01	0.08	1.51
2	0.60	0.16	2.00
6	0.97	0.03	3.00
<i>Average technology user and producer*</i>	0.84	0.07	2.66
1	0.73	0.04	1.00
3	0.53	0.07	1.00
9	1.24	0.07	1.00
14	0.83	0.02	3.00
<i>Average technology user*</i>	0.87	0.04	2.11
7	0.50	0.07	1.00
8	-0.13	0.04	1.00
13	0.37	0.02	1.00
<i>Average low technology*</i>	0.37	0.03	1.00

** weighted average, weights being the group employment shares*

The predominance of the effect of investment-induced technological change with respect to the internally generated one may be explained by the fact that most innovations need to be embodied into some goods (in particular investment goods) in

order to be adopted and used. Moreover, an increasing share of capital is accounted for by information and communication technology (ICT) capital goods. Oulton (2001) estimates that, since 1979, ICT has contributed to around half of all capital deepening, and has accounted for substantial and increasing shares of labour productivity growth⁷⁰. The analysis of the lags structure suggests that past innovative efforts are more important in determining productivity performances in those industries in which technological progress is mainly of the embodied form. As said before, this result is far from being a definite one.

Table I.12 shows the average effect of changes in the capital share and in the technological variables over the employment shares for the four technological groups.

Increases in the capital share (i.e. investment ratios above average) always produces on average a positive effect on employment shares. This effect may be explained in terms of both embodied technological innovations and production expansion at constant technology. In the case of embodied technological innovations, it would mean that the demand expansion effect of technological change more than offset the labour saving effect. However, employment shares may increase with capital shares and constant technology just because of demand driven increases in production.

The positive effect of changes in capital shares effect is largest in *technology user and producer* industries and lowest in *technology producer* ones. Group 12 (Production and Distribution of energy, gas and water) is the only industry for which this effect is negative, suggesting a high degree of substitution between capital and labour.

⁷⁰ 33% in 1979-89 and 46% in 1989-98. Cfr. Oulton (2001).

Table I.12: Average effects of capital share and technological variables growth on employment share growth

<i>Groups</i>	$\Delta \ln(K_t/K)$	<i>Technological variables</i>	<i>Number of lags of the technological variables</i>
4	0.32	0.06	1.00
5	0.87	0.19	2.00
10	0.05	0.26	5.00
11	0.04	0.27	3.00
12	-0.49	0.12	1.00
15	0.32	0.15	3.00
<i>Average technology producer*</i>	0.28	0.16	2.8
2	0.73	0.24	1.00
6	1.18	0.14	3.00
<i>Average technology user and producer*</i>	1	0.17	2.3
1	0.32	0.56	5.00
3	0.84	0.53	3.00
9	0.34	-0.03	2.00
14	0.39	0.05	3.00
<i>Average technology user*</i>	0.41	0.15	3
7	0.65	-0.03	2.00
8	0.29	-0.08	3.00
13	0.93	-0.01	1.00
<i>Average low technology*</i>	0.86	-0.02	1.2

* weighted average, weights being the group employment shares

Internally generated innovative efforts have a positive impact on employment shares in *technology producer*, *technology user and producer*, and *technology user* industries. The effect is negative in low technology industries. Quite surprisingly, the positive effect is relatively strong in *technology user* industries.

For all *low technology* industries and for one *technology user* (Group 9, Manufacture of paper and paper products, Printing and Publishing) there is evidence of technological unemployment deriving by internal innovative activities. However, these industries experience among the highest positive effects of investment on employment shares. This suggests that externally generated technological innovations and demand phenomena may be particularly important in determining their economic performance.

Our results are overall consistent with those found in other empirical studies analysing the issue of the employment effect of technological change at the industry or firm level. For two-digit UK manufacturing industries over the years 1974-85, Nickell and Kong (1987) find that, with the exception of Textiles, Bricks and glass industries, technical progress generally increases employment. Berndt et al. (1992) report that, for two-digit US manufacturing industries over the years 1952-86, increases in the share of high technology capital are positively correlated to labour intensity growth⁷¹. These results confirm the evidence reported here for groups 7 (Textile, manufacture of leather and eather goods, footwear and clthing) and 8 (Timber and wooden furniture). Studies referring at the firm, establishment, or plant level normally find an overall positive effect of technological change on employment growth⁷². Distinguishing

⁷¹ With the exception of chemicals, furniture and textiles industries.

⁷² Cfr. Chennells and Van Reenen (1999).

between product and process innovations, product innovations are almost consistently found to increase employment⁷³ while the evidence for process innovations is mixed⁷⁴. However, a large number of studies finds that, even in the absence of an overall effect of innovation on employment, firms investing in information technology (IT) capital, or directing R&D towards IT goods, have higher rates of employment than other firms⁷⁵. This is further evidence of the importance of the technological content of capital goods for growth. This issue will be extensively analysed in the next chapter.

I.6 Conclusions

We have begun in this chapter the analysis of the sectoral contribution to overall economic growth in the UK in the period 1966-1993. The investigation has mainly concerned the analysis of the determinants of such contribution and the impact of internally generated and externally acquired technological change. We have established the following results. First, we have identified an industrial technological classification which is fairly stable over the years 1966-1993. Then we have seen that the sectoral contribution to aggregate productivity growth is determined by the joint effect of productivity and employment changes. The contribution of *technology producer* industries is permanently highest both in terms of employment and productivity. Moreover, we found some evidence suggesting technological catching up phenomena at the industry level. Finally, we have seen that the effects of internally generated technological efforts and embodied technological improvements on labour

⁷³ Cfr. Van Reenen (1997) and Entorf and Pohlmeier (1991).

⁷⁴ Cfr. Smolny (1998), Brouwer et al. (1993), Klette and Førre (1998).

productivity and employment share growth vary in direction and intensity among industries and technological groups. The work will develop in the following directions. First, we will work towards a better definition of the distinction between internally generated and externally acquired technical change. We will test on our data the embodiment hypothesis and propose a methodology to determine the technology flow consequent to investment decisions. We will also analyse the effect of technological improvements external to the industry considered and not embodied in capital; i.e. the so called spillover effect. Second, we will investigate the importance of technologically induced demand transmissions for value added and employment shares growth. Finally, we will pursue further the analysis of the determinants of the sectoral contribution to aggregate growth. We will explicitly analyse how internal and externally acquired technological change affect such contributions in terms of productivity and employment changes.

⁷⁵ Cfr. Bower et al. (1993), and Duguet and Greenan (1997).

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Data Appendix (Chapter 1)

The dataset we are using in this study is based on the following 15 groups of industries as defined in the 2-digit Sectoral Industrial Classification 1980:

		<i>2- digit SIC80 class</i>
Group 1	Agriculture	01, 02, 03
Group 2	Extractive industries	11, 12, 13, 21, 23
Group 3	Non Metallic industries	24
Group 4	Metal and Mechanical industries	22, 31, 32, 33
Group 5	Electrical and Instruments industries	34, 37
Group 6	Food, Drink and Tobacco	41, 42
Group 7	Textile, Leather and Clothing industries	43, 44, 45
Group 8	Timber and Wood	46
Group 9	Paper	47
Group 10	Chemicals, Transport and nec	14, 15, 25, 26, 35, 36, 48, 49
Group 11	Construction	50
Group 12	Electricity, Gas and Water	16, 17
Group 13	Distribution, Hotels and Repairs	6
Group 14	Transport and Communications	7
Group 15	Financial, Education, Health and Other Serv.	8, 9

For each group we collected the following variables: Expenditures on Research and Development, Weekly Hours worked, Price Index, Investment, Capital Stock, Number of patents, Number of Scientists and Engineers engaged in research activities, Employment, Value Added.

In general we had to deal with missing data and disaggregation problems. Disaggregation problems arose when the data were referred to more than one group of

our final classification. We have dealt with this problem in two different ways, depending on how many years had to be disaggregated. If the disaggregation involved just a few years, we have used the average of the appropriate shares over the available years to decompose the total. When the disaggregation involved longer time periods, we have used employment or capital shares⁷⁶ to decompose the total.

What follows is the list of the data sources used, the availability by year of the official data, and the general methods we have used to estimate missing values.

Expenditures on Research and Development:

Data are from: Statistics of Science and Technology 1967; Business Monitor 1975, 1978, 1989; Research and Development in UK business 1993, 1994.

Data were available for the years 1964-65, 1967, 1968, 1969, 1972, 1975, 1978, 1981, 1983, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1992, and 1993.

Missing data for the total of R&D expenditures and manufacturing industries have been estimated by linear interpolation. For industries in the services sector even uncompleted data were not available before 1981. To get these data we have estimated econometric relationships between R&D expenditures performed in services industries and R&D expenditures performed in manufacturing industries, and have used the estimated coefficients to get backward estimates of the missing data. For Group1, Agriculture, official data are available for the years 1991 to 1993 only. The R&D expenditure data for this group have been estimated by interpolation with respect to a linear trend of the share over the total.

⁷⁶ Depending on the series under consideration.

Weekly Hours worked:

Data are from: Employment Gazette 1971, 1973, 1978, 1982, 1986, and 1996.

Data were available for the years 1966-1993.

When only data by sex were available, we have computed the aggregate data as the weighted average of the data by sex using as weights the industrial employment share of males and females (we took these data from the Employment Gazette, various issues).

The data by group are the weighted average, using the appropriate employment shares as weights, of the data by industry.

Capital Stock:

Data for Gross Capital Stock by industry at constant prices for the years 1970 to 1991 are from the OECD International Sectoral Database⁷⁷. For the years 1966 to 1969 and 1992 to 1993 the Capital Stock has been estimated according to the formula

$$K_{t+1} = K_t * (1-\delta) + I_t$$

for forward estimates and

$$K_t = (K_{t+1} - I_t) / (1-\delta)$$

for backward estimates.

The depreciation rate used as been computed on the basis of the ISDB data, according to the formulas above, and it is the 4 years average of the latest available data.

Investment:

Data for Gross Fixed Capital Formation by industry at constant prices for the years 1970 to 1991 are from the OECD International Sectoral Database. The series is

available at both current and constant prices, so we were able to get the appropriate deflators for Investment and Capital. For the years 1966 to 1969 and 1992, 1993 data are from Annual Abstract of Statistics 1970, 1993.

Value Added:

Data for Value Added by industry at constant and current prices for the years 1966 to 1993 are from the OECD International Sectoral Database. Data for groups 13, 14 and 15 were not available in the years 1966 to 1969. They have been backward estimated on the basis of the average growth rate of the latest 3 available years. The same method has been used to get the 1993 data of groups 4 and 5.

Price index:

The price index by industry on base 1985=100 has been computed on the basis of the Value Added series at constant and current prices from the ISDB. It is given by the ratio of the two series.

Employment:

Data for employment by industry are from: Annual Abstract of Statistics 1976, 1980, 1983, 1987, 1990, 1993, 1996; Employment Gazette 1975.

Data were available for the years 1966 to 1993.

This was the series for which most detailed and complete data were available, so we have often used employment shares to aggregate and disaggregate industries and groups. Moreover, we have used employment data by industry to create the linkage

⁷⁷ Andrew Glyn has kindly supplied the database.

between SIC 1980 and ISIC classifications, for which we could not find any official document.

Number of patents:

Data for the number of patents by company come from one of the databases at the Patents Office, London⁷⁸. Data were not available for the years before 1969, so the coverage of this series is 1969-1993.

The patent data we use here are those granted by the US Patent Office to UK firms or to multinationals whose main centre of activity is in the UK. We attributed the patents to the industries on the basis of the main sector of activity of the owner firm. In the case of holdings, the data have been classified under the code corresponding to the main productive activity. To get the data at the industry level, we first found the SIC firms' codes, and then aggregated the data according to the needed classification. The databases we used to get the SIC firms' codes are: Exstat, Extel - Company Research, Key British Enterprises and the UNITSIC codes from the SPRU database user manual. We were not able to get a SIC code for 9% of the total number of patents. We have distributed the unclassified patents among industries according to their year by year patent share over the total.

Number of Scientists and Engineers engaged in research activities:

Data are from: Ministry of Labour Gazette 1966, 1967, 1968; Employment and Productivity Gazette 1969, 1970; Employment Gazette 1971, 1972, 1973, 1974, 1975;

⁷⁸ I wish to thank the staff at the Patent Office for their help and kindness. Data for the years 1969 to 1982 at the company level and most valuable information about how to deal with them were kindly provided by Daphne Nicolitsas.

the Labour Force Survey for the years 1975, 1977, 1979, 1981, and 1983 to 1993⁷⁹. Before 1975 only data for manufacturing industries are available. These refer to the occupational category “Scientists and technologists”. We took the Labour Force Survey 1975 occupational category “Professional and related in science, engineering, technology and similar fields”; and similar occupational groups for other years⁸⁰. We used linear interpolation to estimate the missing years between surveys (i.e. 1976, 1978, 1980, 1982).

We used econometric estimates to get the pre-1975 data for service industries⁸¹. For each group of industries we estimated, on the available years⁸², an econometric model linking the number of scientists at time t to the number of scientists in $t+1$ and $t+2$ and the whole economy R&D expenditures⁸³. The model has the form:

$$Sci_{it} = \alpha + \beta * Sci_{it+1} + \gamma * Sci_{it+2} + \delta * Total\ R\&D_t + \epsilon_t$$

i = group indicator

We then run backward the model up to the year 1966.

Finally, to get the population data from the sample survey one, we computed the percentage coverage in the survey of total employment by industry and adjusted the data according to this value.

Research and development expenditures deflator:

To deflate R&D expenditures we have used a Divisia price index developed in Cameron (1996). Cameron (1996) computes Divisia indices of the cost of R&D

⁷⁹ Jane Roberts at the Faculty of Social Studies, Oxford, has kindly provided me with the needed subset of data and the various manuals for the LFS codes.

⁸⁰ The coding system and occupational breakdown of the LFS have changed during years.

⁸¹ In terms of our groups of industries, we had to estimate data for the years before 1975 for the following groups: 1, 2, 11, 12, 13, 14 and 15.

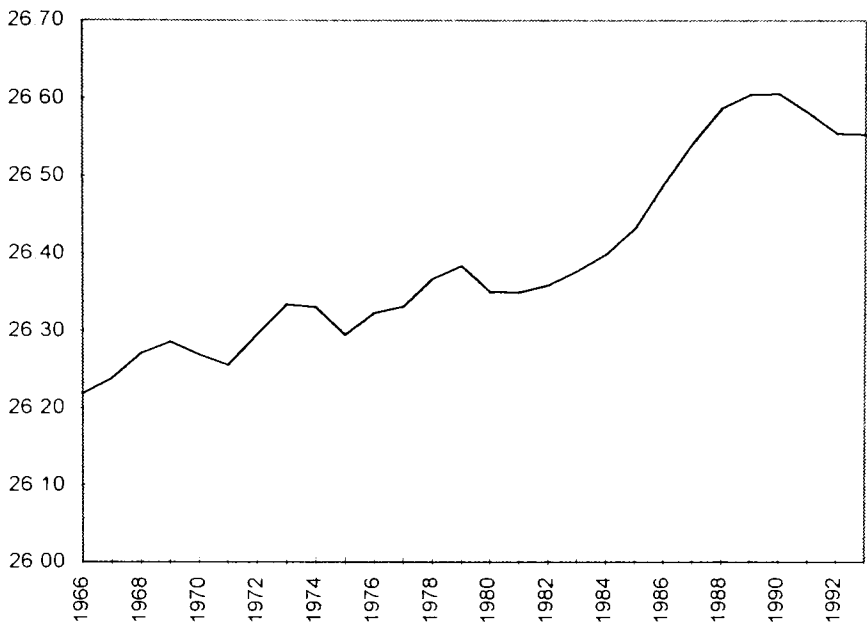
⁸² We have LFS data up to 1995.

between 1970 and 1992 for seven broad sectors of UK manufacturing. We have estimated the missing data for our time period (1966 to 1969, and 1993) by replicating the 3-years average growth rate of the latest available data. When necessary, data at the industry level have been aggregated into groups on the basis of the appropriate employment shares.

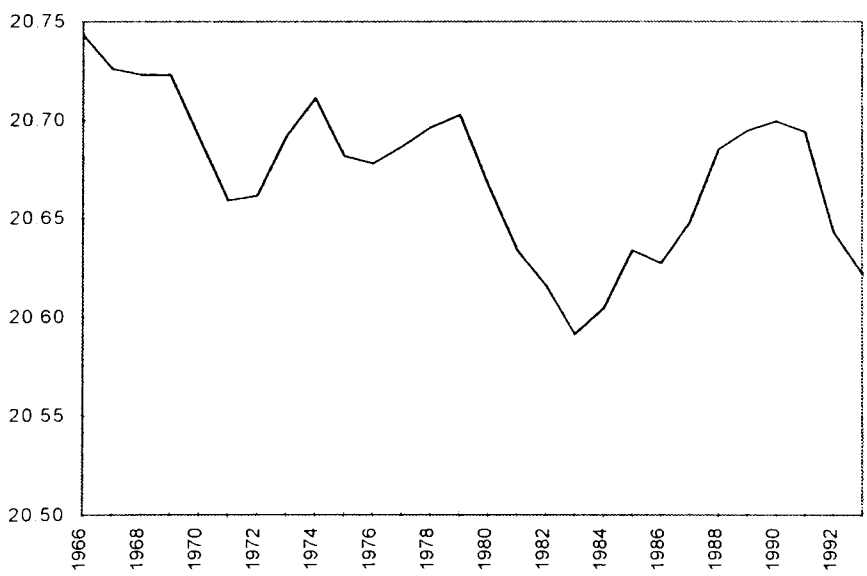
⁸³ Clearly the small sample size (20 years of observations by group) does not allow any robust statistical inference.

APPENDIX I.A

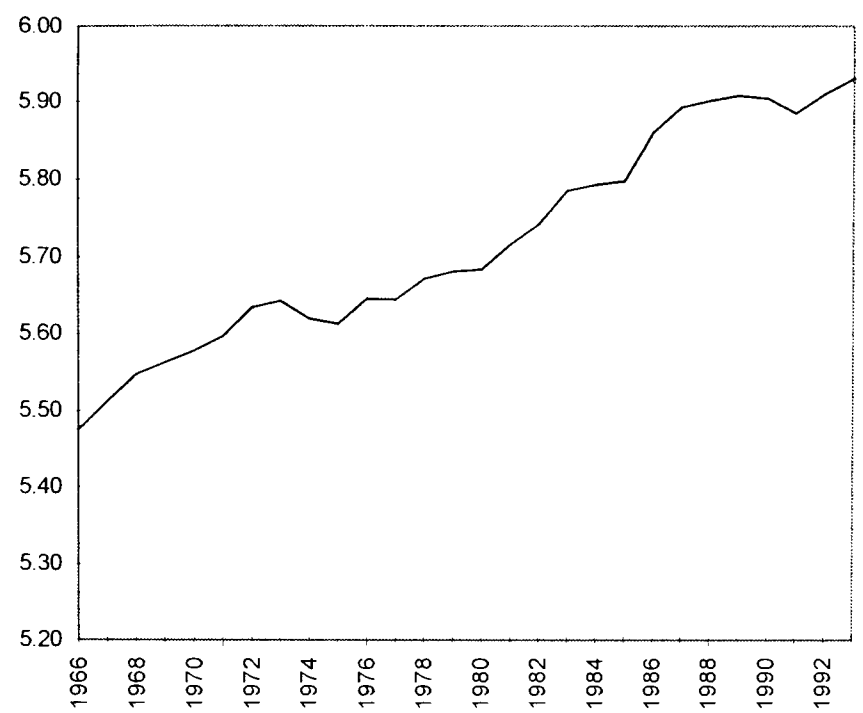
Graph A.1: UK Gross Domestic Product 1966-1993
Logarithmic scale



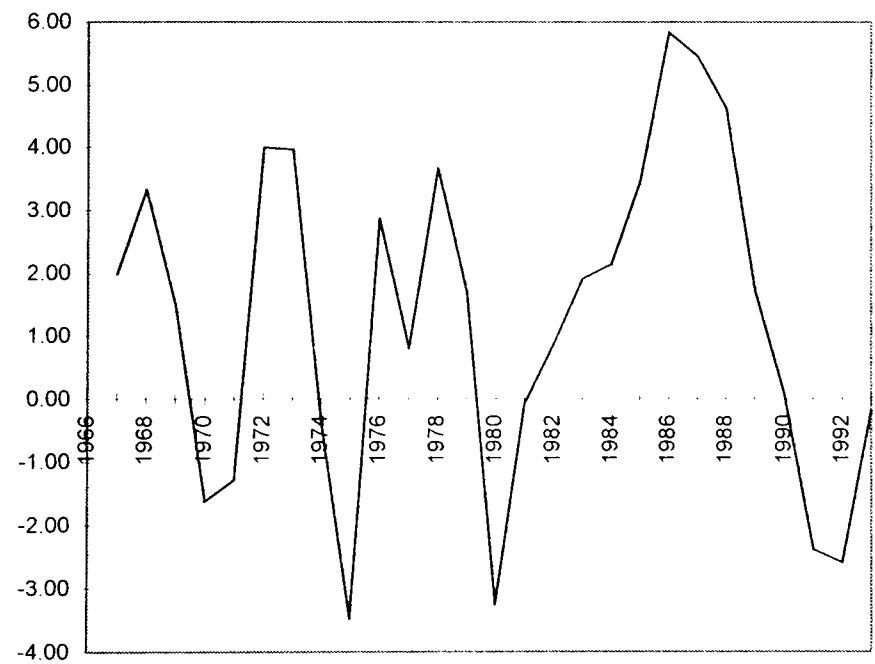
Graph A.2: UK Employment 1966-1993
Logarithmic scale



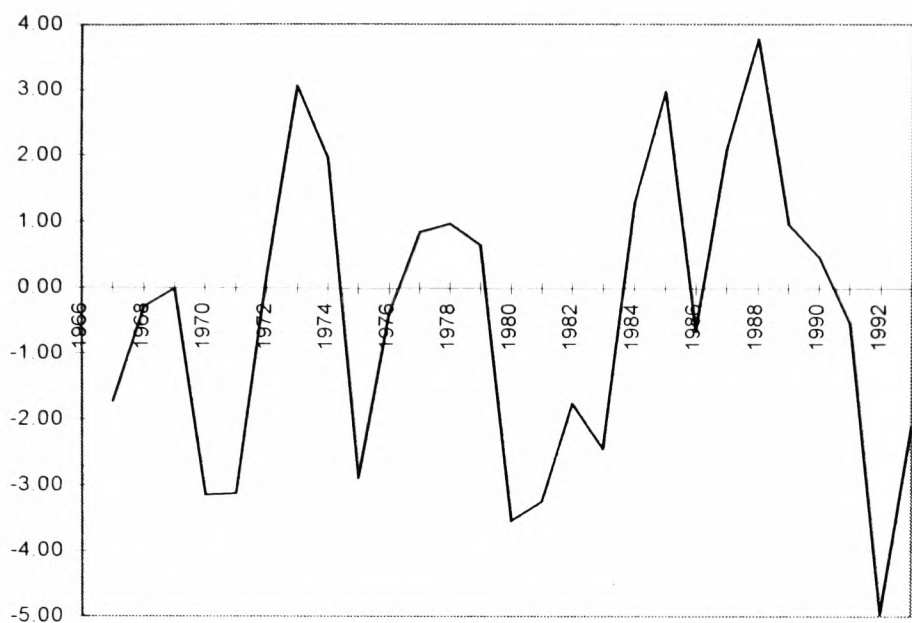
Graph A.3: UK Labour Productivity 1966-1993
Logarithmic scale



Graph A.4: GDP growth rate 1966-1993 (%)



Graph A.5: Employment growth rate 1966-1993 (%)



Graph A.6: Labour Productivity growth rate 1966-1993 (%)

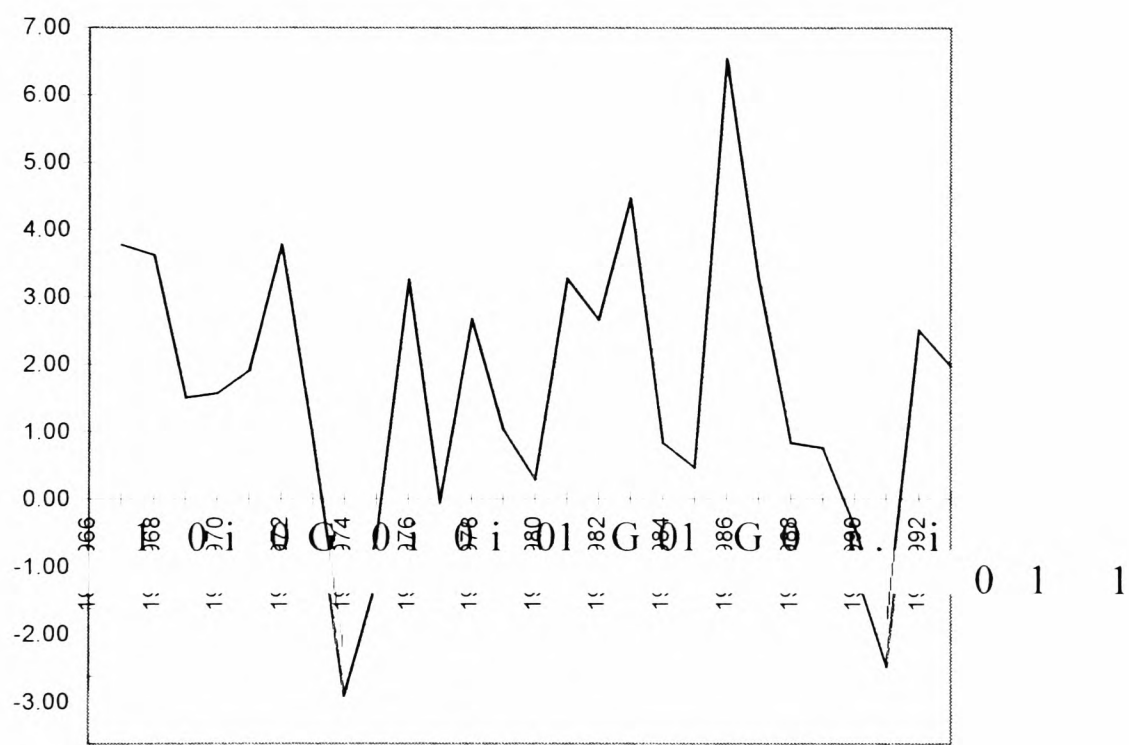


Table A.1: Contribution of Divisions 8 and 9 to aggregate labour productivity growth, 1966-1993

	% Contribution $[(\lambda_{i,T}x_{i,T}-\lambda_{i,0}x_{i,0})/\Delta_Tx_i]*100$	Within effect	Between effect	Productivity adjusted L share effect	Pure L share growth effect	% Growth Employment Shares $[(\lambda_{i,T}-\lambda_{i,0})/\lambda_{i,0}]*100$	Share Employment 1993 $\lambda_{i,T}$	Level of Labour Productivity 1966 $x_{i,0}$	% Growth Labour Productivity $[(x_{i,T}-x_{i,0})/x_{i,0}]*100$	% Growth Value Added	% Growth Employment	% Deviation from average labour productivity 1966
Whole economy								239	54	40	-11	
Division 8	30.9	-17	47.9	34.1	13.8	178	0.12	829	-23	91	147	247
Division 9	22.5	2.9	19.6	-5.9	25.5	79	0.33	183	7	70	59	-23

Table A.2: Contribution of Divisions 8 and 9 to aggregate labour productivity growth, 1966-1991

	% Contribution $[(\lambda_{i,T}x_{i,T}-\lambda_{i,0}x_{i,0})/\Delta_Tx_i]*100$	Within effect	Between effect	Productivity adjusted L share effect	Pure L share growth effect	% Growth Employment Shares $[(\lambda_{i,T}-\lambda_{i,0})/\lambda_{i,0}]*100$	Share Employment 1991 $\lambda_{i,T}$	Level of Labour Productivity 1966 $x_{i,0}$	% Growth Labour Productivity $[(x_{i,T}-x_{i,0})/x_{i,0}]*100$	% Growth Value Added	% Growth Employment	% Deviation from average labour productivity 1966
Whole economy								239	47	44	-5	
Division 8	33.6	-18.7	52.4	37.3	15.1	172	0.12	829	-23	100	159	247
Division 9	22.5	2.6	19.9	-6	25.9	71	0.32	183	5	72	63	-23

Table A.3: Contribution of Divisions 8 and 9 to aggregate labour productivity growth, 1966-1974

	% Contribution [$(\lambda_{i,T}x_{i,T}-\lambda_{i,0}x_{i,0})/\Delta_Tx_i$]*100	Within effect	Between effect	Productivit y adjusted L share effect	Pure L share growth effect	% Growth Employment Shares [$(\lambda_{i,T}-\lambda_{i,0})/\lambda_{i,0}$]*100	Share Employment 1974 $\lambda_{i,T}$	Level of Labour Productivity 1966 $x_{i,0}$	% Growth Labour Productivity [$(x_{i,T}-x_{i,0})$ / $x_{i,0}$]*100	% Growth Value Added	% Growth Employment	% Deviation from average labour productivity 1966
Whole economy								239	15	12	-3	
Division 8	9.9	-26	35.9	25.5	10.3	36	0.06	829	-19	6	32	247
Division 9	30	7.1	22.9	-6.9	29.8	25	0.23	183	6	28	21	-23

Table A.4: Contribution of Divisions 8 and 9 to aggregate labour productivity growth, 1974-1979

	% Contribution [$(\lambda_{i,T}x_{i,T}-\lambda_{i,0}x_{i,0})/\Delta_Tx_i$]*100	Within effect	Between effect	Productivit y adjusted L share effect	Pure L share growth effect	% Growth Employment Shares [$(\lambda_{i,T}-\lambda_{i,0})/\lambda_{i,0}$]*100	Share Employment 1979 $\lambda_{i,T}$	Level of Labour Productivity 1974 $x_{i,0}$	% Growth Labour Productivity [$(x_{i,T}-x_{i,0})$ / $x_{i,0}$]*100	% Growth Value Added	% Growth Employment	% Deviation from average labour productivity 1974
Whole economy								276	6	5	-0.8	
Division 8	57.2	35.3	21.9	12.9	9	9.5	0.07	670	14	24	8	143
Division 9	28	1.5	26.4	-11	37.3	10.3	0.26	195	0.5	10	9	-29

Table A.5: Contribution of Divisions 8 and 9 to aggregate labour productivity growth, 1979-1991

	% Contribution $[(\lambda_{i,T}x_{i,T}-\lambda_{i,0}x_{i,0})/\Delta_Tx_i]*100$	Within effect	Between effect	Productivit y adjusted L share effect	Pure L share growth effect	% Growth Employment Shares $[(\lambda_{i,T}-\lambda_{i,0})/\lambda_{i,0}]*100$	Share Employment 1991 $\lambda_{i,T}$	Level of Labour Productivity 1979 $x_{i,0}$	% Growth Labour Productivity $[(x_{i,T}-x_{i,0})/x_{i,0}]*100$	% Growth Value Added	% Growth Employment	% Deviation from average labour productivity 1979
Whole economy								293	21	22	-0.9	
Division 8	40.6	-22.1	62.7	38.6	24.1	83	0.12	763	-16	52	81	160
Division 9	17	-1.1	18.1	-9	27.1	24	0.32	196	-1	22	23	-33

APPENDIX I.B

To assess if the relative contribution of within and between sectors growth (equation [1]) reflects to some extent the level of aggregation of the data used, we have considered the following simple example. It consists in first evaluating equation [1] over 3 industries, and then compare the results with those obtained for 2 industries, where industries 2 and 3 are aggregated in a unique industry.

For the 3 industries case, equation [1] is:

$$\Delta_{0T} \left(\frac{Y}{L} \right) = \left[\left(\frac{Y_{1T}}{L_{1T}} - \frac{Y_{10}}{L_{10}} \right) * \frac{L_{1T}}{L_T} + \left(\frac{Y_{2T}}{L_{2T}} - \frac{Y_{20}}{L_{20}} \right) * \frac{L_{2T}}{L_T} + \left(\frac{Y_{3T}}{L_{3T}} - \frac{Y_{30}}{L_{30}} \right) * \frac{L_{3T}}{L_T} \right] + \left[\left(\frac{L_{1T}}{L_T} - \frac{L_{10}}{L_0} \right) * \frac{Y_{10}}{L_{10}} + \left(\frac{L_{2T}}{L_T} - \frac{L_{20}}{L_0} \right) * \frac{Y_{20}}{L_{20}} + \left(\frac{L_{3T}}{L_T} - \frac{L_{30}}{L_0} \right) * \frac{Y_{30}}{L_{30}} \right] \quad [1.B]$$

where 0 and T are the initial and final year, Y_j and L_j , for $j = 1, 2, 3$, are value added and employment of each industry, and Y and L are the corresponding whole economy variables.

Let us focus on the second and third term of equation [1.B], i.e. weighted productivity growth of industries 2 and 3. These can be rewritten as:

$$-\frac{1}{L_T} * \left(Y_{20} \cdot \frac{L_{2T}}{L_{20}} + Y_{30} \cdot \frac{L_{3T}}{L_{30}} \right) + \frac{1}{L_T} * (Y_{2T} + Y_{3T}) \quad [2.B]$$

Similarly, the fifth and sixth term of equation [1.B], i.e. weighted labour shares growth of industries 2 and 3, can be rewritten as:

$$\frac{1}{L_T} * \left(Y_{20} \cdot \frac{L_{2T}}{L_{20}} + Y_{30} \cdot \frac{L_{3T}}{L_{30}} \right) - \frac{1}{L_0} * (Y_{20} + Y_{30}) \quad [3.B]$$

Let us now consider the case in which industries 2 and 3 are aggregated in a unique industry, industry 4. Then $Y_4 = Y_2 + Y_3$ and $L_4 = L_2 + L_3$.

Equation [1] is:

$$\Delta_{0T}\left(\frac{Y}{L}\right) = \left[\left(\frac{Y_{1T}}{L_{1T}} - \frac{Y_{10}}{L_{10}} \right) * \frac{L_{1T}}{L_T} + \left(\frac{(Y_{2T} + Y_{3T})}{(L_{2T} + L_{3T})} - \frac{(Y_{20} + Y_{30})}{(L_{20} + L_{30})} \right) * \frac{(L_{2T} + L_{3T})}{L_T} \right] + \left[\left(\frac{L_{1T}}{L_r} - \frac{L_{10}}{L_0} \right) * \frac{Y_{10}}{L_{10}} + \left(\frac{(L_{2T} + L_{3T})}{L_T} - \frac{(L_{20} + L_{30})}{L_0} \right) * \frac{(Y_{20} + Y_{30})}{(L_{20} + L_{30})} \right] \quad [4.B]$$

The second term of equation [4.B] can be rewritten as:

$$-\frac{1}{L_T} * \left(Y_{20} \cdot \frac{(L_{2T} + L_{3T})}{(L_{20} + L_{30})} + Y_{30} \cdot \frac{(L_{2T} + L_{3T})}{(L_{20} + L_{30})} \right) + \frac{1}{L_T} * (Y_{2T} + Y_{3T}) \quad [5.B]$$

and the fourth as:

$$\frac{1}{L_T} * \left(Y_{20} \cdot \frac{(L_{2T} + L_{3T})}{(L_{20} + L_{30})} + Y_{30} \cdot \frac{(L_{2T} + L_{3T})}{(L_{20} + L_{30})} \right) - \frac{1}{L_0} * (Y_{20} + Y_{30}) \quad [6.B]$$

Equations [2.B] and [5.B], and [3.B] and [6.B] are two by two identical except for the value added weighting structure. In particular, in the 3 industries case (eqns. [2.B] and [3.B]) value added is weighted by – approximately – the growth rate of own employment. In the 2 industries case, instead, value added is weighted by – approximately – the growth rate of overall (2 + 3) employment. For decreasing employment, as has been the case in UK manufacturing industries over the years 1966-91, the weights in [5.B] and [6.B] are likely to be smaller than those in [2.B] and [3.B]. However, the overall effect of aggregation also depends on the relative magnitude of initial year values added. This can be shown with a numerical example.

Let us assume that, at time 0, $Y_2 = 17$, $L_2 = 15$, $Y_3 = 20$, $L_3 = 9$. At time T, $L_2 = 11$ and $L_3 = 7$.

Equation [2.B] is then equal to $-1/L_T * 48.92$, and equation [5.B] to $-1/L_T * 49.21$. In this case, aggregation decreases within sectors growth contribution.

However, for $Y_2 = 20$ and $Y_3 = 17$, equation [2.B] is equal to $-1/L_T * 54.53$, while equation [5.B] remains at $-1/L_T * 49.21$. For these value added values, aggregation enhances within sectors growth contribution.

Although we were unable to derive a simple general mathematical rule relating relative contributions to aggregation, these results show that within and between contributions may be not invariant to aggregation⁸⁴.

⁸⁴ It is considered as a possibility because it might be that for particular value added and employment share values contributions result invariant to aggregation.

APPENDIX I.C

Table C.1: Group 1, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR1}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.007249	0.038248	-0.189529	0.8513
$\Delta \text{LN}(\text{K/L})\text{GR1}$	0.733975	0.470722	1.559255	0.1326
$\Delta \text{LN}(\text{hours})\text{GR1}$	0.442076	0.801900	0.551286	0.5868
$\Delta \text{LN}(\text{sci})\text{GR1}$	0.036448	0.024817	1.468652	0.1555
R-squared	0.204563	Mean dependent var		0.053403
Adjusted R-squared	0.100810	S.D. dependent var		0.068379
S.E. of regression	0.064841	Akaike info criterion		-5.335687
Sum squared resid	0.096700	Schwarz criterion		-5.143711
Log likelihood	37.72043	F-statistic		1.971641
Durbin-Watson stat	2.438180	Prob(F-statistic)		0.146367

Employment model

Dependent Variable: $\Delta \text{LN}(\text{L}_i/\text{L})\text{GR1}$				
Method: Least Squares				
Sample(adjusted): 1971 1993				
Included observations: 23 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.041538	0.011584	-3.585703	0.0021
$\Delta \text{LN}(\text{hours})\text{GR1}$	0.091439	0.201963	0.452753	0.6561
$\Delta \text{LN}(\text{K}_i/\text{K})\text{GR1}$	0.320613	0.217850	1.471713	0.1584
$\Delta \text{LN}(\text{R\&D}_i/\text{R\&D})\text{GR1}$	0.280661	0.133062	2.109246	0.0492
$\Delta 4 \text{LN}(\text{R\&D}_i/\text{R\&D})\text{GR1}$	0.287493	0.142666	2.015149	0.0591
R-squared	0.352457	Mean dependent var		-0.022127
Adjusted R-squared	0.208559	S.D. dependent var		0.023794
S.E. of regression	0.021168	Akaike info criterion		-4.682993
Sum squared resid	0.008066	Schwarz criterion		-4.436146
Log likelihood	58.85442	F-statistic		2.449347
Durbin-Watson stat	1.583325	Prob(F-statistic)		0.083517

Table C.2: Group 2, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR2}$				
Method: Least Squares				
Sample(adjusted): 1971 1993				
Included observations: 23 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.013173	0.021863	0.602529	0.5543
$\Delta \text{LN}(\text{K/L})\text{GR2}$	0.599517	0.124966	4.797456	0.0001
$\Delta \text{LN}(\text{hours})\text{GR2}$	0.094676	0.657251	0.144049	0.8871
$\Delta \text{LN}(\text{pat})\text{GR2}$	0.046755	0.023295	2.007080	0.0600
$\Delta \text{ILN}(\text{pat})\text{GR2}$	0.123325	0.024710	4.991006	0.0001
R-squared	0.713841	Mean dependent var		0.078414
Adjusted R-squared	0.650250	S.D. dependent var		0.112068
S.E. of regression	0.066277	Akaike info criterion		-5.238179
Sum squared resid	0.079066	Schwarz criterion		-4.991333
Log likelihood	32.60347	F-statistic		11.22550
Durbin-Watson stat	1.864121	Prob(F-statistic)		0.000096

Employment model

Dependent Variable: $\Delta \text{LN}(\text{L}_t/\text{L})\text{GR2}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.064367	0.018242	-3.528498	0.0018
$\Delta \text{LN}(\text{hours})\text{GR2}$	-0.350535	0.706479	-0.496172	0.6245
$\Delta \text{LN}(\text{K}_t/\text{K})\text{GR2}$	0.732194	0.223307	3.278873	0.0033
$\Delta \text{LN}(\text{R\&D}_t/\text{R\&D})\text{GR2}$	0.243752	0.100403	2.427742	0.0234
R-squared	0.391638	Mean dependent var		-0.062211
Adjusted R-squared	0.312287	S.D. dependent var		0.109675
S.E. of regression	0.090952	Akaike info criterion		-1.821015
Sum squared resid	0.190262	Schwarz criterion		-1.629039
Log likelihood	28.58370	F-statistic		4.935487
Durbin-Watson stat	1.799732	Prob(F-statistic)		0.008625

Table C.3: Group 3, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR3}$				
Method: Least Squares				
Sample(adjusted): 1970 1993				
Included observations: 24 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.042758	0.028607	-1.494685	0.1506
$\Delta \text{LN}(\text{K/L})\text{GR3}$	0.531067	0.217835	2.437930	0.0242
$\Delta \text{LN}(\text{hours})\text{GR3}$	1.107481	1.031258	1.073913	0.2956
$\Delta \text{LN}(\text{pat})\text{GR3}$	0.069935	0.039908	1.752407	0.0950
R-squared	0.426477	Mean dependent var		0.009310
Adjusted R-squared	0.340448	S.D. dependent var		0.104186
S.E. of regression	0.084612	Akaike info criterion		-4.788339
Sum squared resid	0.143185	Schwarz criterion		-4.591997
Log likelihood	27.40555	F-statistic		4.957385
Durbin-Watson stat	1.346692	Prob(F-statistic)		0.009845

Employment model

Dependent Variable: $\Delta \text{LN}(\text{L}_i/\text{L})\text{GR3}$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.027106	0.017006	-1.593870	0.1266
$\Delta \text{LN}(\text{hours})\text{GR3}$	0.168824	0.730677	0.231051	0.8196
$\Delta \text{LN}(\text{K}_i/\text{K})\text{GR3}$	0.840782	0.414883	2.026552	0.0563
$\Delta 1 \text{LN}(\text{R\&D}_i/\text{R\&D})\text{GR3}$	0.454840	0.162179	2.804564	0.0109
$\Delta 2 \text{LN}(\text{sci}_i/\text{sci})\text{GR3}$	0.085475	0.027134	3.150137	0.0050
R-squared	0.471479	Mean dependent var		-0.028243
Adjusted R-squared	0.365775	S.D. dependent var		0.072125
S.E. of regression	0.057439	Akaike info criterion		-2.699331
Sum squared resid	0.065985	Schwarz criterion		-2.455556
Log likelihood	38.74164	F-statistic		4.460366
Durbin-Watson stat	1.987507	Prob(F-statistic)		0.009719

Table C.4: Group 4, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta \text{LN}(Y/L)\text{GR4}$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.036616	0.023669	1.546996	0.1368
$\Delta \text{LN}(K/L)\text{GR4}$	-0.298504	0.344534	-0.866400	0.3961
$\Delta \text{LN}(\text{hours})\text{GR4}$	-0.202876	0.736086	-0.275615	0.7855
$\Delta 2 \text{LN}(\text{sci})\text{GR4}$	0.141500	0.064437	2.195921	0.0395
R-squared	0.192236	Mean dependent var		0.021921
Adjusted R-squared	0.076841	S.D. dependent var		0.059201
S.E. of regression	0.056881	Akaike info criterion		-2.750080
Sum squared resid	0.067943	Schwarz criterion		-2.555059
Log likelihood	38.37599	F-statistic		1.665892
Durbin-Watson stat	2.334437	Prob(F-statistic)		0.204750

Employment model

Dependent Variable: $\Delta \text{LN}(L_i/L)\text{GR4}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.024875	0.005170	-4.810983	0.0001
$\Delta \text{LN}(\text{hours})\text{GR4}$	0.065910	0.255385	0.258081	0.7986
$\Delta \text{LN}(K_i/K)\text{GR4}$	0.324008	0.137382	2.358448	0.0272
$\Delta \text{LN}(\text{sci}/\text{sci})\text{GR4}$	0.065941	0.030366	2.171540	0.0405
R-squared	0.378854	Mean dependent var		-0.025765
Adjusted R-squared	0.297835	S.D. dependent var		0.027161
S.E. of regression	0.022760	Akaike info criterion		-4.591670
Sum squared resid	0.011914	Schwarz criterion		-4.399694
Log likelihood	65.98755	F-statistic		4.676113
Durbin-Watson stat	1.617098	Prob(F-statistic)		0.010807

Table C.5: Group 5, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta \text{LN}(Y/L)_{GR5}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.012846	0.020990	-0.611990	0.5465
$\Delta \text{LN}(K/L)_{GR5}$	0.692249	0.252827	2.738038	0.0117
$\Delta \text{LN}(\text{hours})_{GR5}$	0.323588	0.716517	0.451612	0.6558
$\Delta \text{LN}(\text{sci})_{GR5}$	0.110508	0.052234	2.115627	0.0454
R-squared	0.361694	Mean dependent var		0.042014
Adjusted R-squared	0.278437	S.D. dependent var		0.054652
S.E. of regression	0.046424	Akaike info criterion		-6.003923
Sum squared resid	0.049569	Schwarz criterion		-5.811947
Log likelihood	46.74162	F-statistic		4.344297
Durbin-Watson stat	2.245115	Prob(F-statistic)		0.014507

Employment model

Dependent Variable: $\Delta \text{LN}(L_i/L)_{GR5}$				
Method: Least Squares				
Sample(adjusted): 1971 1993				
Included observations: 23 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.030119	0.005035	-5.982122	0.0000
$\Delta \text{LN}(\text{hours})_{GR5}$	0.159837	0.381153	0.419350	0.6799
$\Delta \text{LN}(K_i/K)_{GR5}$	0.874729	0.173110	5.053027	0.0001
$\Delta \text{LN}(R\&D_i/R\&D)_{GR5}$	0.152202	0.072328	2.104313	0.0497
$\Delta \text{LN}(\text{pat}_i/\text{pat})_{GR5}$	0.046339	0.020628	2.246438	0.0375
R-squared	0.626138	Mean dependent var		-0.023192
Adjusted R-squared	0.543057	S.D. dependent var		0.032672
S.E. of regression	0.022085	Akaike info criterion		-4.598132
Sum squared resid	0.008780	Schwarz criterion		-4.351286
Log likelihood	57.87852	F-statistic		7.536511
Durbin-Watson stat	1.841984	Prob(F-statistic)		0.000947

Table C.6: Group 6, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR6}$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.032054	0.033093	-0.968623	0.3438
$\Delta \text{LN}(\text{K/L})\text{GR6}$	0.975407	0.480279	2.030917	0.0551
$\Delta \text{LN}(\text{hours})\text{GR6}$	-0.869965	1.255045	-0.693174	0.4958
$\Delta 2 \text{LN}(\text{sci})\text{GR6}$	0.026384	0.073734	0.357822	0.7240
R-squared	0.250360	Mean dependent var		0.028874
Adjusted R-squared	0.143268	S.D. dependent var		0.080591
S.E. of regression	0.074595	Akaike info criterion		-2.207841
Sum squared resid	0.116853	Schwarz criterion		-2.012821
Log likelihood	31.59801	F-statistic		2.337810
Durbin-Watson stat	1.900883	Prob(F-statistic)		0.102758

Employment model

Dependent Variable: $\Delta \text{LN}(\text{L}_i/\text{L})\text{GR6}$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.015916	0.005745	-2.770418	0.0118
$\Delta \text{LN}(\text{hours})\text{GR6}$	-0.056069	0.280609	-0.199811	0.8436
$\Delta \text{LN}(\text{K}_i/\text{K})\text{GR6}$	1.185480	0.207462	5.714209	0.0000
$\Delta 2 \text{LN}(\text{R\&D}_i/\text{R\&D})\text{GR6}$	0.088689	0.041210	2.152272	0.0438
$\Delta 2 \text{LN}(\text{sci}_i/\text{sci})\text{GR6}$	0.061036	0.040813	1.495508	0.1504
R-squared	0.548958	Mean dependent var		-0.016828
Adjusted R-squared	0.458750	S.D. dependent var		0.032065
S.E. of regression	0.023590	Akaike info criterion		-4.479136
Sum squared resid	0.011130	Schwarz criterion		-4.235361
Log likelihood	60.98920	F-statistic		6.085452
Durbin-Watson stat	2.019859	Prob(F-statistic)		0.002261

Table C.7: Group 7, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR7}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.008655	0.027394	-0.315939	0.7549
$\Delta \text{LN}(\text{K/L})\text{GR7}$	0.502851	0.321582	1.563679	0.1315
$\Delta \text{LN}(\text{hours})\text{GR7}$	0.406530	0.806457	0.504094	0.6190
$\Delta \text{LN}(\text{sci})\text{GR7}$	0.073507	0.032317	2.274540	0.0326
R-squared	0.250580	Mean dependent var		0.028342
Adjusted R-squared	0.152830	S.D. dependent var		0.073741
S.E. of regression	0.067872	Akaike info criterion		-5.244302
Sum squared resid	0.105953	Schwarz criterion		-5.052326
Log likelihood	36.48674	F-statistic		2.563466
Durbin-Watson stat	1.913161	Prob(F-statistic)		0.079507

Employment model

Dependent Variable: $\Delta \text{LN}(\text{L}_i/\text{L})\text{GR7}$				
Method: Least Squares				
Sample(adjusted): 1968 1993				
Included observations: 26 after adjusting endpoints				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.031275	0.006954	-4.497497	0.0002
$\Delta \text{LN}(\text{hours})\text{GR7}$	-0.563321	0.179395	-3.140115	0.0048
$\Delta \text{LN}(\text{K}_i/\text{K})\text{GR7}$	0.653030	0.263347	2.479728	0.0213
$\Delta \text{LN}(\text{sci}_i/\text{sci})\text{GR7}$	-0.030713	0.014898	-2.061617	0.0513
R-squared	0.424186	Mean dependent var		-0.038229
Adjusted R-squared	0.345666	S.D. dependent var		0.042797
S.E. of regression	0.034619	Akaike info criterion		-3.748194
Sum squared resid	0.026366	Schwarz criterion		-3.554641
Log likelihood	52.72652	F-statistic		5.402267
Durbin-Watson stat	1.336152	Prob(F-statistic)		0.006127

Table C.8: Group 8, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR8}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.009238	0.018523	0.498723	0.6227
$\Delta\text{LN}(\text{K/L})\text{GR8}$	-0.130150	0.266315	-0.488706	0.6297
$\Delta\text{LN}(\text{hours})\text{GR8}$	0.036299	0.717457	0.050594	0.9601
$\Delta\text{LN}(\text{sci})\text{GR8}$	0.038217	0.022683	1.684817	0.1055
R-squared	0.113549	Mean dependent var		0.007003
Adjusted R-squared	-0.002075	S.D. dependent var		0.064667
S.E. of regression	0.064734	Akaike info criterion		-5.338991
Sum squared resid	0.096381	Schwarz criterion		-5.147015
Log likelihood	37.76503	F-statistic		0.982053
Durbin-Watson stat	2.041307	Prob(F-statistic)		0.418460

Employment model

Dependent Variable: $\Delta\text{LN}(\text{L}_i/\text{L})\text{GR8}$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.015891	0.008511	-1.867131	0.0759
$\Delta\text{LN}(\text{hours})\text{GR8}$	-0.281908	0.421760	-0.668408	0.5112
$\Delta\text{LN}(\text{K}_i/\text{K})\text{GR8}$	0.295120	0.390652	0.755456	0.4584
$\Delta 2\text{LN}(\text{R}\&\text{D}_i/\text{R}\&\text{D})\text{GR8}$	-0.089095	0.047179	-1.888444	0.0729
R-squared	0.198108	Mean dependent var		-0.015599
Adjusted R-squared	0.083552	S.D. dependent var		0.039700
S.E. of regression	0.038005	Akaike info criterion		-3.556550
Sum squared resid	0.030332	Schwarz criterion		-3.361530
Log likelihood	48.45688	F-statistic		1.729356
Durbin-Watson stat	1.377344	Prob(F-statistic)		0.191642

Table C.9: Group 9, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR9}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.055172	0.034884	-1.581612	0.1274
$\Delta \text{LN}(\text{K/L})\text{GR9}$	1.247392	0.567905	2.196481	0.0384
$\Delta \text{LN}(\text{hours})\text{GR9}$	2.242588	0.895968	2.502976	0.0199
$\Delta \text{LN}(\text{sci})\text{GR9}$	0.073524	0.021766	3.377863	0.0026
R-squared	0.371068	Mean dependent var		0.024109
Adjusted R-squared	0.289033	S.D. dependent var		0.057585
S.E. of regression	0.048555	Akaike info criterion		-5.914151
Sum squared resid	0.054225	Schwarz criterion		-5.722175
Log likelihood	45.52970	F-statistic		4.523302
Durbin-Watson stat	1.735095	Prob(F-statistic)		0.012366

Employment model

Dependent Variable: $\Delta \text{LN}(\text{L}_i/\text{L})\text{GR9}$				
Method: Least Squares				
Sample(adjusted): 1968 1993				
Included observations: 26 after adjusting endpoints				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.010454	0.004456	-2.346674	0.0284
$\Delta \text{LN}(\text{hours})\text{GR9}$	0.093143	0.197953	0.470533	0.6426
$\Delta \text{LN}(\text{K}_i/\text{K})\text{GR9}$	0.342294	0.341279	1.002974	0.3268
$\Delta 1\text{LN}(\text{sci}_i/\text{sci})\text{GR9}$	-0.032525	0.009688	-3.357111	0.0028
R-squared	0.255701	Mean dependent var		-0.009186
Adjusted R-squared	0.154206	S.D. dependent var		0.019843
S.E. of regression	0.018249	Akaike info criterion		-5.028769
Sum squared resid	0.007327	Schwarz criterion		-4.835216
Log likelihood	69.37400	F-statistic		2.519338
Durbin-Watson stat	2.229599	Prob(F-statistic)		0.084370

Table C.10: Group 10, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR10}$				
Method: Least Squares				
Sample: 1972 1993				
Included observations: 22				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.003480	0.023468	-0.148289	0.8838
$\Delta \text{LN}(\text{K/L})\text{GR10}$	0.846103	0.325226	2.601586	0.0180
$\Delta \text{LN}(\text{hours})\text{GR10}$	3.822398	1.238343	3.086703	0.0064
$\Delta^2 \text{LN}(\text{pat})\text{GR10}$	0.238862	0.071440	3.343515	0.0036
R-squared	0.452817	Mean dependent var		0.039857
Adjusted R-squared	0.361620	S.D. dependent var		0.073769
S.E. of regression	0.058940	Akaike info criterion		-5.499497
Sum squared resid	0.062531	Schwarz criterion		-5.301126
Log likelihood	33.27782	F-statistic		4.965255
Durbin-Watson stat	1.634937	Prob(F-statistic)		0.011027

Employment model

Dependent Variable: $\Delta \text{LN}(\text{L}_i/\text{L})\text{GR10}$				
Method: Least Squares				
Sample(adjusted): 1971 1993				
Included observations: 22 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.028359	0.005433	-5.219542	0.0001
$\Delta \text{LN}(\text{hours})\text{GR10}$	-0.099783	0.435641	-0.229049	0.8214
$\Delta \text{LN}(\text{K}_i/\text{K})\text{GR10}$	0.052019	0.306551	0.169692	0.8671
$\Delta \text{LN}(\text{R\&D}_i/\text{R\&D})\text{GR10}$	0.148627	0.144493	1.028612	0.3173
$\Delta^4 \text{LN}(\text{sci}_i/\text{sci})\text{GR10}$	0.120592	0.051034	2.362996	0.0296
R-squared	0.325685	Mean dependent var		-0.024411
Adjusted R-squared	0.175838	S.D. dependent var		0.025702
S.E. of regression	0.023333	Akaike info criterion		-4.488236
Sum squared resid	0.009800	Schwarz criterion		-4.241389
Log likelihood	56.61471	F-statistic		2.173443
Durbin-Watson stat	1.395437	Prob(F-statistic)		0.113314

Table C.11: Group 11, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR11}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002658	0.019436	0.136760	0.8924
$\Delta\text{LN}(\text{K/L})\text{GR11}$	0.371449	0.215641	1.722533	0.0984
$\Delta\text{LN}(\text{hours})\text{GR11}$	0.578301	0.960672	0.601975	0.5531
$\Delta\text{LN}(\text{sci})\text{GR11}$	0.083700	0.066980	1.249624	0.2240
R-squared	0.160805	Mean dependent var		0.029588
Adjusted R-squared	0.051345	S.D. dependent var		0.052572
S.E. of regression	0.051204	Akaike info criterion		-5.807902
Sum squared resid	0.060304	Schwarz criterion		-5.615926
Log likelihood	44.09534	F-statistic		1.469076
Durbin-Watson stat	1.341148	Prob(F-statistic)		0.249103

Employment model

Dependent Variable: $\Delta\text{LN}(\text{L}_i/\text{L})\text{GR11}$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.010741	0.006745	-1.592342	0.1270
$\Delta\text{LN}(\text{hours})\text{GR11}$	0.210184	0.558352	0.376435	0.7106
$\Delta\text{LN}(\text{K}_i/\text{K})\text{GR11}$	0.039561	0.173183	0.228432	0.8216
$\Delta 2\text{LN}(\text{R\&D}_i/\text{R\&D})\text{GR11}$	0.136395	0.049651	2.747066	0.0124
$\Delta 1\text{LN}(\text{sci}_i/\text{sci})\text{GR11}$	0.141013	0.068377	2.062297	0.0524
R-squared	0.438057	Mean dependent var		-0.021141
Adjusted R-squared	0.325668	S.D. dependent var		0.036495
S.E. of regression	0.029969	Akaike info criterion		-4.000462
Sum squared resid	0.017963	Schwarz criterion		-3.756686
Log likelihood	55.00577	F-statistic		3.897696
Durbin-Watson stat	1.405111	Prob(F-statistic)		0.016895

Table C.12: Group 12, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR12}$				
Method: Least Squares				
Sample(adjusted): 1968 1993				
Included observations: 26 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.027991	0.036795	0.760731	0.4549
$\Delta \text{LN}(\text{K/L})\text{GR12}$	0.936858	0.571767	1.638531	0.1155
$\Delta \text{LN}(\text{hours})\text{GR12}$	1.363697	1.028336	1.326120	0.1984
$\Delta \text{LN}(\text{R\&D})\text{GR12}$	0.323931	0.156072	2.075526	0.0498
R-squared	0.200366	Mean dependent var		0.085363
Adjusted R-squared	0.091325	S.D. dependent var		0.087874
S.E. of regression	0.083765	Akaike info criterion		-4.818833
Sum squared resid	0.154366	Schwarz criterion		-4.625280
Log likelihood	29.75243	F-statistic		1.837532
Durbin-Watson stat	2.620622	Prob(F-statistic)		0.169839

Employment model

Dependent Variable: $\Delta \text{LN}(\text{L}_t/\text{L})\text{GR12}$				
Method: Least Squares				
Sample(adjusted): 1970 1993				
Included observations: 24 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.029733	0.007307	-4.069090	0.0007
$\Delta \text{LN}(\text{hours})\text{GR12}$	-0.403921	0.360826	-1.119435	0.2769
$\Delta \text{LN}(\text{K}_t/\text{K})\text{GR12}$	-0.496035	0.203528	-2.437186	0.0248
$\Delta \text{LN}(\text{R\&D}_t/\text{R\&D})\text{GR12}$	0.113941	0.114568	0.994531	0.3325
$\Delta \text{LN}(\text{pat}_t/\text{pat})\text{GR12}$	0.014382	0.010330	1.392221	0.1799
R-squared	0.338308	Mean dependent var		-0.024873
Adjusted R-squared	0.199005	S.D. dependent var		0.034956
S.E. of regression	0.031285	Akaike info criterion		-3.908279
Sum squared resid	0.018597	Schwarz criterion		-3.662851
Log likelihood	51.89934	F-statistic		2.428569
Durbin-Watson stat	1.546638	Prob(F-statistic)		0.083352

Table C.13: Group 13, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR13}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.016903	0.014745	-1.146323	0.2634
$\Delta\text{LN}(\text{K/L})\text{GR13}$	0.369544	0.294373	1.255362	0.2220
$\Delta\text{LN}(\text{hours})\text{GR13}$	1.998016	0.968881	2.062190	0.0507
$\Delta\text{LN}(\text{sci})\text{GR13}$	0.025258	0.017234	1.465637	0.1563
R-squared	0.197387	Mean dependent var		-0.000342
Adjusted R-squared	0.092699	S.D. dependent var		0.034899
S.E. of regression	0.033242	Akaike info criterion		-6.671921
Sum squared resid	0.025416	Schwarz criterion		-6.479945
Log likelihood	55.75959	F-statistic		1.885473
Durbin-Watson stat	1.825022	Prob(F-statistic)		0.160223

Employment model

Dependent Variable: $\Delta\text{LN}(\text{L}_i/\text{L})\text{GR13}$				
Method: Least Squares				
Sample(adjusted): 1971 1993				
Included observations: 23 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004123	0.002160	1.909219	0.0688
$\Delta\text{LN}(\text{hours})\text{GR13}$	-0.498784	0.285806	-1.745183	0.0943
$\Delta\text{LN}(\text{K}_i/\text{K})\text{GR13}$	0.933641	0.158125	5.904454	0.0000
$\Delta\text{LN}(\text{sci}_i/\text{sci})\text{GR13}$	-0.012601	0.005117	-2.462657	0.0217
R-squared	0.632146	Mean dependent var		0.007193
Adjusted R-squared	0.584165	S.D. dependent var		0.016933
S.E. of regression	0.010921	Akaike info criterion		-6.060232
Sum squared resid	0.002743	Schwarz criterion		-5.868256
Log likelihood	85.81313	F-statistic		13.17495
Durbin-Watson stat	1.588926	Prob(F-statistic)		0.000033

Table C.14: Group 14, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR14}$				
Method: Least Squares				
Sample(adjusted): 1972 1993				
Included observations: 22 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.017206	0.012074	-1.425079	0.1722
$\Delta\text{LN}(\text{K/L})\text{GR14}$	0.826333	0.190828	4.330242	0.0005
$\Delta\text{LN}(\text{hours})\text{GR14}$	0.622050	0.295472	2.105277	0.0504
$\Delta\text{1LN}(\text{pat})\text{GR14}$	0.009266	0.004588	2.019474	0.0595
$\Delta\text{2LN}(\text{pat})\text{GR14}$	0.011329	0.004418	2.564367	0.0201
R-squared	0.659807	Mean dependent var		0.034685
Adjusted R-squared	0.579761	S.D. dependent var		0.024883
S.E. of regression	0.016131	Akaike info criterion		-8.057363
Sum squared resid	0.004423	Schwarz criterion		-7.809399
Log likelihood	62.41435	F-statistic		8.242905
Durbin-Watson stat	2.209675	Prob(F-statistic)		0.000691

Employment model

Dependent Variable: $\Delta\text{LN}(\text{L}_t/\text{L})\text{GR14}$				
Method: Least Squares				
Sample(adjusted): 1968 1993				
Included observations: 26 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.002920	0.003490	-0.836730	0.4117
$\Delta\text{LN}(\text{hours})\text{GR14}$	-0.339367	0.165135	-2.055082	0.0519
$\Delta\text{LN}(\text{K}_t/\text{K})\text{GR14}$	0.398810	0.185453	2.150465	0.0428
$\Delta\text{1LN}(\text{R\&D}_t/\text{R\&D})\text{GR14}$	0.057983	0.041287	1.404412	0.1742
R-squared	0.350466	Mean dependent var		-0.006275
Adjusted R-squared	0.261893	S.D. dependent var		0.016345
S.E. of regression	0.014043	Akaike info criterion		-5.552768
Sum squared resid	0.004338	Schwarz criterion		-5.359215
Log likelihood	76.18598	F-statistic		3.956806
Durbin-Watson stat	1.999323	Prob(F-statistic)		0.021325

Table C.15: Group 15, estimates of the production function and employment models

Production function model

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR15}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.011120	0.018037	0.616505	0.5436
$\Delta \text{LN}(\text{K/L})\text{GR15}$	-0.254297	0.362535	-0.701441	0.4901
$\Delta \text{LN}(\text{hours})\text{GR15}$	-0.983731	0.858117	-1.146383	0.2634
$\Delta \text{LN}(\text{R\&D})\text{GR15}$	0.014045	0.041215	0.340772	0.7364
R-squared	0.069664	Mean dependent var		-0.001061
Adjusted R-squared	-0.051684	S.D. dependent var		0.026207
S.E. of regression	0.026876	Akaike info criterion		-4.259215
Sum squared resid	0.016613	Schwarz criterion		-4.067239
Log likelihood	61.49940	F-statistic		0.574086
Durbin-Watson stat	1.413635	Prob(F-statistic)		0.637807

Employment model

Dependent Variable: $\Delta \text{LN}(\text{L}_i/\text{L})\text{GR15}$				
Method: Least Squares				
Sample(adjusted): 1971 1993				
Included observations: 23 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.027262	0.002784	9.793883	0.0000
$\Delta \text{LN}(\text{hours})\text{GR15}$	-0.482891	0.287446	-1.679935	0.1113
$\Delta \text{LN}(\text{K}_i/\text{K})\text{GR15}$	0.325145	0.190801	1.704103	0.1066
$\Delta \text{LN}(\text{pat}_i/\text{pat})\text{GR15}$	0.049408	0.014800	3.338417	0.0039
$\Delta 1 \text{LN}(\text{pat}_i/\text{pat})\text{GR15}$	0.059064	0.016869	3.501295	0.0027
$\Delta 2 \text{LN}(\text{sci}_i/\text{sci})\text{GR15}$	0.060581	0.024273	2.495823	0.0231
R-squared	0.598616	Mean dependent var		0.022165
Adjusted R-squared	0.480562	S.D. dependent var		0.015196
S.E. of regression	0.010952	Akaike info criterion		-5.971158
Sum squared resid	0.002039	Schwarz criterion		-5.674942
Log likelihood	74.66831	F-statistic		5.070688
Durbin-Watson stat	1.616910	Prob(F-statistic)		0.005018

Chapter 2: The intersectoral flows of innovations - embodied technology and the spillover effect

Introduction

The importance of intersectoral flows of innovations in determining industrial productivity performances is emphasised by many theoretical and empirical works⁸⁵.

Innovations may flow embodied in technologically improved intermediate and capital goods or via free additions to the general pool of knowledge⁸⁶. In addition, if the prices of intermediate and capital goods are not correctly measured, supplied industries may appear to have a free benefit from the technological efforts of the capital producing industries.

In Chapter 1 we worked with the simplifying assumption that all innovations flows were embodied in capital goods and took changes in capital stock, investment in particular⁸⁷, as a proxy for externally acquired technology. We thus abstracted from both the role played by technologically improved intermediate goods and spillover effects, and also assumed that all investment goods were externally acquired and embodied new technology.

However, not all investment goods are externally acquired. Given the level of aggregation of our data, this might cause, in some cases, a strong over estimation of the effect of externally acquired technology. Then, not all investment is in technologically improved capital goods. In fact, it is possible to think of changes in

⁸⁵ See, among the others, Griliches (1979), Scherer (1982), Geroski (1994).

⁸⁶ See Papacostantinou, Sakurai, Wyckoff (1996).

⁸⁷ Investments are only a proxy for changes in Capital stock. In fact, changes in the stock of Capital between time $t-1$ and time t are given by the amount of Investment in the period **minus** the depreciation of Capital. However, if the rate of depreciation of Capital is approximately constant, Investments are a good indicator for changes in Capital stock.

capital and employment shares determined by demand expansion while the level of technology is constant. In this case, we would in general over estimate the effect of technological change by assuming that all investment embodies new technology. Given the importance of changes in capital stock (as capital shares or capital labour ratios) to determine changes in employment shares and labour productivity⁸⁸, a more detailed analysis of the intersectoral flows of innovations and the technological content of capital goods is advisable.

This chapter analyses the issue of the technological content of capital goods, in order to assess more precisely the importance of internal and external sources of innovations for employment share and productivity growth. In particular, we want to answer the following questions. First of all, is there a linkage between investment and indicators of technological change? What is the direction of the linkage, i.e. does technological change cause investment or do investment cause technological change? Then, if it is true that investments embody new technology, is there any way to distinguish among technology-neutral capital deepening, embodied technology developed in-house and embodied technology externally acquired? The importance of spillover effects for changes in labour productivity will also be analysed. In the first part of the Chapter, we will review some theoretical and empirical models linking changes in the stock of capital to GDP and productivity growth. In the second part, we will estimate Vector Autoregression models to analyse the causality effect between investment and indicators of technological change. In the third part, we will estimate on our data an investment model proposed by Nickell and Nicolitsas (1997), explicitly relating investment to total factor productivity and internal and external R&D expenditures. In this way, we will be able to assess the technological content of investment goods and

⁸⁸ As from the results of Chapter 1.

the degree of embodied technology deriving from internal and external innovative activities. In the fourth part, we will investigate the extent of the spillover effect for changes in labour productivity at the industry level. Finally, we will link these results to those obtained in Chapter 1 in order to define the impact of internal and external sources of innovation.

II.1 Theoretical and empirical models of capital accumulation and productivity growth

The concept of embodied technology is central in theoretical models linking the process of capital accumulation to technological change. The embodiment hypothesis is based on the observation that many new discoveries need to be materialised into machines or products in order to be made available and spread through the economy. Thinking about capital goods in particular, this implies that new capital goods will embody the latest technological advances of the producing industry. For the industries buying capital goods this means that capital accumulation will affect production and productivity not only in terms of a neutral expansion of output, but also will change the input mix requirement as an effect of the new embodied technology. As a consequence, the vintage structure of the capital stock is an important factor in determining the actual productivity performances of the firm or industry. Moreover, technological change may affect the vintage structure of capital by delaying or accelerating the scrapping rate. Many authors have recognised this channel of intra and inter industry transmissions of technological change. Hulten⁸⁹, for example, points out that “...models of disembodied technical change are based on a concept of capital

⁸⁹ Cfr. Hulten (1992).

in which investment goods of different generations (or “vintages”) differ only by some fixed factor associated with wear, tear and retirement ... in contrast, the “new view” of capital assumes that successive vintages of investment also embody differences in technical design. In this view, capital stock computed under the assumption that design improvements can be ignored will tend to understate the true productivity of the capital stock”. Similarly, Greenwood and Jovanovic⁹⁰ note that the traditional Solow framework fails to take into account the technological heterogeneity of the capital stock and the skill composition of the labour force. As a result, the importance of investment in new capital goods as a tool of implementing technological change is disregarded. Moreover, as showed by Nelson⁹¹, this causes an upward bias in the estimates of the residual, or exogenous rate of technological progress, in a Solow-type production function model. In fact, he shows that terms expressing the vintage structure of capital stock in a standard production function model increase the sensitivity of GDP growth to Capital growth. In the extreme hypothesis that all of total factor productivity growth is due to technological change that needs to be embodied, it is possible to explain all GDP fluctuations in the terms of changes in the vintage-adjusted capital stock.

However, the association between capital formation and productivity growth goes well beyond the pure technological embodiment effect. Nelson (1964) and Wolff (1991) indicate, for example, the fact that the introduction of new capital may lead to better organisation, management, and in general provide the economy with more flexibility. As such, productivity may grow even in absence of embodied technological change.

⁹⁰ Cfr. Greenwood, Jovanovic (1998).

⁹¹ Cfr. Nelson (1964).

Similarly, whenever the rate of learning is affected by the rate of new investments, learning by doing effects provide another avenue of complementarity between capital formation and productivity growth. In general, high expected rates of return and a favourable economic environment act as enhancing factors of both productivity, technology and investment growth. Finally, Nelson (1964) shows how the different pace of technological progress in various industries plays a major role to determine the efficient inter industry allocation of resources.

The embodiment hypothesis has led to re-specifications of macro models of growth, where the technological heterogeneity of the capital stock is explicitly considered. More specifically, investment are measured in terms of efficiency units and the aggregate measure of capital stock depends both on the relative efficiency of each vintage of capital goods and on the relative amount of surviving investment in each vintage⁹². Greenwood and Jovanovic (1998) show how modifications of the standard Solow framework taking into account lags in learning and diffusion of new technologies, and the complementarities between labour skills and technological change, may explain most of the empirical facts of the US post-war growth experience.

In order to maintain our focus on the complementarities between technological change and capital accumulation, we will present here their baseline vintage-capital model. This model has been developed by Solow in 1960s and is based on the assumption that technological progress is exogenous and embodied in the form of new capital goods. The vintage structure of the model and the specification of technologically

⁹² Cfr. Hulten (1992).

adjusted investment are however common to many recent vintage-capital models. Moreover, the model has the evident advantage of being simple.

The structure of the model is the following. Output is produced according to the constant returns to scale production function:

$$y = F(k, l) \quad [12]$$

Output can be either consumed, c , or invested, i . Then:

$$c + i = F(k, l) \quad [13]$$

Suppose now that capital accumulation is governed by the law of motion:

$$dk / dt = iq - \delta k \quad [14]$$

where i is gross investment and δ is the rate of physical depreciation on capital. q represents the current state of technology for producing new equipment. As q rises more new capital goods can be produced for a unit of forgone output or consumption. This form of technological progress is specific to the investment goods sector of the economy. Therefore, changes in q are dubbed investment-specific technological progress. Two important implications are:

- 1) In order to realise the gains from this form of technological progress there must be investment in the economy
- 2) Efficiency units of capital of different vintages can be aggregated linearly using the appropriate weights on past investments. Then:

$$k(t) = \int_0^{\infty} e^{-\delta s} q(t-s) i(t-s) ds \quad [15]$$

Finally, in a competitive equilibrium the relative price of new capital goods, p , would be given by:

$$p = l / q \quad [16]$$

since this shows how much output or consumption must be given up in order to purchase a new unit of equipment.

The price equation completes the model. Greenwood and Jovanovic (1998) have used this structure to investigate how much of post-war economic growth is due to investment-specific versus neutral technological progress. By specifying a functional form for the production function they find that the rate of growth of income on the economy's balanced path is given by:

$$g_y = \left(\frac{1}{1 - \alpha_e - \alpha_s} \right) g_z + \left(\frac{\alpha_c}{1 - \alpha_e - \alpha_s} \right) g_q \quad [17]$$

where g_z is the growth rate of neutral technical progress, g_q is the growth rate of investment-specific technical progress and α_e and α_s are the shares of the stocks of equipment and structures in production.

Other theoretical models of embodied technology include Campbell (1997), Caballero (1997) and Lach and Rob (1996). Campbell analyses how permanent shocks to embodied technology affect entry and exit decisions of firms. He finds that, in accordance with the empirical patterns, permanent technology shocks cause first an increase in the exit rate, by making some of the plants in production obsolete. New entrants whose plants embody updated technology fill the market and, as entering plants become operational, both output and productivity increase. Caballero (1997) develops a probabilistic model of investment decisions where investments take place once some critical boundaries are reached. The model is based on the empirical observation that investment at the firm level is basically lumpy, and that aggregate dynamics are strongly affected by the micro ones. That is, aggregation does not

smooth the data. Even without addressing at length the role of embodied technology,
Caballero (1997) sta] g(b]dlch1hc0 hrl(v)tv, E)q)..v(b yao0TF

]v1v.bgt) g(bq)qh.htchl wb]v. bm hrlvtcwvrc]vlhthbrt unv(v hrlvtcwvrc c)4v g.)lv
brlv tbwv l(hchl). qbdr]](hvt)(v (v)lnv], pnv wb]v. ht q)tv] br cnv vwgh(hl).
bqtv(1)chbr cn)c hrlvtcwvrc)c cnv mh(w .v1v. ht q)thl)..0 .dwg0S)r] cn)c)[[v()cv
]0r)whlt)(v tc(br[.0)mmvlev] q0 cnv whl(b brvt, pn)c htS)[[v()chbr]bvt rbc

smooth the data. Even without addressing at length the role of embodied technology, Caballero (1997) states that⁹³: "The sunk nature of technological embodiment is a source of lumpy and discontinuous actions at the microeconomic level. The (S,s) apparatus, with its implications for aggregates, is well suited for studying many aspects of vintage and putty-clay models. In particular, episodes of large investment which leave their technological fingerprints, and remain in the economy, reverberating over time." Finally, Lach and Rob (1996) present a model of industry evolution whose dynamics are driven by the linkages among R&D expenditures, probability of innovation and investment necessary in order to practically implement innovations.

One common and important characteristic of all theoretical models is that technological improvements in capital goods are perfectly reflected in price reductions. Thus, however investment decisions are taken, prices act as efficient conveyors of information. For example, in the Solow vintage-capital model seen before, prices were determined by the extent of technological progress embodied in new capital goods. Consequently, the rate of embodied technical change may be inferred by the price series for new capital goods. In this way it might be possible to test theoretical models on empirical data. Unfortunately, this procedure presents some difficulties. First, price setting behaviour depends, *inter alia*, on the competitive structure of the market. It is certainly possible to accommodate competitive structures different from perfect competition in a vintage-capital theoretical model. However, the problem remains of how much, and especially with what implications for prices, the theoretical structure is far from the real one. Second, and more important, currently available price series are generally bad at taking into account changes in the quality of

⁹³ Cfr Caballero (1997) pag.37.

goods. Hulten (1992) bases his study on a dataset of quality adjusted price series for US manufacturing. On the basis of this information, he is able to quantify the best-practice level of technology by year and the average embodied technical efficiency of capital goods.

However, properly quality adjusted price series are not generally available. Moreover, there is empirical evidence that investment responds, among the others, to scale and financial variables. In the framework of the analysis of the consequences of embodied technical change, the effect of these other variables may be expressed as an idiosyncratic component of investment.

For these reasons, most empirical studies take into account other variables thought to efficiently convey information about the firms' investment behaviour. One of the variables most used is q , the stock market valuation of the firm, whose theoretical justification is provided by an investment model by Lucas and Prescott⁹⁴ (1971). The rationale behind this approach is to identify first all the independent sources of investment variation and then relate the technologically induced dynamics to the innovative behaviour of firms. As Lucas and Prescott (1971) state⁹⁵: "An interesting feature of our theory is the role played by the securities prices in informing firms of the market (not shadow) price placed on additions to capital stock. We have found that securities prices as a variable in a firm level investment function have a much stronger justification than simply as a "proxy" variable for future demand". Or, as Lach and Schankerman (1989) put it⁹⁶ "... q_t serves as an indicator of the news in the information

⁹⁴ The investment model is based on cost of adjustment and demand uncertainty.

⁹⁵ Cfr. Lucas, Prescott (1971) pag. 680.

⁹⁶ Cfr. Lach, Schankerman (1989) pag. 884.

set that governs both optimal R&D and investment decisions and the associated value of the firm”.

The empirical analysis of the embodiment hypothesis follows two main avenues. The first one is based on Vector Autoregression models usually linking investment, R&D expenditures and some measure of the market valuation of the firm. Other variables sometimes included are firm sales⁹⁷ and suppliers' R&D expenditures⁹⁸. This approach has all the advantages and disadvantages of not being explicitly derived from a theoretical model. Moreover, in order to identify the shocks affecting the various variables, it is necessary to impose orthogonality conditions (i.e. restrictions) on the variance-covariance structure of the error term. One result common to most studies⁹⁹ is that the measure of the market valuation of the firm, q_t , while responding to the same shocks affecting investment and R&D expenditures, has an additional idiosyncratic component. Moreover, q_t does not Granger cause either investment or R&D expenditures. The empirical evidence is normally in favour of R&D expenditures Granger causing investment. Lach and Schankerman (1989), analysing a panel of 191 US manufacturing firms in the scientific sector over the years 1973-1981, find that R&D expenditures Granger cause investment while investment do not Granger cause R&D expenditures. The same result is in Nickell and Nicolitsas (1997), who analyse a panel of 100 manufacturing UK companies over the years 1976-1994. Also, Lach and Rob (1996) find evidence of one-way Granger causality from R&D expenditures to investment for a sample of 20 US industry groups over the years

⁹⁷ Nickell and Nicolitsas (1997).

⁹⁸ Shea (1998) and Nickell and Nicolitsas (1997).

⁹⁹ Cfr., for example, Lach, Schankerman (1989), Toivanen, Stoneman (1998), and Nickell and Nicolitsas (1997).

1958-1983. An exception is Toivanen and Stoneman (1998) who, analysing a panel of 185 UK companies over the years 1984-92, find the causality relation reversed. That is, R&D expenditures do not Granger cause investment while investment does Granger cause R&D expenditures.

Finally, whenever R&D expenditures of supplying industries are included in the analysis¹⁰⁰, there is evidence of a positive effect over investment of the supplied industry. As Nickell and Nicolitsas put it¹⁰¹ “If (a firm undertaking R&D) produces something new, this may also increase investment expenditures in the firms which it supplies. This is not a spillover effect but merely the consequence of the invention of something different”.

The second way to empirically test the embodiment hypothesis is through the specification of an equilibrium investment model directly relating investment decisions and indicators of technological change. This is the approach followed in Nickell and Nicolitsas (1997), who analyse the linkages among investment decisions, total factor productivity and own and suppliers' R&D expenditures at the firm level¹⁰². This is the approach we will adopt here. In particular, we will estimate the Nickell and Nicolitsas model on the panels of technological groups of industries. The panel data choice is due to the fact that the length of the individual time series would have not allowed a precise parametric estimate of the model. In accordance to the original formulation, we will use total factor productivity and R&D expenditures as indicators of the technological status. This approach has certainly its problems, being based among the others on the behavioural and informational hypothesis underlying the

¹⁰⁰ Cfr. for example Nickell and Nicolitsas (1997) and Shea (1998).

¹⁰¹ Cfr. Nickell and Nicolitsas (1997) pag. 19.

theoretical model. However, the VAR formulation is intrinsically recursive in nature. Patterns of response of one variable with respect to changes in another may be obtained only at the cost of imposing *a priori* restrictions on the variance-covariance structure of the shocks. As such, we would rather base our result on explicit if not completely plausible assumptions.

The next section is addressed to the investigation of the direction of Granger causality between R&D expenditures and investment. In particular, we will investigate if the causality flow at the base of the theoretical model, running from R&D expenditures to investment, is reflected in our data or not.

II.2 R&D expenditures and Investment: what causality flow?

We start our investigation of the technological embodiment hypothesis by analysing Vector Autoregression models between R&D expenditures and investment. As said before, data constraints make it advisable to estimate the empirical models on pooled data rather than on individual time series. We pooled the industries into three big groups. The first comprises all the *technology producer* industries (groups 4, 5, 10, 11, 12, and 15). The second comprises the *technology user and producer*, and *technology user* industries (groups 2, 6 and 1, 3, 9, 14)¹⁰³. The third is made of the *low technology* industries (groups 7, 8, 13)¹⁰⁴.

¹⁰² The model will be presented in detail in section 3.

¹⁰³ We had to aggregate the two technological groups because the number of data for the technology users and producers industries did not allow robust estimates of the parameters.

¹⁰⁴ For the exact definition of the groups of industries cfr. Chapter 1, section 2.

A first established empirical result, suggesting that the causality flow run from R&D expenditures to investment, is based on the observation that R&D expenditures are much less volatile than investment¹⁰⁵. Table II.1 reports the mean and standard deviation for the one-year growth rates of investment and R&D expenditures for the three panels¹⁰⁶.

Table II.1: Mean and Standard Deviation of one-year growth rates of investment and R&D expenditures (1966-1993)

	<i>Technology producer</i>	<i>Technology user and producer and technology user</i>	<i>Low technology</i>
Mean one period growth rate Investment	0.005	0.02	0.03
Mean one period growth rate R&D expenditures	0.007	0.001	0.01
Standard deviation one period growth rate Investment	0.09	0.08	0.11
Standard deviation one period growth rate R&D expenditures	0.05	0.06	0.12

Our results broadly confirm that investments are more volatile than R&D expenditures, although the difference in terms of standard deviation is not striking. This is however a positive finding in terms of causality in that it gives an approximate indication that a causality linkage exists. Exceptions are *Low technology* industries for which R&D expenditures are slightly more volatile than investment.

A more precise examination of the causality flow goes through the specification of Vector Autoregression models (VARs) and the analysis of Granger causality. Vector autoregression models relate the current value of each variable in a vector to its past

¹⁰⁵ Cfr. for example Lach, Schankerman (1989) and Nickell and Nicolitsas (1997). The results of Toivanen and Stoneman (1998) differ again in this respect. In fact, they find that the growth rate of investment is more volatile than the one of R&D expenditures, while for the levels R&D expenditures appear to be more volatile than investment.

¹⁰⁶ We concentrate on the growth rates of the series because, being the time series relatively long, the comparison in terms of standard deviation of levels is meaningless.

realisations and to those of all the other variables in the vector. The appropriate length of the VAR, i.e. the number of lags of each variable included in the specification, has been determined with a ‘general to specific’ procedure. Starting from a VAR (4)¹⁰⁷, the model was subsequently reduced on the basis of a Wald test on joint coefficients restrictions. This procedure brought to the selection of a VAR (2) as the preferred econometric specification for the *technology producer* and *low technology* panels. For the *technology user and producer* and *technology user* panel the preferred econometric specification is instead a VAR (4). However, the equilibrium investment model includes only up to two lags of value added and own and suppliers R&D. Therefore, for the *technology user and producer* and *technology user* panel we will present the results for both the VAR (4) and VAR (2) specifications.

We estimated, for each panel of data, four different VARs. The first one is based on the vector autoregression among log levels of investment, own industry R&D expenditures and R&D expenditures of the supplying industries. Following the standard procedure in the literature¹⁰⁸, we computed suppliers R&D expenditures on the basis of the coefficients of the UK input-output tables for investment purchases^{109,110}. The second specification of the VAR includes log levels of investment, value added, own industry R&D expenditures and R&D expenditures of the supplying industries. In the third one, investment is normalised by the capital stock and value added is excluded. Finally, the fourth one includes investment and valued

¹⁰⁷ The length of our time series prevented considering longer lags.

¹⁰⁸ See e.g. Griliches (1979); Papacostantinou, Sakurai, Wyckoff (1996); and Nickell and Nicolitsas (1997).

¹⁰⁹ Data sources are CSO “Input-Output Tables” 1974 and 1985.

¹¹⁰ More precisely, the coefficients we used to aggregate suppliers R&D expenditures are the average of the 1974 and 1985 input-output coefficients. We first took the original coefficients from the input-output tables of investment flows. Then, we took off the intra-industry investment flows and normalised the coefficients to one. Finally, we took the average of the 1974 and 1985 coefficients and computed accordingly the weighted average of suppliers R&D expenditures.

added normalised by the stock of capital and own and suppliers R&D expenditures. We tried all these specifications to see if the inclusion of value added and the normalisation for the stock of capital would substantially affect the result. The results are fairly robust with respect to the inclusion of these two variables¹¹¹. As such, we will present here only the results for the specification with investment and value added normalised by capital¹¹². The reason is that this specification is the one that resembles most the investment model we will estimate. All models have been estimated with fixed industry effects and time dummies in order to control for industry specific and deterministic components. The log levels representation is correct in that the variables are integrated of order 0 over the estimation period¹¹³. We did not explicitly address endogeneity problems because they are likely to be mitigated by considering the relationship between actual and lagged values. This adjustment is however at best only partial, so we cannot completely exclude a degree of endogeneity bias in our estimates. Tables II.2 to II.5 report the results of the VAR estimation.

We find that R&D expenditures Granger cause investment¹¹⁴ in *technology producer*, *technology user and producer* and *technology user* industries. However, the causality relation is reversed for *low technology* industries. That is, for this panel investment Granger cause R&D expenditures. As to the other variables, we find that in the *technology producer* panel investment Granger cause value added.

¹¹¹ The only exception is the not normalised investment and valued added model for the high technology panel. For this particular group, the above specification has the effect of breaking the causality link between investment and R&D expenditures.

¹¹² The results for the other specifications are in Appendix II.C to this Chapter.

¹¹³ As resulting from DF and ADF unit root tests.

¹¹⁴ I.e. past realisations of R&D expenditures are predictors of current investment, while past Investment realisations are not predictors of current R&D expenditures.

Table II.2: AR(2) Vector Autoregression model for technology producer industries

Sample 1972 1992				
Included observations: 21				
Total panel (balanced) observations 126				
Standard errors & t-statistics in parentheses				
	ln(Investment/Capital) I/K (t)	ln(Value Added/Capital) VA/K (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I/K (t-1)	0.713180* (0.111530) (6.394504)	-0.038816 (0.036874) (-1.052672)	-0.024462 (0.053300) (-0.458939)	0.032931 (0.028560) (1.153033)
I/K (t-2)	-0.231356* (0.123954) (-1.866467)	-0.077508* (0.040982) (-1.891284)	-0.080549 (0.059238) (-1.359754)	-0.011021 (0.031742) (-0.347222)
VA/K (t-1)	-0.085582 (0.305874) (-0.279796)	0.886370* (0.101128) (8.764833)	-0.054188 (0.146177) (-0.370698)	-0.062594 (0.078327) (-0.799136)
VA/K (t-2)	0.218574 (0.314267) (0.695503)	0.100742 (0.103903) (0.969579)	0.091740 (0.150189) (0.610835)	0.026647 (0.080476) (0.331116)
R&D (t-1)	0.518891* (0.272142) (1.906688)	0.092975 (0.089976) (1.033331)	1.151580* (0.130057) (8.854423)	0.012554 (0.069689) (0.180140)
R&D (t-2)	-0.407924 (0.295632) (-1.379836)	-0.117924 (0.097742) (-1.206479)	-0.151552 (0.141283) (-1.072683)	-0.019868 (0.075704) (-0.262446)
R&DS (t-1)	0.018038 (0.490305) (0.036788)	0.215375 (0.162105) (1.328618)	0.239303 (0.234317) (1.021279)	0.979980* (0.125555) (7.805156)
R&DS(t-2)	0.153033 (0.533002) (0.287115)	-0.248311 (0.176221) (-1.409090)	-0.236338 (0.254722) (-0.927826)	-0.102887 (0.136489) (-0.753810)
Fixed effects				
Group 4	-7.372268	0.772101	-0.386877	2.632568
Group 5	-7.098565	0.840800	-0.367185	2.582642
Group 10	-7.303874	0.815669	-0.367992	2.590744
Group 11	-6.898784	0.771242	-0.431189	2.656925
Group 12	-6.939812	0.749567	-0.299739	2.560189
Group 15	-6.841330	0.847090	-0.246261	2.591358

* At least 10% significant

Dependent variable: *ln (Investment/Capital)*

R-squared	0.877906	Mean dependent var	-3.195089
Adjusted R-squared	0.834112	S.D. dependent var	0.406149
S.E. of regression	0.165422	Sum squared resid	2.517518
F-statistic	24.50077	Durbin-Watson stat	1.937525
Prob(F-statistic)	0.000000		

Dependent variable: *ln (Value Added/Capital)*

R-squared	0.997883	Mean dependent var	-1.166781
Adjusted R-squared	0.997123	S.D. dependent var	1.019733
S.E. of regression	0.054692	Sum squared resid	0.275189
F-statistic	1606.039	Durbin-Watson stat	2.002664
Prob(F-statistic)	0.000000		

Dependent variable: *ln (own R&D expenditures)*

R-squared	0.998363	Mean dependent var	19.56509
Adjusted R-squared	0.997775	S.D. dependent var	1.676095
S.E. of regression	0.079055	Sum squared resid	0.574973
F-statistic	2077.649	Durbin-Watson stat	2.010701
Prob(F-statistic)	0.000000		

Dependent variable: *ln (suppliers R&D expenditures)*

R-squared	0.986906	Mean dependent var	20.54779
Adjusted R-squared	0.982209	S.D. dependent var	0.317589
S.E. of regression	0.042360	Sum squared resid	0.165086
F-statistic	256.8215	Durbin-Watson stat	2.102131
Prob(F-statistic)	0.000000		

Table II.3: AR(4) Vector Autoregression model for technology user and producer and technology user industries

Sample 1972 1992				
Included observations: 21				
Total panel (balanced) observations 126				
Standard errors & t-statistics in parentheses				
	ln(Investment/Capital) I/K (t)	ln(Value Added/Capital) VA/K (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I/K (t-1)	0.958166* (0.117129) (8.180461)	-0.010512 (0.049243) (-0.213470)	-0.005801 (0.080533) (-0.072038)	0.045340* (0.023118) (1.961275)
I/K (t-2)	-0.339338* (0.177289) (-1.914039)	-0.035828 (0.074535) (-0.480686)	-0.033905 (0.121897) (-0.278141)	-0.050829 (0.034992) (-1.452600)
I/K (t-3)	0.001795 (0.175766) (0.010214)	0.171538* (0.073895) (2.321376)	-0.038452 (0.120850) (-0.318175)	0.042416 (0.034691) (1.222669)
I/K (t-4)	0.090170 (0.112338) (0.802664)	-0.158879* (0.047229) (-3.364027)	0.031928 (0.077240) (0.413368)	-0.018600 (0.022172) (-0.838858)
VA/K (t-1)	0.570418* (0.229103) (2.489789)	0.943285* (0.096318) (9.793406)	0.194566 (0.157523) (1.235165)	-0.042204 (0.045218) (-0.933341)
VA/K (t-2)	-0.150854 (0.306512) (-0.492162)	-0.019782 (0.128862) (-0.153515)	-0.167635 (0.210746) (-0.795434)	0.078336 (0.060497) (1.294885)
VA/K (t-3)	-0.165240 (0.315658) (-0.523478)	-0.140066 (0.132708) (-1.055451)	0.337347 (0.217035) (1.554343)	-0.050756 (0.062302) (-0.814675)
VA/K (t-4)	0.059241 (0.238405) (0.248489)	0.105245 (0.100229) (1.050040)	-0.093730 (0.163918) (-0.571811)	0.018858 (0.047054) (0.400763)
R&D (t-1)	0.237895 (0.159901) (1.487761)	0.127298* (0.067225) (1.893609)	0.949529* (0.109942) (8.636614)	-0.031540 (0.031560) (-0.999371)
R&D (t-2)	-0.839820* (0.226357) (-3.710156)	-0.053996 (0.095164) (-0.567399)	-0.254575 (0.155635) (-1.635722)	-0.014244 (0.044676) (-0.318822)
R&D (t-3)	0.681644* (0.239931) (2.840997)	0.049391 (0.100871) (0.489647)	0.093998 (0.164968) (0.569796)	0.043668 (0.047356) (0.922136)
R&D (t-4)	-0.396302* (0.170827) (-2.319906)	-0.036460 (0.071818) (-0.507668)	-0.036792 (0.117454) (-0.313243)	0.005378 (0.033716) (0.159522)

R&DS (t-1)	-0.918549* (0.527111) (-1.742612)	0.044873 (0.221605) (0.202490)	-0.029205 (0.362422) (-0.080584)	0.894988* (0.104037) (8.602619)
R&DS(t-2)	0.680985 (0.648258) (1.050484)	0.000705 (0.272538) (0.002585)	0.148196 (0.445718) (0.332489)	0.047083 (0.127948) (0.367984)
R&DS(t-3)	-0.660131 (0.662628) (-0.996233)	0.110981 (0.278579) (0.398384)	-0.105710 (0.455598) (-0.232025)	-0.398597* (0.130784) (-3.047752)
R&DS(t-4)	-1.282042* (0.707610) (-1.811792)	-0.102039 (0.297490) (-0.342999)	0.199664 (0.486527) (0.410387)	0.504944* (0.139662) (3.615466)
Fixed effects				
Group 2	49.22291	-2.791094	0.207105	-1.094671
Group 6	49.26274	-2.866867	0.290965	-1.083702
Group 1	48.85268	-2.765612	0.164957	-1.068118
Group 3	49.30962	-2.869890	0.164715	-1.097035
Group 9	48.69382	-2.676171	-0.237643	-1.085408
Group 14	51.14747	-2.917788	0.291225	-1.129791

* At least 10% significant

Dependent variable: ln (Investment/Capital)

R-squared	0.898146	Mean dependent var	-2.915313
Adjusted R-squared	0.848431	S.D. dependent var	0.348740
S.E. of regression	0.135771	Sum squared resid	1.548431
F-statistic	21.16312	Durbin-Watson stat	1.891006
Prob(F-statistic)	0.000000		

Dependent variable: ln (Value Added/Capital)

R-squared	0.990072	Mean dependent var	-1.292518
Adjusted R-squared	0.985226	S.D. dependent var	0.469604
S.E. of regression	0.057080	Sum squared resid	0.273684
F-statistic	239.3328	Durbin-Watson stat	2.030500
Prob(F-statistic)	0.000000		

Dependent variable: ln (own R&D expenditures)

R-squared	0.988311	Mean dependent var	17.87310
Adjusted R-squared	0.982606	S.D. dependent var	0.707807
S.E. of regression	0.093351	Sum squared resid	0.732010
F-statistic	202.9214	Durbin-Watson stat	2.067641
Prob(F-statistic)	0.000000		

Dependent variable: ln (suppliers R&D expenditures)

R-squared	0.996214	Mean dependent var	20.45041
Adjusted R-squared	0.994366	S.D. dependent var	0.357003
S.E. of regression	0.026797	Sum squared resid	0.060320
F-statistic	631.4747	Durbin-Watson stat	1.891783
Prob(F-statistic)	0.000000		

Table II.4: AR(2) Vector Autoregression model for technology user and producer and technology user industries

Sample 1972 1992				
Included observations: 21				
Total panel (balanced) observations 126				
Standard errors & t-statistics in parentheses				
	ln(Investment/Capital) I/K (t)	ln(Value Added/Capital) VA/K (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I/K (t-1)	0.916618* (0.104010) (8.812770)	-0.018622 (0.042101) (-0.442323)	-0.029861 (0.065423) (-0.456426)	0.016331 (0.020257) (0.806201)
I/K (t-2)	-0.226915* (0.102214) (-2.219028)	0.022290 (0.041373) (0.538745)	-0.026551 (0.064293) (-0.412979)	-0.006914 (0.019907) (-0.347328)
VA/K (t-1)	0.545682* (0.241501) (2.259545)	0.946721* (0.097753) (9.684790)	0.194322 (0.151905) (1.279238)	-0.027993 (0.047034) (-0.595155)
VA/K (t-2)	-0.207402 (0.238613) (-0.869200)	-0.050642 (0.096584) (-0.524329)	0.059888 (0.150088) (0.399021)	0.054768 (0.046472) (1.178522)
R&D (t-1)	0.163739 (0.164447) (0.995698)	0.128675* (0.066564) (1.933110)	0.934435* (0.103437) (9.033825)	-0.042295 (0.032027) (-1.320600)
R&D (t-2)	-0.477997* (0.174232) (-2.743351)	-0.030065 (0.070524) (-0.426299)	-0.181427 (0.109592) (-1.655479)	0.017105 (0.033933) (0.504073)
R&DS (t-1)	-0.695777 (0.529644) (-1.313670)	-0.016390 (0.214386) (-0.076449)	0.022943 (0.333147) (0.068867)	0.789162* (0.103153) (7.650428)
R&DS(t-2)	-0.265069 (0.560345) (-0.473046)	0.078019 (0.226813) (0.343979)	0.057209 (0.352458) (0.162314)	-0.021009 (0.109132) (-0.192513)
Fixed effects				
Group 2	24.42006	-3.074664	2.843642	5.072318
Group 6	24.43086	-3.131926	2.919872	5.096677
Group 1	24.13044	-3.017082	2.776074	5.067167
Group 3	24.50519	-3.133191	2.798099	5.070195
Group 9	23.84621	-2.927056	2.403312	5.042152
Group 14	25.37913	-3.191281	3.014993	5.281573

* At least 10% significant

Dependent variable: *ln (Investment/Capital)*

R-squared	0.873521	Mean dependent var	-2.915313
Adjusted R-squared	0.828153	S.D. dependent var	0.348740
S.E. of regression	0.144568	Sum squared resid	1.922792
F-statistic	23.53307	Durbin-Watson stat	1.793929
Prob(F-statistic)	0.000000		

Dependent variable: *ln (Value Added/Capital)*

R-squared	0.988572	Mean dependent var	-1.292518
Adjusted R-squared	0.984472	S.D. dependent var	0.469604
S.E. of regression	0.058517	Sum squared resid	0.315034
F-statistic	294.7461	Durbin-Watson stat	2.017960
Prob(F-statistic)	0.000000		

Dependent variable: *ln (own R&D expenditures)*

R-squared	0.987852	Mean dependent var	17.87310
Adjusted R-squared	0.983495	S.D. dependent var	0.707807
S.E. of regression	0.090934	Sum squared resid	0.760740
F-statistic	277.0893	Durbin-Watson stat	2.075440
Prob(F-statistic)	0.000000		

Dependent variable: *ln (suppliers R&D expenditures)*

R-squared	0.995422	Mean dependent var	20.45041
Adjusted R-squared	0.993780	S.D. dependent var	0.357003
S.E. of regression	0.028156	Sum squared resid	0.072933
F-statistic	740.9003	Durbin-Watson stat	2.080697
Prob(F-statistic)	0.000000		

Table II.5: AR(2) Vector Autoregression model for low technology industries

Sample 1972 1992				
Included observations: 21				
Total panel (balanced) observations 63				
Standard errors & t-statistics in parentheses				
	ln(Investment/Capital) I/K (t)	ln(Value Added/Capital) VA/K (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I/K (t-1)	0.532429* (0.181149) (2.939170)	0.072777 (0.062537) (1.163729)	0.370759* (0.186854) (1.984219)	0.010602 (0.039744) (0.266754)
I/K (t-2)	-0.375919* (0.166491) (-2.257891)	-0.108623* (0.057477) (-1.889846)	-0.006938 (0.171734) (-0.040401)	-0.035123 (0.036528) (-0.961556)
VA/K (t-1)	0.447158 (0.459189) (0.973799)	0.702470* (0.158524) (4.431319)	-0.359456 (0.473650) (-0.758908)	0.104682 (0.100745) (1.039076)
VA/K (t-2)	0.684827 (0.453527) (1.510002)	-0.251443 (0.156569) (-1.605953)	-0.357818 (0.467810) (-0.764879)	-0.018088 (0.099503) (-0.181786)
R&D (t-1)	0.227401 (0.176523) (1.288222)	0.043577 (0.060940) (0.715084)	1.322510* (0.182082) (7.263257)	0.043322 (0.038729) (1.118597)
R&D (t-2)	-0.185955 (0.163826) (-1.135078)	-0.033323 (0.056557) (-0.589198)	-0.372936* (0.168985) (-2.206916)	-0.046669 (0.035943) (-1.298410)
R&DS (t-1)	-0.728550 (0.788067) (-0.924478)	0.013712 (0.272061) (0.050400)	1.650204* (0.812884) (2.030060)	0.558597* (0.172900) (3.230749)
R&DS(t-2)	-0.461736 (0.806312) (-0.572653)	0.177982 (0.278360) (0.639395)	0.049500 (0.831703) (0.059516)	-0.150811 (0.176903) (-0.852505)
<i>Fixed effects</i>				
Group 7	21.34618	-4.494862	-32.66895	11.86382
Group 8	21.65526	-4.445950	-32.95693	11.92390
Group 13	22.43847	-4.497866	-33.53091	12.06685

* At least 10% significant

Dependent variable: *ln (Investment/Capital)*

R-squared	0.953478	Mean dependent var	-3.298694
Adjusted R-squared	0.909864	S.D. dependent var	0.382644
S.E. of regression	0.114880	Sum squared resid	0.422318
F-statistic	24.29060	Durbin-Watson stat	1.965888
Prob(F-statistic)	0.000000		

Dependent variable: *ln (Value Added/Capital)*

R-squared	0.968828	Mean dependent var	-0.906010
Adjusted R-squared	0.939605	S.D. dependent var	0.161379
S.E. of regression	0.039660	Sum squared resid	0.050332
F-statistic	36.83601	Durbin-Watson stat	2.033056
Prob(F-statistic)	0.000000		

Dependent variable: *ln (own R&D expenditures)*

R-squared	0.999268	Mean dependent var	14.366663
Adjusted R-squared	0.998582	S.D. dependent var	3.146309
S.E. of regression	0.118489	Sum squared resid	0.449336
F-statistic	1617.677	Durbin-Watson stat	1.892697
Prob(F-statistic)	0.000000		

Dependent variable: *ln (suppliers R&D expenditures)*

R-squared	0.995107	Mean dependent var	20.52440
Adjusted R-squared	0.990502	S.D. dependent var	0.258871
S.E. of regression	0.025204	Sum squared resid	0.020328
F-statistic	241.0527	Durbin-Watson stat	2.045382
Prob(F-statistic)	0.000000		

In the *technology user and producer* and *technology user* panel we find, corresponding to the VAR (4) specification, bi-directional¹¹⁵ Granger causality between investment, valued added and suppliers R&D expenditures. Moreover, own R&D Granger cause value added. For the VAR(2) specification we have instead that value added Granger causes investment and own R&D Granger cause value added. For *low technology* industries, investment Granger cause value added and suppliers R&D Granger cause own R&D.

A word of caution is necessary: these relations are meaningful for the coefficients on the lagged dependent variable adding to substantially less than 1. Otherwise, the strongly autoregressive dynamic of the dependent variable biases the effects of the explanatory variables. We thus computed the long run effects for those Granger caused variables that did not show a too strong autoregressive component. Table II.6 shows the results. Long run effects are computed summing together the coefficients of the various variables.

Thus, for:

$$\begin{aligned} (I/K)_{ijt} = & \alpha + \beta_{j1}(I/K)_{ijt-1} + \beta_{j2}(I/K)_{ijt-2} + \gamma_{j1}(Y/K)_{ijt-1} + \gamma_{j2}(Y/K)_{ijt-2} \\ & + \delta_{j1}(R \& D)_{ijt-1} + \delta_{j2}(R \& D)_{ijt-2} + \xi_{j1}(R \& DS)_{ijt-1} + \xi_{j2}(R \& DS)_{ijt-2} \end{aligned} \quad [18]$$

where $j = \text{technology producer, technology user and producer, technology user, and low technology}$ and i is the indicator of the industries belonging to the technological group j .

the long run effects of the explanatory variables are given by:

$$\begin{aligned} (I/K) = & \alpha/(1 - \beta_1 - \beta_2) + [(\gamma_1 + \gamma_2)/(1 - \beta_1 - \beta_2)] * (Y/K) + \\ & [(\delta_1 + \delta_2)/(1 - \beta_1 - \beta_2)] * (R \& D) + [(\xi_1 + \xi_2)/(1 - \beta_1 - \beta_2)] * (R \& DS) \end{aligned} \quad [19]$$

¹¹⁵ i.e. variables Granger cause each other.

Table II.6: Computed long run effects

Technology producer		
<i>Granger causality</i>		
<i>From:</i>	<i>To:</i>	<i>Effect</i>
own R&D	I/K	0.21
Low technology		
I/K	VA/K	0.14

We find only two effects of some significance. The first is for the *technology producer* panel and shows that own R&D expenditures do indeed Granger cause investment with a positive long run effect. The second is for the *low technology* panel and shows that investment Granger cause value added with a positive long run effect. Unfortunately, our data do not tell anything more about the role of own and suppliers R&D expenditures in these or other industries.

To sum up our results: we have found some evidence of Granger causality between R&D expenditures and investment for the technological groups of industries. It would seem that the causality direction is not uniform, but the substantial autoregressive component of some dependent variables does not allow precise inferences. Tentatively, the causality direction goes from R&D expenditures to investment for *technology producer, technology user and producer* and *technology user* industries. It goes instead from investment to R&D expenditures in *low technology* industries. By comparing standard deviations of the growth rates of R&D expenditures and investment, we have found that investment growth is generally more volatile than R&D expenditures growth, although as expected the difference is not striking. Finally, the few robust long run effects we get show that R&D expenditures positively affect investment in *technology producer* industries and investments positively affect value added in *low technology* ones.

In order to pursue our analysis of the technological embodiment hypothesis, we present in the next section the empirical results from a theoretical model of investment decisions. As said before, this approach has the advantage of being based on explicit behavioural assumptions, avoiding, among the others, the recursive structure of VAR models. The theoretical model has been proposed by Nickell and Nicolitsas (1997), who have tested it empirically on a panel of manufacturing UK companies over the years 1976-1994. We will re-estimate¹¹⁶ the model here on the technological groups of industries over the years 1966-1993.

II.3 The Nickell and Nicolitsas 1997 investment model: theoretical structure and empirical results

The investment model proposed by Nickell and Nicolistas (1997) is a strictly convex cost of adjustment model where the present value of the marginal returns to capital is modelled directly. We choose this framework because it allows a direct investigation of the effect of own and suppliers R&D expenditures on investment. In this section we will first present the theoretical structure of the model and then its empirical formulation and the estimation results.

II.3.1 The theoretical structure¹¹⁷

The basic convex adjustment costs model has the following form. The firm has a real net earnings stream, $\pi(K(t), t)$, and the total instantaneous cost of purchasing a stream

¹¹⁶ Some minor modifications in the definitions of variables have been necessary in order to get the industry level relationships.

¹¹⁷ This section is taken from Nickell and Nicolitsas (1997). Cfr. the original paper for a more detailed discussion.

of new capital goods, $I(t)$, is given by $C(I(t), t)$. This includes both the adjustment costs and the purchase price, and is strictly convex in I ($C_{11} > 0$). If one unit of new capital is purchased at time t , this costs $C_1(I(t), t)$, and generates an additional revenue stream $e^{-\delta s} \pi_k(K(t+s), t+s)$ from $s = 0$ to ∞ . The parameter δ is the autonomous rate at which capital decays. Investment at t continues until the total cost of a new unit of capital just balances the (expected) present value of the additional revenue stream, using a real discount rate, r . Thus:

$$C_1(I(t), t) = \int_0^{\infty} e^{-(r+\delta)s} \pi_k(K(t+s), t+s) ds \quad [20]$$

The evaluation of this integral (not observed) along the optimal path is at the core of the empirical formulation of the model. Two of the most used ways to deal with it in the literature are:

1. Replacement of the integral with the total stock market valuation of the firm's capital stock at time t divided by the value of this capital stock at replacement cost $\Rightarrow$ Q investment model
2. Discrete time approximation of the flow equivalent of the integral expression $\Rightarrow$ Euler equation model.

However, Nickell and Nicolitsas argue that the two above methods are unsatisfactory for the purpose because of endogeneity problems (Q model), and generally poor empirical performances¹¹⁸. As such, they propose to model the present value of the marginal returns to capital directly. This involves the exact definition of the real net earnings stream of the firm, π , and, consequently, of its production technology.

¹¹⁸ Cfr. also Caballero (1997) for a critique to the Q model.

On the assumptions that :

(a) the firm has a constant returns production function of the form $AF(K,N)$ and faces a demand curve $P^{-\eta}$ where A is the total factor productivity coefficient, N is employment and P is the real price of output

(b) there are no employment adjustments costs

then, given a real wage W , the firm will choose N and P at each point in time to solve:

$$\text{Max}_{P,N} (PAF(K,N) - WN) \quad [21]$$

subject to $AF(K,N) = P^{-\eta}$

The optimal price and employment level given K and W will satisfy the constraint plus the usual marginal revenue product condition:

$$(1-1/\eta)PAF_N(K,N) = W \quad [22]$$

Moreover, on the assumption that the function C is strictly convex in I and also depends positively on the real price of capital goods $P^I(t)$, and negatively on the scale of the firm S , then the net earnings stream π is given by:

$$\pi = PAF(K,N) - WN - C(I, P^I, S) \quad [23]$$

with N satisfying the marginal revenue product condition at any point in time. Using the envelope theorem, the marginal net earnings, π_k , satisfy:

$$\pi_k = (1-1/\eta)PAF_K(K,N) = (1-1/\eta)PAF_K(K/N, 1) \quad [24]$$

for the hypothesis of constant returns.

But, at each point in time the capital labour ratio is determined by the marginal revenue product condition for labour, because F_N is a function only of K/N via constant returns. This implies:

$$K/N = F_N^{-1}(W/(1-l/\eta)AP) \quad [25]$$

And hence π_k is given by:

$$\pi_k = (1-l/\eta)PAF_K(F_N^{-1}(W/(1-l/\eta)AP), l) \quad [26]$$

or

$$\pi_k = MAf(W/MA) \quad [27]$$

where $M = (1-l/\eta)P =$ marginal revenue, and $f' < 0$.

The basic adjustment costs investment condition can then be written as:

$$C_1(I(t), P^l(t), S) = E \int_0^\infty e^{-(r(t)+\delta)s} M(t+s)A(t+s)f[W(t+s)/M(t+s)A(t+s)]ds \quad [28]$$

where the expectations operator emphasises that the future values of M, A and W are unknown at time t.

Taking as explicit functional forms for C_1 and f :

$$C_1 = B_1 I(t)^{b_1} P^l(t)^{b_2} S \quad f = B_2 x^{-b_3}$$

Supposing that the future variables $M(t+s)$, $A(t+s)$ and $W(t+s)$ can be written as:

$$\begin{aligned} M(t+s) &= M(t)e^{g_m s} \\ A(t+s) &= A(t)e^{g_a s} \\ W(t+s) &= W(t)e^{g_w s} \end{aligned} \quad [29]$$

with g_m , g_a , g_w expected growth rates that are assumed small relative to the total discount factor, $(r(t)+\delta)$, then the adjustment costs equation can be rewritten in log linear form as:¹¹⁹

$$\ln I_t = \alpha_0 - \alpha_1 \ln P_t^l + \alpha_2 \ln M_t + \alpha_3 \ln A_t - \alpha_4 \ln W_t + \alpha_5 g_{mt} + \alpha_6 g_{at} - \alpha_7 g_{wt} - \alpha_8 r_t \quad [30]$$

This equation gives the basis for the empirical investigation of the model. However, in order to make it operational at the industry level, a few modifications and the exact definition of the total factor productivity and expected growth rates terms are necessary. The next subsection will describe the transformations involved.

II.3.2 Empirical formulation and estimation results

As said before, some modifications are necessary in order to make the model operational for empirical implementation. These involve both the exact definition of the total factor productivity and expected growth rates terms and the aggregation from firm to industry level. We will describe first how we computed the total factor productivity and expected growth rates terms, and next the specification of the model at the industry level.

II.3.2.1 Computation of total factor productivity

Following Nickell and Nicolitsas (1997), we computed the total factor productivity term on the basis of the Solow residual. At this stage the analysis is at the individual industry group level, i.e. not on panels.

Thus, for each industry j , $j = 1, \dots, 15$ we first computed the Solow residual:

$$\Delta \ln \tilde{A}_{jt} = \Delta \ln Y_{jt} - \alpha_j \Delta \ln N_{jt} - (1 - \alpha_j) \Delta \ln K_{jt} \quad [31]$$

with $\ln A_{j0} = 0$.

Y_{jt} , N_{jt} , and K_{jt} are, respectively, value added, employment and capital stock of industry j at time t .

¹¹⁹ This formulation relies on gross investment never going negative, which in our sample it does not. It also relies on the scale factor being absorbed into the constant term, which must, therefore be firm or industry specific.

α_j has been computed as the product of the average wage share in value added by mark-up¹²⁰. In fact, under imperfect competition in the product market, α_j is given by:

$$\alpha_j = \partial \ln Y_j / \partial \ln N_j = N_j / Y_j * \partial Y_j / \partial N_j = N_j / Y_j * W_j / MR_j = (W_j N_j / P_j Y_j) * (\text{mark-up})_j \quad [32]$$

being MR_j the marginal revenue in industry j , given by:

$$MR_j = P_j / (\text{mark-up of prices on marginal cost})_j \quad [33]$$

Second, to explicitly assess the impact of own and suppliers R&D expenditures on total factor productivity, we estimated the models:

$$\ln \tilde{A}_{jt} - (1 - \delta) \ln \tilde{A}_{j,t-1} = \beta_0 + \beta_1 \ln R \& D_{j,t-1} + \beta_2 \ln R \& D_{j,t-2} + \beta_3 \ln R \& DS_{j,t-1} + \beta_4 \ln R \& DS_{j,t-2} + \beta_5 OH_{jt} + \beta_6 (OH_{jt})^{-1} + \beta_7 t + \varepsilon_t \quad [34]$$

where $R \& D_j$ are R&D expenditures in industry j , $R \& DS_j$ are industry j suppliers R&D expenditures, OH_j are overtime hours divided by standard hours in industry j , t is a linear time trend, and $(OH_j)^{-1}$ is to control for cyclical fluctuations.

This model is derived on the assumptions that total factor productivity depends on knowledge capital through a constant elasticity form and that both own and suppliers R&D expenditures contribute to knowledge capital with a lag¹²¹. Following Blundell et al., 1995, we estimated the models with $\delta = 0.4$. Estimation of the parameter δ on the basis of our data confirms that $\delta = 0.4$ is indeed a good approximation for the decay rate of R&D generated knowledge. The estimation results are reported in Appendix II.A: we find that, in general, changes in total factor productivity are positively related to suppliers R&D expenditures. With the exception of two industries

¹²⁰ Data sources are OECD International Sectoral Database, compensation of employees, and Martins et al. (1996), Table A6, for the mark-up data.

(groups 3 and 10) own R&D expenditures do not seem to play much of a role. Moreover, for some industries we could not find any significant relation between R&D expenditures in general and changes in total factor productivity. These results indicate that, when total factor productivity is taken as a measure of technological change, own R&D expenditures may not be good indicators of disembodied technological efforts. However, it is not our interest to pursue here this line of investigation.

Finally, we defined trend total factor productivity A_{jt} by:

$$\ln A_{jt} = (1 - \delta) \ln A_{jt-1} + \hat{\beta}_0 + \hat{\beta}_1 \ln R \& D_{jt-1} + \hat{\beta}_2 \ln R \& D_{jt-2} + \hat{\beta}_3 \ln R \& DS_{jt-1} + \hat{\beta}_4 \ln R \& DS_{jt-2} + \hat{\beta}_5 \ln OH_{jt} + \hat{\beta}_6 (OH_{jt})^{-1} + \hat{\beta}_7 t \quad [35]$$

where the β s are the fitted values of the coefficients of equation [34], and the overtime hours terms are set to their means in order to capture trend productivity.

II.3.2.2 Estimation of the expected growth rates terms

We estimated the expected growth rates of value added (g_{yjt}), real industry output price (g_{pjt}), wages (g_{wjt}), and total factor productivity (g_{ajt}) by using subsidiary regressions. For each industry variable z_j we first run a regression of the form:

$$\Delta_2 \ln z_{jt+2} = \gamma_0 + \gamma_1 \Delta \ln z_{jt} + \gamma_2 \Delta \ln z_{jt-1} + \sum_k \gamma_{3k} x_{kjt} \quad [36]$$

where x are variables which may help to forecast z .

We then defined the expected growth rate as:

$$g_{z_{jt}} = 1/2 * (\hat{\Delta}_2 \ln z_{jt+2}) \quad [37]$$

¹²¹ Cfr. Nickell and Nicolistas (1997) for more details.

that is, 1/2 of the fitted values of the above regression.

The x variables for each term are as follows:

g_{wjt} profits per employee¹²², aggregate unemployment rate

g_{ajt} own and suppliers R&D expenditures

We did not use any extra variable for g_{yjt} and g_{pjt} , that is, for these two terms the equations only contain lags of the dependent variable.

II.3.2.3 Other modifications and empirical model

The final steps before proceeding to the empirical estimation of the model are:

- 1) Marginal revenues at the industry level are proxied by value added, own R&D expenditures and the real industry output price. Then:

$$\ln M_{jt} = \alpha_1 \ln Y_{jt} + \alpha_2 \ln R\&D_{jt} + \alpha_3 \ln P_{jt}$$

and [38]

$$g_{mjt} = \beta_1 g_{yjt} + \beta_2 g_{pjt}$$

where we omit the own R&D effect in the growth rate term because it is expressed in other variables in the final model.

- 2) All explanatory variables in the final model are lagged one period. This is because empirical evidence supports a one-year lag between investment decisions and actual expenditures¹²³. Moreover, following the results of the VAR analysis, we add the one and two-years lagged values of investment, value added, and suppliers R&D expenditures¹²⁴; and the two-years lagged value of own R&D expenditures.

¹²² Data source: OECD Statistical Compendium.

¹²³ Cfr. Nickell and Nicolitsas (1997).

¹²⁴ For the technology user and producer and technology user panel the model also includes the three-years lagged values of suppliers R&D expenditures. The first lag of the variable was in fact non-

3) The industry's real price of capital has been proxied with the industry output price.

4) Investment and value added are normalised by the one-period lagged capital stock in order to control for scale factors. Because of data limitation at the single industry level, the investment model is estimated on the *technology producer*, *technology user and producer* and *technology user*, and *low technology* panels of industries. However, the dimension of the time series at the single industry level allowed estimating industry specific coefficients for the lagged values of investment and value added normalised by capital. We found empirical evidence supporting the one-period lagged effects of investment and value added to be industry specific, thus the restriction of common coefficients on these variables was dropped¹²⁵. Moreover, preliminary empirical results indicated that own and supplier R&D expenditures should enter the model in difference form, hence the final specification of the model includes these restrictions. All equations have been estimated using the fixed effects estimator and include time dummies.

Thus, for each industry i in the technological group j , $j = \text{technology producer, technology user and producer and technology user, low technology}$, we estimated the investment model:

$$\begin{aligned} \ln(I_{ijt}/K_{ijt-1}) = & \alpha_{0j} + \beta_{1j} \ln(I_{ijt-1}/K_{ijt-2}) + \beta_{2j} \ln(I_{ijt-2}/K_{ijt-3}) + \\ & \gamma_{1j} \ln(Y_{ijt-1}/K_{ijt-1}) + \gamma_{2j} \ln(Y_{ijt-2}/K_{ijt-2}) + \delta_{1j} \ln(R \& D_{ijt-1}/R \& D_{ijt-2}) + \\ & \delta_{2j} \ln(R \& DS_{ijt-1}/R \& DS_{ijt-2}) + \varphi_{1j} \ln(P_{ijt-1}^Y) + \varphi_{2j} \ln(A_{ijt-1}) + \\ & \varphi_{3j} \ln(W_{ijt-1}/P_{ijt-1}^Y) + \varphi_{4j} g_{Yijt-1} + \varphi_{5j} g_{P^Y_{ijt-1}} + \varphi_{6j} g_{(w/P)_{ijt-1}} + \varphi_{7j} g_{a_{ijt-1}} \end{aligned} \quad [39]$$

Tables II.7 to II.9 show the estimation results for the technological panels.

significant, while the third lag was strongly significant. For the low technology group the model includes the five and six-years lagged values of suppliers R&D expenditures. These are the first lags for which suppliers R&D expenditures are significant. Note however that the small dimension of the panel (3 industries) does not allow any robust inference to be drawn from the results.

¹²⁵ Industry specific coefficients for the two-period lagged value added over capital did not appear to improve significantly the model, so common coefficients were kept.

Table II.7: Investment model - estimation results for *technology producer* industries

Dependent Variable: $\ln(I_{jt}/K_{jt-1})$				
Method: Pooled Least Squares				
Sample(adjusted): 1968 1993				
Included observations: 26 after adjusting endpoints				
Total panel (balanced) observations: 156				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
$\ln(Y_{jt-2}/K_{jt-2})$	-0.271728	0.278489	-0.975721	0.3315
$\ln(R\&D_{jt-1}/R\&D_{jt-2})$	0.523800	0.187142	2.798947	0.0061
$\ln(R\&DS_{jt-1}/R\&DS_{jt-2})$	-0.064048	0.411140	-0.155781	0.8765
$\ln(P^y_{jt-1})$	-0.331827	0.608035	-0.545736	0.5864
$\ln(A_{jt-1})$	0.843399	0.260775	3.234204	0.0016
$\ln(W_{jt-1}/P^y_{jt-1})$	-0.162141	0.569110	-0.284902	0.7763
g_{yjt-1}	0.990417	0.927806	1.067483	0.2882
g_{pyjt-1}	0.052573	0.774342	0.067894	0.9460
$g_{(w/p)jt-1}$	-2.245965	0.945742	-2.374818	0.0194
$\ln(I_{jt-1}/K_{jt-2})_4$	0.484578	0.176644	2.743247	0.0072
$\ln(I_{jt-1}/K_{jt-2})_5$	0.469991	0.253708	1.852489	0.0668
$\ln(I_{jt-1}/K_{jt-2})_{10}$	0.416408	0.118835	3.504076	0.0007
$\ln(I_{jt-1}/K_{jt-2})_{11}$	0.615853	0.154289	3.991562	0.0001
$\ln(I_{jt-1}/K_{jt-2})_{12}$	0.774656	0.178445	4.341149	0.0000
$\ln(I_{jt-1}/K_{jt-2})_{15}$	0.934510	0.264130	3.538064	0.0006
$\ln(Y_{jt-1}/K_{jt-1})_4$	1.044908	0.429844	2.430902	0.0168
$\ln(Y_{jt-1}/K_{jt-1})_5$	0.888813	0.377553	2.354140	0.0204
$\ln(Y_{jt-1}/K_{jt-1})_{10}$	0.722442	0.329522	2.192394	0.0306
$\ln(Y_{jt-2}/K_{jt-2})_{11}$	-0.309980	0.474249	-0.653623	0.5148
$\ln(Y_{jt-1}/K_{jt-1})_{12}$	-0.506058	0.406696	-1.244316	0.2162
$\ln(Y_{jt-1}/K_{jt-1})_{15}$	-0.220536	1.117526	-0.197343	0.8439
Fixed Effects				
GR4--C	-0.579222			
GR5--C	-0.894540			
GR10--C	-0.812335			
GR11--C	-0.376313			
GR12--C	-2.858793			
GR15--C	-0.462921			
R-squared	0.921794	Mean dependent var	-3.154523	
Adjusted R-squared	0.883442	S.D. dependent var	0.421641	
S.E. of regression	0.143950	Sum squared resid	2.155061	
Log likelihood	112.6445	F-statistic	27.24029	
Durbin-Watson stat	1.985827	Prob(F-statistic)	0.000000	

Table II.8: Investment model – estimation results for *technology user and producer* and *technology user* industries

Dependent Variable: $\ln(I_{jt}/K_{jt-1})$				
Method: Pooled Least Squares				
Sample: 1971 1993				
Included observations: 23				
Total panel (balanced) observations: 138				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
$\ln(Y_{jt-2}/K_{jt-2})$	-0.214498	0.255330	-0.840084	0.4031
$\ln(R\&D_{jt-1}/R\&D_{jt-2})$	0.297817	0.163999	1.815968	0.0727
$\ln(R\&DS_{jt-2}/R\&DS_{jt-3})$	0.707753	0.503853	1.404681	0.1636
$\ln(P^y_{jt-1})$	0.724814	0.373024	1.943078	0.0552
$\ln(A_{jt-1})$	0.376558	0.333179	1.130199	0.2614
$\ln(W_{jt-1}/P^y_{jt-1})$	0.657909	0.358520	1.835067	0.0698
g_{yjt-1}	-0.182628	0.826576	-0.220945	0.8256
g_{pyjt-1}	1.037500	0.565769	1.833789	0.0700
$g_{(w/p)jt-1}$	-0.845564	0.442780	-1.909669	0.0594
$\ln(I_{jt-1}/K_{jt-2})_1$	0.448113	0.209867	2.135229	0.0355
$\ln(I_{jt-1}/K_{jt-2})_3$	0.711048	0.151223	4.701976	0.0000
$\ln(I_{jt-1}/K_{jt-2})_9$	0.607704	0.160302	3.790994	0.0003
$\ln(I_{jt-1}/K_{jt-2})_{14}$	0.138207	0.320743	0.430895	0.6676
$\ln(I_{jt-1}/K_{jt-2})_2$	0.811933	0.101581	7.992935	0.0000
$\ln(I_{jt-1}/K_{jt-2})_6$	0.284899	0.348158	0.818304	0.4154
$\ln(Y_{jt-1}/K_{jt-1})_1$	-0.482913	0.466284	-1.035662	0.3032
$\ln(Y_{jt-1}/K_{jt-1})_3$	0.018564	0.264855	0.070090	0.9443
$\ln(Y_{jt-1}/K_{jt-1})_9$	-0.243703	0.349376	-0.697538	0.4873
$\ln(Y_{jt-1}/K_{jt-1})_{14}$	1.245354	0.624344	1.994658	0.0491
$\ln(Y_{jt-1}/K_{jt-1})_2$	0.408537	0.325895	1.253585	0.2133
$\ln(Y_{jt-1}/K_{jt-1})_6$	0.247090	0.367553	0.672258	0.5032
Fixed Effects				
GR1--C	-6.371679			
GR3--C	-4.446818			
GR9--C	-4.870798			
GR14--C	-4.351881			
GR2--C	-3.702496			
GR6--C	-5.678654			
R-squared	0.895081	Mean dependent var	-2.929401	
Adjusted R-squared	0.838495	S.D. dependent var	0.345677	
S.E. of regression	0.138919	Sum squared resid	1.717578	
Log likelihood	106.8438	F-statistic	18.07793	
Durbin-Watson stat	1.694266	Prob(F-statistic)	0.000000	

Table II.9: Investment model – estimation results for *low technology* industries

Dependent Variable: $\ln(I_{jt}/K_{jt-1})$				
Method: Pooled Least Squares				
Sample(adjusted): 1972 1993				
Included observations: 22 after adjusting endpoints				
Total panel (balanced) observations: 66				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
$\ln(Y_{jt-2}/K_{jt-2})$	-0.342376	0.576025	-0.594378	0.5572
$\ln(R\&D_{jt-5}/R\&D_{jt-6})$	0.448116	0.173587	2.581501	0.0156
$\ln(R\&DS_{jt-5}/R\&DS_{jt-6})$	1.369110	1.025786	1.334694	0.1931
$\ln(P^y_{jt-1})$	1.271700	0.940912	1.351562	0.1877
$\ln(A_{jt-1})$	0.165133	0.354339	0.466030	0.6449
$\ln(W_{jt-1}/P^y_{jt-1})$	1.397178	0.864000	1.617104	0.1175
g_{yjt-1}	-2.860357	2.136170	-1.339012	0.1917
g_{pyjt-1}	0.520486	1.548988	0.336017	0.7395
$g_{(w/p)jt-1}$	0.320878	1.445544	0.221977	0.8260
$\ln(I_{jt-1}/K_{jt-2})_7$	0.460982	0.217271	2.121693	0.0432
$\ln(I_{jt-1}/K_{jt-2})_8$	0.512127	0.209031	2.450008	0.0211
$\ln(I_{jt-1}/K_{jt-2})_{13}$	0.970966	0.280961	3.455876	0.0018
$\ln(Y_{jt-1}/K_{jt-1})_7$	0.882194	0.715535	1.232916	0.2282
$\ln(Y_{jt-1}/K_{jt-1})_8$	0.424429	0.578314	0.733907	0.4693
$\ln(Y_{jt-1}/K_{jt-1})_{13}$	-1.495734	1.063485	-1.406446	0.1710
Fixed Effects				
GR7--C	-8.582108			
GR8--C	-8.613493			
GR13--C	-9.127755			
R-squared	0.968525	Mean dependent var		-3.316196
Adjusted R-squared	0.924227	S.D. dependent var		0.389885
S.E. of regression	0.107323	Sum squared resid		0.310992
Log likelihood	83.15227	F-statistic		23.73793
Durbin-Watson stat	2.036535	Prob(F-statistic)		0.000000

The expected growth rate of total factor productivity was dropped from the model because not significant. We find that, in general, the signs of the coefficients are broadly consistent with the predictions from the theoretical model. One period lagged normalised value added has a positive (although not always significant) effect on normalised investment for all industries except group 13 (*low technology*), groups 1, 9 (*technology user*), and groups 11, and 12 (*technology producer*). Note however that all significant effects are estimated positive. The expected growth rate of real wages has always a negative and significant effect on normalised investment for all industries except the *low technology* ones, for which however the coefficient is not significant. Moreover, we always get a positive effect of own R&D expenditures in first differences and trend total factor productivity on investment, although the coefficient for trend total factor productivity is significant for the *technology producer* panel only. Other incorrectly signed variables are the real output price in the *technology producer* panel, the expected growth rate of value added in the *technology user and producer* and *technology user* panel, and the expected growth rates of value added and real wages in the *low technology* panel. Anyway, the coefficients on these variables are strongly not significant. It is interesting to note that the level of real wages has a negative (although not significant) effect on investment in the *technology producer* panel while the effect is positive for the *technology user and producer* and *technology user*, and *low technology* ones. This effect may be explained by the fact that increases in real wages have a twofold effect on investment decisions. On the one hand, increases in real wages depress total profits and, as such, the amount of resources available and the incentives to invest. On the other hand, increases in real wages may push to substitute capital for labour¹²⁶ thus enhancing investment. The

¹²⁶ Wherever it is possible to do so.

results we get suggest a short run substitution effect between capital and labour in *technology user and producer* and *technology user*, and *low technology* industries. It is also interesting to note that the results we get for the technological variables agree with the technological characterisation of our panels. In fact, we get the most noticeable direct effect of own R&D expenditures in the *technology producer* panel¹²⁷. For *technology user and producer* and *technology user*, and *low technology* industries suppliers R&D expenditures have instead the highest effect. *Low technology* industries show stronger effects for both own and suppliers R&D than *technology user and producer* and *technology user*. Note however that the lag specification of the two R&D variables is different and also, as said before, the small panel size of *low technology* industries does not allow precise inference on the results.

The next step in order to identify the sources of labour productivity growth at the industry level is to analyse the importance of spillover effects. This will be the topic of the next section.

II.4 Spillover effect on labour productivity growth at the industry level

We have elsewhere discussed¹²⁸ the rationale for spillover effects in the context of productivity growth. In short, a spillover effect arises whenever a firm or industry may benefit for free from the innovative efforts of other firms or industries. A classical distinction in the literature is between knowledge and rent spillover effects. Knowledge spillover originates whenever the economic benefits of new knowledge

¹²⁷ Remember that the own R&D term, together with the suppliers R&D one, also enters in the definition of trend total factor productivity.

cannot be entirely appropriated by the firm developing them. Rent spillover instead arises whenever the price of technologically improved goods does not completely reflect their quality improvements, in particular under evaluates them. The scope of this section is to investigate if innovative efforts generated in industry i , and not embodied in capital goods, affect labour productivity growth of industry j . Following one of the classical methodologies in the literature¹²⁹, we take as a proxy for external innovative efforts the ones performed in supplying industries. By doing so, we focus on rent spillover arising from the purchase of “incorrectly” priced technologically improved capital goods¹³⁰. We will use the technological index computed in Chapter 1, section 1.3, as an indicator of suppliers innovative activities. Following the discussion in Chapter 1, we believe it a more comprehensive indicator than R&D expenditures. Consequently, the spillover term we use in the regressions is the weighted average, on the basis of the coefficients of the input-output tables for investment purchases¹³¹, of the technological indices.

In order to assess the importance of spillover effect on labour productivity growth, we estimate for each industry the production function model of Chapter 1 - equation [5] augmented by the spillover term. Two specifications of equation [5], with the spillover term in log levels or first differences, have been estimated.

The first model, with the spillover term in log levels, is given by:

$$\begin{aligned} \Delta \ln(Y/L)_{jt} = & \alpha_{j1} + \beta_{j1} * \Delta \ln(K/L)_{jt} + \Theta_{1j} (L) (\Delta \ln(R \& D)_{jt}) \\ & + \Theta_{2j} (L) (\Delta \ln(Sci)_{jt}) + \Theta_{3j} (L) (\Delta \ln(Pat)_{jt}) + \Theta_{4j} (\ln(TI)_{jt}) + \varepsilon_{jt} \end{aligned} \quad [40]$$

¹²⁸ Cfr. Chapter 1, section 1.

¹²⁹ See e.g. Griliches (1979).

¹³⁰ Again, we are not considering the role of intermediate goods in our analysis. However these considerations apply to technologically improved intermediate goods as well.

¹³¹ Cfr. note 85 to this Chapter.

The second model, with the spillover term in first differences, is given by:

$$\begin{aligned} \Delta \ln(Y/L)_{jt} = & \alpha_{j1} + \beta_{j1} * \Delta \ln(K/L)_{jt} + \Theta_{1j}(L)(\Delta \ln(R \& D)_{jt}) \\ & + \Theta_{2j}(L)(\Delta \ln(Sci)_{jt}) + \Theta_{3j}(L)(\Delta \ln(Pat)_{jt}) + \Theta_{4j} \Delta \ln(TI)_{jt} + \varepsilon_{jt} \end{aligned} \tag{41}$$

where $j = 1, \dots, 15$ is the group indicator and $(TI)_{jt}$ is the technological index based spillover term.

We find that the spillover term in first differences has a positive and significant impact on labour productivity growth in 6 industrial groups (groups 1, 6, 7, 10, 11 and 13)¹³². In the log levels specification, it has a positive and significant coefficient for industries 13 and 15 only. Table II.10 reports the estimated significant coefficients for the spillover effect.

Table II.10: Coefficients for the spillover term

<i>Impact on labour productivity growth</i>		
<i>Group</i>	<i>Spillover term</i>	<i>Effect</i>
1	$\Delta \ln(TI_{jt-1})$	0.1
6	$\Delta \ln(TI_{jt-1})$	0.2
7	$\Delta \ln(TI_{jt-1})$	0.12
10	$\Delta \ln(TI_{jt}) + \Delta \ln(TI_{jt-3})$	0.5
11	$\Delta \ln(TI_{jt-2})$	0.05
13	$\ln(TI)_{jt}$	0.03
15	$\ln(TI)_{jt-3}$	0.03

Even if for the majority of industries there is no evidence of significant spillover effects, the results indicate that for some industries the spillover effect is indeed important. Moreover, in some cases it would seem that the spillover effect on productivity growth is even bigger than the one generated by internal innovative

activities. However, to precisely assess the relative importance of these effects, it is necessary to take into account the amount of technology internally generated and embodied in capital goods. This is what we proceed to do in the next section.

II.5 The technological sources of labour productivity and employment shares growth

In this section we link the results obtained up to now to define the impact of internal and external sources of innovation on labour productivity and employment shares growth. The procedure adopted is the following. We first compute the total effect at time t of own and suppliers' R&D expenditures on investment. Next, we compute the effect of embodied technology on labour productivity and employment shares' growth as the product of the own and suppliers R&D effect on investment by the coefficient on investment in the production function and employment models of Chapter 1 (equations [4] and [10]). Finally, own R&D effects via investment are added up to the ones of the disembodied technological variables in order to get the total effects of internal (and external) innovative activities. Given that the models with the spillover term are based on different samples than the ones excluding it¹³³, for those industries showing an important spillover effect we will report the results both with and without the spillover term.

The total effect on investment of own and suppliers R&D expenditures for each industry (i.e. disaggregating the panels) are computed on the basis of equations [35] and [39]. From equation [35], the effect on investment via trend total factor productivity of own R&D expenditures at time t is given by $\hat{\beta}_1 + \hat{\beta}_2$, and the one of

¹³² Tables B.1 to B.30 in Appendix II.B report the results of the estimation.

suppliers R&D expenditures by $\hat{\beta}_3 + \hat{\beta}_4$. From equation [39], the direct effect on investment of own R&D expenditures at time t is given by $\hat{\delta}_{1,t}$, and of suppliers R&D expenditures by $\hat{\delta}_{2,t}$.

The total effect at time t of own R&D expenditures on investment is given by:

$$\hat{\delta}_{1,t} + \hat{\phi}_{2,t}(\hat{\beta}_1 + \hat{\beta}_2) \quad [42]$$

and of suppliers R&D expenditures by:

$$\hat{\delta}_{2,t} + \hat{\phi}_{2,t}(\hat{\beta}_3 + \hat{\beta}_4) \quad [43]$$

Note that the total effect at time t of own and suppliers R&D expenditures on investment is a combination of short and long run effects. In fact, own and suppliers R&D expenditures would affect investment in the long run via trend total factor productivity only. However, the magnitude of the short run effects proved to be considerable in our estimates, and often more important than the long run effects. Moreover, given the autoregressive components of both trend total factor productivity and investment, we believe that computing the total effect at time t rather than the long run effect gives a more accurate measure of the global effect of R&D expenditures on investment.

The results of the computation (equations [42] and [43]) for each industry are shown in Table II.11.

¹³³ And so we cannot ascertain if differences in the estimated coefficients are due to the addition of one

Table II.11: Own and suppliers R&D expenditures total effect at time t on investment

<i>Groups</i>	<i>Own R&D expenditures</i>	<i>Suppliers R&D expenditures</i>
<i>Technology producers</i>		
4.00	0.52	0.16
5.00	0.52	0
10.00	0.78	0
11.00	0.52	0.18
12.00	0.52	0.18
15.00	0.52	0.11
<i>Technology users and producers</i>		
2.00	0.30	0.71
6.00	0.30	0.79
<i>Technology users</i>		
1.00	0.30	0.77
3.00	0.50	0.71
9.00	0.30	0.71
14.00	0.30	0.71
<i>Low technology</i>		
7.00	0.45	1.39
8.00	0.45	1.37
13.00	0.45	1.37

Again, the results are broadly in accordance with the technological characterisation of each group. As expected, the total effect of own R&D on investment is biggest in *technology producer* industries. Also, the total effect of suppliers R&D on investment is generally stronger in *technology user and producer* and *technology user* industries. Both own and suppliers R&D expenditures appear to have a sizeable positive effect on *low technology* industries investment, somehow at odds with their technological characterisation. However, it must be remembered that the small panel size of this technological group does not allow drawing precise inference from the estimation results, and also the lag structure of the investment model is different from that adopted for the other technological groups.

explanatory variable or to the different sample size.

Multiplying the coefficients of Table II.11 by the investment coefficients of the production function model (with and without spillover term) and employment shares model estimated in Chapter 1 (equations [5] and [11]) gives, respectively, the total effect on labour productivity growth and employment shares growth of own and suppliers technological innovations embodied in investment. Adding up the effect of own technological innovations embodied in investment with the ones of the disembodied technological variables allows us to compute the total effect of internal and external sources of innovations on labour productivity and employment shares growth (Tables II.12 to II.14).

Thus, for equations [5] and [11] of Chapter 1:

$$\begin{aligned} \Delta \ln(Y/L)_t = & \alpha_{11} + \beta_{11} * \Delta \ln(K/L)_t + \Theta_{11}(L)(\Delta \ln(R \& D)_t) \\ & + \Theta_{21}(L)(\Delta \ln(Sci)_t) + \Theta_{31}(L)(\Delta \ln(Pat)_t) + \varepsilon_{1t} \end{aligned} \quad [\text{eq. 5-Chp. 1}]$$

$$\begin{aligned} \Delta \ln(L_t/L)_t = & \alpha_{12} + \beta_{12} * \Delta \ln(K_t/K)_t + \Phi_{11}(L)(\Delta \ln(R \& D_t/R \& D)_t) \\ & + \Phi_{21}(L)(\Delta \ln(Sci_t/Sci)_t) + \Phi_{31}(L)(\Delta \ln(Pat_t/Pat)_t) + \gamma_t \Delta \ln H_t + \varepsilon_{1t} \end{aligned} \quad [\text{eq. 11-Chp. 1}]$$

the effects of own and suppliers R&D expenditures on labour productivity and employment shares growth via investment are given by:

$$Effect(ownR \& D \rightarrow \Delta(Y/L)_t) = \hat{\beta}_{11} * [\hat{\delta}_{1,t} + \hat{\phi}_{2,t}(\hat{\beta}_1 + \hat{\beta}_2)] \quad [44]$$

$$Effect(R \& DS \rightarrow \Delta(Y/L)_t) = \hat{\beta}_{11} * [\hat{\delta}_{2,t} + \hat{\phi}_{2,t}(\hat{\beta}_3 + \hat{\beta}_4)] \quad [45]$$

$$Effect(ownR \& D \rightarrow \Delta(L_t/L)) = \hat{\beta}_{12} * [\hat{\delta}_{1,t} + \hat{\phi}_{2,t}(\hat{\beta}_1 + \hat{\beta}_2)] \quad [46]$$

$$Effect(R \& DS \rightarrow \Delta(L_t/L)) = \hat{\beta}_{12} * [\hat{\delta}_{2,t} + \hat{\phi}_{2,t}(\hat{\beta}_3 + \hat{\beta}_4)] \quad [47]$$

The total effects of, respectively, internal and external sources of innovation on labour productivity growth are given by:

$$TotEffInternalSources = \Theta_{,1} + \Theta_{,2} + \Theta_{,3} + \hat{\beta}_{,1} * [\hat{\delta}_{1,j} + \hat{\phi}_{2,j} (\hat{\beta}_1 + \hat{\beta}_2)] \quad [48]$$

$$TotEffExternalSources = \hat{\beta}_{,1} * [\hat{\delta}_{2,j} + \hat{\phi}_{2,j} (\hat{\beta}_3 + \hat{\beta}_4)] \quad [49]$$

And the total effects of, respectively, internal and external sources of innovation on employment shares growth are given by:

$$TotEffInternalSources = \Phi_{,1} + \Phi_{,2} + \Phi_{,3} + \hat{\beta}_{,2} * [\hat{\delta}_{1,j} + \hat{\phi}_{2,j} (\hat{\beta}_1 + \hat{\beta}_2)] \quad [50]$$

$$TotEffExternalSources = \hat{\beta}_{,2} * [\hat{\delta}_{2,j} + \hat{\phi}_{2,j} (\hat{\beta}_3 + \hat{\beta}_4)] \quad [51]$$

In general, both internally generated and externally acquired technology always produce an average positive effect on labour productivity and employment shares growth of the technological groups. The only exception is for the average effect of externally acquired technology on labour productivity growth of *technology producer* industries (production function model without spillover term). Unfortunately, the results we get for the *technology producer* industries are strongly biased by the effects of groups 4 and 15. They have the biggest employment shares in the panel, but we could not get for the two groups robust estimates of the production function model. However, the results show that internal sources of innovation are the most important determinant of productivity growth in *technology producer* industries.

Table II.12: Impact of internal and external sources of innovation with spillover effect on labour productivity growth

<i>Groups</i>	<i>Internal sources of innovation</i>	<i>External sources of innovation</i>	<i>Spillover effect</i>
<i>Technology producer</i>			
<i>4.00</i>	-0.01	-0.05	0
<i>5.00</i>	0.47	0	0
<i>10.00</i>	0.64	0	0.51
<i>11.00</i>	0.20	0.04	0.06
<i>12.00</i>	0.81	0.17	0
<i>15.00</i>	0.04	-0.0005	0.03
<i>Average technology producer*</i>	0.16	0.002	0.08
<i>Average without groups 4 and 15</i>	0.48	0.03	0.22
<i>Technology user and producer</i>			
<i>2.00</i>	0.34	0.42	0
<i>6.00</i>	0.41	0.96	0.2
<i>Average technology user and producer*</i>	0.39	0.78	0.1
<i>Technology user</i>			
<i>1.00</i>	0.21	0.45	0.1
<i>3.00</i>	0.34	0.37	0
<i>9.00</i>	0.44	0.88	0
<i>14.00</i>	0.27	0.59	0
<i>Average technology user*</i>	0.30	0.61	0.01
<i>Low technology</i>			
<i>7.00</i>	0.24	0.50	0.1
<i>8.00</i>	-0.02	-0.18	0
<i>13.00</i>	0.27	0.75	0.03
<i>Average low technology*</i>	0.25	0.67	0.05
<i>Average without group 8</i>	0.26	0.71	0.04

* weighted average, weights being the group employment shares

Table II.13: Impact of internal and external sources of innovation on labour productivity growth. No spillover effect.

<i>Groups</i>	<i>Internal sources of innovation</i>	<i>External sources of innovation</i>
<i>Technology producer</i>		
<i>4.00</i>	-0.01	-0.05
<i>5.00</i>	0.47	0
<i>10.00</i>	0.90	0
<i>11.00</i>	0.27	0.07
<i>12.00</i>	0.81	0.17
<i>15.00</i>	-0.12	-0.03
<i>Average technology producer*</i>	0.10	-0.01
<i>Average without groups 4 and 15</i>	0.61	0.04
<i>Technology user and producer</i>		
<i>2.00</i>	0.34	0.42
<i>6.00</i>	0.32	0.77
<i>Average technology user and producer*</i>	0.32	0.66
<i>Technology user</i>		
<i>1.00</i>	0.26	0.56
<i>3.00</i>	0.34	0.37
<i>9.00</i>	0.44	0.88
<i>14.00</i>	0.27	0.59
<i>Average technology user*</i>	0.31	0.62
<i>Low technology</i>		
<i>7.00</i>	0.29	0.70
<i>8.00</i>	-0.02	-0.18
<i>13.00</i>	0.18	0.51
<i>Average low technology*</i>	0.19	0.50
<i>Average without group 8</i>	0.20	0.54

** weighted average, weights being the group employment shares*

Table II.14: Impact of internal and external sources of innovation on employment shares growth

<i>Groups</i>	<i>Internal sources of innovation</i>	<i>External sources of innovation</i>
<i>Technology producer</i>		
<i>4.00</i>	0.23	0.05
<i>5.00</i>	0.65	0
<i>10.00</i>	0.30	0
<i>11.00</i>	0.29	0.007
<i>12.00</i>	-0.14	-0.09
<i>15.00</i>	0.32	0.03
<i>Average technology producer*</i>	0.31	0.03
<i>Technology user and producer</i>		
<i>2.00</i>	0.46	0.52
<i>6.00</i>	0.49	0.94
<i>Average technology user and producer*</i>	0.48	0.80
<i>Technology user</i>		
<i>1.00</i>	0.65	0.25
<i>3.00</i>	0.95	0.59
<i>9.00</i>	0.07	0.24
<i>14.00</i>	0.17	0.28
<i>Average technology user*</i>	0.29	0.29
<i>Low technology</i>		
<i>7.00</i>	0.26	0.90
<i>8.00</i>	0.05	0.40
<i>13.00</i>	0.41	1.27
<i>Average low technology*</i>	0.37	1.18

* weighted average, weights being the group employment shares

For *technology user and producer*, *technology user*, and *low technology* industries instead, external sources of innovation play the most important role to determine productivity advances. Internal sources of innovations are still important but the magnitude of their effect is less than one-half of the one we get for externally acquired technology. Moreover, spillover effects contribute significantly to productivity growth in *technology user and producer* industries. At the single industry level, productivity growth of group 10 (*technology producer* industry) is the most affected by spillover effects.

Excluding groups 4 and 15, we find that the maximum impact of internal innovative activities on productivity growth takes place in *technology producer* industries¹³⁴. The effect of internal innovative activities on technological groups then decreases according to the technological characterisation. The effect of external innovative activities on technological groups is also broadly in accordance with their technological characterisation. It is maximum in *technology user and producer* industries and minimum in *technology producer* industries.

The same general patterns of effects are found for employment shares growth. First of all, technological change, both internally generated and externally acquired, produces on average a positive effect on employment shares growth. At the single industry level, the only exception is group 12 (Electricity, Gas and Water). This means that, at least in terms of employment shares and with only one exception, technological change usually induces jobs creation and not jobs destruction. The effects of internal innovative activities on employment shares growth are broadly similar among technological groups, with the maximum effect taking place in *technology user and producer* industries. External innovative activities have a particularly strong effect on

employment shares growth of *technology user and producer* and *low technology* industries. External innovative activities are also important for employment shares growth of *technology user* industries. However, the magnitude of this effect is equal to the one generated by internal innovative activities.

Employment shares growth of *technology producer* industries is the less affected by external innovative activities. Although the impact of internal innovative activities on employment shares growth is not the maximum observed, it is nevertheless around ten times bigger than the one generated by external innovative activities.

Finally, for *low technology* industries we find important effects on employment shares growth from both internally generated and externally acquired technology, suggesting a bigger scope for technological innovation.

II.6 Conclusions

The aim of this chapter has been the analysis of the embodiment hypothesis in order to assess the total effect of internally generated and externally acquired technology on labour productivity and employment shares growth. We have found that a causality relation between R&D expenditures and investment exists, but that its direction may vary according to industrial groups. In particular, R&D expenditures Granger cause investment in *technology producer*, *technology user and producer* and *technology user* industries. In *low technology* industries, instead, investment appears to Granger cause R&D expenditures.

Next, we empirically estimated an investment model proposed by Nickell and Nicolitsas (1997), in order to define the technological content of new capital goods.

¹³⁴ The general tendencies do not change if spillover effects are included or excluded.

The model explicitly relates investment to own and suppliers R&D expenditures and to trend total factor productivity. We find that in general the technological variables have a positive effect on investment, even if some of our estimates are not very precise. We then analysed the importance of spillover effects for labour productivity growth. Although they are not generalised effects, for some industries spillover effects have substantial impacts on labour productivity growth, sometimes even bigger than the ones induced by internal innovative activities. Finally, we linked the results obtained in this Chapter to those of Chapter 1 and computed the total effect of internal and external technological efforts on labour productivity and employment shares growth. The main finding of this chapter is that, once the sources of embodied technology are taken into account, the impact of technological change on productivity and employment shares growth becomes substantial. The relative importance of internal and external sources of innovations changes in accordance with the technological characterisation of each industry. Moreover, we find that, with a few exceptions, technological change usually has a positive impact on employment share growth. That is, the net effect of technological change is to create jobs, not to destroy them. The next Chapter investigates how technologically induced demand changes affect employment shares in supplying industries. In fact, we have until now considered the net effects of productivity changes in industry j (internally generated or externally acquired) on its employment shares. However, employment shares in industry j may change for a fixed level of its technology because the industries they supply succeed in expanding their demand as a consequence of technological change. Economic theory suggests that this demand transmission effect might be important.

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APPENDIX II.A

Impact of own and suppliers R&D expenditures on Total Factor Productivity:
Estimation results

Dependent Variable: $(\ln A_{it} - 0.6 \cdot \ln A_{it-1})GR1$				
Method: Least Squares				
Sample(adjusted): 1968 1993				
Included observations: 26 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.033378	1.637319	-1.852650	0.0780
$\ln(R\&DS_{it-2})GR1$	0.160621	0.086192	1.863525	0.0764
$(OH_{it})GR1$	-0.021893	0.027703	-0.790270	0.4382
$(OH_{it})^{-1}GR1$	-0.306161	0.355383	-0.861498	0.3987
t	0.006450	0.002607	2.473934	0.0220
R-squared	0.674643	Mean dependent var		0.143187
Adjusted R-squared	0.612670	S.D. dependent var		0.093045
S.E. of regression	0.057907	Akaike info criterion		-2.688912
Sum squared resid	0.070418	Schwarz criterion		-2.446970
Log likelihood	39.95586	F-statistic		10.88610
Durbin-Watson stat	2.692792	Prob(F-statistic)		0.000061

Dependent Variable: $(\ln A_{it} - 0.6 \cdot \ln A_{it-1})GR2$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.317456	0.415425	0.764172	0.4525
$(OH_{it})GR2$	-0.017897	0.021625	-0.827600	0.4164
$(OH_{it})^{-1}GR2$	-0.777963	2.009541	-0.387135	0.7022
t	0.005340	0.002946	1.812428	0.0830
R-squared	0.479849	Mean dependent var		0.140581
Adjusted R-squared	0.412003	S.D. dependent var		0.087660
S.E. of regression	0.067218	Akaike info criterion		-2.425784
Sum squared resid	0.103921	Schwarz criterion		-2.233808
Log likelihood	36.74808	F-statistic		7.072632
Durbin-Watson stat	1.182022	Prob(F-statistic)		0.001550

Dependent Variable: $(\ln A_{it} - 0.6 \cdot \ln A_{it-1})GR3$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
<i>Variable</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-Statistic</i>	<i>Prob.</i>
C	-9.577089	4.088938	-2.342194	0.0296
$\ln(R\&D_{it-3})GR3$	0.542916	0.220976	2.456895	0.0233
$(OH_{it})GR3$	-0.009685	0.021656	-0.447211	0.6595
$(OH_{it})^{-1}GR3$	-0.455464	0.336903	-1.351912	0.1915
t	0.011092	0.006842	1.621271	0.1206
R-squared	0.462538	Mean dependent var		0.030599
Adjusted R-squared	0.355045	S.D. dependent var		0.090241
S.E. of regression	0.072472	Akaike info criterion		-2.234384
Sum squared resid	0.105043	Schwarz criterion		-1.990609
Log likelihood	32.92980	F-statistic		4.302981
Durbin-Watson stat	1.764163	Prob(F-statistic)		0.011314

Dependent Variable: $(\ln A_{it} - 0.6 \cdot \ln A_{it-1})GR4$				
Method: Least Squares				
Sample(adjusted): 1968 1993				
Included observations: 26 after adjusting endpoints				
<i>Variable</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-Statistic</i>	<i>Prob.</i>
C	-3.584665	2.165847	-1.655087	0.1128
$\ln(R\&DS_{it-2})GR4$	0.180740	0.104503	1.729510	0.0984
$(OH_{it})GR4$	0.001032	0.012209	0.084491	0.9335
$(OH_{it})^{-1}GR4$	-0.132526	0.061912	-2.140542	0.0442
t	0.002037	0.002066	0.985558	0.3356
R-squared	0.521712	Mean dependent var		0.136732
Adjusted R-squared	0.430610	S.D. dependent var		0.069489
S.E. of regression	0.052435	Akaike info criterion		-2.887451
Sum squared resid	0.057738	Schwarz criterion		-2.645509
Log likelihood	42.53686	F-statistic		5.726650
Durbin-Watson stat	1.707399	Prob(F-statistic)		0.002807

Dependent Variable: $(\ln A_{it} - 0.6 \cdot \ln A_{it-1})GR5$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.105957	0.043259	2.449325	0.0223
$(OH_{it})GR5$	-0.012094	0.009511	-1.271672	0.2162
$(OH_{it})^{-1}GR5$	-0.050852	0.026468	-1.921294	0.0672
t	0.014105	0.001101	12.81333	0.0000
R-squared	0.881781	Mean dependent var		0.241568
Adjusted R-squared	0.866362	S.D. dependent var		0.121608
S.E. of regression	0.044456	Akaike info criterion		-3.252695
Sum squared resid	0.045455	Schwarz criterion		-3.060719
Log likelihood	47.91138	F-statistic		57.18495
Durbin-Watson stat	2.243097	Prob(F-statistic)		0.000000

Dependent Variable: $(\ln A_{it} - 0.6 \cdot \ln A_{it-1})GR6$				
Method: Least Squares				
Sample(adjusted): 1970 1993				
Included observations: 24 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4.338234	1.915517	-2.264785	0.0354
$\ln(R\&DS_{it-4})GR6$	0.232014	0.091625	2.532226	0.0203
$(OH_{it})GR6$	-0.017369	0.016728	-1.038314	0.3122
$(OH_{it})^{-1}GR6$	-0.279285	0.186477	-1.497689	0.1506
t	-0.002784	0.002093	-1.330071	0.1992
R-squared	0.533404	Mean dependent var		0.175003
Adjusted R-squared	0.435173	S.D. dependent var		0.067609
S.E. of regression	0.050811	Akaike info criterion		-2.938350
Sum squared resid	0.049054	Schwarz criterion		-2.692922
Log likelihood	40.26020	F-statistic		5.430112
Durbin-Watson stat	2.378678	Prob(F-statistic)		0.004344

Dependent Variable: $(\ln A_{it} - 0.6 \cdot \ln A_{it-1})GR7$				
Method: Least Squares				
Sample(adjusted): 1968 1993				
Included observations: 26 after adjusting endpoints				
<i>Variable</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-Statistic</i>	<i>Prob.</i>
C	-2.820392	1.743265	-1.617879	0.1206
$\ln(R\&DS_{it-2})GR7$	0.144203	0.086778	1.661751	0.1114
$(OH_{it})GR7$	-0.013600	0.007782	-1.747470	0.0952
$(OH_{it})^{-1}GR7$	0.002926	0.002385	1.226894	0.2334
t	0.006001	0.002339	2.565784	0.0180
R-squared	0.655426	Mean dependent var		0.189705
Adjusted R-squared	0.589793	S.D. dependent var		0.089087
S.E. of regression	0.057058	Akaike info criterion		-2.718460
Sum squared resid	0.068368	Schwarz criterion		-2.476518
Log likelihood	40.33998	F-statistic		9.986222
Durbin-Watson stat	2.616677	Prob(F-statistic)		0.000109

Dependent Variable: $(\ln A_{it} - 0.6 \cdot \ln A_{it-1})GR8$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
<i>Variable</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-Statistic</i>	<i>Prob.</i>
C	0.311188	0.116212	2.677758	0.0134
$(OH_{it})GR8$	-0.036781	0.016941	-2.171169	0.0405
$(OH_{it})^{-1}GR8$	-0.417993	0.157489	-2.654106	0.0142
t	-0.000479	0.001384	-0.346141	0.7324
R-squared	0.238275	Mean dependent var		0.035597
Adjusted R-squared	0.138919	S.D. dependent var		0.057563
S.E. of regression	0.053415	Akaike info criterion		-2.885485
Sum squared resid	0.065623	Schwarz criterion		-2.693510
Log likelihood	42.95405	F-statistic		2.398206
Durbin-Watson stat	2.276460	Prob(F-statistic)		0.094083

Dependent Variable: $(\ln A_{it} - 0.6 \cdot \ln A_{it-1})GR9$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.240413	0.101642	2.365291	0.0268
$(OH_{it})GR9$	-0.033852	0.015558	-2.175905	0.0401
$(OH_{it})^{-1}GR9$	-0.364951	0.134074	-2.722012	0.0122
t	0.005336	0.001380	3.867513	0.0008
R-squared	0.499401	Mean dependent var		0.071455
Adjusted R-squared	0.434105	S.D. dependent var		0.074063
S.E. of regression	0.055714	Akaike info criterion		-2.801204
Sum squared resid	0.071394	Schwarz criterion		-2.609228
Log likelihood	41.81625	F-statistic		7.648319
Durbin-Watson stat	1.694413	Prob(F-statistic)		0.001015

Dependent Variable: $(\ln A_{it} - 0.6 \cdot \ln A_{it-1})GR10$				
Method: Least Squares				
Sample(adjusted): 1968 1993				
Included observations: 26 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-6.427650	3.591496	-1.789686	0.0879
$\ln(R\&D_{it-2})GR10$	0.309774	0.165839	1.867921	0.0758
$(OH_{it})GR10$	-0.030654	0.021644	-1.416286	0.1714
$(OH_{it})^{-1}GR10$	-0.461281	0.214252	-2.152981	0.0431
t	0.004743	0.002702	1.755485	0.0938
R-squared	0.640001	Mean dependent var		0.033399
Adjusted R-squared	0.571430	S.D. dependent var		0.108920
S.E. of regression	0.071305	Akaike info criterion		-2.272665
Sum squared resid	0.106772	Schwarz criterion		-2.030723
Log likelihood	34.54464	F-statistic		9.333389
Durbin-Watson stat	1.832071	Prob(F-statistic)		0.000169

Dependent Variable: $(\ln A_{it} - 0.6 \ln A_{it-1})GR11$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
<i>Variable</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-Statistic</i>	<i>Prob.</i>
C	-3.551558	1.727032	-2.056452	0.0518
$\ln(R\&DS_{it-1})GR11$	0.219418	0.099149	2.213021	0.0376
$(OH_{it})GR11$	-0.076632	0.052039	-1.472586	0.1550
$(OH_{it})^{-1}GR11$	-2.898508	1.300430	-2.228885	0.0364
t	-2.11E-05	0.002565	-0.008213	0.9935
R-squared	0.737208	Mean dependent var		0.012926
Adjusted R-squared	0.689428	S.D. dependent var		0.069784
S.E. of regression	0.038890	Akaike info criterion		-3.490591
Sum squared resid	0.033273	Schwarz criterion		-3.250621
Log likelihood	52.12298	F-statistic		15.42912
Durbin-Watson stat	1.652086	Prob(F-statistic)		0.000004

Dependent Variable: $(\ln A_{it} - 0.6 \ln A_{it-1})GR12$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
<i>Variable</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-Statistic</i>	<i>Prob.</i>
C	-4.570682	2.190325	-2.086760	0.0487
$\ln(R\&DS_{it-1})GR12$	0.217959	0.105336	2.069169	0.0505
$(OH_{it})GR12$	0.003181	0.013492	0.235776	0.8158
$(OH_{it})^{-1}GR12$	-0.043596	0.086065	-0.506546	0.6175
t	0.023336	0.002281	10.23081	0.0000
R-squared	0.924511	Mean dependent var		0.274433
Adjusted R-squared	0.910786	S.D. dependent var		0.220564
S.E. of regression	0.065880	Akaike info criterion		-2.436402
Sum squared resid	0.095482	Schwarz criterion		-2.196432
Log likelihood	37.89143	F-statistic		67.35853
Durbin-Watson stat	2.179435	Prob(F-statistic)		0.000000

Dependent Variable: $(\ln A_{it} - 0.6 \ln A_{it-1})GR13$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
<i>Variable</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-Statistic</i>	<i>Prob.</i>
C	-0.070430	0.013838	-5.089700	0.0000
$(OH_{it})GR13$	0.033095	0.011935	2.772916	0.0108
$(OH_{it})^{-1}GR13$	-0.000151	0.002252	-0.067001	0.9472
t	-0.004270	0.001764	-2.420344	0.0238
R-squared	0.251825	Mean dependent var		-0.075178
Adjusted R-squared	0.154237	S.D. dependent var		0.036844
S.E. of regression	0.033884	Akaike info criterion		-3.795817
Sum squared resid	0.026406	Schwarz criterion		-3.603841
Log likelihood	55.24353	F-statistic		2.580490
Durbin-Watson stat	1.187249	Prob(F-statistic)		0.078148

Dependent Variable: $(\ln A_{it} - 0.6 \ln A_{it-1})GR14$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
<i>Variable</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-Statistic</i>	<i>Prob.</i>
C	0.113732	0.496971	0.228849	0.8210
$(OH_{it})GR14$	-0.000201	0.035607	-0.005648	0.9955
$(OH_{it})^{-1}GR14$	-0.658970	1.683310	-0.391473	0.6991
t	0.011676	0.000704	16.58643	0.0000
R-squared	0.932439	Mean dependent var		0.178974
Adjusted R-squared	0.923626	S.D. dependent var		0.092977
S.E. of regression	0.025695	Akaike info criterion		-4.349094
Sum squared resid	0.015185	Schwarz criterion		-4.157118
Log likelihood	62.71277	F-statistic		105.8105
Durbin-Watson stat	1.388462	Prob(F-statistic)		0.000000

Dependent Variable: $(\ln A_{it} - 0.6 \cdot \ln A_{it-1})GR15$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
<i>Variable</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-Statistic</i>	<i>Prob.</i>
C	-2.750936	0.698624	-3.937646	0.0007
$\ln(R\&DS_{it-1})GR15$	0.134506	0.034679	3.878596	0.0008
$(OH_{it})GR15$	0.004732	0.007634	0.619830	0.5417
$(OH_{it})^{-1}GR15$	0.008079	0.020647	0.391299	0.6993
t	-0.002260	0.001189	-1.900972	0.0705
R-squared	0.461557	Mean dependent var		0.008421
Adjusted R-squared	0.363659	S.D. dependent var		0.023185
S.E. of regression	0.018495	Akaike info criterion		-4.977074
Sum squared resid	0.007525	Schwarz criterion		-4.737104
Log likelihood	72.19049	F-statistic		4.714641
Durbin-Watson stat	1.783741	Prob(F-statistic)		0.006702

APPENDIX II.B

Production Function Models with spillover term (loglevels and differences):
estimation results

Table B.1

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR1}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.021994	0.095173	-0.231093	0.8194
$\Delta\text{LN}(\text{K/L})\text{GR1}$	0.783671	0.562930	1.392128	0.1778
$\Delta\text{LN}(\text{hours})\text{GR1}$	0.519207	0.936729	0.554277	0.5850
$\Delta\text{LN}(\text{sci})\text{GR1}$	0.035934	0.025539	1.407047	0.1734
$\ln(\text{TI})_t\text{GR1}$	0.005850	0.034428	0.169911	0.8666
R-squared	0.205605	Mean dependent var		0.053403
Adjusted R-squared	0.061170	S.D. dependent var		0.068379
S.E. of regression	0.066255	Akaike info criterion		-2.425047
Sum squared resid	0.096573	Schwarz criterion		-2.185077
Log likelihood	37.73813	F-statistic		1.423512
Durbin-Watson stat	2.438573	Prob(F-statistic)		0.259321

Table B.2

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR2}$				
Method: Least Squares				
Sample(adjusted): 1971 1993				
Included observations: 23 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.043161	0.367492	0.117448	0.9079
$\Delta\text{LN}(\text{K/L})\text{GR2}$	0.602792	0.134659	4.476435	0.0003
$\Delta\text{LN}(\text{hours})\text{GR2}$	0.096477	0.676531	0.142605	0.8883
$\Delta\text{LN}(\text{pat})\text{GR2}$	0.046044	0.025492	1.806264	0.0886
$\Delta 1\text{LN}(\text{pat})\text{GR2}$	0.123208	0.025461	4.839058	0.0002
$\ln(\text{TI})_t\text{GR2}$	-0.015249	0.186526	-0.081755	0.9358
R-squared	0.713953	Mean dependent var		0.078414
Adjusted R-squared	0.629822	S.D. dependent var		0.112068
S.E. of regression	0.068185	Akaike info criterion		-2.313739
Sum squared resid	0.079035	Schwarz criterion		-2.017523
Log likelihood	32.60800	F-statistic		8.486163
Durbin-Watson stat	1.867276	Prob(F-statistic)		0.000352

Table B.3

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR3}$				
Method: Least Squares				
Sample(adjusted): 1970 1993				
Included observations: 24 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.317934	0.400174	-0.794490	0.4367
$\Delta\text{LN}(\text{K/L})\text{GR3}$	0.569188	0.227569	2.501166	0.0217
$\Delta\text{LN}(\text{hours})\text{GR3}$	1.015672	1.053506	0.964088	0.3471
$\Delta\text{LN}(\text{pat})\text{GR3}$	0.071048	0.040474	1.755402	0.0953
$\ln(\text{TI})_{t-1}\text{GR3}$	0.136949	0.198634	0.689452	0.4989
R-squared	0.440475	Mean dependent var		0.009310
Adjusted R-squared	0.322680	S.D. dependent var		0.104186
S.E. of regression	0.085744	Akaike info criterion		-1.891839
Sum squared resid	0.139690	Schwarz criterion		-1.646411
Log likelihood	27.70207	F-statistic		3.739340
Durbin-Watson stat	1.329004	Prob(F-statistic)		0.020845

Table B.4

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR4}$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.155934	0.243028	-0.641631	0.5284
$\Delta\text{LN}(\text{K/L})\text{GR4}$	-0.374099	0.360313	-1.038260	0.3115
$\Delta\text{LN}(\text{hours})\text{GR4}$	-0.315586	0.755962	-0.417463	0.6808
$\Delta^2\text{LN}(\text{sci})\text{GR4}$	0.180922	0.081717	2.213996	0.0386
$\ln(\text{TI})_t\text{GR4}$	0.090083	0.113148	0.796148	0.4353
R-squared	0.217049	Mean dependent var		0.021921
Adjusted R-squared	0.060459	S.D. dependent var		0.059201
S.E. of regression	0.057383	Akaike info criterion		-2.701280
Sum squared resid	0.065856	Schwarz criterion		-2.457505
Log likelihood	38.76600	F-statistic		1.386098
Durbin-Watson stat	2.411614	Prob(F-statistic)		0.274455

Table B.5

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR5}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.022516	0.039628	0.568173	0.5757
$\Delta \text{LN}(\text{K/L})\text{GR5}$	0.724544	0.254117	2.851222	0.0093
$\Delta \text{LN}(\text{hours})\text{GR5}$	0.307107	0.715062	0.429483	0.6717
$\Delta \text{LN}(\text{sci})\text{GR5}$	0.109604	0.052123	2.102814	0.0471
$\ln(\text{TI})_t\text{GR5}$	-0.021752	0.020695	-1.051091	0.3046
R-squared	0.392216	Mean dependent var		0.042014
Adjusted R-squared	0.281710	S.D. dependent var		0.054652
S.E. of regression	0.046319	Akaike info criterion		-3.140969
Sum squared resid	0.047199	Schwarz criterion		-2.901000
Log likelihood	47.40309	F-statistic		3.549266
Durbin-Watson stat	2.382809	Prob(F-statistic)		0.022217

Table B.6

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR6}$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.293858	0.360936	0.814155	0.4251
$\Delta \text{LN}(\text{K/L})\text{GR6}$	1.107542	0.503854	2.198142	0.0399
$\Delta \text{LN}(\text{hours})\text{GR6}$	-0.608630	1.292917	-0.470742	0.6429
$\Delta 2 \text{LN}(\text{sci})\text{GR6}$	0.017541	0.074687	0.234863	0.8167
$\ln(\text{TI})_t\text{GR6}$	-0.163683	0.180503	-0.906816	0.3753
R-squared	0.279964	Mean dependent var		0.028874
Adjusted R-squared	0.135957	S.D. dependent var		0.080591
S.E. of regression	0.074913	Akaike info criterion		-2.168134
Sum squared resid	0.112238	Schwarz criterion		-1.924359
Log likelihood	32.10167	F-statistic		1.944101
Durbin-Watson stat	1.993536	Prob(F-statistic)		0.142325

Table B.7

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR7}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.037907	0.075621	0.501277	0.6212
$\Delta\text{LN}(\text{K/L})\text{GR7}$	0.467560	0.329922	1.417184	0.1704
$\Delta\text{LN}(\text{hours})\text{GR7}$	0.337669	0.823095	0.410243	0.6856
$\Delta\text{LN}(\text{sci})\text{GR7}$	0.072442	0.032759	2.211357	0.0377
$\ln(\text{TI})_t\text{GR7}$	-0.022653	0.034227	-0.661847	0.5149
R-squared	0.265210	Mean dependent var		0.028342
Adjusted R-squared	0.131612	S.D. dependent var		0.073741
S.E. of regression	0.068717	Akaike info criterion		-2.352066
Sum squared resid	0.103884	Schwarz criterion		-2.112097
Log likelihood	36.75290	F-statistic		1.985135
Durbin-Watson stat	1.888818	Prob(F-statistic)		0.132063

Table B.8

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR8}$				
Method: Least Squares				
Sample(adjusted): 1968 1993				
Included observations: 26 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.025711	0.057859	-0.444384	0.6613
$\Delta\text{LN}(\text{K/L})\text{GR8}$	-0.138232	0.275442	-0.501857	0.6210
$\Delta\text{LN}(\text{hours})\text{GR8}$	-0.044244	0.752449	-0.058800	0.9537
$\Delta\text{LN}(\text{sci})\text{GR8}$	0.039829	0.024416	1.631236	0.1177
$\ln(\text{TI})_{t-2}\text{GR8}$	0.017501	0.028024	0.624496	0.5390
R-squared	0.118019	Mean dependent var		0.005215
Adjusted R-squared	-0.049977	S.D. dependent var		0.065263
S.E. of regression	0.066874	Akaike info criterion		-2.400970
Sum squared resid	0.093915	Schwarz criterion		-2.159029
Log likelihood	36.21261	F-statistic		0.702511
Durbin-Watson stat	2.029363	Prob(F-statistic)		0.598982

Table B.9

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR9}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.049881	0.052304	-0.953679	0.3506
$\Delta\text{LN}(\text{K/L})\text{GR9}$	1.256430	0.482020	2.606591	0.0161
$\Delta\text{LN}(\text{hours})\text{GR9}$	2.244482	0.777633	2.886302	0.0086
$\Delta\text{LN}(\text{sci})\text{GR9}$	0.073830	0.028742	2.568684	0.0175
$\ln(\text{TI})_t\text{GR9}$	-0.003034	0.024357	-0.124577	0.9020
R-squared	0.371511	Mean dependent var		0.024109
Adjusted R-squared	0.257240	S.D. dependent var		0.057585
S.E. of regression	0.049629	Akaike info criterion		-3.002905
Sum squared resid	0.054187	Schwarz criterion		-2.762935
Log likelihood	45.53922	F-statistic		3.251147
Durbin-Watson stat	1.730069	Prob(F-statistic)		0.030740

Table B.10

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR10}$				
Method: Least Squares				
Sample(adjusted): 1972 1993				
Included observations: 22 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.433623	0.265990	-1.630222	0.1214
$\Delta\text{LN}(\text{K/L})\text{GR10}$	0.735435	0.318778	2.307045	0.0339
$\Delta\text{LN}(\text{hours})\text{GR10}$	3.750153	1.186532	3.160600	0.0057
$\Delta^2\text{LN}(\text{pat})\text{GR10}$	0.217620	0.069644	3.124751	0.0062
$\ln(\text{TI})_t\text{GR10}$	0.217506	0.134020	1.622941	0.1230
R-squared	0.526223	Mean dependent var		0.039857
Adjusted R-squared	0.414746	S.D. dependent var		0.073769
S.E. of regression	0.056434	Akaike info criterion		-2.714757
Sum squared resid	0.054142	Schwarz criterion		-2.466793
Log likelihood	34.86233	F-statistic		4.720463
Durbin-Watson stat	1.650722	Prob(F-statistic)		0.009563

Table B.11

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR11}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.054869	0.065186	0.841722	0.4090
$\Delta \text{LN}(\text{K/L})\text{GR11}$	0.299553	0.233318	1.283881	0.2125
$\Delta \text{LN}(\text{hours})\text{GR11}$	0.533130	0.968388	0.550533	0.5875
$\Delta \text{LN}(\text{sci})\text{GR11}$	0.090161	0.067851	1.328803	0.1975
$\ln(\text{TI})_t\text{GR11}$	-0.020957	0.024959	-0.839645	0.4101
R-squared	0.186863	Mean dependent var		0.029588
Adjusted R-squared	0.039020	S.D. dependent var		0.052572
S.E. of regression	0.051536	Akaike info criterion		-2.927494
Sum squared resid	0.058431	Schwarz criterion		-2.687524
Log likelihood	44.52117	F-statistic		1.263926
Durbin-Watson stat	1.345512	Prob(F-statistic)		0.313966

Table B.12

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR12}$				
Method: Least Squares				
Sample(adjusted): 1968 1993				
Included observations: 26 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.038854	0.165281	0.235081	0.8164
$\Delta \text{LN}(\text{K/L})\text{GR12}$	0.944168	0.595096	1.586580	0.1276
$\Delta \text{LN}(\text{hours})\text{GR12}$	1.389799	1.121212	1.239551	0.2288
$\Delta \text{LN}(\text{R\&D})\text{GR12}$	0.330172	0.184555	1.789014	0.0880
$\ln(\text{TI})_{t-2}\text{GR12}$	-0.005155	0.076373	-0.067503	0.9468
R-squared	0.200540	Mean dependent var		0.085363
Adjusted R-squared	0.048262	S.D. dependent var		0.087874
S.E. of regression	0.085727	Akaike info criterion		-1.904250
Sum squared resid	0.154333	Schwarz criterion		-1.662308
Log likelihood	29.75525	F-statistic		1.316930
Durbin-Watson stat	2.626707	Prob(F-statistic)		0.296157

Table B.13

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR13}$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.096025	0.048085	-1.997013	0.0596
$\Delta \text{LN}(\text{K/L})\text{GR13}$	0.551422	0.309786	1.780007	0.0903
$\Delta \text{LN}(\text{hours})\text{GR13}$	1.833462	0.922291	1.987943	0.0607
$\Delta \text{LN}(\text{sci})\text{GR13}$	0.016574	0.016636	0.996236	0.3310
$\ln(\text{TI})_{t-3}\text{GR13}$	0.033865	0.019620	1.726051	0.0998
R-squared	0.317591	Mean dependent var		0.001155
Adjusted R-squared	0.181110	S.D. dependent var		0.034017
S.E. of regression	0.030783	Akaike info criterion		-3.946849
Sum squared resid	0.018952	Schwarz criterion		-3.703074
Log likelihood	54.33561	F-statistic		2.326987
Durbin-Watson stat	1.992171	Prob(F-statistic)		0.091453

Table B.14

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR14}$				
Method: Least Squares				
Sample(adjusted): 1972 1993				
Included observations: 22 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.075692	0.110918	-0.682414	0.5047
$\Delta \text{LN}(\text{K/L})\text{GR14}$	0.829904	0.195109	4.253529	0.0006
$\Delta \text{LN}(\text{hours})\text{GR14}$	0.630793	0.302370	2.086162	0.0533
$\Delta \text{LN}(\text{pat})\text{GR14}$	0.009075	0.004702	1.929896	0.0715
$\Delta 2\text{LN}(\text{pat})\text{GR14}$	0.011666	0.004559	2.559026	0.0210
$\ln(\text{TI})_t\text{GR14}$	0.022432	0.042278	0.530581	0.6030
R-squared	0.665689	Mean dependent var		0.034685
Adjusted R-squared	0.561217	S.D. dependent var		0.024883
S.E. of regression	0.016483	Akaike info criterion		-5.146019
Sum squared resid	0.004347	Schwarz criterion		-4.848462
Log likelihood	62.60621	F-statistic		6.371927
Durbin-Watson stat	2.243195	Prob(F-statistic)		0.001945

Table B.15

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR15}$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.067902	0.035870	-1.893012	0.0729
$\Delta \text{LN}(\text{K/L})\text{GR15}$	-0.004799	0.340050	-0.014114	0.9889
$\Delta \text{LN}(\text{hours})\text{GR15}$	-0.929777	0.771124	-1.205742	0.2420
$\Delta \text{LN}(\text{R\&D})\text{GR15}$	0.039022	0.058621	0.665669	0.5132
$\ln(\text{TI})_{t-3}\text{GR15}$	0.030841	0.014507	2.125985	0.0461
R-squared	0.331426	Mean dependent var		-0.003048
Adjusted R-squared	0.197711	S.D. dependent var		0.025828
S.E. of regression	0.023134	Akaike info criterion		-4.518134
Sum squared resid	0.010704	Schwarz criterion		-4.274359
Log likelihood	61.47668	F-statistic		2.478605
Durbin-Watson stat	1.796737	Prob(F-statistic)		0.076984

Table B.16

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR1}$				
Method: Least Squares				
Sample(adjusted): 1968 1993				
Included observations: 26 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000730	0.039132	0.018645	0.9853
$\Delta\text{LN}(\text{K/L})\text{GR1}$	0.591595	0.499947	1.183315	0.2499
$\Delta\text{LN}(\text{hours})\text{GR1}$	0.906657	0.878968	1.031502	0.3140
$\Delta\text{LN}(\text{sci})\text{GR1}$	0.035801	0.024002	1.491589	0.1507
$\ln(\text{Ti}_{t-1} - \text{Ti}_{t-2})\text{GR1}$	0.100545	0.052582	1.912156	0.0696
R-squared	0.310159	Mean dependent var		0.051510
Adjusted R-squared	0.178761	S.D. dependent var		0.069008
S.E. of regression	0.062537	Akaike info criterion		-2.535078
Sum squared resid	0.082128	Schwarz criterion		-2.293136
Log likelihood	37.95601	F-statistic		2.360448
Durbin-Watson stat	2.232058	Prob(F-statistic)		0.086285

Table B.17

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR2}$				
Method: Least Squares				
Sample(adjusted): 1971 1993				
Included observations: 23 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.017217	0.025839	0.666338	0.5141
$\Delta\text{LN}(\text{K/L})\text{GR2}$	0.560783	0.177556	3.158346	0.0057
$\Delta\text{LN}(\text{hours})\text{GR2}$	0.148944	0.695948	0.214016	0.8331
$\Delta\text{LN}(\text{pat})\text{GR2}$	0.050435	0.026598	1.896210	0.0751
$\Delta 1\text{LN}(\text{pat})\text{GR2}$	0.117316	0.031716	3.698957	0.0018
$\ln(\text{Ti}_t - \text{Ti}_{t-1})\text{GR2}$	0.139935	0.443753	0.315344	0.7563
R-squared	0.715505	Mean dependent var		0.078414
Adjusted R-squared	0.631830	S.D. dependent var		0.112068
S.E. of regression	0.067999	Akaike info criterion		-2.319178
Sum squared resid	0.078607	Schwarz criterion		-2.022962
Log likelihood	32.67055	F-statistic		8.550993
Durbin-Watson stat	1.915690	Prob(F-statistic)		0.000337

Table B.18

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR3}$				
Method: Least Squares				
Sample(adjusted): 1970 1993				
Included observations: 24 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.046775	0.028670	-1.631509	0.1192
$\Delta \text{LN}(\text{K/L})\text{GR3}$	0.532375	0.216574	2.458165	0.0237
$\Delta \text{LN}(\text{hours})\text{GR3}$	1.225327	1.030745	1.188778	0.2492
$\Delta \text{LN}(\text{pat})\text{GR3}$	0.073269	0.039790	1.841405	0.0812
$\ln(\text{Ti}_{t-2} - \text{Ti}_{t-3})\text{GR3}$	0.086145	0.077542	1.110944	0.2805
R-squared	0.461459	Mean dependent var		0.009310
Adjusted R-squared	0.348082	S.D. dependent var		0.104186
S.E. of regression	0.084121	Akaike info criterion		-1.930064
Sum squared resid	0.134451	Schwarz criterion		-1.684636
Log likelihood	28.16077	F-statistic		4.070125
Durbin-Watson stat	1.461140	Prob(F-statistic)		0.015055

Table B.19

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR4}$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.030421	0.023458	1.296842	0.2094
$\Delta \text{LN}(\text{K/L})\text{GR4}$	-0.263332	0.336646	-0.782223	0.4432
$\Delta \text{LN}(\text{hours})\text{GR4}$	-0.009846	0.729576	-0.013496	0.9894
$\Delta 2 \text{LN}(\text{sci})\text{GR4}$	0.150734	0.063120	2.388050	0.0269
$\ln(\text{Ti}_{t-1} - \text{Ti}_{t-2})\text{GR4}$	0.112174	0.077224	1.452571	0.1619
R-squared	0.269321	Mean dependent var		0.021921
Adjusted R-squared	0.123185	S.D. dependent var		0.059201
S.E. of regression	0.055434	Akaike info criterion		-2.770376
Sum squared resid	0.061460	Schwarz criterion		-2.526600
Log likelihood	39.62970	F-statistic		1.842949
Durbin-Watson stat	2.233184	Prob(F-statistic)		0.160203

Table B.20

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR5}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.015448	0.021602	-0.715117	0.4821
$\Delta \text{LN}(\text{K/L})\text{GR5}$	0.711252	0.257507	2.762070	0.0114
$\Delta \text{LN}(\text{hours})\text{GR5}$	0.371920	0.728913	0.510240	0.6150
$\Delta \text{LN}(\text{sci})\text{GR5}$	0.105386	0.053429	1.972454	0.0613
$\ln(\text{Ti}_t - \text{Ti}_{t-1})\text{GR5}$	0.022081	0.033072	0.667659	0.5113
R-squared	0.374371	Mean dependent var		0.042014
Adjusted R-squared	0.260620	S.D. dependent var		0.054652
S.E. of regression	0.046994	Akaike info criterion		-3.112032
Sum squared resid	0.048585	Schwarz criterion		-2.872062
Log likelihood	47.01243	F-statistic		3.291152
Durbin-Watson stat	2.320615	Prob(F-statistic)		0.029417

Table B.21

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR6}$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.058097	0.022157	-2.622014	0.0163
$\Delta \text{LN}(\text{K/L})\text{GR6}$	1.211695	0.316901	3.823579	0.0011
$\Delta \text{LN}(\text{hours})\text{GR6}$	0.122930	0.840532	0.146252	0.8852
$\Delta 2 \text{LN}(\text{sci})\text{GR6}$	0.048369	0.048358	1.000236	0.3291
$\ln(\text{Ti}_{t-1} - \text{Ti}_{t-2})\text{GR6}$	0.203834	0.037739	5.401099	0.0000
R-squared	0.695094	Mean dependent var		0.028874
Adjusted R-squared	0.634113	S.D. dependent var		0.080591
S.E. of regression	0.048748	Akaike info criterion		-3.027430
Sum squared resid	0.047528	Schwarz criterion		-2.783655
Log likelihood	42.84288	F-statistic		11.39848
Durbin-Watson stat	1.926730	Prob(F-statistic)		0.000055

Table B.22

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR7}$				
Method: Least Squares				
Sample(adjusted): 1968 1993				
Included observations: 26 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.005154	0.025124	-0.205156	0.8394
$\Delta\text{LN}(\text{K/L})\text{GR7}$	0.365015	0.305769	1.193761	0.2459
$\Delta\text{LN}(\text{hours})\text{GR7}$	0.605310	0.740463	0.817476	0.4228
$\Delta\text{LN}(\text{sci})\text{GR7}$	0.075294	0.029522	2.550464	0.0186
$\ln(\text{Ti}_{t-1} - \text{Ti}_{t-2})\text{GR7}$	0.125479	0.048919	2.565026	0.0180
R-squared	0.431452	Mean dependent var		0.028188
Adjusted R-squared	0.323157	S.D. dependent var		0.075197
S.E. of regression	0.061865	Akaike info criterion		-2.556698
Sum squared resid	0.080372	Schwarz criterion		-2.314756
Log likelihood	38.23707	F-statistic		3.984051
Durbin-Watson stat	1.782568	Prob(F-statistic)		0.014716

Table B.23

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR8}$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004197	0.021448	0.195682	0.8468
$\Delta\text{LN}(\text{K/L})\text{GR8}$	-0.100173	0.300798	-0.333026	0.7426
$\Delta\text{LN}(\text{hours})\text{GR8}$	0.137042	0.769763	0.178031	0.8605
$\Delta\text{LN}(\text{sci})\text{GR8}$	0.034499	0.024236	1.423484	0.1700
$\ln(\text{Ti}_{t-2} - \text{Ti}_{t-3})\text{GR8}$	0.052885	0.049381	1.070950	0.2969
R-squared	0.146334	Mean dependent var		0.004321
Adjusted R-squared	-0.024399	S.D. dependent var		0.066446
S.E. of regression	0.067252	Akaike info criterion		-2.383887
Sum squared resid	0.090456	Schwarz criterion		-2.140112
Log likelihood	34.79859	F-statistic		0.857092
Durbin-Watson stat	2.072429	Prob(F-statistic)		0.506295

Table B.24

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR9}$				
Method: Least Squares				
Sample(adjusted): 1967 1993				
Included observations: 27 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.056986	0.031432	-1.812972	0.0835
$\Delta\text{LN}(\text{K/L})\text{GR9}$	1.270582	0.485877	2.615030	0.0158
$\Delta\text{LN}(\text{hours})\text{GR9}$	2.269708	0.785003	2.891335	0.0085
$\Delta\text{LN}(\text{sci})\text{GR9}$	0.071863	0.029443	2.440736	0.0232
$\ln(\text{Ti}_t - \text{Ti}_{t-1})\text{GR9}$	0.009456	0.039583	0.238893	0.8134
R-squared	0.372695	Mean dependent var		0.024109
Adjusted R-squared	0.258639	S.D. dependent var		0.057585
S.E. of regression	0.049582	Akaike info criterion		-3.004791
Sum squared resid	0.054085	Schwarz criterion		-2.764821
Log likelihood	45.56467	F-statistic		3.267663
Durbin-Watson stat	1.761596	Prob(F-statistic)		0.030186

Table B.25

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR10}$				
Method: Least Squares				
Sample(adjusted): 1972 1993				
Included observations: 22 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000470	0.021465	-0.021919	0.9828
$\Delta\text{LN}(\text{K/L})\text{GR10}$	0.580295	0.321164	1.806851	0.0896
$\Delta\text{LN}(\text{hours})\text{GR10}$	3.800751	1.090270	3.486063	0.0031
$\Delta^2\text{LN}(\text{pat})\text{GR10}$	0.194203	0.067365	2.882823	0.0108
$\ln(\text{Ti}_t - \text{Ti}_{t-1})\text{GR10}$	0.391366	0.206808	1.892410	0.0767
$\ln(\text{Ti}_{t-3} - \text{Ti}_{t-4})\text{GR10}$	0.115915	0.051741	2.240286	0.0396
R-squared	0.623686	Mean dependent var		0.039857
Adjusted R-squared	0.506088	S.D. dependent var		0.073769
S.E. of regression	0.051844	Akaike info criterion		-2.854162
Sum squared resid	0.043004	Schwarz criterion		-2.556605
Log likelihood	37.39578	F-statistic		5.303538
Durbin-Watson stat	1.745352	Prob(F-statistic)		0.004622

Table B.26

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR11}$				
Method: Least Squares				
Sample(adjusted): 1969 1993				
Included observations: 25 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006687	0.019290	0.346666	0.7325
$\Delta \text{LN}(\text{K/L})\text{GR11}$	0.241890	0.227446	1.063504	0.3002
$\Delta \text{LN}(\text{hours})\text{GR11}$	0.555164	0.953658	0.582141	0.5670
$\Delta \text{LN}(\text{sci})\text{GR11}$	0.074755	0.068277	1.094874	0.2866
$\ln(\text{Ti}_{t-2} - \text{Ti}_{t-3})\text{GR11}$	0.059139	0.032711	1.807914	0.0857
R-squared	0.239774	Mean dependent var		0.025679
Adjusted R-squared	0.087729	S.D. dependent var		0.052261
S.E. of regression	0.049916	Akaike info criterion		-2.980077
Sum squared resid	0.049833	Schwarz criterion		-2.736301
Log likelihood	42.25096	F-statistic		1.576991
Durbin-Watson stat	1.265228	Prob(F-statistic)		0.219088

Table B.27

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR12}$				
Method: Least Squares				
Sample(adjusted): 1968 1993				
Included observations: 26 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.027975	0.037663	0.742774	0.4658
$\Delta \text{LN}(\text{K/L})\text{GR12}$	0.935180	0.587368	1.592155	0.1263
$\Delta \text{LN}(\text{hours})\text{GR12}$	1.367776	1.059606	1.290835	0.2108
$\Delta \text{LN}(\text{R\&D})\text{GR12}$	0.323090	0.161721	1.997824	0.0589
$\ln(\text{Ti}_{t-1} - \text{Ti}_{t-2})\text{GR12}$	0.003954	0.118669	0.033320	0.9737
R-squared	0.200408	Mean dependent var		0.085363
Adjusted R-squared	0.048105	S.D. dependent var		0.087874
S.E. of regression	0.085734	Akaike info criterion		-1.904086
Sum squared resid	0.154358	Schwarz criterion		-1.662144
Log likelihood	29.75311	F-statistic		1.315853
Durbin-Watson stat	2.621835	Prob(F-statistic)		0.296536

Table B.28

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR13}$				
Method: Least Squares				
Sample(adjusted): 1970 1993				
Included observations: 24 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.023849	0.012916	-1.846504	0.0805
$\Delta\text{LN}(\text{K/L})\text{GR13}$	0.608356	0.272402	2.233298	0.0378
$\Delta\text{LN}(\text{hours})\text{GR13}$	2.418467	0.825471	2.929801	0.0086
$\Delta\text{LN}(\text{sci})\text{GR13}$	0.023514	0.014339	1.639812	0.1175
$\ln(\text{Ti}_{t-3} - \text{Ti}_{t-4})\text{GR13}$	0.045355	0.027697	1.637544	0.1180
R-squared	0.393802	Mean dependent var		0.003867
Adjusted R-squared	0.266182	S.D. dependent var		0.031869
S.E. of regression	0.027300	Akaike info criterion		-4.180812
Sum squared resid	0.014160	Schwarz criterion		-3.935384
Log likelihood	55.16974	F-statistic		3.085729
Durbin-Watson stat	2.169357	Prob(F-statistic)		0.040805

Table B.29

Dependent Variable: $\Delta\text{LN}(\text{Y/L})\text{GR14}$				
Method: Least Squares				
Sample(adjusted): 1972 1993				
Included observations: 22 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.017270	0.012462	-1.385797	0.1848
$\Delta\text{LN}(\text{K/L})\text{GR14}$	0.826418	0.196653	4.202419	0.0007
$\Delta\text{LN}(\text{hours})\text{GR14}$	0.626102	0.307745	2.034484	0.0588
$\Delta\text{LN}(\text{pat})\text{GR14}$	0.009323	0.004770	1.954395	0.0684
$\Delta^2\text{LN}(\text{pat})\text{GR14}$	0.011308	0.004558	2.480729	0.0246
$\ln(\text{Ti}_{t-1} - \text{Ti}_{t-2})\text{GR14}$	0.007689	0.084742	0.090730	0.9288
R-squared	0.659982	Mean dependent var		0.034685
Adjusted R-squared	0.553726	S.D. dependent var		0.024883
S.E. of regression	0.016623	Akaike info criterion		-5.129091
Sum squared resid	0.004421	Schwarz criterion		-4.831534
Log likelihood	62.42000	F-statistic		6.211262
Durbin-Watson stat	2.223166	Prob(F-statistic)		0.002204

Table B.30

Dependent Variable: $\Delta \text{LN}(\text{Y/L})\text{GR15}$				
Method: Least Squares				
Sample(adjusted): 1970 1993				
Included observations: 24 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.002235	0.018412	-0.121401	0.9046
$\Delta \text{LN}(\text{K/L})\text{GR15}$	-0.199783	0.352485	-0.566785	0.5775
$\Delta \text{LN}(\text{hours})\text{GR15}$	-0.833435	0.797686	-1.044817	0.3092
$\Delta \text{LN}(\text{R\&D})\text{GR15}$	0.118003	0.057749	2.043393	0.0551
$\ln(\text{Ti}_{t-3} - \text{Ti}_{t-4})\text{GR15}$	0.018354	0.021276	0.862667	0.3991
R-squared	0.298833	Mean dependent var		-0.003942
Adjusted R-squared	0.151218	S.D. dependent var		0.025985
S.E. of regression	0.023940	Akaike info criterion		-4.443505
Sum squared resid	0.010889	Schwarz criterion		-4.198077
Log likelihood	58.32206	F-statistic		2.024416
Durbin-Watson stat	1.113432	Prob(F-statistic)		0.131678

APPENDIX II.C- Other Estimates of VAR models

I. Variables: Investment, own R&D and suppliers R&D expenditures

Table C.1: AR(2) Vector Autoregression model for technology producers industries

Sample 1971 1992			
Included observations: 22			
Total panel (balanced) observations 132			
Standard errors & t-statistics in parentheses			
Method: Fixed Effects			
	ln(Investment) I (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I (t-1)	0.827439* (0.103487) (7.995621)	-0.017155 (0.048010) (-0.357326)	0.020687 (0.025660) (0.806215)
I(t-2)	-0.107741 (0.108282) (-0.994998)	-0.047078 (0.050235) (-0.937157)	-0.002029 (0.026849) (-0.075560)
R&D (t-1)	0.528379* (0.268594) (1.967205)	1.181082* (0.124608) (9.478341)	0.002533 (0.066599) (0.038033)
R&D (t-2)	-0.367330 (0.292395) (-1.256279)	-0.155426 (0.135650) (-1.145786)	-0.026498 (0.072501) (-0.365485)
R&DS (t-1)	-0.116934 (0.480729) (-0.243243)	0.224521 (0.223024) (1.006713)	0.986460* (0.119199) (8.275730)
R&DS(t-2)	0.316171 (0.524425) (0.602891)	-0.182386 (0.243296) (-0.749648)	-0.133856 (0.130034) (-1.029396)
<i>Fixed effects</i>			
Group 4	-1.447982	-0.044177	3.042995
Group 5	-1.642290	-0.112603	3.000532
Group 10	-1.460661	-0.042953	3.013191
Group 11	-1.123543	-0.051881	2.988714
Group 12	-0.926950	0.067205	2.994674
Group 15	-0.516864	0.196172	2.975001

* At least 10% significant

Dependent variable: ln (Investment)

R-squared	0.987761	Mean dependent var	21.65491
Adjusted R-squared	0.983805	S.D. dependent var	1.315199
S.E. of regression	0.167373	Sum squared resid	2.773368
F-statistic	307.2983	Durbin-Watson stat	1.929486
Prob(F-statistic)	0.000000		

Dependent variable: ln (own R&D expenditures)

R-squared	0.998377	Mean dependent var	19.54904
Adjusted R-squared	0.997852	S.D. dependent var	1.675515
S.E. of regression	0.077649	Sum squared resid	0.596913
F-statistic	2342.144	Durbin-Watson stat	1.986355
Prob(F-statistic)	0.000000		

Dependent variable: ln (suppliers R&D expenditures)

R-squared	0.987300	Mean dependent var	20.53592
Adjusted R-squared	0.983196	S.D. dependent var	0.320146
S.E. of regression	0.041501	Sum squared resid	0.170512
F-statistic	296.0216	Durbin-Watson stat	2.135459
Prob(F-statistic)	0.000000		

Table C.2: AR(4) Vector Autoregression model for technology users and producers and technology users industries

Sample 1971 1992			
Included observations: 22			
Total panel (balanced) observations 132			
Standard errors & t-statistics in parentheses			
Method: Fixed Effects			
	ln(Investment) I (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I (t-1)	1.102666* (0.098791) (11.16165)	-0.008384 (0.077122) (-0.108707)	0.029823 (0.021992) (1.356087)
I (t-2)	-0.448784* (0.158276) (-2.835446)	-0.005506 (0.123560) (-0.044561)	-0.043582 (0.035235) (-1.236917)
I (t-3)	0.108436 (0.161964) (0.669510)	-0.024892 (0.126439) (-0.196872)	0.043066 (0.036056) (1.194448)
I (t-4)	0.037800 (0.100871) (0.374735)	0.000888 (0.078746) (0.011276)	-0.021422 (0.022455) (-0.953990)
R&D (t-1)	0.221720 (0.134154) (1.652732)	1.029942* (0.104728) (9.834418)	-0.028640 (0.029865) (-0.958984)
R&D (t-2)	-0.572148* (0.195974) (-2.919513)	-0.188574 (0.152989) (-1.232598)	-0.009392 (0.043627) (-0.215270)
R&D (t-3)	0.441862* (0.201140) (2.196794)	0.102415 (0.157022) (0.652237)	0.026750 (0.044777) (0.597410)
R&D (t-4)	-0.251566* (0.144389) (-1.742275)	0.002691 (0.112719) (0.023876)	0.009327 (0.032143) (0.290168)
R&DS (t-1)	-0.585703 (0.460161) (-1.272821)	0.149284 (0.359230) (0.415568)	0.868020* (0.102439) (8.473543)
R&DS(t-2)	0.346495 (0.567475) (0.610590)	0.054485 (0.443005) (0.122989)	0.052785 (0.126329) (0.417840)
R&DS(t-3)	-0.519087 (0.582051) (-0.891824)	-0.097951 (0.454384) (-0.215569)	-0.370725* (0.129573) (-2.861120)
R&DS(t-4)	-0.863224 (0.553648) (-1.559156)	0.279016 (0.432211) (0.645555)	0.326884* (0.123251) (2.652190)
Fixed effects			
Group 2	39.89933	-6.064653	2.241944
Group 6	39.88898	-6.082700	2.249447
Group 1	39.51121	-6.086260	2.246691
Group 3	39.78781	-6.178794	2.237800
Group 9	39.53381	-6.216445	2.249261
Group 14	41.40873	-6.299539	2.329732

* At least 10% significant

Dependent variable: *ln (Investment)*

R-squared	0.978069	Mean dependent var	21.27954
Adjusted R-squared	0.969108	S.D. dependent var	0.687033
S.E. of regression	0.120754	Sum squared resid	1.356078
F-statistic	129.6117	Durbin-Watson stat	1.763913
Prob(F-statistic)	0.000000		

Dependent variable: *ln (own R&D expenditures)*

R-squared	0.987464	Mean dependent var	17.86175
Adjusted R-squared	0.982342	S.D. dependent var	0.709407
S.E. of regression	0.094268	Sum squared resid	0.826436
F-statistic	228.9325	Durbin-Watson stat	2.057118
Prob(F-statistic)	0.000000		

Dependent variable: *ln (suppliers R&D expenditures)*

R-squared	0.996030	Mean dependent var	20.43818
Adjusted R-squared	0.994407	S.D. dependent var	0.359458
S.E. of regression	0.026882	Sum squared resid	0.067204
F-statistic	729.0855	Durbin-Watson stat	1.857533
Prob(F-statistic)	0.000000		

Table C.3: AR(2) Vector Autoregression model for technology users and producers and technology users industries

Sample 1971 1992			
Included observations: 22			
Total panel (balanced) observations 132			
Standard errors & t-statistics in parentheses			
Method: Fixed Effects			
	ln(Investment) I (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I (t-1)	1.042091* (0.090729) (11.48577)	-0.013557 (0.066723) (-0.203181)	0.014578 (0.020102) (0.725178)
I (t-2)	-0.277767* (0.088858) (-3.125959)	-0.023937 (0.065347) (-0.366307)	-0.006806 (0.019688) (-0.345675)
R&D (t-1)	0.162391 (0.137015) (1.185204)	1.019882* (0.100762) (10.12167)	-0.033285 (0.030358) (-1.096409)
R&D (t-2)	-0.319734* (0.139786) (-2.287312)	-0.082420 (0.102800) (-0.801756)	0.028188 (0.030972) (0.910128)
R&DS (t-1)	-0.384764 (0.452247) (-0.850783)	0.127916 (0.332586) (0.384609)	0.815540* (0.100202) (8.138939)
R&DS(t-2)	-0.373083 (0.475138) (-0.785210)	0.048126 (0.349420) (0.137731)	-0.056195 (0.105274) (-0.533798)
Fixed Effects			
Group 2	23.07409	-1.662864	4.698092
Group 6	23.03061	-1.671449	4.709551
Group 1	22.71913	-1.706774	4.693010
Group 3	22.94053	-1.774353	4.695141
Group 9	22.65083	-1.815539	4.706111
Group 14	23.93257	-1.730586	4.880560

* At least 10% significant

Dependent variable: ln (Investment)

R-squared	0.974879	Mean dependent var	21.27954
Adjusted R-squared	0.966759	S.D. dependent var	0.687033
S.E. of regression	0.125261	Sum squared resid	1.553331
F-statistic	147.7661	Durbin-Watson stat	1.699283
Prob(F-statistic)	0.000000		

Dependent variable: ln (own R&D expenditures)

R-squared	0.987257	Mean dependent var	17.86175
Adjusted R-squared	0.983139	S.D. dependent var	0.709407
S.E. of regression	0.092118	Sum squared resid	0.840080
F-statistic	295.0079	Durbin-Watson stat	2.046208
Prob(F-statistic)	0.000000		

Dependent variable: ln (suppliers R&D expenditures)

R-squared	0.995495	Mean dependent var	20.43818
Adjusted R-squared	0.994039	S.D. dependent var	0.359458
S.E. of regression	0.027753	Sum squared resid	0.076255
F-statistic	841.3952	Durbin-Watson stat	2.105172
Prob(F-statistic)	0.000000		

Table C.4: AR(2) Vector Autoregression model for low technology industries

Sample 1971 1992			
Included observations: 22			
Total panel (balanced) observations 66			
Standard errors & t-statistics in parentheses			
Method: Fixed Effects			
	ln(Investment) I (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I (t-1)	0.715298* (0.170790) (4.188171)	0.314122* (0.173081) (1.814891)	0.022487 (0.036718) (0.612413)
I (t-2)	-0.113376 (0.119389) (-0.949638)	-0.158016 (0.120990) (-1.306023)	-0.034195 (0.025667) (-1.332225)
R&D (t-1)	0.130706 (0.159078) (0.821645)	1.364892* (0.161212) (8.466465)	0.052653 (0.034200) (1.539545)
R&D (t-2)	-0.093872 (0.147249) (-0.637505)	-0.415326* (0.149224) (-2.783247)	-0.054473* (0.031657) (-1.720729)
R&DS (t-1)	-0.522487 (0.743567) (-0.702676)	1.433541* (0.753540) (1.902409)	0.590332* (0.159860) (3.692810)
R&DS(t-2)	-0.202473 (0.787753) (-0.257026)	-0.124598 (0.798319) (-0.156075)	-0.139304 (0.169359) (-0.822532)
<i>Fixed Effects</i>			
Group 7	21.97754	-28.73291	11.26354
Group 8	21.89493	-28.86550	11.31442
Group 13	23.50393	-29.68096	11.46957

* At least 10% significant

Dependent variable: *ln (Investment)*

R-squared	0.996401	Mean dependent var	20.45461
Adjusted R-squared	0.993502	S.D. dependent var	1.399838
S.E. of regression	0.112837	Sum squared resid	0.458362
F-statistic	383.3754	Durbin-Watson stat	1.851545
Prob(F-statistic)	0.000000		

Dependent variable: *ln (own R&D expenditures)*

R-squared	0.999370	Mean dependent var	14.24243
Adjusted R-squared	0.998862	S.D. dependent var	3.390485
S.E. of regression	0.114351	Sum squared resid	0.470739
F-statistic	2196.403	Durbin-Watson stat	1.930935
Prob(F-statistic)	0.000000		

Dependent variable: *ln (suppliers R&D expenditures)*

R-squared	0.995232	Mean dependent var	20.51280
Adjusted R-squared	0.991392	S.D. dependent var	0.261468
S.E. of regression	0.024259	Sum squared resid	0.021186
F-statistic	289.0396	Durbin-Watson stat	2.082629
Prob(F-statistic)	0.000000		

II. Variables: Investment, Value Added, own R&D and suppliers R&D expenditures

Table C.5: AR(2) Vector Autoregression model for technology producers industries

Sample 1972 1992				
Included observations: 21				
Total panel (balanced) observations 126				
Standard errors & t-statistics in parentheses				
Method: Fixed Effects				
	ln(Investment) I (t)	ln(Value Added) VA (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I (t-1)	0.800277* (0.104015) (7.693886)	-0.075658* (0.033955) (-2.228174)	-0.024169 (0.049568) (-0.487596)	0.029629 (0.026076) (1.136242)
I (t-2)	-0.064705 (0.108328) (-0.597302)	0.030730 (0.035363) (0.868989)	-0.042628 (0.051623) (-0.825763)	0.005587 (0.027158) (0.205726)
VA (t-1)	0.616620* (0.290914) (2.119592)	0.908954* (0.094967) (9.571245)	0.069239 (0.138634) (0.499437)	0.091197 (0.072932) (1.250443)
VA (t-2)	-0.461447 (0.299516) (-1.540640)	0.058473 (0.097775) (0.598039)	-0.033636 (0.142733) (-0.235660)	-0.127678* (0.075088) (-1.700370)
R&D (t-1)	0.440364* (0.265785) (1.656842)	0.010840 (0.086764) (0.124936)	1.166856* (0.126659) (9.212606)	0.003713 (0.066632) (0.055723)
R&D (t-2)	-0.365726 (0.288444) (-1.267925)	0.017528 (0.094161) (0.186150)	-0.160046 (0.137457) (-1.164338)	-0.010569 (0.072312) (-0.146158)
R&DS (t-1)	-0.191539 (0.473886) (-0.404187)	-0.030260 (0.154697) (-0.195606)	0.219531 (0.225828) (0.972115)	0.964354* (0.118802) (8.117294)
R&DS(t-2)	0.286323 (0.521749) (0.548775)	0.002373 (0.170322) (0.013934)	-0.199954 (0.248637) (-0.804202)	-0.091795 (0.130801) (-0.701785)
Fixed effects				
Group 4	-1.560023	1.713587	0.011670	2.802715
Group 5	-1.599062	1.626983	-0.025494	2.738011
Group 10	-1.507336	1.695087	0.028735	2.754784
Group 11	-1.518033	1.777425	-0.062354	2.819790
Group 12	-1.059578	1.840469	0.128772	2.725092
Group 15	-0.979640	1.943696	0.191543	2.751802

* At least 10% significant

Dependent variable: ln (Investment)

R-squared	0.988481	Mean dependent var	21.65491
Adjusted R-squared	0.984443	S.D. dependent var	1.315199
S.E. of regression	0.164039	Sum squared resid	2.610169
F-statistic	297.2813	Durbin-Watson stat	1.955402
Prob(F-statistic)	0.000000		

Dependent variable: ln (Value Added)

R-squared	0.997422	Mean dependent var	23.69019
Adjusted R-squared	0.996518	S.D. dependent var	0.907528
S.E. of regression	0.053550	Sum squared resid	0.278154
F-statistic	1340.290	Durbin-Watson stat	1.989419
Prob(F-statistic)	0.000000		

Dependent variable: ln (own R&D expenditures)

R-squared	0.998388	Mean dependent var	19.54904
Adjusted R-squared	0.997823	S.D. dependent var	1.675515
S.E. of regression	0.078172	Sum squared resid	0.592756
F-statistic	2145.878	Durbin-Watson stat	1.976981
Prob(F-statistic)	0.000000		

Dependent variable: ln (suppliers R&D expenditures)

R-squared	0.987782	Mean dependent var	20.53592
Adjusted R-squared	0.983499	S.D. dependent var	0.320146
S.E. of regression	0.041124	Sum squared resid	0.164048
F-statistic	280.0725	Durbin-Watson stat	2.097148
Prob(F-statistic)	0.000000		

Table C.6: AR(4) Vector Autoregression model for technology users and producers and technology users industries

Sample 1971 1992				
Included observations: 22				
Total panel (balanced) observations 132				
Standard errors & t-statistics in parentheses				
Method: Fixed Effects				
	ln(Investment) I (t)	ln(Value Added) VA (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I (t-1)	1.086600* (0.100593) (10.80191)	-0.020787 (0.058234) (-0.356964)	-0.018858 (0.079972) (-0.235810)	0.028009 (0.023222) (1.206136)
I (t-2)	-0.461524* (0.157239) (-2.935171)	0.175443* (0.091027) (1.927383)	-0.005781 (0.125006) (-0.046246)	-0.040429 (0.036299) (-1.113759)
I (t-3)	0.105379 (0.164651) (0.640016)	-0.132113 (0.095317) (-1.386037)	-0.055923 (0.130898) (-0.427227)	0.042586 (0.038010) (1.120366)
I (t-4)	0.047578 (0.103700) (0.458803)	-0.004892 (0.060033) (-0.081491)	0.010504 (0.082442) (0.127410)	-0.021114 (0.023940) (-0.881976)
VA (t-1)	-0.096687 (0.185622) (-0.520883)	0.832992* (0.107458) (7.751822)	0.086396 (0.147570) (0.585461)	0.006025 (0.042852) (0.140612)
VA (t-2)	0.485603* (0.238662) (2.034685)	0.216782 (0.138163) (1.569035)	0.077231 (0.189738) (0.407040)	-0.045023 (0.055096) (-0.817167)
VA (t-3)	-0.158318 (0.262120) (-0.603992)	-0.239073 (0.151743) (-1.575514)	-0.148745 (0.208386) (-0.713795)	0.056558 (0.060512) (0.934669)
VA (t-4)	-0.231967 (0.192951) (-1.202210)	-0.011687 (0.111700) (-0.104630)	0.165736 (0.153397) (1.080442)	-0.025212 (0.044544) (-0.566005)
R&D (t-1)	0.219072 (0.134977) (1.623025)	0.200561* (0.078139) (2.566715)	0.986757* (0.107308) (9.195593)	-0.028109 (0.031160) (-0.902072)
R&D (t-2)	-0.512497* (0.196964) (-2.601990)	-0.292849* (0.114023) (-2.568327)	-0.217713 (0.156587) (-1.390364)	-0.009276 (0.045470) (-0.204005)
R&D (t-3)	0.329878 (0.204119) (1.616103)	0.274891* (0.118166) (2.326313)	0.083649 (0.162276) (0.515474)	0.032751 (0.047122) (0.695038)
R&D (t-4)	-0.197846 (0.143654) (-1.377239)	-0.104757 (0.083162) (-1.259676)	-0.010222 (0.114205) (-0.089502)	0.006886 (0.033163) (0.207646)
R&DS (t-1)	-0.564050 (0.459137) (-1.228501)	-0.075088 (0.265797) (-0.282501)	0.039566 (0.365016) (0.108395)	0.877403* (0.105994) (8.277860)

R&DS(t-2)	0.242535 (0.559857) (0.433208)	0.380949 (0.324105) (1.175390)	0.080563 (0.445089) (0.181004)	0.052060 (0.129246) (0.402802)
R&DS(t-3)	-0.439633 (0.572397) (-0.768055)	-0.192919 (0.331364) (-0.582197)	-0.107437 (0.455058) (-0.236095)	-0.375721* (0.132141) (-2.843345)
R&DS(t-4)	-0.883814 (0.550819) (-1.604546)	-0.046504 (0.318872) (-0.145840)	0.124167 (0.437904) (0.283548)	0.335395* (0.127159) (2.637598)
Fixed effects				
Group 2	40.88558	1.542780	-2.638459	2.071101
Group 6	40.86515	1.498309	-2.620302	2.077280
Group 1	40.47987	1.482346	-2.654949	2.075590
Group 3	40.77736	1.366506	-2.652145	2.062626
Group 9	40.49649	1.578317	-2.881117	2.081989
Group 14	42.42904	1.590700	-2.735814	2.152261

* At least 10% significant

Dependent variable: ln (Investment)

R-squared	0.979862	Mean dependent var	21.27954
Adjusted R-squared	0.970359	S.D. dependent var	0.687033
S.E. of regression	0.118283	Sum squared resid	1.245192
F-statistic	120.2936	Durbin-Watson stat	1.795274
Prob(F-statistic)	0.000000		

Dependent variable: ln (Value Added)

R-squared	0.990589	Mean dependent var	22.91785
Adjusted R-squared	0.986147	S.D. dependent var	0.581784
S.E. of regression	0.068475	Sum squared resid	0.417304
F-statistic	260.2092	Durbin-Watson stat	2.068960
Prob(F-statistic)	0.000000		

Dependent variable: ln (own R&D expenditures)

R-squared	0.988062	Mean dependent var	17.86175
Adjusted R-squared	0.982429	S.D. dependent var	0.709407
S.E. of regression	0.094036	Sum squared resid	0.787002
F-statistic	204.6248	Durbin-Watson stat	2.036343
Prob(F-statistic)	0.000000		

Dependent variable: ln (suppliers R&D expenditures)

R-squared	0.996079	Mean dependent var	20.43818
Adjusted R-squared	0.994229	S.D. dependent var	0.359458
S.E. of regression	0.027306	Sum squared resid	0.066361
F-statistic	628.1089	Durbin-Watson stat	1.851740
Prob(F-statistic)	0.000000		

Table C.7: AR(2) Vector Autoregression model for technology users and producers and technology users industries

Sample 1971 1992				
Included observations: 22				
Total panel (balanced) observations 132				
Standard errors & t-statistics in parentheses				
Method: Fixed Effects				
	ln(Investment) I (t)	ln(Value Added) VA (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I (t-1)	1.055781* (0.093026) (11.34933)	0.027312 (0.054918) (0.497327)	-0.017080 (0.067606) (-0.252634)	0.013239 (0.020799) (0.636510)
I (t-2)	-0.302857* (0.090932) (-3.330583)	0.020240 (0.053682) (0.377026)	-0.050527 (0.066084) (-0.764588)	-0.006803 (0.020331) (-0.334595)
VA (t-1)	-0.117367 (0.179093) (-0.655343)	0.799634* (0.105728) (7.563099)	0.035547 (0.130154) (0.273114)	0.011878 (0.040042) (0.296635)
VA (t-2)	0.206565 (0.169580) (1.218096)	0.039993 (0.100113) (0.399476)	0.114281 (0.123241) (0.927295)	-0.007787 (0.037915) (-0.205374)
R&D (t-1)	0.141653 (0.139439) (1.015873)	0.164635* (0.082319) (1.999973)	0.983548* (0.101336) (9.705775)	-0.034347 (0.031176) (-1.101714)
R&D (t-2)	-0.343290* (0.143429) (-2.393451)	-0.091081 (0.084674) (-1.075666)	-0.126780 (0.104236) (-1.216282)	0.026752 (0.032068) (0.834239)
R&DS (t-1)	-0.381704 (0.454092) (-0.840588)	0.053416 (0.268075) (0.199257)	0.097578 (0.330008) (0.295684)	0.813049* (0.101526) (8.008266)
R&DS(t-2)	-0.412568 (0.477558) (-0.863912)	0.040102 (0.281929) (0.142242)	-0.016980 (0.347061) (-0.048924)	-0.057916 (0.106773) (-0.542420)
Fixed effects				
Group 2	22.80432	-0.489962	-1.092557	4.761637
Group 6	22.77479	-0.514597	-1.077121	4.773780
Group 1	22.466445	0.507178	-1.122085	4.756276
Group 3	22.71896	-0.616486	-1.118701	4.761222
Group 9	22.34502	-0.406938	-1.320838	4.766885
Group 14	23.65610	-0.513002	-1.132837	4.946668

* At least 10% significant

Dependent variable: *ln (Investment)*

R-squared	0.975353	Mean dependent var	21.27954
Adjusted R-squared	0.966714	S.D. dependent var	0.687033
S.E. of regression	0.125345	Sum squared resid	1.523993
F-statistic	137.0943	Durbin-Watson stat	1.661278
Prob(F-statistic)	0.000000		

Dependent variable: *ln (Value Added)*

R-squared	0.988021	Mean dependent var	22.91785
Adjusted R-squared	0.983822	S.D. dependent var	0.581784
S.E. of regression	0.073998	Sum squared resid	0.531140
F-statistic	285.7360	Durbin-Watson stat	1.855224
Prob(F-statistic)	0.000000		

Dependent variable: *ln (own R&D expenditures)*

R-squared	0.987791	Mean dependent var	17.86175
Adjusted R-squared	0.983511	S.D. dependent var	0.709407
S.E. of regression	0.091093	Sum squared resid	0.804904
F-statistic	280.2831	Durbin-Watson stat	2.048826
Prob(F-statistic)	0.000000		

Dependent variable: *ln (suppliers R&D expenditures)*

R-squared	0.995499	Mean dependent var	20.43818
Adjusted R-squared	0.993922	S.D. dependent var	0.359458
S.E. of regression	0.028025	Sum squared resid	0.076182
F-statistic	766.2480	Durbin-Watson stat	2.101968
Prob(F-statistic)	0.000000		

Table C.8: AR(2) Vector Autoregression model for low technology industries

Sample 1972 1992				
Included observations: 21				
Total panel (balanced) observations 126				
Standard errors & t-statistics in parentheses				
Method: Fixed Effects				
	ln(Investment) I (t)	ln(Value Added) VA (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I (t-1)	0.620468* (0.185856) (3.338430)	-0.016634 (0.056426) (-0.294784)	0.280087 (0.184685) (1.516563)	0.011773 (0.040714) (0.289163)
I (t-2)	-0.142138 (0.121733) (-1.167619)	0.008280 (0.036959) (0.224032)	-0.168137 (0.120966) (-1.389954)	-0.037442 (0.026667) (-1.404060)
VA (t-1)	0.556382 (0.518963) (1.072103)	0.540563* (0.157558) (3.430874)	0.625610 (0.515693) (1.213144)	0.067827 (0.113684) (0.596623)
VA (t-2)	0.192780 (0.400921) (0.480842)	-0.280740* (0.121721) (-2.306433)	-0.634653 (0.398394) (-1.593026)	0.013572 (0.087826) (0.154537)
R&D (t-1)	0.090315 (0.162561) (0.555576)	0.090752* (0.049354) (1.838789)	1.371114* (0.161537) (8.487925)	0.048331 (0.035611) (1.357208)
R&D (t-2)	-0.073159 (0.148527) (-0.492412)	-0.057030 (0.045107) (-1.264320)	-0.419395* (0.147636) (-2.840731)	-0.052267 (0.032546) (-1.605935)
R&DS (t-1)	-0.441258 (0.750795) (-0.587722)	-0.222450 (0.227943) (-0.975901)	1.552196* (0.746064) (2.080513)	0.600553* (0.164469) (3.651462)
R&DS(t-2)	0.096807 (0.834135) (0.116057)	-0.289418 (0.253246) (-1.142835)	-0.338530 (0.828879) (-0.408420)	-0.109238 (0.182726) (-0.597826)
Fixed effects				
Group 7	0.189191	26.65463	-25.75320	8.927845
Group 8	0.517891	26.20909	-25.90607	9.023235
Group 13	0.247497	28.57614	-26.53601	8.976085

* At least 10% significant

Dependent variable: ln (Investment)

R-squared	0.996580	Mean dependent var	20.45461
Adjusted R-squared	0.993462	S.D. dependent var	1.399839
S.E. of regression	0.113187	Sum squared resid	0.435584
F-statistic	353.8592	Durbin-Watson stat	2.008185
Prob(F-statistic)	0.000000		

Dependent variable: ln (Value Added)

R-squared	0.999562	Mean dependent var	22.84438
Adjusted R-squared	0.999164	S.D. dependent var	1.188173
S.E. of regression	0.034364	Sum squared resid	0.040150
F-statistic	2774.091	Durbin-Watson stat	2.240625
Prob(F-statistic)	0.000000		

Dependent variable: ln (own R&D expenditures)

R-squared	0.999424	Mean dependent var	14.24243
Adjusted R-squared	0.998900	S.D. dependent var	3.390485
S.E. of regression	0.112474	Sum squared resid	0.430112
F-statistic	2108.269	Durbin-Watson stat	2.057651
Prob(F-statistic)	0.000000		

Dependent variable: ln (suppliers R&D expenditures)

R-squared	0.995296	Mean dependent var	20.51280
Adjusted R-squared	0.991007	S.D. dependent var	0.261468
S.E. of regression	0.024795	Sum squared resid	0.020903
F-statistic	256.9359	Durbin-Watson stat	2.120150
Prob(F-statistic)	0.000000		

III. Variables: (Investment/Capital), own R&D and suppliers R&D expenditures

Table C.9: AR(2) Vector Autoregression model for technology producers industries

Sample 1972 1992			
Included observations: 21			
Total panel (balanced) observations 126			
Standard errors & t-statistics in parentheses			
Method: Fixed Effects			
	ln(Investment/Capital) I/K (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I/K (t-1)	0.719557* (0.108274) (6.645678)	-0.024958 (0.051459) (-0.485005)	0.024649 (0.027800) (0.886654)
I/K (t-2)	-0.184768 (0.112829) (-1.637586)	-0.062865 (0.053624) (-1.172334)	-0.010682 (0.028970) (-0.368740)
R&D (t-1)	0.531020* (0.267733) (1.983394)	1.150904* (0.127244) (9.044881)	-0.002434 (0.068742) (-0.035411)
R&D (t-2)	-0.355688 (0.288925) (-1.231072)	-0.131234 (0.137316) (-0.955707)	-0.018087 (0.074184) (-0.243816)
R&DS (t-1)	-0.083750 (0.477370) (-0.175439)	0.200911 (0.226877) (0.885550)	0.979934* (0.122568) (7.995010)
R&DS(t-2)	0.291203 (0.519552) (0.560489)	-0.189218 (0.246924) (-0.766298)	-0.117090 (0.133399) (-0.877745)
Fixed Effects			
Group 4	-9.349487	-0.935112	3.195755
Group 5	-9.068253	-0.916455	3.134765
Group 10	-9.368604	-0.943585	3.170027
Group 11	-8.505274	-0.870978	3.130654
Group 12	-9.060172	-0.886451	3.167614
Group 15	-8.903483	-0.819366	3.174969

* At least 10% significant

Dependent variable: *ln (Investment/Capital)*

R-squared	0.875520	Mean dependent var	-3.195089
Adjusted R-squared	0.834468	S.D. dependent var	0.406149
S.E. of regression	0.165244	Sum squared resid	2.566734
F-statistic	26.44557	Durbin-Watson stat	1.954969
Prob(F-statistic)	0.000000		

Dependent variable: *ln (own R&D expenditures)*

R-squared	0.998349	Mean dependent var	19.56509
Adjusted R-squared	0.997805	S.D. dependent var	1.676095
S.E. of regression	0.078535	Sum squared resid	0.579762
F-statistic	2273.671	Durbin-Watson stat	1.995157
Prob(F-statistic)	0.000000		

Dependent variable: *ln (suppliers R&D expenditures)*

R-squared	0.986579	Mean dependent var	20.547779
Adjusted R-squared	0.982153	S.D. dependent var	0.317589
S.E. of regression	0.042428	Sum squared resid	0.169210
F-statistic	276.3986	Durbin-Watson stat	2.131505
Prob(F-statistic)	0.000000		

Table C.10: AR(4) Vector Autoregression model for technology users and producers and technology users industries

Sample 1972 1992			
Included observations: 21			
Total panel (balanced) observations 126			
Standard errors & t-statistics in parentheses			
Method: Fixed Effects			
	ln(Investment/Capital) I/K (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I/K (t-1)	1.034694* (0.117274) (8.822899)	0.023155 (0.080733) (0.286806)	0.045896* (0.022198) (2.067542)
I/K (t-2)	-0.377231* (0.178252) (-2.116285)	-0.031221 (0.122711) (-0.254428)	-0.049418 (0.033741) (-1.464649)
I/K (t-3)	0.035039 (0.177888) (0.196974)	-0.005216 (0.122460) (-0.042590)	0.039611 (0.033672) (1.176398)
I/K (t-4)	0.072008 (0.114740) (0.627575)	0.004791 (0.078989) (0.060658)	-0.016852 (0.021719) (-0.775900)
R&D (t-1)	0.356280* (0.155305) (2.294063)	1.026969* (0.106914) (9.605541)	-0.028523 (0.029397) (-0.970277)
R&D (t-2)	-0.830703* (0.230794) (-3.599321)	-0.217763 (0.158882) (-1.370599)	-0.020177 (0.043686) (-0.461867)
R&D (t-3)	0.781533* (0.243531) (3.209172)	0.135036 (0.167650) (0.805464)	0.047981 (0.046097) (1.040865)
R&D (t-4)	-0.361757* (0.171274) (-2.112155)	0.024821 (0.117907) (0.210517)	0.006997 (0.032420) (0.215812)
R&DS (t-1)	-0.791653 (0.535500) (-1.478344)	0.142703 (0.368645) (0.387100)	0.881372* (0.101363) (8.695228)
R&DS(t-2)	0.706578 (0.657379) (1.074841)	0.073289 (0.452548) (0.161946)	0.069314 (0.124433) (0.557040)
R&DS(t-3)	-0.734245 (0.679157) (-1.081113)	-0.089604 (0.467541) (-0.191650)	-0.411243* (0.128555) (-3.198962)
R&DS(t-4)	-1.012163 (0.722253) (-1.401396)	0.302661 (0.497209) (0.608721)	0.508236* (0.136712) (3.717554)
Fixed Effects			
Group 2	37.37952	-8.173542	-1.137652
Group 6	37.30840	-8.190835	-1.128000
Group 1	37.11914	-8.151047	-1.111113
Group 3	37.38952	-8.266521	-1.139478
Group 9	37.28239	-8.257837	-1.122684
Group 14	38.78247	-8.476186	-1.176253

* At least 10% significant

Dependent variable: *ln (Investment/Capital)*

R-squared	0.886798	Mean dependent var	-2.915313
Adjusted R-squared	0.839202	S.D. dependent var	0.348740
S.E. of regression	0.139843	Sum squared resid	1.720940
F-statistic	22.23789	Durbin-Watson stat	1.821999
Prob(F-statistic)	0.000000		

Dependent variable: *ln (own R&D expenditures)*

R-squared	0.986977	Mean dependent var	17.87310
Adjusted R-squared	0.981501	S.D. dependent var	0.707807
S.E. of regression	0.096270	Sum squared resid	0.815576
F-statistic	215.1312	Durbin-Watson stat	2.080465
Prob(F-statistic)	0.000000		

Dependent variable: *ln (suppliers R&D expenditures)*

R-squared	0.996130	Mean dependent var	20.45041
Adjusted R-squared	0.994502	S.D. dependent var	0.357003
S.E. of regression	0.026470	Sum squared resid	0.061660
F-statistic	730.6133	Durbin-Watson stat	1.904205
Prob(F-statistic)	0.000000		

Table C.11: AR(2) Vector Autoregression model for technology users and producers and technology users industries

Sample 1972 1992			
Included observations: 21			
Total panel (balanced) observations 126			
Standard errors & t-statistics in parentheses			
Method: Fixed Effects			
	ln(Investment/Capital) I/K (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I/K (t-1)	0.955481* (0.106803) (8.946209)	-0.008634 (0.067292) (-0.128312)	0.016775 (0.020084) (0.835239)
I/K (t-2)	-0.214288* (0.104919) (-2.042413)	-0.009252 (0.066105) (-0.139967)	-0.003321 (0.019730) (-0.168330)
R&D (t-1)	0.277639* (0.163973) (1.693205)	1.018040* (0.103312) (9.854058)	-0.033936 (0.030834) (-1.100586)
R&D (t-2)	-0.327608* (0.169493) (-1.932873)	-0.069170 (0.106790) (-0.647726)	0.028761 (0.031872) (0.902392)
R&DS (t-1)	-0.540865 (0.545091) (-0.992247)	0.132060 (0.343437) (0.384525)	0.799016* (0.102502) (7.795102)
R&DS(t-2)	-0.307337 (0.579854) (-0.530024)	0.025305 (0.365340) (0.069263)	-0.024401 (0.109039) (-0.223785)
Fixed Effects			
Group 2	17.28227	-2.329364	4.570336
Group 6	17.18207	-2.336954	4.585775
Group 1	17.06522	-2.351926	4.567784
Group 3	17.28867	-2.424734	4.565061
Group 9	17.15974	-2.432111	4.575373
Group 14	17.88415	-2.426326	4.751355

* At least 10% significant

Dependent variable: ln (Investment/Capital)

R-squared	0.861489	Mean dependent var	-2.915313
Adjusted R-squared	0.815810	S.D. dependent var	0.348740
S.E. of regression	0.149670	Sum squared resid	2.105707
F-statistic	23.38584	Durbin-Watson stat	1.732334
Prob(F-statistic)	0.000000		

Dependent variable: ln (own R&D expenditures)

R-squared	0.986652	Mean dependent var	17.87310
Adjusted R-squared	0.982250	S.D. dependent var	0.707807
S.E. of regression	0.094300	Sum squared resid	0.835900
F-statistic	277.9313	Durbin-Watson stat	2.055623
Prob(F-statistic)	0.000000		

Dependent variable: ln (suppliers R&D expenditures)

R-squared	0.995326	Mean dependent var	20.45041
Adjusted R-squared	0.993785	S.D. dependent var	0.357003
S.E. of regression	0.028145	Sum squared resid	0.074461
F-statistic	800.7165	Durbin-Watson stat	2.117487
Prob(F-statistic)	0.000000		

Table C.12: AR(2) Vector Autoregression model for low technology industries

Sample 1972 1992			
Included observations: 21			
Total panel (balanced) observations 126			
Standard errors & t-statistics in parentheses			
Method: Fixed Effects			
	ln(Investment/Capital) I/K (t)	ln(own R&D) R&D (t)	ln(suppliers R&D) R&DS (t)
I/K (t-1)	0.691808* 0.171589 4.031784	0.266768 0.169267 1.576019	0.025573 0.035620 0.717944
I/K (t-2)	-0.275159 0.164796 -1.669692	-0.063984 0.162567 -0.393585	-0.033712 0.034210 -0.985438
R&D (t-1)	0.187714 0.174322 1.076828	1.336340* 0.171963 7.771081	0.050765 0.036187 1.402824
R&D (t-2)	-0.146185 0.161469 -0.905346	-0.387497* 0.159284 -2.432734	-0.053477 0.033519 -1.595414
R&DS (t-1)	-0.280847 0.795139 -0.353206	1.374191* 0.784381 1.751943	0.585743* 0.165063 3.548604
R&DS(t-2)	-0.008081 0.810259 -0.009974	-0.216547 0.799297 -0.270921	-0.135929 0.168202 -0.808131
<i>Fixed Effects</i>			
Group 7	3.320319	-21.80896	11.00521
Group 8	3.565475	-22.06103	11.06464
Group 13	3.949688	-22.38915	11.18353

* At least 10% significant

Dependent variable: *ln (Investment/Capital)*

R-squared	0.946204	Mean dependent var	-3.298694
Adjusted R-squared	0.901902	S.D. dependent var	0.382644
S.E. of regression	0.119846	Sum squared resid	0.488346
F-statistic	23.92086	Durbin-Watson stat	1.933442
Prob(F-statistic)	0.000000		

Dependent variable: *ln (own R&D expenditures)*

R-squared	0.999226	Mean dependent var	14.36663
Adjusted R-squared	0.998588	S.D. dependent var	3.146309
S.E. of regression	0.118225	Sum squared resid	0.475222
F-statistic	1755.093	Durbin-Watson stat	1.888171
Prob(F-statistic)	0.000000		

Dependent variable: *ln (suppliers R&D expenditures)*

R-squared	0.994935	Mean dependent var	20.52440
Adjusted R-squared	0.990764	S.D. dependent var	0.258871
S.E. of regression	0.024879	Sum squared resid	0.021045
F-statistic	267.1480	Durbin-Watson stat	2.054782
Prob(F-statistic)	0.000000		

Chapter 3: Intersectoral demand transmissions and changes in employment shares: explaining the historical data

Introduction

In the two previous chapters we determined the effects of internal and external sources of innovation on labour productivity and the growth of employment shares. However, there is one more technology-related channel, potentially affecting employment share growth but not labour productivity, which we want to investigate. The effect we are thinking about propagates through inter-sectoral linkages, in particular via demand transmissions. Consider a successful technological innovation in industry k leading to an increase of industry k value added share. The value added expansion starting from k will affect the whole economy distribution of value added shares, and in particular the shares of the industries supplying k , through the input-output structure of the economy and the expansion of final demand. Keeping fixed the labour productivity of the industries supplying k , changes of their value added shares would be exactly reflected in changes of employment shares.

The idea that inter-sectoral demand linkages are an important transmission mechanism for the propagation of industry specific shocks is common in the real business cycle literature¹³⁵. The capability of industry specific shocks to explain aggregate dynamics is however very uncertain. Some recent studies¹³⁶ suggest that it may depend on the structure and aggregation of the input-output form of production. The aim of this chapter is to investigate the extent to which technologically induced inter-industry

¹³⁵ See, for example, Long and Plosser (1983) and Horvath (1998).

demand transmissions affect employment shares at the industry level. More specifically, we want to determine how the value added and employment shares of a supplying industry j , not experiencing technological change, vary as a consequence of technologically induced changes in demand of its customer industries. Because of the structure of the models and data limitations, the analysis will refer to the technological groups defined in Chapter 1. In the first part of the chapter, we will review some literature and models investigating sectoral linkages and aggregate dynamics. In the second part, we will specify and estimate a demand-supply model determining both the linkage between “own” value added shares and internal technological innovation, and the inter-industry impact of changes in value added shares. Finally, we will link these results to those obtained in the previous Chapters and analyse the relative importance of the various innovative shocks on observed labour productivity and employment share growth at the industry level.

III.1 Sectoral linkages and their relevance for aggregate dynamics

The idea that inter-sectoral demand linkages are important for the diffusion of industry specific shocks is established in the economic literature. For example, in the real business cycle literature, inter-sectoral demand linkages are the main candidates to explain, in a neoclassical framework and as a result of sector specific shocks, the observed sectoral comovement of main economic variables over the business cycle. As pointed out by Horvath (2000)¹³⁷ “...These two fundamental regularities of

¹³⁶ Cfr. Horvath (2000), Dupor (1999).

¹³⁷ Cfr. Horvath (2000).

business cycles, sectoral comovement and persistence, have motivated a plethora of models in which exogenous disturbances affect all sectors equally, are inherently highly persistent, and serve as the driving force for fluctuations in real aggregate variables. ...Without relying on aggregate shocks, the outside observer of the economy needs an alternative synchronisation mechanism to explain what he or she sees. The organisation of production in the economy presents itself as a natural candidate. Most commodities are inputs to the production processes of other commodities. Depending on substitution possibilities, higher production in one sector may necessitate higher production in the sectors supplying its intermediate inputs.” Gregory and Greenhalgh (1996), and Greenhalgh and Gregory (1997), use input-output data to investigate de-industrialisation and the transmissions of product quality improvements in the UK economy. Also, most of the literature on spillover effects relies on input-output information in order to define a measure of technological closeness.

While the concept in itself is recognised, it is surprising to see how little empirical investigation it has attracted. To our knowledge, the empirical investigation of inter-sectoral demand linkages is limited to the two following approaches. The first one, as in Gregory and Greenhalgh (1996), and Greenhalgh and Gregory (1997), uses input-output matrices to decompose changes in sectors’ total output¹³⁸ between the part originating within the sector itself and the part transmitted across sectors. This approach does not really investigate inter-sectoral demand linkages, but rather takes them from the input-output tables and analyses their effects on industry and aggregate dynamics. While certainly useful for the insights it provides on the functioning of the

economic system, its application to the current work is prevented by the limited availability of data. Only four years of input-output tables (1968, 1979, 1985, and 1990) are in fact available for the UK, and their extensions to a complete time series asks for assumptions on the dynamics of technological progress that we would rather not make.

The second approach, typical of the real business cycle literature, is based on the development of theoretical models characterised by inter-sectoral demand linkages and smoothing mechanisms¹³⁹. Inter-sectoral demand linkages normally arise because of the use of intermediate inputs acquired from other sectors and /or final demand effects¹⁴⁰. The main parameters of the model are then calibrated to the observed values of the economy under study, and the dynamics generated by the model are compared with the ones observed in the real economy. Some examples of this type of models are Long and Plosser (1983), Cooper and Haltiwanger (1990 and 1992), Hornstein and Praschnik (1997), Andolfatto and MacDonald (1998), and Horvath (2000 and 1997).

For example, Long and Plosser (1983) derive the following dynamic equation for output as the equilibrium solution of a maximising agent¹⁴¹:

$$y_{t+1} = Ay_t + k + \eta_{t+1} \quad [52]$$

where y is the output vector; A is an input-output matrix expressed in terms of cost shares; k is a vector of constant preferences parameters; and η_{t+1} is a vector of stochastic technology shocks.

¹³⁸ Obviously, the same applies to changes in employment, labour productivity etc....

¹³⁹ For example, consumption smoothing in Long and Plosser (1983), inventory holdings in Cooper and Haltiwanger (1990); and hours of work smoothing in Horvath (2000).

¹⁴⁰ Cfr. in particular Cooper and Haltiwanger (1990).

¹⁴¹ See Long and Plosser (1983) for more details.

Preferences' structure implies consumption and leisure smoothing. Production possibilities assume that any given commodity may be used as input in the production of other commodities, and production of any one commodity requires positive inputs of other commodities. Calibrating the matrix A on an actual US input-output matrix, and assuming uncorrelated (among sectors) technology shocks, Long and Plosser show that the model exhibits business cycle dynamics.

There is however much uncertainty about the capability of industry specific shocks to explain aggregate dynamics. Recent results by Dupor (1999) and Horvath (2000 and 1997) suggest that the structure of the input-output form of production is particularly relevant to the determination of the aggregate impact of sector specific shocks. The more the input-output structure is concentrated around a few large suppliers, the more shocks to these sectors will affect aggregates.

While these models are interesting in their own right, their structure is specially designed for simulations, and as such not really applicable to our setting.

Given the difficulties with the existing (and scarce) empirical methods, we had to resort to an alternative framework in order to be able to proceed with the analysis. The most natural candidate seems the specification of a supply-demand model in which both supply and demand of each industry are affected by the technological performance of other industries. Its specification and estimation results are presented in the next section.

III.2 A supply-demand model

We present in this section a possible framework to determine how value added and employment shares of a supplying industry j , not experiencing technological change, vary as a consequence of the technologically induced changes in demand of its customers industries. In order to accomplish this, we need to specify a model determining both the linkage between value added shares and technological innovation for industry k ; and the impact of changes in value added share of industry k on the value added share of industry j .

The global effect of technological change on value added shares is determined by the interaction of supply and demand effects. The supply effect depends on both the impact of technological change on production prices and the responsiveness of supply to production prices; the demand effect mainly depends on the responsiveness of demand to selling prices. We estimate supply and demand equations to determine this total effect. The equations are estimated in level form, identifying the long-run relationship among variables. Also, due to the number of variables otherwise necessary and the relatively short time length of our sample, they are estimated over the technological groups defined in Chapter 1.

The supply equations we estimate relate the share of value added of one technological group to the whole economy structure of relative prices and of relative technology. The form of the equations follows the one proposed in Harrigan (1997) in the context of an empirical application of the neoclassical model of trade. As shown in Harrigan (1997) “The model comes from applying a flexible functional form to the revenue function representation of the general equilibrium of the production sector, where

there are Hicks-neutral technology differences across countries and over time”¹⁴². The basic idea behind the model is that technology differences and factor supplies jointly determine the comparative advantage of countries and thus the pattern of international trade. Most interesting for our purpose, Harrigan (1997) analyses the determinants of supply at the industry as well as country level.

The supply equations we estimate have the form:

$$\ln\left(\frac{Y_k}{Y_{tot}}\right)_t^s = \alpha_s + \beta_{1k} * \ln\left(\frac{p_{ht}}{p_{tot}}\right)_t + \beta_{2k} * \ln\left(\frac{p_{tup}}{p_{tot}}\right)_t + \beta_{3k} * \ln\left(\frac{p_{tu}}{p_{tot}}\right)_t + \beta_{4k} * \ln\left(\frac{p_{lt}}{p_{tot}}\right)_t + \gamma_{1k} * \ln\left(\frac{TFP_{ht}}{TFP_{tot}}\right)_t + \gamma_{2k} * \ln\left(\frac{TFP_{tup}}{TFP_{tot}}\right)_t + \gamma_{3k} * \ln\left(\frac{TFP_{tu}}{TFP_{tot}}\right)_t + \gamma_{4k} * \ln\left(\frac{TFP_{lt}}{TFP_{tot}}\right)_t + \varepsilon_t \quad [53]$$

where k = Technology producers industries (HT), Technology Users and Producers industries (TUP), Technology Users industries (TU), and Low Technology industries (LT).

$p_{ht, tup, tu, lt}$ is the domestic price index deflator by technological group; p_{tot} is the total final expenditure deflator; $TFP_{ht, tup, tu, lt}$ is the total factor productivity level by technological group and TFP_{tot} is the whole economy total factor productivity level. We decided to use total factor productivity as an indicator of technology because of the high endogeneity between labour productivity and value added shares.

The demand equations we estimate refer to the standard demand function $Q^d = f(P)$, and relate the value added share of each technological group to all domestic and world relative prices (by technological group) and to the world demand for the output of that group¹⁴³. World output shares are used as a proxy for unobserved domestic customer

¹⁴² Cfr. Harrigan (1997), pag. 476.

¹⁴³ World variables are actually proxied by weighted averages of the relevant variables for US, Japan and Germany.

preferences, and are used simply as a control. The variable we use is defined by the weighted average of world industry value added shares, with weights equal to the use of the output of the industry concerned in producing the output of all the other industries¹⁴⁴. The form of the demand equations is thus:

$$\begin{aligned} \ln\left(\frac{Y_k}{Y_{tot}}\right)_t^{1D} = & \alpha_D + \delta_{1k} * \ln\left(\frac{p_{ht}}{p_{tot}}\right)_t + \delta_{2k} * \ln\left(\frac{p_{tup}}{p_{tot}}\right)_t + \delta_{3k} * \ln\left(\frac{p_{tu}}{p_{tot}}\right)_t + \delta_{4k} * \ln\left(\frac{p_{lt}}{p_{tot}}\right)_t \\ & + \varphi_{1k} * \ln\left(\frac{wp_{ht}}{wp_{tot}}\right)_t + \varphi_{2k} * \ln\left(\frac{wp_{tup}}{wp_{tot}}\right)_t + \varphi_{3k} * \ln\left(\frac{wp_{tu}}{wp_{tot}}\right)_t + \varphi_{4k} * \ln\left(\frac{wp_{lt}}{wp_{tot}}\right)_t \\ & + \theta_k * \left[\sum_{l \neq K} \psi_{kl} \ln\left(\frac{Y_l^W}{Y_{tot}^W}\right)_t \right] + \varepsilon_t \end{aligned} \quad [54]$$

where k = Technology producers (HT), Technology Users and Producers (TUP), Technology Users (TU), and Low Technology (LT).

$p_{ht, tup, tu, lt}$ is the domestic price index deflator by technological group; p_{tot} is the Total final expenditure deflator; $wp_{ht, tup, tu, lt}$ is the world price index deflator by technological group; wp_{tot} is the world price index deflator; and $\sum_{l \neq K} \psi_{kl} \ln\left(\frac{Y_l^W}{Y_{tot}^W}\right)$ are the relative world output shares weighted by the input weights for the technological group k, ψ_k .

Given the interdependence between technology and domestic prices¹⁴⁵, we estimate the supply equations by Two-Stage Least Squares and use relative world prices and weighted world output shares as instruments for relative domestic prices¹⁴⁶. The demand equations are also estimated by Two-Stage Least Squares, because of the

¹⁴⁴ These weights are generated via input-output tables. See the data appendix to this chapter for more details.

¹⁴⁵ Theoretically, technological improvements as signalled by changes in TFP, are at least partially transmitted into changes in relative prices.

endogeneity of domestic prices and value added shares; and relative TFPs are used as instruments¹⁴⁷. The validity of relative TFPs as instruments for value added shares is questionable, being TFP determined as a residual from value added. On the other hand, it is very difficult to think about national economic series exogenous to value added. TFP has been chosen in the light of the interpretation we intend to give to the results, but with the drawback that our estimates are likely to still suffer endogeneity biases.

In this way, we identify from the supply equations the effects on value added shares of changes in relative total factor productivities and exogenous movements of relative domestic prices. Economic theory predicts that increases of relative own TFP and exogenous increases of relative domestic prices will increase the share of output supplied. The demand equations identify the effects on value added shares of technologically induced changes in relative domestic prices, changes in relative world prices, and changes in world output shares. The expected signs are of negative dependence between share of output demanded and relative domestic prices, and of positive dependence between share of output demanded and “own” relative world prices¹⁴⁸. Tables III.1 and III.2 show the estimation results for the supply and demand equations.

¹⁴⁶ As before, world customers demand controls for the value added shift from manufacturing to services industries.

¹⁴⁷ Relative TFPs are computed as the ratio of each technological group TFP to whole economy TFP.

¹⁴⁸ The reason for this is that price changes at the world level should not affect the relative allocation of expenditures. As such, the share of output demand will increase purely because of the price effect. This reasoning is based on very limited substitutability among goods. It is not a too strong assumption given the level of aggregation of our analysis.

Table III.1: supply equations, estimation results

Estimation method: Two-Stage Least Squares				
Instrument list: $\ln(w_{p_{ht}}/w_{p_{tot}})$, $\ln(w_{p_{tup}}/w_{p_{tot}})$, $\ln(w_{p_{tu}}/w_{p_{tot}})$, $\ln(w_{p_{lt}}/w_{p_{tot}})$, $\ln(w_{p_{ht}}/w_{p_{tot}})_{-1}$, $\ln(w_{p_{tup}}/w_{p_{tot}})_{-1}$, $\ln(w_{p_{tu}}/w_{p_{tot}})_{-1}$, $\ln(w_{p_{lt}}/w_{p_{tot}})_{-1}$, $\ln(TFP_{ht}/TFP_{tot})$, $\ln(TFP_{tup}/TFP_{tot})$, $\ln(TFP_{tu}/TFP_{tot})$, $\ln(TFP_{lt}/TFP_{tot})$				
Dependent variable:	$\ln\left(\frac{Y_{HT}}{Y_{tot}}\right)$	$\ln\left(\frac{Y_{TUP}}{Y_{tot}}\right)$	$\ln\left(\frac{Y_{TU}}{Y_{tot}}\right)$	$\ln\left(\frac{Y_{LT}}{Y_{tot}}\right)$
costant	1.26 (0.36)	-8.28 (1.45)	-3.78 (0.79)	-1.53 (0.18)
$\ln(p_{ht}/p_{tot})$	0.40 (0.15)	-0.84 (0.48)	-0.60 (0.19)	0.17 (0.07)
$\ln(p_{tup}/p_{tot})$	-0.07 (0.02)	0.41 (0.12)	-0.002 (0.04)	0.04 (0.01)
$\ln(p_{tu}/p_{tot})$	0.10 (0.07)	-0.50 (0.25)	0.34 (0.12)	-0.12 (0.04)
$\ln(p_{lt}/p_{tot})$	-0.02 (0.08)	-0.44 (0.27)	-0.08 (0.17)	0.008 (0.03)
$\ln(TFP_{ht}/TFP_{tot})$	0.77 (0.40)	0.52 (1.22)	-0.42 (0.73)	-0.79 (0.16)
$\ln(TFP_{tup}/TFP_{tot})$	0.03 (0.08)	1.36 (0.23)	-0.29 (0.15)	-0.12 (0.03)
$\ln(TFP_{tu}/TFP_{tot})$	-0.06 (0.10)	-0.64 (0.36)	1.09 (0.07)	-0.10 (0.06)
$\ln(TFP_{lt}/TFP_{tot})$	-0.21 (0.12)	0.39 (0.40)	0.32 (0.13)	0.85 (0.08)
R-squared	0.904425	0.978654	0.991752	0.997794
Adj. R-squared	0.853827	0.967353	0.987113	0.996218
S.E. of regression	0.006885	0.022847	0.009218	0.002804
Durbin-Watson stat	2.001121	1.951183	2.062302	2.297465

*standard errors in brackets
*HT = technology producer; TUP = technology user and producer; TU = technology user; LT = low technology

Table III.2: Demand equations, estimation results

Estimation method: Two-Stage Least Squares				
Instrument list: $\ln(wp_{ht}/wp_{tot})$, $\ln(wp_{tup}/wp_{tot})$, $\ln(wp_{tu}/wp_{tot})$, $\ln(wp_{lt}/wp_{tot})$, $\ln(TFP_{ht}/TFP_{tot})$, $\ln(TFP_{tup}/TFP_{tot})$, $\ln(TFP_{tu}/TFP_{tot})$, $\ln(TFP_{lt}/TFP_{tot})$, $\ln(TFP_{ht}/TFP_{tot})_{-1}$, $\ln(TFP_{tup}/TFP_{tot})_{-1}$, $\ln(TFP_{tu}/TFP_{tot})_{-1}$, $\ln(TFP_{lt}/TFP_{tot})_{-1}$, $\ln(TFP_{ht}/TFP_{tot})_{-2}$, $\ln(TFP_{tup}/TFP_{tot})_{-2}$, $\ln(TFP_{tu}/TFP_{tot})_{-2}$, $\ln(TFP_{lt}/TFP_{tot})_{-2}$				
Dependent variable:	$\ln\left(\frac{Y_{HT}}{Y_{tot}}\right)$	$\ln\left(\frac{Y_{TUP}}{Y_{tot}}\right)$	$\ln\left(\frac{Y_{TU}}{Y_{tot}}\right)$	$\ln\left(\frac{Y_{LT}}{Y_{tot}}\right)$
costant	-1.21 (0.28)	-21.75 (1.73)	-9.97 (1.77)	-8.30 (0.45)
$\ln(p_{ht}/p_{tot})$	-0.19 (0.04)	-1.47 (0.23)	-0.63 (0.28)	-0.07 (0.08)
$\ln(p_{tup}/p_{tot})$	-0.05 (0.008)	-0.24 (0.06)	-0.28 (0.05)	-0.08 (0.02)
$\ln(p_{tu}/p_{tot})$	0.30 (0.03)	-0.29 (0.19)	-0.84 (0.17)	-0.41 (0.05)
$\ln(p_{lt}/p_{tot})$	0.06 (0.03)	0.29 (0.26)	0.05 (0.18)	-0.26 (0.08)
$\ln(wp_{ht}/wp_{tot})$	1.29 (0.44)	17.97 (2.56)	5.54 (2.61)	2.89 (0.89)
$\ln(wp_{tup}/wp_{tot})$	0.43 (0.10)	4.84 (0.62)	1.30 (0.64)	0.40 (0.23)
$\ln(wp_{tu}/wp_{tot})$	0.17 (0.12)	2.92 (0.71)	1.44 (0.73)	1.44 (0.24)
$\ln(wp_{lt}/wp_{tot})$	0.42 (0.21)	6.81 (1.43)	2.08 (1.35)	1.71 (0.45)
World Output Shares (weighted)	-0.42 (0.03)	-19.06 (2.13)	-0.31 (0.16)	-4.51 (0.35)
R-squared	0.982734	0.987252	0.883210	0.994567
Adj. R-squared	0.969168	0.978753	0.791447	0.990946
S.E. of regression	0.003094	0.018469	0.014542	0.004927
Durbin-Watson stat	2.221506	2.288637	1.999440	2.188361

*standard errors in brackets
*HT = technology producer; TUP = technology user and producer; TU = technology user; LT = low technology

The supply equation for the *technology user* group has been estimated excluding group 14¹⁴⁹. The reason for this is that, including group 14, the estimated long-run elasticity of the group value added share to own prices was negative. Further inspection of the equation revealed that group 14 alone (accounting for 55% of total value added of the technological group on average) caused this effect. A possible explanation is that most of the industries comprised in group 14 were nationalised after the Second World War. The privatisation of some industries¹⁵⁰ started in the early 80s with the Thatcher government. However, most of them are still either state owned or under a regulator to promote and control competition. As such, the group as a whole receives substantial government subsidies, and is thus enabled to expand despite apparently adverse price signals. This is reflected in the trends followed by relative prices and value added shares. While the value added share of group 14 has followed a clear upward trend over the period 1966-1993, the relative prices of the group have been on a downward trend up to 1980, and since then only started to increase. Regulatory reforms effects are pertinent also to other industries in different technological groups (e.g. the steel industry, cfr. the general introduction). However, only for group 14 these effects were strong enough to bias the results for the whole technological group. As said before, this is likely because of the high value added weight of the group. Overall, we choose not to adjust the data unless strictly necessary, hence we did not correct for competition framework effects in the other technological groups.

¹⁴⁹ Railways, Other Inland Transport, Sea Transport, Air Transport, Supporting Services to Transport, Miscellaneous Transport Services and Storage not elsewhere specified, Postal Services and Telecommunications.

¹⁵⁰ Noticeably telecommunications, and air and road transports.

As expected, we get from the supply block positive and significant own relative prices and total factor productivity effects¹⁵¹. Exogenous increases in relative prices and total factor productivities of other technological groups normally cause a decrease of the value added share¹⁵². The only positive effect for other industries' total factor productivity comes from the *low technology* group towards the *technology user* group. This result is mainly imputable to the effect of group 1 in the *technology user* category, that accounts (excluding group 14) for 30% of the total group value added on average, and for which we found in Chapter 2 significant spillover effects.

The estimated coefficients of the demand equations are also generally in accordance with economic theory. For all technological groups, a reduction of own relative prices increases the share of output demanded, and the same effect comes from an increase of “own” world prices. Reductions of other industries relative domestic prices generally cause increases of value added shares¹⁵³, however the magnitude of this effect is normally smaller than the one coming from own price reductions¹⁵⁴.

Two quite unexpected effects are that increases in world prices of other industries increase value added shares, with an effect stronger than the one caused by own world prices increases. Also, the effect of world output shares is always negative, although much more so for “manufacturing based” technological groups than for “services based” technological groups. One possible explanation is that the world output shares' negative coefficients reflect growth differentials at the country level.

¹⁵¹ The only exception is the own price effect for the *low technology* group that is equal to zero.

¹⁵² Again, the exception is the *low technology group* that has positive effects from relative prices of *technology producer* and *technology user and producer* industries. However, most probably these results are biased by the own price coefficient equal to zero.

¹⁵³ The exception is the value added share of the *technology producer* group that decreases if relative domestic prices of the *technology user* group decrease.

¹⁵⁴ The exceptions are *technology producer* domestic relative prices over *technology user and producer* value added share, and *technology user* relative domestic prices over *low technology* value added share.

The reduced form solution of the demand-supply system gives the global impact of relative TFPs and world prices on relative domestic prices and value added shares.

In order to compute the reduced form solution of the system we use:

$$\ln\left(\frac{Y_k}{Y_{tot}}\right)_t^S = \alpha_S + \beta_{1k} * \ln\left(\frac{p_{ht}}{p_{tot}}\right)_t + \beta_{2k} * \ln\left(\frac{p_{tup}}{p_{tot}}\right)_t + \beta_{3k} * \ln\left(\frac{p_{tu}}{p_{tot}}\right)_t + \beta_{4k} * \ln\left(\frac{p_{lt}}{p_{tot}}\right)_t + \gamma_{1k} * \ln\left(\frac{TFP_{ht}}{TFP_{tot}}\right)_t + \gamma_{2k} * \ln\left(\frac{TFP_{tup}}{TFP_{tot}}\right)_t + \gamma_{3k} * \ln\left(\frac{TFP_{tu}}{TFP_{tot}}\right)_t + \gamma_{4k} * \ln\left(\frac{TFP_{lt}}{TFP_{tot}}\right)_t \quad [55]$$

$$\ln\left(\frac{Y_k}{Y_{tot}}\right)_t^D = \alpha_D + \delta_{1k} * \ln\left(\frac{p_{ht}}{p_{tot}}\right)_t + \delta_{2k} * \ln\left(\frac{p_{tup}}{p_{tot}}\right)_t + \delta_{3k} * \ln\left(\frac{p_{tu}}{p_{tot}}\right)_t + \delta_{4k} * \ln\left(\frac{p_{lt}}{p_{tot}}\right)_t + \varphi_{1k} * \ln\left(\frac{wp_{ht}}{wp_{tot}}\right)_t + \varphi_{2k} * \ln\left(\frac{wp_{tup}}{wp_{tot}}\right)_t + \varphi_{3k} * \ln\left(\frac{wp_{tu}}{wp_{tot}}\right)_t + \varphi_{4k} * \ln\left(\frac{wp_{lt}}{wp_{tot}}\right)_t + \theta_k * \left[\sum_{i \neq K} \psi_{ki} \ln\left(\frac{Y_i^W}{Y_{tot}^W}\right) \right] \quad [56]$$

$$\ln\left(\frac{Y_k}{Y_{tot}}\right)_t^S = \ln\left(\frac{Y_k}{Y_{tot}}\right)_t^D \quad [57]$$

The supply and demand equations for each technological group k can be rewritten in vector form as:

$$\underline{y}_{k,t}^S = \alpha_{k,s} + \underline{\beta}_k' * \underline{p}_t + \underline{\gamma}_k' * \underline{TFP}_t \quad [58]$$

$$\underline{y}_{k,t}^D = \tilde{\alpha}_{k,D} + \underline{\delta}_k' * \underline{p}_t + \underline{\varphi}_k' * \underline{wp}_t + \theta_k * WOS_{k,t} \quad [59]$$

setting $\underline{y}_{k,t}^S = \underline{y}_{k,t}^D$ for each t and k = 1,...,4 (technology user, technology user and

producer, technology user, low technology) gives:

$$\alpha_{k,s} + \underline{\beta}_k' * \underline{p}_t + \underline{\gamma}_k' * \underline{TFP}_t = \tilde{\alpha}_{k,D} + \underline{\delta}_k' * \underline{p}_t + \underline{\varphi}_k' * \underline{wp}_t + \theta_k * WOS_{k,t} \quad [60]$$

and

$$\left[\underline{\beta}_k' - \underline{\delta}_k' \right] * \underline{p}_t = \left[\tilde{\alpha}_{k,D} - \alpha_{k,S} \right] - \underline{\gamma}_k' * \underline{TFP}_t + \underline{\varphi}_k' * \underline{wp}_t + \theta_k * \underline{WOS}_{k,t} \quad [61]$$

Stacking all k together gives:

$$A * \underline{p}_t = c_1 - \Gamma * \underline{TFP}_t + \Phi * \underline{wp}_t + \Theta * \underline{WOS}_t \quad [62]$$

where p is the 4*1 vector of relative domestic prices by technological group; TFP is the 4*1 vector of relative TFPs by technological group; wp is the 4*1 vector of relative world prices by technological group; and WOS is the 4*1 vector of world output shares by technological group. c_1 is the 4*1 vector with the differences, for each technological group, of the constant from the demand equation from the constant of the supply equation; A is a 4*4 matrix each column of which is made of the differences, for a technological group k, between the supply and demand coefficients for domestic prices. Γ is a 4*4 matrix each column of which is made of the TFP coefficients from the supply equation for a technological group k. Φ is a 4*4 matrix each column of which is made of the world prices coefficients from the demand equation for a technological group k. Θ is a 4*4 diagonal matrix whose diagonal terms are the world customers demand coefficients from the demand equation for each technological group k.

The reduced form solution for domestic prices is then:

$$\underline{p}_t = A^{-1} * c_1 - A^{-1} * \Gamma * \underline{TFP}_t + A^{-1} * \Phi * \underline{wp}_t + A^{-1} * \Theta * \underline{WOS}_t \quad [63]$$

Substituting the reduced form solution for domestic prices in the (stacked) supply equation gives the reduced form solution for value added shares as:

$$\begin{aligned} \underline{y}_i = & c_2 + B * A^{-1} * c_1 - B * A^{-1} * \Gamma * \underline{TFP}_i + B * A^{-1} * \Phi * \underline{wp}_i \\ & + B * A^{-1} * \Theta * \underline{WOS}_i + \Gamma * \underline{TFP}_i \end{aligned} \quad [64]$$

where B is the matrix of domestic prices coefficients from the supply equations.

Table III.3 shows the reduced form solution results.

The reduced form solution provides the overall demand-supply effects on relative domestic prices and value added shares following changes in total factor productivity and world relative prices. As expected and predicted from economic theory, we get for all technological groups a negative own TFP effect over own relative domestic prices and a positive own TFP effect over own value added share. Interestingly, these effects are strongest for industries less engaged in internal innovative activities, possibly reflecting the bigger scope for catching-up in the industries farthest from the technological frontier. Given the framework we have used, the extent of the demand transmission effects will be given by the TFP coefficients in the reduced form solution for value added shares. In 50% of the cases supplying industries increase their value added share following a demand expansion of their customers, while for the remaining 50% of the cases the value added share of the supplying industry decreases. In particular, *technology producer* industries increase their value added share following value added expansion in *technology user and producer*, and *low technology* industries¹⁵⁵, but will contract if *technology user* industries expand.

¹⁵⁵ Although this effect is very small, being 0.07 the coefficient on relative TFP of *low technology* industries.

Table III.3: Reduced form solution to the demand-supply system

$$\ln(p_{ht}/p_{tot}) = c_{ht1} - 0.88 \ln(TFP_{ht}/TFP_{tot}) + 0.16 \ln(TFP_{tup}/TFP_{tot}) - 0.12 \ln(TFP_{tu}/TFP_{tot}) + 0.04 \ln(TFP_{lt}/TFP_{tot}) + 2.50 \ln(wp_{ht}/wp_{tot}) + 0.65 \ln(wp_{tup}/wp_{tot}) + 0.76 \ln(wp_{tu}/wp_{tot}) + 1.04 \ln(wp_{lt}/wp_{tot}) - 0.69 \text{ WOS}_{ht} + 1.69 \text{ WOS}_{tup} - 0.06 \text{ WOS}_{tu} - 1.52 \text{ WOS}_{lt}$$

$$\ln(p_{tup}/p_{tot}) = c_{tup1} + 2.83 \ln(TFP_{ht}/TFP_{tot}) - 1.67 \ln(TFP_{tup}/TFP_{tot}) + 1.83 \ln(TFP_{tu}/TFP_{tot}) - 2.93 \ln(TFP_{lt}/TFP_{tot}) + 23.81 \ln(wp_{ht}/wp_{tot}) + 5.41 \ln(wp_{tup}/wp_{tot}) + 6.00 \ln(wp_{tu}/wp_{tot}) + 10.76 \ln(wp_{lt}/wp_{tot}) + 1.01 \text{ WOS}_{ht} - 25.45 \text{ WOS}_{tup} + 0.25 \text{ WOS}_{tu} - 11.42 \text{ WOS}_{lt}$$

$$\ln(p_{tu}/p_{tot}) = c_{tu1} - 0.02 \ln(TFP_{ht}/TFP_{tot}) + 0.67 \ln(TFP_{tup}/TFP_{tot}) - 1.24 \ln(TFP_{tu}/TFP_{tot}) + 0.19 \ln(TFP_{lt}/TFP_{tot}) - 1.08 \ln(wp_{ht}/wp_{tot}) - 0.32 \ln(wp_{tup}/wp_{tot}) + 0.008 \ln(wp_{tu}/wp_{tot}) - 0.65 \ln(wp_{lt}/wp_{tot}) - 0.18 \text{ WOS}_{ht} + 6.30 \text{ WOS}_{tup} - 0.29 \text{ WOS}_{tu} + 1.42 \text{ WOS}_{lt}$$

$$\ln(p_{lt}/p_{tot}) = c_{lt1} + 2.48 \ln(TFP_{ht}/TFP_{tot}) + 0.32 \ln(TFP_{tup}/TFP_{tot}) + 1.00 \ln(TFP_{tu}/TFP_{tot}) - 2.10 \ln(TFP_{lt}/TFP_{tot}) - 0.94 \ln(wp_{ht}/wp_{tot}) - 1.16 \ln(wp_{tup}/wp_{tot}) + 2.00 \ln(wp_{tu}/wp_{tot}) + 1.33 \ln(wp_{lt}/wp_{tot}) + 0.36 \text{ WOS}_{ht} + 3.08 \text{ WOS}_{tup} + 0.25 \text{ WOS}_{tu} - 11.90 \text{ WOS}_{lt}$$

$$\ln(Y_{ht}/Y_{tot}) = c_{ht2} + 0.17 \ln(TFP_{ht}/TFP_{tot}) + 0.27 \ln(TFP_{tup}/TFP_{tot}) - 0.38 \ln(TFP_{tu}/TFP_{tot}) + 0.07 \ln(TFP_{lt}/TFP_{tot}) - 0.76 \ln(wp_{ht}/wp_{tot}) - 0.13 \ln(wp_{tup}/wp_{tot}) - 0.15 \ln(wp_{tu}/wp_{tot}) - 0.43 \ln(wp_{lt}/wp_{tot}) - 0.37 \text{ WOS}_{ht} + 3.03 \text{ WOS}_{tup} - 0.07 \text{ WOS}_{tu} + 0.57 \text{ WOS}_{lt}$$

$$\ln(Y_{tup}/Y_{tot}) = c_{tup2} + 1.33 \ln(TFP_{ht}/TFP_{tot}) + 0.06 \ln(TFP_{tup}/TFP_{tot}) + 0.39 \ln(TFP_{tu}/TFP_{tot}) - 0.01 \ln(TFP_{lt}/TFP_{tot}) + 8.62 \ln(wp_{ht}/wp_{tot}) + 2.34 \ln(wp_{tup}/wp_{tot}) + 0.93 \ln(wp_{tu}/wp_{tot}) + 3.28 \ln(wp_{lt}/wp_{tot}) + 0.93 \text{ WOS}_{ht} - 16.36 \text{ WOS}_{tup} + 0.18 \text{ WOS}_{tu} + 1.11 \text{ WOS}_{lt}$$

$$\ln(Y_{tu}/Y_{tot}) = c_{tu2} - 0.10 \ln(TFP_{ht}/TFP_{tot}) - 0.18 \ln(TFP_{tup}/TFP_{tot}) + 0.66 \ln(TFP_{tu}/TFP_{tot}) + 0.53 \ln(TFP_{lt}/TFP_{tot}) - 1.84 \ln(wp_{ht}/wp_{tot}) - 0.41 \ln(wp_{tup}/wp_{tot}) - 0.63 \ln(wp_{tu}/wp_{tot}) - 0.97 \ln(wp_{lt}/wp_{tot}) + 0.32 \text{ WOS}_{ht} + 0.93 \text{ WOS}_{tup} - 0.09 \text{ WOS}_{tu} + 2.37 \text{ WOS}_{lt}$$

$$\ln(Y_{lt}/Y_{tot}) = c_{lt2} - 0.80 \ln(TFP_{ht}/TFP_{tot}) - 0.24 \ln(TFP_{tup}/TFP_{tot}) + 0.11 \ln(TFP_{tu}/TFP_{tot}) + 0.70 \ln(TFP_{lt}/TFP_{tot}) + 1.50 \ln(wp_{ht}/wp_{tot}) + 0.35 \ln(wp_{tup}/wp_{tot}) + 0.38 \ln(wp_{tu}/wp_{tot}) + 0.70 \ln(wp_{lt}/wp_{tot}) - 0.05 \text{ WOS}_{ht} - 1.46 \text{ WOS}_{tup} + 0.04 \text{ WOS}_{tu} - 0.98 \text{ WOS}_{lt}$$

Technology user and producer industries increase their value added share if value added increases in *technology producer* and *technology user* industries, and contract if *low technology* industries expand¹⁵⁶.

Technology user industries increase their value added share following value added expansion in *low technology* industries; and *low technology* industries increase their value added share if the value added share of *technology user* industries increases. Both technological groups contract if *technology producer* and *technology user and producer* industries expand.

Increases in other industries' TFP generally cause increases in "own" relative prices. Exceptions are the negative price effects of *technology user* TFP over *technology producer* prices, *low technology* TFP over *technology user and producer* prices, and *technology producer* TFP over *technology user* prices. This last effect is expected considering the technological flows going from *technology producer* industries to *technology user*.

III.3 The sources of changes in labour productivity and employment shares at the industry level: from the mid-1970s to the early 1990s

In this last part we decompose the observed historical changes in labour productivity and employment shares at the industry level, described in Chapter 1, into their technological sources. This also constitutes a framework in which to interpret the observed pattern of the sectoral contribution to aggregate labour productivity growth. For labour productivity, we will base our analysis on the production function model of

¹⁵⁶ Again, the magnitude of this effect is very small, being -0.01 the coefficient on relative TFP of *low technology* industries.

Chapter 1 (equation [4]) and the investment model of Chapter 2 (equation [39]). We will determine how much of the observed variations in labour productivity are due to internal and external sources of innovation, to the capital-labour ratio, and how much is left to be explained by other sources¹⁵⁷.

Some strong assumptions and simplifications are necessary in order to make the investment model of Chapter 2 (equation [39]) operational for the current analysis. First, the total effects of own and suppliers' R&D expenditures on investment computed in Chapter 2 (equations [42] and [43]) refer to the growth rates and levels of own and suppliers' R&D expenditures at different lags. For computational ease, we will treat R&D expenditures as if they were growing at a constant rate and apply the effect to the current growth rate. Second, the effect of own and suppliers R&D expenditures on investment via total factor productivity is computed on (time t) first differences rather than on de-meaned levels of R&D. This approximation, although not exact, allows taking into account some of the R&D effects present in the autoregressive part of the total factor productivity equation. In fact, by successive substitutions of the autoregressive term, it is possible to rewrite equation [35] of Chapter 2 as:

$$\begin{aligned} \ln A_{jt} = & c + 0.6^n \ln A_{jt-n} + \beta_1 \Delta \ln R \& D_{jt} + \beta_2 \Delta \ln R \& DS_{jt} - 0.4\beta_1 \ln R \& D_{jt-1} \\ & - 0.4\beta_2 \ln R \& DS_{jt-1} + 0.6^2 \beta_1 \ln R \& D_{jt-2} + 0.6^2 \beta_2 \ln R \& DS_{jt-2} + \dots \\ & \dots + 0.6^{n-1} \beta_1 \ln R \& D_{jt-n+1} + 0.6^{n-1} \beta_2 \ln R \& DS_{jt-n+1} \end{aligned} \quad [65]$$

¹⁵⁷ The effects of international trade and privatisations, for example, that we did not consider in this work.

Finally, we want to separate the effects of own and suppliers R&D expenditures on investment from those of other variables. All other variables¹⁵⁸ of the investment equation (equation [39], Chapter 2) and its error term are expressed by the variable Φ_{jt} , computed as actual investment minus “own and suppliers’ R&D expenditures predicted” investment.

Thus for:

$$\Delta \ln(Y/L)_{it} = \hat{\alpha} + \hat{\beta} * \Delta \ln(K/L)_{it} + \hat{\Theta}_1(L) * \Delta \ln(R \& D)_{it} + \hat{\Theta}_2(L) * \Delta \ln(Sci)_{it} + \hat{\Theta}_3(L) * \Delta \ln(Pat)_{it} + \hat{\varepsilon}_{it}$$

[eq. 4-Chp. 1]

and:

$$\Delta \ln(K)_{it} = \hat{\gamma} * \Delta \ln(R \& D)_{it} + \hat{\phi} * \Delta \ln(R \& DS)_{it} + \Phi_{it} \quad [66]^{159}$$

fitted labour productivity changes for industry i are given by:

$$\Delta \ln(Y/L)_{Fitted, it} = \hat{\alpha} + \hat{\beta} * \Phi_{it} + (\hat{\Theta}_1(L) + \hat{\beta} * \hat{\gamma} * \Delta \ln(R \& D)_{it}) + \hat{\Theta}_2(L) * \Delta \ln(Sci)_{it} + \hat{\Theta}_3(L) * \Delta \ln(Pat)_{it} + \hat{\beta} * \hat{\phi} * \Delta \ln(R \& DS)_{it} - \beta * \Delta \ln(L)_{it} \quad [67]$$

For employment shares, we use constant returns to scale Cobb-Douglas production functions at the industry and whole economy level:

$$\ln(Y_i)_t = \ln(A_i)_t + \alpha_i \ln(L_i)_t + (1-\alpha_i) * \ln(K_i)_t \quad [68]$$

$$\ln(Y)_t = \ln(A)_t + \alpha \ln(L)_t + (1-\alpha) * \ln(K)_t \quad [69]$$

to derive:

$$\Delta \ln(L_i/L)_t = -(1/\alpha_i) * \Delta \ln(A_i/A)_t + [(\alpha-\alpha_i)/\alpha_i] * \ln(L)_t - [(1-\alpha_i)/\alpha_i] * \Delta \ln(K_i)_t + [(1-\alpha)/\alpha_i] * \ln(K)_t + (1/\alpha_i) * \Delta \ln(Y_i/Y)_t \quad [70]$$

¹⁵⁸ Such as real wages, part of total factor productivity, lagged investments etc...

¹⁵⁹ Derived from equation [39], Chapter 2.

using equation [66] to substitute for $\Delta \ln(K_i)_t$, and the estimates of A_i as from equation [4], Chapter 1, gives fitted employment shares as:

$$\begin{aligned} \Delta \ln(L_i / L)_t \text{ Fitted} = & -(1/\tilde{\alpha}_i) * (\hat{\Theta}_1(L) * \Delta \ln(R \& D_i / R \& D)_t + \\ & \hat{\Theta}_2(L) * \Delta \ln(Sci_i / Sci)_t + \hat{\Theta}_3(L) * \Delta \ln(Pat_i / Pat)_t) \\ & - (1 - \tilde{\alpha}_i / \tilde{\alpha}_i) * (\Phi_{it} + \hat{\gamma} * \Delta \ln(R \& D)_{it} + \hat{\phi} * \Delta \ln(R \& DS)_{it}) \\ & + (1/\tilde{\alpha}_i) * \Delta \ln(Y_i / Y)_t + (\tilde{\alpha} - \tilde{\alpha}_i / \tilde{\alpha}_i) * \ln(L)_t + (1 - \tilde{\alpha} / \tilde{\alpha}_i) * \ln(K)_t \end{aligned} \quad [71]$$

where the change in value added shares consequent to demand transmissions is given by the reduced form solution to the demand-supply model expressed in first differences (equation [64]), plus the difference between actual and fitted values¹⁶⁰:

$$\begin{aligned} \Delta \ln\left(\frac{Y_i}{Y_{tot}}\right)_t = & \hat{\alpha} + \hat{\lambda}_{1i} * \Delta \ln\left(\frac{TFP_{ht}}{TFP_{tot}}\right)_t + \hat{\lambda}_{2i} * \Delta \ln\left(\frac{TFP_{tup}}{TFP_{tot}}\right)_t + \hat{\lambda}_{3i} * \Delta \ln\left(\frac{TFP_{tu}}{TFP_{tot}}\right)_t \\ & + \hat{\lambda}_{4i} * \Delta \ln\left(\frac{TFP_{ht}}{TFP_{tot}}\right)_t + \hat{\mu}_{1i} * \Delta \ln\left(\frac{wp_{ht}}{wp_{tot}}\right)_t + \hat{\mu}_{2i} * \Delta \ln\left(\frac{wp_{tup}}{wp_{tot}}\right)_t + \hat{\mu}_{3i} * \Delta \ln\left(\frac{wp_{tu}}{wp_{tot}}\right)_t \quad [72] \\ & + \hat{\mu}_{4i} * \Delta \ln\left(\frac{wp_{ht}}{wp_{tot}}\right)_t + \theta_i \sum_j \psi_j \Delta(\ln Y_i^w)_t + \hat{E}_{it} \end{aligned}$$

$\hat{E}_{it}$ is the difference between actual and fitted (as from equation [64]) changes in value added shares. L and K are, respectively, whole economy employment and capital.

In equation [71] whole economy total factor productivity (entering in the relative total factor productivity terms, $\Delta \ln(A_i/A)$) has been computed for each industry on the basis of one of three equations relating the observed value for whole economy total factor

¹⁶⁰ We decided to include this term in the equation, and thus to have a perfect “fitting” for changes in value added shares, because the demand-supply models are estimated at the technological group level and not at the industry one. As such, the error terms would have been disproportionately inflated when computing the fitted values at the industry level.

productivity, A , to either total R&D expenditures, either the total number of Scientist and Engineers, or the total number of Patents¹⁶¹.

The models expressing demand transmission effects on value added shares also include relative total factor productivity terms. However, given that the total factor productivity terms refer to technological groups, they are not expressed as a function of any technological indicator. This implies that it will not be possible to have the detailed demand transmission effects at the industry level.

Given that not all the production function estimates of Chapter 1 (equation [4]) gave economically sensible values of α_i , to get fitted employment shares we compute the parameter α_i (and α) as the product of the average wage share in value added by markup¹⁶².

The technological sources of the observed changes in labour productivity and employment shares are given by the relative contribution of each variable¹⁶³ to the determination of the fitted values of equations [67] and [71]. Because of the sample period over which some equations are specified, we will limit our analysis to the time periods 1974-1979 and 1979-1991¹⁶⁴. These are also two of the most interesting periods in recent UK economic history. The UK entered the Common Market in 1973, while 1979 signals the beginning, with the first Thatcher government, of the privatisation and deregulation programme. Also, we will concentrate on the more

¹⁶¹ The reason for doing this is that R&D expenditures, number of Scientists and Engineers, and number of Patents alternate and do not overlap to explain labour productivity at the industry level. In order to have comparable ratios in equation [70], we estimated three models for the whole economy total factor productivity, each of which uses only one of the three technological variables, plus its lags, as explanatory variables.

¹⁶² This is the same methodology used in Chapter 2.

¹⁶³ Specifically pure capital deepening, internal innovative activities (embodied and disembodied), external embodied innovative activities and demand effects.

relevant changes observed in these periods. Clearly, computing fitted values imply that often we will under-predict or over-predict the observed changes. We will keep the results coming from an over-predicted value as long as the fitted value is of the same sign as the observed one. For those unfortunate cases in which actual and fitted values are of opposite sign, the most we will be able to do is to highlight the eventual sources acting in the direction of the observed changes.

III.3.1 1974-1979: some stylised facts and their technological interpretation

As observed in Chapter 1, the period 1974-1979 was particularly difficult for the UK economy. According to the analysis of Owen (1999), most UK industries were badly equipped, both in terms of production methods and organisation, to face the competition with other European industries that followed the entrance of the UK in the Common Market. Furthermore, the first oil shock caused considerable macro dislocation.

The growth rate of aggregate labour productivity is at its lowest level (+6%), and only six industries give a positive contribution to aggregate productivity growth (1, 2, 12, 13, 14, and 15). Employment shares have decreased for all industries except groups 13 and 15 (+5.4% and +10% respectively), and the biggest falls are for groups 7, 3, 1, 4, 5, and 8¹⁶⁵. Labour productivity has increased for all industrial groups except groups 3, 4, 10 and 13 (-1%, -12%, -8%, -1% respectively). The biggest increases in labour

¹⁶⁴ These are two of the three periods for which we computed the industry contribution to aggregate labour productivity in Chapter 1.

¹⁶⁵ With employment shares falling respectively of -15%, -15%, -12%, -10.3%, -10.4%, -9.6%.

productivity are for groups 12, 2, 1 and 14¹⁶⁶. The most important positive contributions to aggregate productivity growth come either from industries which, starting from a below average productivity level in 1974, have experienced employment reduction and above average productivity growth (groups 1 and 12); or from industries which, starting from an above average productivity level in 1974, have experienced either increasing employment (groups 13 and 15) or strong productivity growth (groups 2 and 14). The most important negative contributions to aggregate productivity growth are from groups 10, 4, and 3. These are the result of both within and between-industry growth reductions, with the latter particularly relevant for groups 3 and 4. The facts we would like to explain, in terms of technological sources of innovation, are thus:

- ◆ for the positive contributions to aggregate productivity growth: the employment reduction and above average productivity growth for groups 2, 12, and 14; the employment increase in groups 13 and 15
- ◆ for the negative contributions to aggregate productivity growth: the employment reduction and negative productivity growth for groups 10, 4, and 3.

Tables III.4 and III.5 show, for labour productivity and employment share growth, the actual values and the contribution of the explanatory variables to the actual values.

The employment share and labour productivity models have an overall good fitting over this sub-period, and for only, respectively, two and one industrial groups the contribution of the main explanatory variables implies tendencies opposite to the observed ones. Unfortunately, the two industrial groups for which changes in

¹⁶⁶ With labour productivity increasing respectively of 93%, 72%, 15%, and 10%.

employment shares are miss-predicted are among the ones we are most interested in (groups 12 and 13). As to labour productivity changes, only group 10 has completely miss-predicted fitted values.

The interpretation of the general tendencies at the technological group level naturally depends on the ability of the model to fit the observed tendencies.

The employment share model replicates the decline of employment in *technology user*, *technology user and producer*, and *low technology* industries, while miss-predicts the tendency in *technology producer* industries.

Fitted values for labour productivity changes by technological group are instead always consistent with the observed tendencies and actually replicate surprisingly well the actual changes.

Table III.4: 1974 -1979 actual changes in employment shares and contribution of main variables

	Technology producer					Technology user and producer				
	Group 4	Group 5	Group 10	Group 11	Group 12	Group 15	Group average	Group 2	Group 6	Group average
Actual change of employment shares	-0.10	-0.10	-0.04	-0.06	-0.009	0.10	-0.04	-0.008	-0.08	-0.05
Contribution to actual change:										
Technology embodied in K	-0.04	0	-0.03	-0.02	-0.42	-0.14	-0.11	-0.36	-0.06	-0.21
Pure K deepening (no technology)	0.02	0	-0.01	-0.05	0.39	0.08	0.07	-0.17	0.04	-0.06
Internal innovative activities	-0.06	-0.07	0.05	-0.05	-0.12	0.06	-0.03	-0.01	-0.06	-0.03
Technologically induced demand transmissions*	0.08	0.07	0.09	0.11	0.16	0.10	0.10	-0.07	-0.04	-0.05
Other factors**	-0.10	-0.10	-0.14	-0.05	-0.02	0	-0.07	0.62	0.04	0.30

* Technologically induced demand transmission effects are those due to changes in the growth rate of relative TFP as from equation [72]. Note that changes in embodied technology and internal innovative activities are instead defined in terms of R&D, patents, and employment share of scientists and engineers.

** World prices, world output shares and error term

Table III.4 (continued): 1974 -1979 actual changes in employment shares and contribution of main variables

	Technology user					Low Technology				
	Group 1	Group 3	Group 9	Group 14	Group average	Group 7	Group 8	Group 13	Group average	
Actual change of employment shares	-0.12	-0.15	-0.08	-0.01	-0.10	-0.15	-0.10	0.05	-0.07	
Contribution to actual change:										
Technology embodied in K	-0.61	-0.06	-0.05	-0.13	-0.21	-0.09	-0.03	-0.76	-0.29	
Pure K deepening (no technology)	0.47	-0.02	0.03	0.10	0.14	0.08	0.02	0.71	0.27	
Internal innovative activities	-0.29	0.06	-0.09	0.01	-0.08	-0.05	-0.05	-0.06	-0.05	
Technologically induced demand transmissions*	-0.34	-0.15	-0.14	-0.16	-0.20	-0.09	-0.08	-0.10	-0.09	
Other factors**	0.65	0.02	0.17	0.17	0.25	0	0.04	0.26	0.09	

* Technologically induced demand transmission effects are those due to changes in the growth rate of relative TFP as from equation [72]. Note that changes in embodied technology and internal innovative activities are instead defined in terms of R&D, patents, and employment share of scientists and engineers.

** World prices, world output shares and error term

Table III.5: 1974 -1979 actual changes in labour productivity and contribution of main variables

	Technology producer						Technology user and producer			
	Group 4	Group 5	Group 10	Group 11	Group 12	Group 15	Group average	Group 2	Group 6	Group average
Actual change of labour productivity	-0.001	0.08	-0.08	0.06	0.93	0.07	0.18	0.72	0.02	0.37
Contribution to actual change:										
Pure K deepening (no technology)	0.004	0.03	0.09	0.06	-0.30	0.07	-0.008	0.10	-0.08	0.01
Own technology embodied in K	-0.05	0.16	0.09	-0.001	0.27	-0.08	0.06	0.04	0.04	0.04
Suppliers technology embodied in K	-0.02	0	0	0.01	0.07	-0.008	0.009	0.15	0.23	0.19
Own technology not embodied in K	0.02	0.03	-0.06	-0.004	0.10	0.006	0.01	-0.01	0.01	0
Other factors*	0.045	-0.14	-0.20	-0.005	0.79	0.08	0.11	0.44	-0.18	0.13

* Hours, constant and error term

Table III.5 (continued): 1974 -1979 actual changes in labour productivity and contribution of main variables

	Technology user					Low technology				
	Group 1	Group 3	Group 9	Group 14	Group average	Group 7	Group 8	Group 13	Group average	
Actual change of labour productivity	0.15	-0.12	0.01	0.10	0.03	0.02	0.01	-0.01	0.009	
Contribution to actual change:										
Pure K deepening (no technology)	-0.10	0.14	-0.08	-0.24	-0.07	-0.15	0.02	-0.85	-0.33	
Own technology embodied in K	0.10	-0.08	0.06	0.13	0.05	0.06	-0.002	0.72	0.26	
Suppliers technology embodied in K	0.15	0.13	0.27	0.18	0.18	0.21	-0.05	0.16	0.11	
Own technology not embodied in K	0.07	-0.07	0.04	-0.03	0.002	0.009	0.009	0.01	0.009	
Other factors*	-0.07	-0.24	-0.28	0.06	-0.13	-0.11	0.033	-0.05	-0.04	

* Hours, constant and error term

Overall, embodied technology increases are the main source of both employment share reduction and labour productivity growth in technological groups¹⁶⁷.

More specifically, they are the key factor of employment share reduction in *technology user and producer*, *technology user* and *low technology* industries. Employment in *technology user* industries is also affected by in-group negative demand transmission effects, reflected in the reduction of value added for the group as a whole.

Embodied technology increases are consistently the main source of labour productivity growth for all technological groups. They originate from in-house innovative activities for *technology producer* and *low technology* industries, while are externally acquired by *technology users and producer* and *technology user* industries.

The same main factors determining the changes in employment shares and labour productivity for technological groups are also generally behind the tendencies observed at the single industry level¹⁶⁸.

Embodied technology increases, originated from in-house innovative activities or externally acquired, are thus the key factor for labour productivity growth in groups 12, 1, 2, and 14. Labour productivity of group 12 increases also because in-house disembodied innovative activities have increased, while pure capital deepening has also added to the increase of labour productivity in group 2. Embodied technology increases also explain the fall of employment shares for these groups; however for

¹⁶⁷ Note that in the current analysis increases in relative TFP imply by **construction** decrease of the employment shares. The term expresses in fact the effect of technological change on employment share keeping fixed value added shares. Naturally this is different from explaining overall changes in employment shares as a function of technological efforts, as we have done in Chapter 1.

¹⁶⁸ Groups 13 and 15 are clearly exceptions because they are the only industries experiencing employment share increases.

group 12 other explanatory variables of the employment share model more than compensate this effect.

Reduction of in-house innovative activities (disembodied and/or embodied) and exogenous factors are the main causes for the decrease of labour productivity in group 3. For group 4, the reduction of the technological content of capital appears to have adversely affected labour productivity growth. In group 13 labour productivity has fallen because of the reduction of capital per worker.

The fitted employment share increase for group 15 is essentially the result of positive demand transmission effects originating in *technology user and producer* and *technology user* industries¹⁶⁹. The fitted employment share of group 13 could instead increase because of the reduced capital intensity, but in the employment share model technological increases and negative demand transmission effects more than compensate these effects.

Embodied labour saving technological change, reflected in both above average productivity growth and employment reduction, is thus the main factor behind most of the more important positive contributions to aggregate productivity growth (groups 1, 2, 12, and 14) during the period 1974-79. Note however that these industries are not the ones experiencing the biggest falls in employment shares, but in fact are the ones in which employment has decreased less. Effective technological change has allowed these industries to expand their production in a measure sufficient to maintain employment broadly unchanged. Industries reducing their innovative activities (groups 3, 4, and 10) show instead the biggest declines in productivity, value added

¹⁶⁹ Remember that *technology producer* industries benefit from reductions in productivity and, consequently, value added, of *technology user* industries.

and employment growth, and are the ones giving the most negative contributions to aggregate productivity growth.

The positive contribution of group 15, mainly driven by employment expansion, is largely due to demand effects, while the reduction of capital intensity in group 13 has caused both employment expansion and negative productivity growth.

III.3.2 1979-1991: some stylised facts and their technological interpretation

The period 1979-1991 is overall a time of recovery for the UK economy. The Thatcher government started the privatisation and deregulation programme in 1980, and many industries underwent massive restructuring with beneficial effects for productivity. Aggregate employment decreased over the whole period of -0.9%, compared to -0.8% over 1974-79, and the implied five-year growth rate of labour productivity is around 9%, compared to 6% over 1974-79. Most industrial groups give a positive contribution to aggregate productivity growth, and the most relevant ones come from groups 15, 14, 13, and 12. An important share of aggregate growth has thus originated in *technology producer* industries. It is however puzzling to find group 13 (*low technology*) amongst the bigger contributors. As for 1974-79, employment shares have decreased for all industries except groups 13 and 15 (+14% and 36% respectively), with consistent declines for almost all industries and in particular for groups 7, 2, 4, 12, and 10¹⁷⁰. It is noticeable the employment shift from all manufacturing, and most of service, industries towards groups 13 and 15. Group 15 in

¹⁷⁰ With employment shares falling respectively of -45%, -39%, -34%, -30%, and -310%. Note that these values refer to a 12 years period.

particular accounted in 1991 for 44% of aggregate employment, and its absorption capacity has allowed an almost unchanged aggregate employment.

Labour productivity has increased for all industrial groups except group 8 (-1%), and the biggest increases in labour productivity are for groups 12, 1, 5, 2, and 10¹⁷¹.

The most important contributions to aggregate productivity growth are again concentrating in service sector industries. Among these, the contribution of groups 13 and 15 mainly derives from between-industry growth, while for the others is the result of within-industry growth. Against this framework, it is interesting to note how groups 1, 2, and 5, despite experiencing well above average productivity growth (and, for groups 1 and 5, also favourable productivity adjusted employment share changes), give a relatively modest contribution to aggregate productivity growth.

The employment and value added reductions shown by group 2 are especially puzzling, given the initial productivity level of the group and the productivity growth achieved during the period.

The main facts we concentrate on are thus:

- ◆ for the more sizeable positive contributions to aggregate productivity growth: the growth of labour productivity and decrease of employment shares for groups 12 and 14
- ◆ the employment share increase for groups 13 and 15
- ◆ the fall of the employment share of groups 4, 10 and 7
- ◆ the labour productivity increase in groups 1 and 5
- ◆ the strong productivity increase and fall of employment and value added for group

Tables III.6 and III.7 show, for labour productivity and employment shares, the actual changes and the contribution of the main variables to actual changes.

Exogenous factors seem to be especially important to the determination of employment share changes over this sub-period; in particular the contribution of the main explanatory variables would often imply tendencies opposite to the ones observed. Still, the main focus of this work is on the role of domestic-developed technological advances in the process of growth of UK industries, and as such we will still analyse their relative contribution to the observed changes, even if we recognise that other factors, not considered here, may have been of more importance to the employment dynamics of UK industries over the years 1979-91. Besides, the observed changes in labour productivity are instead mainly determined by non-exogenous factors.

Pure capital deepening is the main factor explaining both employment share reductions and labour productivity growth in *technology user and producer* industries, while embodied technology increases are the main source of employment share reduction and labour productivity growth in *low technology* industries.

Pure capital deepening is also the main source of labour productivity growth in *technology producer* and *technology user* industries, although the employment share model identifies in embodied technology the main factor acting for employment reduction.

¹⁷¹ With labour productivity increasing respectively of 184%, 83%, 61%, 60%, and 59%.

Table III.6: 1979 -1991 actual changes in employment shares and contribution of main variables

	Technology producer					Technology user and producer				
	Group 4	Group 5	Group 10	Group 11	Group 12	Group 15	Group average	Group 2	Group 6	Group average
Actual change of employment shares	-0.35	-0.28	-0.31	-0.24	-0.32	0.34	-0.19	-0.40	-0.20	-0.30
Contribution to actual change:										
Technology embodied in K	-0.005	0	-0.05	0.06	-0.28	-0.19	-0.08	-0.15	-0.004	-0.08
Pure K deepening (no technology)	-0.008	0	0.008	-0.04	-0.17	0.02	-0.03	-0.27	-0.06	-0.16
Internal innovative activities	0.08	0.14	0.16	0.24	-0.50	0.05	0.03	0.52	0.11	0.31
Technologically induced demand transmissions*	-0.04	-0.04	-0.05	-0.06	-0.08	-0.05	-0.05	-0.01	-0.006	-0.008
Other factors**	-0.38	-0.38	-0.38	-0.44	0.71	0.51	-0.06	-0.49	-0.24	-0.36

* Technologically induced demand transmission effects are those due to changes in the growth rate of relative TFP as from equation [72]. Note that changes in embodied technology and internal innovative activities are instead defined in terms of R&D, patents, and employment share of scientists and engineers.

** World prices, world output shares and error term

Table III.6 (continued): 1979 -1991 actual changes in employment shares and contribution of main variables

	Technology user					Low technology				
	Group 1	Group 3	Group 9	Group 14	Group average	Group 7	Group 8	Group 13	Group average	
Actual change of employment shares	-0.24	-0.28	-0.10	-0.13	-0.19	-0.46	-0.11	0.12	-0.15	
Contribution to actual change:										
Technology embodied in K	-0.60	0.07	0.002	-0.03	-0.14	-0.006	-0.01	-0.65	-0.22	
Pure K deepening (no technology)	0.54	-0.23	-0.09	0.008	0.06	0.01	0.006	0.52	0.18	
Internal innovative activities	0.31	-0.06	0.23	-0.17	0.08	0.26	0.18	0.11	0.18	
Technologically induced demand transmissions*	0.02	0.009	0.009	0.01	0.01	-0.02	-0.02	-0.03	-0.02	
Other factors**	-0.51	-0.07	-0.25	0.05	-0.20	-0.70	-0.27	0.17	-0.27	

* Technologically induced demand transmission effects are those due to changes in the growth rate of relative TFP as from equation [72]. Note that changes in embodied technology and internal innovative activities are instead defined in terms of R&D, patents, and employment share of scientists and engineers.

** World prices, world output shares and error term

Table III.7: 1979 -1991 actual changes in labour productivity and contribution of main variables

	Technology producer					Technology user and producer				
	Group 4	Group 5	Group 10	Group 11	Group 12	Group 15	Group average	Group 2	Group 6	Group average
Actual change of labour productivity	0.34	0.61	0.59	0.42	1.84	0.01	0.63	0.60	0.31	0.45
Contribution to actual change:										
Pure K deepening (no technology)	-0.14	0.70	0.28	0.13	0.49	0.08	0.26	0.45	0.47	0.46
Own technology embodied in K	-0.02	-0.17	0.17	-0.05	0.28	-0.11	0.02	0.07	-0.06	0.005
Suppliers technology embodied in K	0.01	0	0	0.01	-0.05	-0.0007	-0.005	0.003	0.08	0.04
Own technology not embodied in K	0.04	-0.03	-0.23	-0.04	0.28	0.009	0.005	-0.34	0.02	-0.16
Other factors*	0.45	0.11	0.37	0.37	0.84	0.032	0.35	0.42	-0.20	0.11

* Hours, constant and error term

Table III.7 (continued): 1979 -1991 actual changes in labour productivity and contribution of main variables

	Technology user				Low technology				
	Group 1	Group 3	Group 9	Group 14	Group average	Group 7	Group 8	Group 13	Group average
Actual change of labour productivity	0.83	0.10	0.59	0.49	0.50	0.46	-0.01	0.08	0.18
Contribution to actual change:									
Pure K deepening (no technology)	-0.03	0.66	0.71	0.09	0.36	0.27	-0.002	-0.65	-0.13
Own technology embodied in K	0.15	-0.14	-0.10	0.13	0.01	-0.04	-0.004	0.79	0.25
Suppliers technology embodied in K	0.09	-0.002	0.09	-0.05	0.03	0.06	-0.02	-0.03	0.003
Own technology not embodied in K	-0.001	-0.05	-0.08	0.03	-0.02	-0.11	-0.06	0.03	-0.05
Other factors*	0.62	-0.37	-0.03	0.29	0.12	0.28	0.076	-0.06	0.11

* Hours, constant and error term

At the single industry level, pure capital deepening (group 10) and embodied technology increases (groups 1 and 14) are the main factors explaining above average productivity growth.

A general decrease of the innovative capability of group 8 (both externally acquired and internally developed) appears to be behind its negative productivity growth.

Exogenous factors (groups 4 and 7), embodied technology increases (groups 10 and 12) and pure capital deepening (group 2) are instead the factors causing the most sizeable employment reductions at the single industry level. Exogenous factors, and the continuing reduction of capital intensity for group 13, explain instead the two observed increases of employment shares (groups 15 and 13).

The growth dynamics of group 2 are largely the result of productivity growth driven by pure capital deepening, and of the reduction of internal innovative activities¹⁷². The capital-driven productivity gain of the group appears to have been insufficient to counteract the slowdown in world demand for the group, which has thus reduced value added and employment. The limited contribution of group 1 is instead just the consequence of its small relative size (in 1991 the group accounted for 1% of aggregate employment).

Capital deepening and embodied technology increases are the economic factors giving rise to the most important positive contributions to aggregate productivity growth during the period 1979-91. These same factors are also generally the sources of above average productivity performances and the biggest declines in employment shares.

¹⁷² It might be called not technologically advanced industrialisation.

Overall, while over the period 1974-79 technological innovations embodied in capital goods are the main sources of aggregate productivity growth, their role is reduced over the years 1979-91, and capital deepening appears among the main sources of aggregate productivity growth. Note also that, while over 1974-79 the industries experiencing above average productivity growth have maintained a relatively stable level of employment, for the years 1979-91 there is a much stronger linkage between above average productivity growth and above average declines in employment.

Our results suggest the following interpretation of the observed dynamic changes intervened in UK industries. Over the years 1974-79, technology driven productivity growth has allowed the most productive industries to expand their output sufficiently to keep their employment broadly unchanged. Relatively unproductive industries have decreased their employment, that however has been redirected towards groups 13 and 15. Some structural substitution of capital with labour has allowed employment to be absorbed by group 13, while the absorption capacity of group 15 has been largely determined by positive demand effects, both specific to the UK economy and world-wide spread.

Over the years 1979-91 instead, productivity growth has been in large part driven by substitution of labour with capital. The output expansion of the most productive industries has not been sufficient to safeguard employment, that has shifted noticeably towards group 13 and especially group 15. The continuing de-industrialisation of group 13 has allowed its employment expansion, while exogenous factors (plausibly the growing trend of world demand) have determined the employment absorption capacity of group 15.

We would have hoped to find a bigger role of innovative activities at explaining the observed growth patterns. However, the results obtained here are consistent with the analysis of Owen (1999), which also gives explanations of why a limited impact of innovative activities may be expected. The two periods analysed correspond in fact to two major “shocks” for the UK economy. As said before, the UK entered the Common Market in 1973, and most UK industries faced an immediate disadvantage with respect to their European counterparts. According to Owen (1999), part of the difficulties were due to general organisational problems, part to the colonial tradition of the UK, but for the most part to the fact that UK industries had to enter markets in which other industries were already operating. Some UK industries¹⁷³ had also a technological disadvantage with respect to their competitors, but overall competitiveness problems were not due to technological conditions. Up to 1979 the government made massive interventions to support declining industries and especially employment. In 1979, with the first Thatcher government, the policy guidelines changed drastically and the UK economy underwent a massive restructuring. This included downward sizing and closure of plants, strong reduction of government intervention to support production, and a general modernisation of the organisational and technical aspects of production. It is thus not surprising to find an overall limited impact of innovative activities on industrial dynamics for the period 1979-91.

¹⁷³ Noticeably Electronics and Engineering, although the competitors were US and Japanese firms.

III.4 Conclusions

We have considered in this chapter a last channel of transmission of technological related dynamics due to inter-industry demand transmissions effects. We have estimated over the technological groups defined in Chapter 1 supply and demand equations in order to determine how the value added and employment shares of a supplying industry j , not experiencing technological change, vary as a consequence of the technologically induced changes in demand of its customers industries.

Next, we have proceeded to decompose the observed changes in labour productivity and employment shares for the periods 1974-79 and 1979-91 into their technological sources. The results we get indicate that for the period 1974-79 embodied technological innovations are among the main sources of aggregate productivity growth. For the period 1979-91 instead, aggregate productivity growth is predominantly determined by pure capital deepening. Although we would have hoped to find a bigger impact of innovative activities explaining the observed growth patterns, our analysis and results are consistent with the main structural and political changes intervened in the UK in the years analysed. Moreover, we find that during the period 1974-79 positive demand transmission effects have contributed to the employment absorption capacity of group 15, and thus to sustain aggregate employment.

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Data Appendix (Chapter 3)

This appendix gives details of the computation and data sources of the variables used in the Chapter.

Value Added Shares by Technological Group

Value added by technological group is the sum of values added of the industries belonging to the group. Value added shares are the ratios to whole economy value added.

Source: OECD International Sectoral Database.

Domestic price index deflators by technological group

Domestic price index deflators by technological group are computed as the weighted average of the domestic price index deflators of the industries belonging to the group. The weights are given by the value added share of each industry in the group.

Source: OECD International Sectoral Database.

Whole economy final expenditure deflator

Total Final Expenditure deflator at factor cost.

Source: UK Blue Book of National Accounts.

Total factor productivity by technological group

It is computed as the Solow residual from the production function of the group, where value added, capital and labour of the group are given by the sum of value added, capital and labour of the industries belonging to the group. The share of labour (and capital) in the production function of the group is the weighted average of the labour

share of the industries belonging to the group, with weights equal to the value added shares of the industries. Labour shares at the industry level have been computed as the product of mark-up by the average wage share. For those industries for which mark-up data were not available, they have been put equal to the weighted average (with weights, again, equal to value added shares) of available mark-up data.

Sources: OECD International Sectoral Database; Martins J.O., Scarpetta S., Pilat D. “Mark-up ratios in Manufacturing industries”, Economics Department Working Paper n. 162, 1996, OECD, Paris.

Whole economy Total Factor Productivity

It is computed as the Solow residual from a "whole economy" production function, where value added, capital and labour equal their whole economy values. The share of labour (and capital) in the production function is computed as the product of the whole economy mark-up by the average wage share for the whole economy. The whole economy mark-up is given by the weighted average (with weights equal to value added shares) of the mark-ups of all industries of the economy. The average wage share for the whole economy is given by the ratio of the average wage bill for the whole economy over whole economy value added.

Sources: OECD International Sectoral Database; Martins J.O., Scarpetta S., Pilat D. “Mark-up ratios in Manufacturing industries”, Economics Department Working Paper n. 162, 1996, OECD, Paris.

World price index deflator by technological group

It is given by the weighted average (with weights equal to value added shares for the group) of the price indexes of output by industry for the United States, Germany and Japan. United States, Germany and Japan's industries are aggregated according to the technological classification of UK industries.

Source: OECD International Sectoral Database.

World price index deflator (aggregate)

Is the weighted average of the world price index deflators by technological groups, with weights given by the value added share of the group.

World Output Shares by technological group

They are the weighted average of the logarithm of the share of world value added by technological group, with weights computed on the basis of the average coefficients of Input-Output tables. The share of world value added by technological group is the weighted average (with weights equal to value added shares over the total value added in the three countries) of the value added shares by technological group for the United States, Germany and Japan. Missing values for world value added by technological group have been computed applying the growth rates of value added by technological group for UK industries.

The Input-Output weights are the average weights of UK Input-Output tables for the years 1968, 1979, 1984 and 1990. In-industry flows have been eliminated and the Input-Output values have been normalised to add to one by column. The weights have been aggregated by technological group and re-normalised to one.

Source: OECD Input-Output tables database, OECD International Sectoral Database.

General Conclusions

The aim of this work has been to investigate empirically the sources and growth effects of technological innovation in UK industries over the years 1966-1993. We have established two main classes of results. The first class is more “general oriented” and is about the effects of internal and external sources of innovation on labour productivity and employment shares growth at the industry level. The second class of results concerns the capability of the empirical models we developed to explain observed industry dynamics. The results we obtain are overall in accordance with the priors we hold at the beginning of the work and with what economic theory predicts. We are also satisfied by the capability of our models to interpret historical data, although economic and political changes in the UK during the period plausibly act to reduce the explanatory potential of the models we develop. The results we obtain are however consistent, and actually reflect, the economic and political changes.

We proceeded on our investigation by considering first the internal sources of innovation, then the external ones, next inter-industry demand transmissions, and finally the fitting of the models to observed data. With the partial exception of chapter 3¹⁷⁴, the methodologies adopted are not original, and in particular heavily rely on Nickell and Nicolitsas (1997) for chapter 2, and Harrigan (1997) for chapter 3.

Chapter 1 investigates the growth effects of internal sources of innovation on labour productivity and employment shares. We first present a technological classification of industries according to two indicators of internally generated and externally acquired technology. Then we proceed to investigate the sectoral contribution to aggregate labour productivity growth, and find that it is approximately determined by the growth

rate of labour productivity and employment shares. Within industry growth generally predominates in the determination of the sectoral contribution to aggregate growth, but for two industries belonging to the service sector, and accounting for more than half of aggregate employment, sectoral shifts of resources have been predominant. We find that non-manufacturing industries, and in particular service industries, account for most of aggregate productivity growth. This is the joint result of high labour productivity and employment share growth. We also find some evidence of catching-up at the industry level, although we do not proceed to further investigate this effect. We observe that the effect of technological change on employment differs among industries and over time periods. In general, the labour saving effect seems predominant in manufacturing industries, while the demand expansion effect seems to dominate in the service industries. Next, we proceed to estimate a first set of models to determine the effect of the internal sources of innovation on labour productivity and employment shares growth. For labour productivity growth, our results indicate that the importance of internal and disembodied sources of innovation changes accordingly to the technological characterisation of industries. Internal sources of innovation are thus most important for *technology producer* industries and least important for *technology user* ones. However, we also find that changes in the capital/labour ratio are the main determinants of labour productivity growth, and their importance noticeably exceeds that of internal sources of innovation. As to employment share growth, we find a positive relation, on average, with internal innovative activities for all technological groups except the *low technology* one. Changes in the relative¹⁷⁵ ratio of capital also have on average a positive effect on employment shares growth.

¹⁷⁴ Cfr. the general introduction.

¹⁷⁵ With respect to whole economy values.

In Chapter 2 possible external sources of innovation are examined. In particular, given the previous evidence of a strong effect of capital, we concentrate on the embodiment hypothesis and on the investigation of spillover effects. First of all, we analyse the Granger causality between R&D expenditures and Investment. We find some evidence that R&D expenditures Granger cause investment in all technological groups except the *low technology* one¹⁷⁶. This evidence is however not too robust. Next, we proceed to estimate an equilibrium investment model¹⁷⁷ directly relating investment decisions and indicators of internal and external technological activities. We obtain that, in general, internal and external technological activities enhance investment. We also find that, once embodied technology is taken into account, the impact of technological activities on labour productivity growth becomes more substantial. Moreover, the relative importance of internal and external sources of innovation for labour productivity growth changes in accordance with the technological characterisation of each industry. Internal and external sources of innovation are thus respectively most and least important for *technology producer* industries while the situation is reversed for *technology user* ones. Besides, we find that, with only a few exceptions, both internal and external innovative activities usually have a positive impact on employment shares growth. Spillover effects seems to be relevant to few industries only, however, in some cases, these effects have a more important impact on labour productivity growth than internal innovative activities.

¹⁷⁶ We present reasons in the Chapter for which this effect may be due to the anomalous behaviour of only one industry of the group.

¹⁷⁷ Proposed originally by Nickell and Nicolitsas (1997).

In Chapter 3 we investigate the importance of inter-industry demand transmission for employment shares growth, and also compare the predictions of our models with the observed data. We estimate supply-demand equations and compute the reduced form solution in order to determine the extent of inter-industry demand transmissions. From the reduced form solution we get a negative own¹⁷⁸ TFP effect over own domestic prices and a positive own TFP effect over own Value Added shares. Positive demand transmission effects, originating in *technology user and producer* and *low technology* industries, emerge for *technology producer* industries. There are also positive demand transmission effects for *technology user and producer* industries originating in *technology producer* and *technology user* ones; for *technology user* industries originating in *low technology* ones; and for *low technology* industries originating in *technology user* ones. We then proceed to compare the actual and fitted data from our models. We concentrate on the time periods 1974-1979 and 1979-1991 including, respectively, the entrance of the UK in the Common Market (1973) and the beginning of the privatisation and deregulation programme (1979). For the period 1974-79, our results indicate that embodied technology increases are the main factor explaining most of the positive contributions to aggregate labour productivity growth. The biggest falls in employment shares are generally observed in industries with below average productivity growth, while industries experiencing above average productivity growth keep their employment broadly unchanged. Moreover, positive demand transmission effects are the main responsables of the employment absorption capacity of group 15. For the period 1979-91, capital deepening and, to a lesser extent, embodied technology, are the economic factors explaining most of the positive contributions to aggregate labour productivity growth. Overall, while over the period

¹⁷⁸ By own we mean variables referring to the same industry.

1974-79 labour productivity, value added and employment share growth have been mainly driven by technological innovations, the main engine of growth during 1979-91 appears to be capital deepening. The implications for value added and employment share growth are clearly different, and a noticeable shift of employment towards group 15 is observed over the period 1979-91.

Although we would have hoped to find a bigger impact of innovative activities explaining the observed growth patterns, our analysis and results are consistent with the main structural and political changes intervened in the UK in the years analysed, and in particular the massive industrial restructuring during 1979-91.

While the UK economy has certainly performed better in terms of growth over the period 1979-91, it would also be interesting to have a complete and possibly micro-based assessment of the consequences of the observed employment shift towards group 15.

