Market Power, Economies of Scale and the Role of Knowledge for Economic Growth

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Abstract

This dissertation studies the empirical relevance of R&D based growth theories. In previous research on this topic, investigators have typically employed the Solow residual approach to study the impact of knowledge and spillovers on productivity. Yet, relying on the assumptions of perfect competition and constant returns to scale, this framework is not in line with R&D based growth theory, which implies that knowledge creation as the driving force of economic growth is inextricably linked to market power and economies of scale. In this study, a cost function and factor demand system is employed to investigate the empirical relevance of R&D based growth theory with a new version of the OECD STAN dataset covering two-digit manufacturing industry data from Canada, France, Germany, Italy, Japan and the US. In contrast to the conventional Solow residual, this framework allows the researcher to investigate economies of scale, market power and the role of knowledge creation and spillovers for productivity growth in an integrated approach. The empirical investigation reveals that in line with R&D based growth theories, there are indeed economies of scale and mark-ups in nearly all of the investigated industries. Excess returns to R&D are found in four relatively R&D-intensive sectors. In addition to this, knowledge spillovers enhance productivity growth in many industries. International intra-industry spillovers seem to be the most important source of knowledge externalites. R&D intensity is low and there is little or no productivity growth in the few industries where no significant impact of R&D can be found. In all the other cases, knowledge variables are found to explain a good part of the observed productivity growth and they are a source of economies of scale, as theory would suggest. In contrast to competing growth theories, R&D based models imply that mark-ups, economies of scale and a productivity enhancing role of knowledge variables should be found in the data. The empirical investigation in this dissertation suggests, that R&D based growth models seem to pass this empirical test very well.

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Chapter 1

Introduction

Between 1870 and 1980 real GDP per capita rose sevenfold in the US, eightfold in West Germany and sixteenfold in Japan (Maddison 1982). Technical change and innovation have been at the heart of this impressive increase in material well-being. Not only are more goods and services available on average for each person in industrialized countries, but entirely new products and production processes have been developed. A century ago satellite communication, personal computers or jet airplanes would have been inconceivable.

Most of the last decade has been marked by impressive output and productivity growth, especially in the Unites States. This is often traced to the productive use of entirely new information and communication technologies, most notably the Internet. Frequently labeled as the "New Economy" this development is viewed by many as a technological revolution. The emergence of new information and communication technologies underlines the role of technological change as an engine of productivity and output growth.

These casual observations suggest that innovation is an important determinant of economic development. This conjecture is reflected in economic theory, as technological change lies at the heart of the growth process in the vast majority of models. Yet, in the neoclassical theory (Solow 1956, Cass 1965, Koopmans 1965), the paradigm of economic growth theory in the 1960s and the 1970s, productivity growth is exogenous. Thus, technological change, which allows capital and output per worker to grow continuously over the long run, remains unexplained. A growing dissatisfaction with this aspect of the neoclassical theory has led a number of researchers to reconsider the investigation of the growth process in an attempt to explain long-run economic growth endogenously. These attempts have gone many different ways, including the introduction of economies of scale due to spillover externalities (Romer 1986), of human capital (Rebelo 1991), or both (Lucas 1988). In these models, knowledge creation and technological change are either the unintentional side effect of the production of a conventional product, e.g. physical or human capital, or they are not important for growth at all (Rebelo 1991, Jones & Manuelli 1990).

This dissertation is devoted to an empirical investigation of research and development (R&D) based endogenous growth models that aim to explain technological change and productivity growth as the result of intentional investments in R&D (Romer 1990, Grossman & Helpman 1991, Aghion & Howitt 1992). While many of these models encompass some type of externalities associated with knowledge creation, all of them rely upon the assumption that investments in research and development occur as a response to market incentives, much in the way as investments in physical capital.

When investigating these theories empirically, most researchers choose a Hall/Solow residual approach to study the impact of knowledge and spillovers on productivity growth (Coe & Helpman 1995, Keller 2001). Yet, stemming from Solow's (1956) growth model, this framework relies on the assumptions of constant returns to scale and perfect competition, while increasing returns and market power are essential features of R&D based models of economic growth.

As emphasized by Romer (1990), recognizing the non-rivalrous nature of knowledge necessarily links it with economies of scale and imperfect competition. The development of an idea, such as the design of a new car or a patent for a new medicine, may require huge initial costs. Yet, once it has been created, the idea can be used over and over again with zero or trivial additional costs. In this sense, knowledge creation is analogous to incurring a fixed cost. Knowledge is a non-rivalrous good, because at a technological level nothing precludes the simultaneous use of an idea in many different production processes. While returns to scale in rival factors should be constant by a standard replication argument, this does not hold for non-rival knowledge, precisely because it does not have to be replicated. Thus, returns to scale in all factors including knowledge should be increasing. Euler's theorem implies that with increasing returns not all factors can be paid their marginal product. So if knowledge creation is assumed to depend on economic decisions, as in the R&D based growth models, then there must be at least some market power so that resources devoted to it can be recompensed.

The inextricable link between economies of scale and imperfect competition with market driven knowledge creation in R&D based models of economic growth has been much overlooked in empirical work investigating these theories. The Solow residual is a biased measure of productivity growth when the assumptions of constant returns to scale and perfect competition do not hold. A few researchers "correct" the Solow residual to account at least for the presence of imperfect competition (Keller 2001). Beyond concerns regarding biases of the Solow residual, however, theory suggests that it may be very revealing to study the role of knowledge and the presence of market power and economies of scale explicitly in an integrated approach.

In this study a cost function and factor demand system is employed to investigate the empirical relevance of R&D based growth theories. In contrast to the popular Hall/Solow residual approach, the appropriateness of productivity growth measures derived from this empirical model does not hinge on perfect competition and constant returns to scale. What is more, it provides a framework to investigate all of the more relevant features of R&D based models of economic growth in an integrated approach.

A new version of the OECD STAN dataset (OECD 2000*a*) covering two-digit manufacturing industry data from Canada, France, Germany, Italy, Japan and the US is employed to investigate economies of scale, market-power and the role of knowledge creation and spillovers for productivity growth. Both domestic and international knowledge spillovers are considered. While all of these features have been investigated before in an isolated fashion, to the best of my knowledge there is no research investigating all of them simultaneously to study potential links between them.

Earlier versions of the STAN dataset have been used before to investigate mark-ups (Beccarello 1996) and the role of knowledge (Keller 2001, Griffith, Redding & van Reenen 2000). However, these studies suffer from the problem that constant price material input data was not available in prior versions of the STAN database. Therefore, authors were previously confined to using value-added data. Yet, according to R&D based models of economic growth, technological change embodied in intermediate inputs will always be associated with market-power. Basu & Fernald (1995) and Basu & Fernald (1997) have shown that using value added data is very likely to bias results concerning estimates of economies of scale and externalities, if the material inputs are not produced in competitive markets. Therefore, value-added is not the ideal output concept for empirical work that investigates R&D based models of economic growth.

A number of these models emphasize the importance of trade as a channel for knowledge spillovers (Grossman & Helpman 1991, Rivera-Batiz & Romer 1991). The attractiveness of the international dataset employed in this study lies in the possibility to investigate the presence of these externalities. Drawing on work by Keller (2001) three different potential spillover sources are considered: domestic inter-industry spillovers, international intra-industry spillovers and international inter-industry spillovers. While Keller pools all industries and countries for his estimations, each industry is pooled individually across countries and investigated separately in this dissertation. The results reveal important differences between industries, which have not been taken into account in Keller's study. The finding of heterogeneity also suggests that it is very revealing to differentiate between industries, rather than estimating international knowledge spillovers with country data, an approach pioneered by Coe & Helpman (1995), which has found many followers.

In contrast to some earlier research that simultaneously studies the impact of R&D investments on the productivity of the investor as well as different types of externalities associated with it (Keller 2001, Verspagen 1997), multicollinearity problems between different spillover variables are carefully taken into account in this dissertation and conclusions are drawn with caution. As it turns out, different R&D variables are highly collinear. This casts some doubts on results of earlier studies that consider a number of different spillover variables without taking multicollinearity problems into account. Nevertheless it can be concluded from the results in this study that international intra-industry spillovers seem to be the most important source of externalities.

The study is organized as follows. Chapter 2 provides an overview over economic growth theory with an emphasis on R&D based models of economic growth to provide a theoretical foundation for the empirical investigation. Chapter 3 discusses the empirical model. Outlining its advantages over more popular frameworks it also discusses the specifics of the data employed in the empirical investigation. Estimates of productivity growth, mark-ups and economies of scale are presented in Chapter 4, which also confronts the results with prior investigations. Chapter 5 outlines the modelling strategy for spillover variables and discusses the empirical results concerning the role of knowledge and its externalities as an engine of productivity growth and as a source of economies of scale. Chapter 6 concludes.

Chapter 2

Growth Theory

2.1 The Neoclassical Growth Model

Sustained growth of per capita macroeconomic variables, such as the aggregate capital stock, output and consumption is a well established empirical regularity. In the long run, the growth rate of these variables seems to be roughly constant. This pattern is captured by the neoclassical growth model (Solow 1956). Relying on the assumption of competitive markets and a constant returns to scale production function, the model implies a stable balanced growth path equilibrium, where all per capita variables grow at the rate of technological progress. The basic features of this model can readily be demonstrated assuming that a large number of firms produces good Y with capital, K, and labor, L, according to a constant returns to scale technology, $Y = F(K, AL)$, which complies with the Inada conditions [1]. An example would be the Cobb-Douglas production function:

$$Y = K^{\alpha}(AL)^{1-\alpha} \tag{2.1}$$

[1] The Inada conditions require that the marginal product of each factor goes to zero, as the factor input goes to infinity and vice versa: $\lim_{K\to 0} F_K(K, AL) = \infty; \lim_{L\to 0} F_L(K, AL) = \infty$
$\lim_{K\to\infty} F_K(K, AL) = 0; \lim_{L\to\infty} F_L(K, AL) = 0;$
where F_{X_i} denotes the first derivative of the production function F with respect to factor X_i.

A is an exogenous technology parameter, which is assumed to grow at a constant rate γ_A. It can be thought of as the technological knowledge in the economy which is a completely non-rival and non-excludable good in this model. Every firm in the economy uses the same A in its production. Because of the constant returns to scale property of the production function, output can be described in terms of the actions of a single price-taking firm.

In the Cass-Koopmans version of the Solow model (Cass 1965, Koopmans 1965) the savings decision is derived from the utility maximization of an infinitely lived agent. Life-time utility, U, is given by

$$U = \int_0^\infty e^{-\rho t} \frac{c^{1-\sigma} - \sigma}{1-\sigma} dt \tag{2.2}$$

where c denotes per capita consumption, t denotes time, $\sigma > 0$ is a parameter determining the intertemporal elasticity of substitution, and ρ is the rate of time preference. Agents receive wage income on inelastically supplied labor, L, and rental income on their capital which they rent to firms. Maximization of lifetime utility (2.2) subject to the intertemporal per capita budget constraint, $\dot{k} = w + rk - c$, implies

$$\frac{\dot{c}}{c} = \frac{1}{\sigma}(r - \rho) \tag{2.3}$$

A lower case variable z is the per capita version of its upper case equivalent $z = \frac{Z}{L}$ and a dot on a variable denotes its derivative with respect to time. w is the real wage rate and r is the real interest rate. For simplicity, the economy's population L is assumed to be constant, but population growth can easily be incorporated into the model. Firms' profit maximization implies that $r = F_K(K, AL) - \delta = \alpha(\frac{K}{AL})^{\alpha-1} - \delta$, where δ is the depreciation rate of capital. Because of the constant returns to scale characteristic of the production function, $F_K(K, AL)$ depends only on capital in efficiency units, $\frac{K}{AL}$. This follows from the rule that the partial derivative of a function that is homogeneous of degree one must be homogeneous of degree zero, which is readily verified with the Cobb-Douglas production function as an example. The Inada conditions imply that $F_K(K, AL)$ converges to zero with continuous growth of per capita capital, if the economy's stock of knowledge, A, is constant. With a constant rate of time preference the right hand side of equation (2.3) converges to a negative constant, -$\frac{\delta+\rho}{\sigma}$, so there is no scope for continuous growth. Thus, exogenous growth in A is needed to offset the effect of diminishing returns to capital.

With constant exogenous productivity growth, γ_A, per capita capital grows at the same rate as A on a balanced growth path and r is constant. Taking account of the constant returns to scale characteristic of the production function, it readily follows that per capita output grows at that same rate. By the economy's budget constraint output must equal the sum of consumption and investment in physical capital, I. Taking account the capital accumulation equation, $\dot{K} = I - \delta K$, it can be derived from this that consumption also grows at the rate of technological progress. Because of the constancy of population, per capita variables grow at the same rate as their counterparts in levels.

Continuous and roughly constant growth of per capita macroeconomic variables, such as consumption, output and the capital stock, is a well established empirical regularity. This is captured very well by the neoclassical growth model with exogenous productivity growth. The drawback of this model is that it does not explain technological change as captured by γ_A which, however, is the ultimate source of growth.

This is why in the mid-1980s economists led by Romer (1986) reassessed growth theory, trying to explain continuous growth endogenously. These attempts have gone many different ways. Some of the models of endogenous growth are discussed in the following sections.

2.2 Growth due to Externalities

The reason why an exogenous source of growth is needed is that in a neoclassical production function returns to capital are diminishing. The problem with exogenous productivity growth is that there is every reason to believe that the economy's stock of knowledge should depend on economic decisions at least as much as the capital stock. It is therefore desirable to explain the evolvement of A as a result of market incentives.

The main problem facing attempts to endogenize A is the difficulty to deal with increasing returns in a dynamic general equilibrium framework, because endogenizing A is not compatible with a competitive equilibrium. To see this, consider a more general production function $F(A, X)$, where $X = (X_1, ..., X_N)$ is a vector of rival inputs, such as labor and capital in the model above. Returns to scale in rival factors should be constant by a standard replication argument, while they should be increasing in the rival factors and knowledge together, as outlined in the introduction.

With a homogeneous, constant returns to scale production function increasing all non-rival factors by a constant factor m increases output by that same factor $F(A, mX) = mF(A, X)$. Euler's theorem can be derived by differentiating both sides with respect to m and evaluating at $m = 1 : \sum_i \frac{\partial F}{\partial X_i} X_i = F(A, X)$. It is obvious from this, that in a competitive equilibrium, where factors are paid their marginal products, revenue is just enough to recompense the non-rival inputs. If a firm had to recompense A as well, it would incur losses. It is compelling to believe that technological knowledge is accumulated deliberately as a result of market incentives. Yet, in a competitive equilibrium firms cannot recompense any resources devoted to knowledge accumulation.

An approach to maintain a competitive equilibrium, while explaining the evolvement of A within the model has been developed by Romer (1986) and Lucas (1988), who model the accumulation of knowledge as an unintentional side-effect of investments in different kinds of capital. In his paper that revived growth theory in the 1980s, Romer (1986) employs Arrow's (1962) setup to eliminate the tendency for diminishing returns by assuming that knowledge creation is a side product of investment in physical capital. Learning how to use new machines, workers create knowledge that allows them to produce more efficiently. As in the Solow-Cass-Koopmans model, technological knowledge is a non-rival production input. Once new knowledge is created, it immediately spills over to the entire economy.

The main ideas of the model can be presented with a simple Cobb-Douglas production function similar as in (2.1). The production function of firm i is $Y_i = F(K_i, AL_i) = K_i^{\alpha}(AL_i)^{1-\alpha}$. Firms operate in a competitive environment and the private factors, capital and labor, earn their marginal product. Since knowledge creation is assumed to be a side effect of investments in physical capital, the technology factor, A, is now a function of the overall capital-labor-ratio: $A = b\frac{K}{L}$, where b is a constant, $K = \sum_i K_i$ is the aggregate physical capital stock and $L = \sum_i L_i$ is the aggregate labor supply. Taking this into account, the individual production function becomes $Y_i = K_i^{\alpha}(b\frac{K}{L}L_i)^{1-\alpha}$. Firms take the overall capital-labor ratio as given. Competitive pricing results in

$$r + \delta = \alpha\frac{Y_i}{K_i}, w = (1-\alpha)\frac{Y_i}{L_i} \tag{2.4}$$

where $r + \delta$ is the user cost of capital and w is the real wage rate as above. Equation (2.4) implies that if all firms face the same factor prices and the same technology, they will hire factors at the same proportions. Writing the individual production functions as $Y_i = (\frac{K_i}{L_i})^{\alpha}(b\frac{K}{L})^{1-\alpha}L_i$, they can be aggregated to yield

$$Y = b^{1-\alpha}K \tag{2.5}$$

Since the constant $b^{1-\alpha}$ is represented by an A in most formulations of this model, they are often called $AK-$models.

To verify quickly that this allows for continuous growth, note that maximization of (2.2) with respect to the representative consumers budget constraint still results in the Euler equation (2.3). The interest rate $r = \frac{\partial Y_i}{\partial K_i} - \delta = \alpha(\frac{K_i}{L_i})^{\alpha-1}(b\frac{K}{L})^{1-\alpha} - \delta = \alpha * b^{1-\alpha} - \delta$ is independent of capital. As long as $\alpha * b^{1-\alpha} > \rho + \delta$, this allows for a growth path where all per capita variables grow at a constant positive rate.

Rather than assuming that technological growth is an unintentional side effect of investments in physical capital, Lucas (1988) assumes in effect that it is proportional to the production of human capital. He introduces a human capital externality, which raises the productivity of all factors. This can be interpreted as being analogous to Romer's assumption that knowledge creation occurs due to spillovers associated with physical capital accumulation. While spillovers in the Romer-model are due to learning-by-investments, they come from interaction of smart people in Lucas' formulation.

In the Lucas-model it is not raw labor, but human capital, H, that is important for the production of output: $Y_i = A^{\varsigma} K_i^{\alpha}(H_i)^{1-\alpha}$. In this model version, the accumulation of knowledge is assumed to be an unintentional side effect of the production of human capital $A = bH$. Aggregate human capital is taken as given by the individual firms. By the same argument as above, all firms will hire human and physical capital at the same proportions and thus individual production functions can be easily aggregated.

To obtain a simplified one-sector version of the Lucas-Model, let's assume that human capital can be produced in the same manner as physical capital by foregoing one unit of consumption, $\dot{H} = I_H - \delta H$, where I_H denotes investment in human capital. Since the cost of accumulating one unit of physical capital is the same as accumulating one unit of human capital, competition will ensure that the marginal products of K and H must the same: $(A)^{\varsigma}\alpha K^{\alpha-1}(H)^{1-\alpha} = (A)^{\varsigma}(1-\alpha)K^{\alpha}H^{-\alpha}$. This equation implies that the ratio of physical to human capital is constant in equilibrium, $\frac{K}{H} = \frac{\alpha}{1-\alpha}$, and so is the rate of return to both types of capital. The aggregate production function can be written as

$$Y = F(K, AL) = Y = b^{\varsigma}(\frac{1-\alpha}{\alpha})^{\varsigma+(1-\alpha)}K^{1+\varsigma} \tag{2.6}$$

If there is no non-rival knowledge in the economy ($\varsigma = 0$), then the final production function is of the AK-type: $Y = (\frac{1-\alpha}{\alpha})^{(1-\alpha)}K$. Broadening the definition of capital, so that it encompasses both physical and human capital, it is possible to obtain a model of endogenous growth even without any technological progress.

Returning to the idea that knowledge is accumulated as a side effect of human capital production ($\varsigma > 0$), it turns out that it is possible to construct a model of endogenous growth with economies of scale at the aggregate level, while maintaining the perfect competition framework. Since knowledge creation occurs as a side effect of the accumulation of a rival factor, resources devoted to it do not have to be recompensed separately. As long as increasing returns are due to spillovers only, while individual firms are faced with technologies that are constant returns to scale in their choice variables, the competitive equilibrium framework does not have to be abandoned to obtain an endogenous growth model. To see that Romer's ideas can be used to construct a model with increasing returns, as well, just reformulate the individual firm's production function as $Y_i = A^\varsigma K_i^\alpha (L_i)^{1-\alpha}$. Assuming that knowledge evolves in fixed proportions to aggregate rather than average capital, $A = bK$, the resulting aggregate production function, $Y = b^\varsigma K^{\varsigma+\alpha} L^{1-\alpha}$, is clearly subject to economies of scale.

An alternative approach to explain growth endogenously is to build a competitive equilibrium model and dismiss the notion that technological change lies at the heart of economic growth, in order to obtain a model without increasing returns. Rebelo (1991) and Jones & Manuelli (1990) have uncovered sets of assumptions that result in endogenous growth with constant returns without a role for technological change. Jones & Manuelli (1990) show that what is important is to bound the marginal productivity of capital away from zero. It is clear from the Euler equation (2.3) that as long as the limit of the marginal product of capital exceeds $\rho + \delta$, ongoing growth of per capita consumption is possible, without a need for A to grow as well in order to offset growth of per capita capital.

Rebelo (1991) studies a multi-sector model and stresses the assumption that there is a set of capital goods, such as human and physical capital, which can be produced without non-reproducible factors (such as land). Together with some regularity conditions, this leads to models of the AK-variety where unceasing growth can take place without exogenous increases in productivity or externalities.

While it is interesting to learn about the conditions for endogenous growth, it may not be desirable to dismiss the assumption that it is technological change due to knowledge accumulation which lies at the heart of economic growth.

If intentional accumulation of non-rival knowledge as a result of market incentives is deemed important for economic growth, market-power has to be introduced into the model. Theories that rely on this notion of technological change have been pioneered by Romer (1990) and Aghion & Howitt (1992).

2.3 R&D based Models of Endogenous Growth

2.3.1 Increasing Varieties

Increasing Varieties of Non-durable Intermediate Inputs

To explain the evolvement of the stock of knowledge endogenously, one metaphor for technological change that has been used extensively is to interpret A as the range of varieties of intermediate or consumption goods. R&D effort results in the development of new goods and thus an increase in A. Technological advancements are thus equivalent to increasing specialization in these models.

Technological change can be associated with consumption goods, material inputs or capital goods. For empirical research it is important to note that in reality technological change is likely to be associated with all of these goods at the same time. In theoretical models, however, nothing much but complexity is gained when modelling all of these phenomena together. Therefore, in what follows models in which technological change is associated with material inputs, capital or consumption goods respectively are presented separately.

In a simple version of an increasing varieties model à la Romer (1990) a final goods sector produces a homogenous output good, Y, using labor, L_Y, and a variety of intermediate goods, x_i, where i indexes the variants of the good. In the simplest case, the technology is Cobb-Douglas:

$$Y = L_Y^{1-\alpha} \int_0^A x_i^\alpha di \tag{2.7}$$

where $0 < \alpha < 1$. A is the "range" of intermediate goods currently available. The final goods sector is competitive and firms choose labor input and the amount of each intermediate good, x_i, to maximize profits. The final goods producers maximize profits, $L_Y^{1-\alpha}\int_0^A x_i^\alpha di - wL_Y - \int_0^A p_i x_i di$, which yields a demand curve for the intermediate good i :

$$p_i = \alpha L_Y^{1-a} x_i^{\alpha-1} \tag{2.8}$$

The intermediate goods sector is composed of an infinite number of local monopolists on the interval $[0, A]$. They can either be thought of as developing patents themselves or as purchasing them from an R&D sector at price P_A. Once they have obtained a patent for good i, they can produce the intermediate good at a constant marginal cost of 1 unit of output per unit of intermediate good. This implies that consumption goods and intermediate goods are produced with the same technology. It is appropriate to think of resources as going directly into the intermediate good production. The somewhat artificial step of producing final output first is introduced for analytical tractability.

Let's first assume that the intermediate good is non-durable. Solving the profit maximization problem, $\max_{x_i} p_i x_i - x_{i,}$, while taking account of the demand function for the intermediate good (2.8), it turns out that the monopolist charges a mark-up of price over marginal cost.

$$p_i = \frac{1}{\alpha} \tag{2.9}$$

This price setting equation readily implies that prices for all intermediate goods are the same. In the steady state, a constant fraction of the labor force, L, will be devoted to final output production. From the demand for intermediate inputs (2.8) it can be inferred that the quantity produced for each variety is the same: $x_i = x$. Profits are equal to $\pi = px - x = \frac{1-\alpha}{\alpha}x$. Note that mark-up-pricing is necessary for the intermediate goods producers to cover the fixed cost of purchasing or developing a patent for good i. Since there is free entry into both the R&D and the intermediate goods sector, the net present value of profits to be gained as a result of the production of intermediate goods will equal the market price of patents, $P_A = \int_t^{\infty} e^{-\int_t^{\tau} r(s)ds}\pi(\tau)d\tau$. Differentiating with respect to time and noting that prices of patents are constant in equilibrium, as will be argued more precisely below, yields

$$rP_A = \pi \tag{2.10}$$

At each point in time the instantaneous profit from producing the intermediate good must cover the interest cost of the original investment in the design.

The sum of all intermediate goods equals the economy wide use of material inputs: $M = \int_0^A x_i di$. Since each intermediate goods firm produces the same amount of x, this relation can also be expressed as $Ax = M$. Therefore, the aggregate production function for the final output good can be written as:

$$Y = (AL_Y)^{1-\alpha}M^{\alpha} \tag{2.11}$$

Holding A constant, returns to scale of the production function of final output are constant in labor and material inputs. However, there are increasing returns in the rival factors and knowledge together.

In Romer's (1990) version of the model, the number of new patents is proportional to labor devoted to research and development:

$$\dot{A} = \zeta L_A A \tag{2.12}$$

The total amount of labor to be divided between the final goods sector and the R&D sector, $L = L_A + L_Y$, is assumed to be constant. It may seem more compelling to interpret L, similarly as in the original Romer-model, not as simple labor, but as the human capital of well-trained individuals. According to this specification of the knowledge production function, the production of new ideas requires only human capital, but no intermediate inputs. The idea behind this is that the production of new ideas is especially human capital intensive.

This specification implies that the number of patents grows at the rate $\gamma_A = \zeta L_A$. The total amount of intermediate inputs will also grow at that same rate because $M = Ax$, and x is constant. It is then obvious from the final production function that final output per capita will grow at the rate of technological progress.

Arbitrage in the labor market ensures that the wage to be earned and thus the marginal product of labor will be the same in the R&D sector and in final goods production:

$$P_A \zeta A = (1-\alpha) L_Y^{-\alpha} A x^{\alpha} = w \tag{2.13}$$

Dividing both sides of (2.13) by A it becomes obvious that P_A is constant, as assumed above.

Again, households maximize lifetime utility (2.2) with respect to their budget constraint. The accumulable assets in this economy are the patents for new products. From equation (2.10) it follows that the return on investments in assets equals the interest rate r. Utility maximization thus results in the familiar Euler equation (2.3).

Final output equals the sum of consumption and material inputs: $Y = C + Ax$. Dividing by the range of intermediate inputs, it turns out that $\frac{C}{A}$ is a constant in equilibrium, because both $\frac{Y}{A}$ and x are constant. So consumption also grows at the rate of technological progress as all other variables. Combining the labor market arbitrage condition, (2.13), with condition (2.10) the demand for intermediate goods (2.8) and the pricing equation (2.9) yields a relation for the amount of labor used in final goods production $L_Y = L - L_A = \frac{r}{\zeta\alpha}$. Inserting this into the Euler equation and combining with the growth rate of the number varieties of intermediate goods, it turns out that the common growth rate of the variables in this model is

$$\gamma_A = \frac{\alpha \zeta L - \rho}{\sigma + \alpha} \tag{2.14}$$

The growth rate is thus increasing in the productivity of research labor ζ and in the size of the economy, L. It is decreasing in the rate of time preference, implying that thriftier societies should grow faster.

Increasing Varieties of Intermediate Capital Inputs

Alternatively, it is possible to interpret the intermediate goods as durable, as in the original Romer model or as in Jones (1995*a*) and Rivera-Batiz & Romer (1991). To decentralize a competitive equilibrium with intermediate capital inputs one possibility is to think of households as accumulating raw capital. This can be captured by the familiar accounting equation, $\dot{K} = Y - C$, which measures investment in capital as the amount of foregone consumption. Households rent out raw capital at the competitive rental rate to intermediate goods monopolists, who transform it one by one into complex capital services of variety i. Intermediate goods producers rent the capital services to final goods producers at the monopolistic rental rate, p_i. Capital is assumed not to depreciate for simplicity. The constant marginal cost of the intermediate goods production therefore equals the competitive rental rate r. The maximization problem of intermediate goods producers thus results in the pricing equation $p = \frac{r}{\alpha}$. As in the non-durable intermediate goods version they charge a mark-up of price over marginal cost of $\frac{1}{\alpha}$.

The sum of all intermediate goods now equals the economy's overall capital stock $K = \int_0^A x_i di$, which can be expressed as $K = Ax$, because both the price and the quantity of intermediate inputs is constant as before. The aggregate production function for the final output can now be written as:

$$Y = (AL_Y)^{1-\alpha} K^{\alpha} \tag{2.15}$$

This reduced form production function is completely equivalent to the production function of the Solow model (2.1). In this model version, households accumulate two different types of assets, physical capital, K, and patents. It follows from equation (2.10), that both yield returns that are equal to the risk-free rate r. Thus, the utility maximization problem results in the usual Euler equation (2.3). Using completely analogous arguments as before, it is not difficult to verify that the divide of labor between research and final production remains the same as in the non-durable goods version of the model and so does the expression for the final growth rate (2.14). Again, per capita output, the number of intermediate inputs, per capita capital and per capita consumption all grow at the same rate.

Increasing Varieties of Consumer Goods

A version of the increasing varieties model in which technological change occurs in the consumption good sector has been formulated by Grossman & Helpman (1991). In this model households maximize lifetime utility as in (2.2). Rather than representing a single homogeneous consumption good, though, c is interpreted as an index of an infinite number of varieties of consumption goods, x_i, that are distributed over the interval $[0, A]$.

$$c = \{\int_0^A x_i^{\varepsilon} di\}^{\frac{1}{\varepsilon}} \quad 0 < \varepsilon \leq 1 \tag{2.16}$$

c reflects the consumers' taste for diversity. Combining the first order conditions of the utility maximization problem for two different varieties yields $\frac{x_i}{x_j} = \frac{p_i}{p_j}^{\frac{1}{\varepsilon-1}}$, where p_i is the price of variety i. Multiplying both sides of the equation by x_j, taking integrals over all varieties j and rearranging yields the demand function for variety $i : x_i = \frac{Ep_i^{\frac{1}{\varepsilon-1}}}{\int_0^A p_j^{\frac{\varepsilon}{\varepsilon-1}} dj}$, where $E = \int_0^A p_j x_j dj$ is the total amount of consumption expenditure. Again consumption goods producers develop their variety themselves or they buy patents for it at price P_A, so that they can act as monopolists. The production technology of the intermediate goods is particularly simple, one unit of labor yielding one unit of variety x_i. Solving the consumption good producers' maximization problem, while taking into account the consumers' demand for variety i yields the pricing equation

$$p_i = \frac{w}{\varepsilon} \tag{2.17}$$

Again, the monopolists charge a mark-up of price over marginal cost, which allows them to cover their research and development costs. The price for consumption goods is constant and the same for each variety: $p_i = p$. Because the different varieties enter the utility function symmetrically, this implies that the quantity demanded of each consumption good is the same as well, so the total amount of consumption $\tilde{X} = \int_0^A x_i di$ can be written as $\tilde{X} = Ax$. The quantity of intermediate goods can then be formulated as

$$x_i = x = \frac{E}{A}\frac{1}{p} \tag{2.18}$$

New varieties of the consumption good are invented according to the same knowledge production function as in the Romer model, (2.12).

The total amount of labor employed in consumption goods production equals $L_c = \tilde{X}$, which is constant in equilibrium. Taking account of (2.18) and the production function of ideas (2.12), it turns out that labor market resource constraint can be written as $L = \frac{E}{p} + \frac{\gamma_A}{\zeta}$. Thus $\frac{E}{p}$ is constant in equilibrium and the quantity consumed of each variety declines at the same rate as the number of varieties increases. Because the amount of resources devoted to production in this economy does not grow, physical output cannot grow either. What does grow is the utility derived from consumption. This can be seen when inserting (2.18) into the consumption index and rearranging, which yields $c = A^{\frac{1-\varepsilon}{\varepsilon}}\frac{E}{p}$. The consumption index is increasing in the number of varieties and so is utility. Thus income grows steadily in terms of its command over utility, although output remains constant in a physical sense.

2.3.2 Increasing Product Quality

As an alternative metaphor for technological change, Aghion & Howitt (1992) assume that research and development increases the quality of intermediate inputs. Innovations improve upon older technologies which are replaced as higher-quality variants are developed. In the spirit of Schumpeter, this theory thus entails an element of creative destruction. As in the increasing varieties models discussed before, technological change manifested in quality improvements can be associated with different types of goods. Grossman & Helpman (Grossman & Helpman (1991), chapter 4) have developed a model where increasing quality is associated with consumption goods. In Aghion & Howitt's (1992) original model of increasing product quality, technological change is associated with non-durable intermediate inputs. In this section, a version of their model is presented in which increasing product quality is associated with capital goods.

In this extended multi-sector version of their original model Aghion & Howitt (1998*a*) assume that consumption goods as well as investments in physical and R&D capital are produced with the same technology

$$Y = C + I + I^R = L^{1-\alpha} \int_0^1 A_i x_i^\alpha di \tag{2.19}$$

where L is the constant amount of labor and x_i the amount of intermediate capital services i. There is a continuum of intermediate goods, indexed on the unit interval $[0, 1]$. The parameter A_i represents the productivity of the latest generation of intermediate good i.

Each intermediate sector is monopolized, similar as in the model above, by the holder of a patent to the latest generation of that good. As local monopolists firms sell capital services of variety i to the competitive final goods producers, so the demand function for intermediate goods equals its marginal product in final production. As in the model discussed above, the intermediate capital services are assumed to be produced with a specified number of units of raw capital. Producing an amount x_i of intermediate capital services requires $A_i x_i$ units of capital. This specification assumes that because of increasing complexity more productive types of intermediate inputs require a larger amount of resources per unit of production.

As in the models discussed before, intermediate goods producers charge a mark-up of price over marginal cost.

$$p_i = \frac{rA_i}{\alpha} \tag{2.20}$$

The profit maximizing supply is $x_i = (\frac{r}{\alpha^2})^{\frac{1}{\alpha-1}}L$, so all sectors produce the same constant amount of capital inputs $x_i = x$. Let A denote the average productivity across all sectors: $A = \int_0^1 A_i di$. Each sector uses $A_i x_i$ units of the capital stock to produce its capital services, so there is a total capital stock, $K = \int_0^1 A_i x_i di$, which can be expressed as $K = Ax$. Substituting this into (2.19) yields a reduced form production function, which is equivalent to the production function of the Solow model

$$Y = C + I + I^R = K^\alpha (AL)^{1-\alpha} \tag{2.21}$$

An innovator who succeeds in improving the quality of an intermediate capital good i replaces the incumbent and monopolizes this sector until the next innovator arrives. In this model version, there is a different research sector for each intermediate good. Firms in each research sector compete to discover the next generation of that particular good. Innovators are assumed to build on the leading edge technology $A^{\max}$, increasing it by a fixed amount γ. When this happens, the productivity parameter A_i in this sector jumps discontinuously to the new leading edge technology parameter. Each discovery is implementable in the innovator's chosen sector only, but by adding to the general knowledge of the society it allows the next innovator to discover a slightly better technology. There are intersectoral spillovers, because innovators in each sector have free access to the technological knowledge embodied in the leading edge technology and are thus able to improve upon it, even when innovating in a different sector. $A^{\max}$ represents the state of technology in the economy.

Innovations are assumed to be governed by a Poisson process with an arrival rate ψi^R, where $i^R = \frac{I^R}{A^{\max}}$ is the productivity adjusted level of research and ψ is a constant. Thus an ever-increasing research level is needed to keep innovations at the same rate. The idea behind this is that as technology advances, it becomes more complex, and thus more resources are needed to improve upon it.

To develop an equation for productivity growth in the increasing varieties model, remember that each innovation raises the leading edge parameter by a factor γ. The expected number of innovations at each point in time equals the Poisson arrival rate ψi^R. Together this implies $\frac{\dot{A}^{\max}}{A^{\max}} = \psi i^R \ln \gamma$. At any point in time there will be a distribution of technology parameters, A_i, ranging from 0 to $A^{\max}$ across the sectors of the economy. This distribution shifts to the right over time as innovating sectors move up to $A^{\max}$, which itself increases due to technological progress. It is shown in appendix B that the long-run distribution of relative productivity $a_i = \frac{A_i}{A^{\max}}$ will always be given by the distribution function $H(a) = a^{\frac{1}{\ln \gamma}}, 0 \leq a \leq 1$, no matter what happens to the absolute size of productivity parameters. Because of this constant distribution, the average productivity parameter, A, grows at the same rate as the leading edge technology.

$$\gamma_A = \psi i^R \ln \gamma \tag{2.22}$$

In this model, ideas are produced with the same technology as final output using both labor/human capital and capital. This is in sharp contrast to Romer's (1990) specification of the knowledge production function (2.12), where the only input to research and development is human capital. While it seems convincing to assume that research and development is human capital intensive, the assumption that no physical capital is required is less obvious. Most researchers use computers and many different kinds of laboratory equipment. A one sector version of the increasing varieties model where ideas are produced with the same technology as final output has been explored by Rivera-Batiz & Romer (1991). They refer to this specification as the lab equipment model.

Aghion & Howitt's (1992) basic model of increasing product quality assumes that labor is the only input to R&D. Thus either of the two alternative specifications of the knowledge production function can be used both in the increasing varieties and in the increasing quality model of R&D based growth. Note that the lab equipment version of the knowledge production function provides a rationale to measure knowledge with the research and development capital stock. As $\frac{\dot{A}}{A} = \psi i^R \ln \gamma$ in the Aghion & Howitt (1998a) model, the number of new ideas can be expressed as $\dot{A} = \phi I^R$. Let a^a denote the constant ratio of the average to the leading-edge productivity $a^a = \frac{A}{A^{\max}}$. Then $\phi = \psi(\ln \gamma)a^a$ is a constant governing the productivity of the research and development input into the knowledge production process. The knowledge production function in Rivera-Batiz & Romer (1991) is completely equivalent. Assuming for simplicity that knowledge does not depreciate and integrating the knowledge production function yields

$$A = \phi \int_0^t I^R(\tau) d\tau = \phi R \tag{2.23}$$

where R is the economy's R&D capital stock. Inserting this into the production function (2.21), it turns out that output is a function of labor, physical and R&D capital. The production function exhibits increasing returns in the rival factors and knowledge together.

In the steady state the growth rate in (2.22) is constant, so investments in R&D grow at the same rate as the leading edge technology. Since $K = Ax$ and x is constant, the capital stock grows at the same rate. It is then apparent from the production function (2.21) that total output grows at that same rate as well. Capital is assumed not to depreciate for simplicity, so $I = \dot{K}$. Dividing by K and recognizing that the growth rate of capital is constant in the steady state it follows that investments in physical capital also grow at the same rate as average productivity. It can then be concluded from the economy's resource constraint $Y = C + I + I^R$ that consumption grows at the rate of technological change as the other variables.

As there is free entry in the intermediate goods sector, the price of a patent equals the net present value of the expected profits to be earned by each intermediate capital goods firm before a new innovator arrives in that sector. The probability of not being replaced before period τ equals $e^{-\psi i^R \tau}$ and operating profits of a firm that innovated at time t are $\pi(t) = (1-\alpha)\alpha L^{1-\alpha}\tilde{k}^{\alpha} A(t)^{\max}$ with $\tilde{k} = x = \frac{K}{A}$. So the price of a patent for this firm's product equals $P_A(t) = \frac{(1-\alpha)\alpha L^{1-\alpha}\tilde{k}^{\alpha} A(t)^{\max}}{\psi i^R + r}$. Increasing investments in R&D by one unit raises research costs by 1 and expected revenues by $P_A \psi \frac{1}{A^{\max}}$. Because there is free entry into the research sector this implies

$$1 = \psi \frac{(1-\alpha)\alpha L^{1-\alpha}\tilde{k}^{\alpha}}{\psi i^R + r} \tag{2.24}$$

As in the increasing varieties model, both types of assets, physical capital and patents, yield the risk free rate r.[2] Thus, the utility maximization problem results in the usual Euler equation (2.3). Together with the zero-profit condition for research and (2.22), this implies that the equilibrium growth rate for output, capital, consumption and productivity will be

$$\gamma_A = \frac{\sigma \ln \gamma}{(\sigma^2 \ln \gamma + \sigma)} (\psi(1-\alpha)\alpha L^{1-\alpha}\tilde{k}^{\alpha} - \rho) \tag{2.25}$$

Similarly as the increasing varieties models, growth is higher in thriftier societies, as the equilibrium growth rate decreases in the rate of time preference. An increase in the arrival rate parameter ψ both increases and decreases the marginal cost of investments in R&D. On the one hand, R&D is more likely to result in a successful invention if ψ is higher, on the other hand the probability of being replaced next period increases. As apparent in (2.25), the first effect dominates. There is the same scale effect as in the increasing varieties model, as the economy's growth rate increases in the number of people in the economy.

This scale effect inherent in all of the R&D based growth models discussed so far is not without problems, as will be discussed in the next section.

[2] Since there is a continuum of sectors with independent rate of creative destruction, the return to a patent just equals the risk-free rate.

2.4 The Problem of Scale Effects

The source of the scale effect in the increasing varieties models discussed before is the knowledge production function (2.12). As the population increases, so does the amount of labor devoted to R&D. According to the knowledge production function, this results in an increase of productivity growth and thus an increase of the common growth rate of all major macroeconomic variables in the model. Jones (1995*b*) shows that this is strongly at odds with the empirical evidence. The size of the labor force in advanced economies has grown dramatically over the past decades, but average growth rates have been relatively constant or have even declined. The direct evidence against the knowledge production function (2.12) is equally compelling. While the number of scientists and engineers engaged in R&D has grown continuously in industrialized countries in the post-war era, total factor productivity (TFP) - if anything - has been declining.

To get rid of this counterfactual scale effect, while maintaining the basic features of R&D based growth models, Jones (1995*a*) reconsiders the intertemporal spillover in the knowledge production function (2.12) in Romer's (1990) model. It may seem plausible to assume that at least some part of previously accumulated knowledge is freely available to researchers helping them to develop ever more complex ideas. Yet, it is rather difficult to argue why this intertemporal spillover should be linear as in (2.12). At the same time linearity is necessary to ensure unceasing growth. Taking a closer look at the arbitrage equation (2.13) it turns out that if the knowledge production function were some concave function in A, rather than being linear, the marginal product of labor in the research sector would decrease as A grows, dragging labor out of research and ultimately bringing growth to a halt. Thus, unceasing growth is possible only because of the specific functional form that is assumed for the knowledge production function.

Jones (1995*a*) generalizes the knowledge production function (2.12) by further specifying the average research productivity ζ. Individual researchers take ζ as given, so that from an individual standpoint, the production function of knowledge is the same as in (2.12). From a society's standpoint, however, the productivity of R&D, ζ, can be further specified, as it may vary with the amount of R&D expenditures and the existing stock of ideas: $\zeta = L_A^{\lambda_k - 1} A^{\varphi_k - 1}$. Thus, the knowledge production function becomes:

$$\dot{A} = L_A^{\lambda_k} A^{\varphi_k} \tag{2.26}$$

$\lambda_k \leq 1$ captures congestion externalities. An increase in R&D effort induces duplication which reduces the average productivity of R&D. This is sometimes called a stepping on toes effect. $\varphi_k \neq 0$ allows for intertemporal knowledge spillovers which may be positive or negative, depending on whether there are diminishing technological opportunities or whether the development of new ideas becomes easier as researchers can build on more and more existing knowledge. All the other elements of Romer's (1990) model remain the same.

In this model version, it is necessary to assume population growth, in order to be able to explain unceasing growth of per capita variables within the model. Let n denote the exogenous rate of population growth. Dividing (2.26) by A, differentiating with respect to time, and observing that the growth rate of A is constant in the steady state, it turns out that the steady state growth rate of the stock of knowledge is equal to

$$\frac{\dot{A}}{A} = \frac{\lambda_k n}{1 - \varphi_k} \tag{2.27}$$

On a balanced growth path all per capita variables grow at the same rate as the number of varieties of intermediate goods, which is the metaphor for technological change in this model. Thus, in this revised version of an increasing varieties model, the economy's growth rate depends on the growth rate of population rather than on its level. Clearly, this is more in line with the empirical evidence than the basic increasing varieties model, although its essential features are maintained. Knowledge creation is a result of deliberate investments in R&D responding to market incentives. Innovative firms have to charge a mark-up of price over marginal cost to cover the fixed costs of knowledge creation. The reduced form aggregate production function (2.15) remains the same as in the Romer model, so there are increasing returns to scale in rival factors and knowledge together.

In models in which innovations are assumed to be produced with both capital and labor as in Aghion & Howitt (1998*a*) and Rivera-Batiz & Romer (1991) the scale effect is less apparent from the knowledge production function itself. In the lab equipment version of the knowledge production function, there is no intertemporal spillover. The number of innovations is proportional to investments in R&D, which thus have to grow at the same rate as the stock of knowledge to guarantee a constant growth rate of new ideas. Yet, there still is a scale effect as apparent in the equation for the equilibrium growth rate (2.25). An increase in L, the size of the economy, increases the total rent to be captured by successful innovators. This should increase the equilibrium amount of resources devoted to innovative activity, which in turn increases the equilibrium growth rate of the economy. In fact, this is the mechanism in which the size of the population, L, influences the equilibrium growth rate in the Aghion & Howitt (1998*a*) model described above. The intermediate goods producers' operating profit is proportional to the size of the economy's population and so is the marginal product of increasing resources devoted to R&D, while the marginal cost is constant. For the research arbitrage condition (2.24) to continue to hold, either the interest rate, r, or the amount of productivity adjusted resources devoted to research, i^R, or both have to increase when the population increases. The Euler equation (2.3) and (2.22) imply that both effects will lead to an increase in the equilibrium growth rate.[3] The mechanism leading to a scale effect in the Rivera-Batiz & Romer (1991) model is very similar.

Attempts by Young (1998) and Aghion & Howitt (1998*b*), chapter 3, and others to eliminate this scale effect are based on the idea that a rise in the profitability of innovative activity due to the exploitation of scale effects may result in an increased

[3]It can be verified that both the interest rate and the Poisson arrival rate ψi^R increase. The interest rate is pinned down by the equilibrium demand for intermediate capital services $r = \alpha^2 \tilde{k}^{\alpha-1} L^{1-\alpha}$. Obviously, it increases with the size of the population. The research arbitrage condition implies that $\psi i^R = \psi(1-\alpha)\alpha L^{1-\alpha}\tilde{k}^{\alpha} - \alpha^2 \tilde{k}^{\alpha-1} L^{1-\alpha}$. In an equilibrium with positive investments in R&D, the first term of the right hand side of the equation has to be greater than the second term. As a direct result of this ψi^R increases in the size of the population as well.

variety of differentiated solutions to similar problems. A higher number of technologies (e.g. an increase is the number and types of cars) raises the utility of the consumers. Yet, if continued improvement of an increasing variety of technologies requires increased research input, because it has to be spread over more sectors, a rise in the scale of the market could increase the equilibrium quantity of R&D without increasing the economy's growth rate.

To see how this effect operates, let's modify the production function of the Aghion & Howitt (1998*a*) model

$$Y = C + I + I^R = L^{1-\alpha} Q^{\alpha-1} \int_0^Q A_i x_i^\alpha di \tag{2.28}$$

where Q is the range of varieties that have been invented. The average productivity of the economy is now defined as $A = \frac{1}{Q}\int_0^Q A_i di$. As in the basic model each sector will supply the same amount of intermediate capital services, which must be the capital intensity per sector, $\breve{k} = \frac{K}{AQ}$, for the capital market to clear. This implies exactly the same aggregate production function as in the basic model (2.21) in which the number of intermediate sectors has no effect.

Horizontal innovations are assumed to occur through serendipitous imitations, so nobody spends any resources on this. Every person in the economy has the same Poisson arrival rate, ψ_i, for innovations, so the number of varieties evolves according to $\dot{Q} = \psi_i L$. The number of workers per sector will converge to a constant $l = \frac{L}{Q} = \frac{n}{\psi_i}$ where n is again the population growth rate.[4]

The growth of knowledge depends only on vertical innovations which arrive with the same arrival rate as before. It is assumed that the rate by which innovations increase the economy's stock of knowledge, $\frac{1}{Q}\ln\gamma$, is inversely related to the number of sectors in the economy. This captures the idea that each vertical innovation represents a smaller proportional increase to the overall stock of knowledge as sectors become more specialized

[4]From $\dot{Q} = \psi_i L$ and $\dot{L} = nL$ it follows that the differential equation driving l is $\dot{l} = nl - \psi_i n^2$, which converges asymptotically to the constant value $l = \frac{n}{\psi_i}$.

due to increases in varieties. The productivity growth rate is thus

$$\gamma_A = \psi \frac{i^R}{Q} \ln \gamma = \psi \check{i}^R \ln \gamma \tag{2.29}$$

where $\check{i}^R = \frac{I^R}{A^{\max} Q}$. As the population grows in this model version, the productivity growth rate is also the common growth rate of all per capita variables, while the level of output consumption and capital grows at the sum of the population and productivity growth rates.

The demand function facing each monopolist has to be modified in that the labor force per sector l enters it where aggregate labor force used to. Thus, the research arbitrage condition becomes $1 = \psi \frac{(1-\alpha)\alpha l^{1-\alpha} \check{k}^{\alpha}}{\psi \check{i}^R + r}$. Since l is proportional to n, this implies that the equilibrium growth rate depends on the population growth rate rather than on its level.

The scale effect implied by the first round of R&D based growth models is clearly at odds with the empirical evidence. Yet, there are several ways to eliminate this scale effect, while preserving the important features of R&D based models, namely the notion that knowledge creation results from market incentives. The next section discusses, how the presented theory is used to structure the empirical investigation in the following chapters.

2.5 Implications for Empirical Research

From the preceding discussion it is clear that technological change can be associated with consumption goods, material inputs or capital goods in R&D based growth models. As stressed before, in reality technological change is likely to be associated with all of these goods at the same time. The production function used in empirical research should include both material inputs and capital as factor inputs to allow for technical change to be associated with either one of them. As technological change embodied in intermediate inputs will always be associated with market-power, value-added is not the ideal output concept for empirical work that investigates R&D based models of economic growth. Basu & Fernald (1995) and Basu & Fernald (1997) have shown that using value added data is very likely to bias results concerning estimates of economies of scale and externalities, if material inputs are not produced in competitive markets. This will be discussed in more detail in the next chapter.

Regardless of the metaphor that is used for technological change and of the type of good with which it is associated, the basic predictions of R&D based growth models are always the same. There is imperfect competition in innovative markets, because somehow firms have to recover the fixed costs of knowledge creation. R&D capital stocks enter the aggregate production function as an additional production factor, because knowledge is embodied in intermediate inputs.

When thinking about industry data, it seems reasonable to assume that each industry engages in several if not all of the activities described in R&D based growth models. Many industries produce consumption goods, capital goods and material inputs. At the same time, they perform R&D to develop new or improved products or more efficient production processes.

R&D based models of economic growth imply several forms of knowledge spillovers. Purchasing material inputs or capital goods from other industries, each industry may take advantage of embodied technological advancements developed elsewhere. Industries can thus enjoy knowledge spillovers through trade, because they do not have to develop this new or improved variety themselves. A second, disembodied spillover associated with the knowledge production process is inherent both in the increasing qualities version of R&D based growth models and in the knowledge production function (2.12). Innovators can take advantage of technological advancements made before, because they have free access to the existing technological knowledge of the economy and are thus able to build upon them.

For empirical purposes, it is preferable to choose a more general production function than the Cobb-Douglas functional form. A general production technology for industry i, which encompasses the more relevant features of R&D based growth models, could be represented as

$$Y_i = F(K_i, L_i, M_i, R_1, ...R_i, ...R_j, t) \tag{2.30}$$

Industry i produces its output, Y_i, using labor, L_i, material inputs, M_i, and its physical capital stock, K_i. Technological progress due to innovations developed in industry i are captured by its R&D capital stock, R_i. Other industries' knowledge capital stocks may enter the production function, because they are embodied in intermediate capital or non-durable inputs that are used in the production process. At the same time, there may be spillovers associated with the knowledge production process, so that other industries' knowledge stocks increase technological change in industry i. The time trend t captures any technological progress due to factors that are exogenous to the model, such as better organization or a change in government regulations.

Each industry that actually conducts research and development, should be expected to charge a mark-up of price over marginal cost to cover the fixed cost associated with knowledge creation. Mark-ups may be expected to be higher in industries where the R&D-intensity, as measured by the ratio of R&D expenditures to output, is relatively high. However, market-power and the size of mark-ups can be related to many other things than a patent or technological knowledge that can effectively be hidden from other producers. Market-power may be due to monopoly rights granted by the government or the level of protection from international trade. Moreover, the size of the mark-up also depends on the price elasticity of market demand.

Economies of scale may be observed in industries conducting research and development because of the fixed cost associated with knowledge creation. In the aggregate production functions (2.21), (2.15) and (2.11) there are economies of scale in rival factors and R&D together. R&D from other industries, which is embodied in intermediate goods, may constitute an external source of economies of scale.

If neither economies of scale nor mark-ups nor any impact of R&D on output and productivity growth can be found in the empirical investigation, this would be clear evidence in favor of the Solow growth model. The source of productivity growth would then remain unclear as in the model. If instead, economies of scale are found, but no mark-ups, this would suggest that Romer's (1986) and Lucas's (1988) models of growth are empirically relevant in that there seem to be increasing returns due to spillovers. Only if mark-ups, economies of scale and a positive impact of R&D on productivity are found together, this would imply that the basic features of R&D based growth models are supported by the data. Such a finding would be strong evidence in favor of the notion that market-driven knowledge creation lies at the heart of the economic growth process.

Chapter 3

Empirical Framework and Data

3.1 Alternative Frameworks for Growth Empirics

3.1.1 The Hall/Solow Residual Approach

The Solow residual is a particularly popular framework to assess the impact of research and development on productivity. To understand its characteristics, consider a general production function $Y = F(X,t)$, where Y is output, $X = (X_1, X_2, ..., X_N)$ is a vector of inputs and t is time. Total differentiation with respect to time, division by Y and rearrangement of terms yields an expression for the primal productivity measure $g \equiv \frac{1}{F(X,t)} \frac{\partial F(X,t)}{\partial t}$:

$$g = \frac{\dot{Y}}{Y} - \sum_i \frac{X_i \frac{\partial F(X,t)}{\partial X_i}}{Y} \frac{\dot{X}_i}{X_i} \tag{3.1}$$

In growth accounting studies input factors are usually confined to capital and labor. Perfect competition is assumed, in which case marginal products can be measured by the corresponding real factor prices $\frac{\partial F(X,t)}{\partial X_i} = \frac{P_i}{P_Y}$, where P_i is the nominal price of factor X_i and P_Y is the price of the output good. Factor i's partial production elasticity, $\frac{\frac{\partial F}{\partial X_i} X_i}{F}$, can thus be measured with the factor's share in income, $s_i = \frac{P_i X_i}{P_Y Y}$: $\frac{\frac{\partial F}{\partial X_i} X_i}{F} = s_i$. Based on this assumption total factor productivity growth can then be calculated as:

$$SR^G = \frac{\dot{Y}}{Y} - \sum_i s_i \frac{\dot{X}_i}{X_i} \qquad (3.2)$$

This is often called the Solow residual. Since partial production elasticities sum to one under constant returns to scale, the production elasticity of capital, $s_K^v = \frac{P_K K}{P_Y Y^v}$ is measured as a residual, $1 - s_L^v$. In this case, the Solow residual corresponds to:

$$SR^v = \frac{\dot{Y}}{Y} - s_L^v \frac{\dot{L}}{L} - (1 - s_L^v)\frac{\dot{K}}{K} \qquad (3.3)$$

If only the competitive final goods' sector is considered R&D based growth models provide a rationale to employ a conventional Solow residual framework to assess their empirical validity (this argument is made by Barro (1999)). In both the increasing varieties and the increasing quality models presented in the previous chapter, the profit maximization condition of the final goods producers with the production function (2.7) and (2.19) respectively can be expressed as $w = (1-\alpha)\frac{Y}{L}$. This implies that the partial production elasticity of labor, $1 - \alpha$, is indeed equal to the labor share of income.

Given that all intermediate capital goods are produced at the same quantity, x, the profit maximization condition for capital goods (2.8) can be expressed as $\alpha x^{(\alpha-1)} L^{(1-\alpha)} = p$. This can be reformulated as $\alpha\frac{Y}{K} = p$, given that $K = Ax$ as outlined in chapter 2. This expression shows that in the final goods market the partial production elasticity of capital services, as well, is correctly measured by the capital income share despite the monopoly pricing in the intermediate capital goods market. The Solow residual corresponds to

$$SR^v = \frac{\dot{Y}}{Y} - (1-\alpha)\frac{\dot{L}}{L} - \alpha\frac{\dot{K}}{K} = (1-\alpha)\frac{\dot{A}}{A} \qquad (3.4)$$

This can easily be derived from the aggregate production function for the final output (2.15) or (2.21). The Solow residual therefore measures part of the endogenous expansion of varieties, $(1-\alpha)\frac{\dot{A}}{A}$, the other part being incorporated in capital input growth $\alpha\frac{\dot{K}}{K} =$

$\alpha(\frac{\dot{A}}{A} + \frac{\dot{x}}{x})$. Based on the lab equipment version of the knowledge production function growth in A can be measured with growth in the R&D capital stock as apparent in (2.23). This suggests, that it should be possible to trace the productivity growth measured by the Solow residual to deliberate research and development effort.

At first sight, it looks as though the popular Hall/Solow residual had a sound theoretical foundation as a framework to test endogenous growth theories. However, this approach is subject to several empirical and theoretical problems when taking a closer look. This derivation of the Solow residual from R&D based models of growth assumes that a competitive final sector, where the goods associated with technological change are merely used, can indeed be separated from those sectors where they are invented and produced. Only if this abstraction could be taken literally in reality and in the very special case where capital inputs alone are associated with technical change, will this derivation of the Solow residual framework from R&D based models of growth be valid.

Yet, in reality it is more likely that technological change is associated with consumption goods, capital goods and material inputs at the same time. Wherever research and development is performed to invent new goods and/or improve their quality, market power should be expected to be present and the equality of factor income shares with partial production elasticities is not a valid assumption. In a theoretical model it may be a permissible simplification to assume that technological change is confined to one specific type of good. Yet, in empirical work it cannot be excluded for any type of good or any market that it is associated with technological change due to knowledge creation. It follows from this that a measure for productivity growth should be robust to the presence of market power by all means.

An important implication from this reasoning is that using value-added to measure productivity growth can be highly problematic, as nothing guarantees that technological change due to research and development effort may not be associated with material inputs. As work by Basu and Fernald has shown (Basu & Fernald 1995, Basu & Fernald 1997), estimates of returns to scale, mark-ups and externalities may be biased when value-added data is used. [1] This occurs, as soon as the market for material inputs is not completely competitive. Constructing value-added measures, researchers attempt in some way to subtract from gross output the productive contribution of intermediate goods, hoping to obtain a measure of net output which only depends on labor and capital. This, however, will be possible only when the assumptions of constant returns to scale and perfect competition hold. Otherwise, the value-added measure still depends on material inputs. Estimates obtained with value-added data may then be seriously biased. Since R&D based models of growth imply that the market for material inputs will be characterized by non-competitive behavior should these goods be associated with technological change, the use of value added data seems questionable.

If endogenous growth theory is right in assuming that innovations as a result of research and development are important in the production of some goods or production processes, then measurement of production elasticities with income shares is flawed.

To see how violation of the perfect competition assumption will bias the Solow residual, note that when market power is present, the optimization condition for factor X_i becomes $\frac{\partial F}{\partial X_i} = \mu \frac{P_i}{P_Y}$, where μ denotes the mark-up of price over marginal cost. Thus production elasticities are equal to $\frac{\frac{\partial F}{\partial X_i} X_i}{F} = \mu s_i$ and the correct measure for productivity growth is

$$g = \frac{\dot{Y}}{Y} - \mu \sum_i s_i \frac{\dot{X}_i}{X_i} \tag{3.5}$$

which does not equal the Solow residual (3.2), unless μ equals 1. In the traditional growth accounting exercise, the weights for factor input growth are too small when market power is present. The Solow residual overestimates productivity growth.

A second bias of the Solow residual as a measure of productivity growth may arise, when returns to scale are not constant. According to the endogenous growth models presented in section 2.2, there may be non-constant returns to scale in rival factors if knowledge is accumulated in fixed proportions to one of them. R&D based models of

[1] Their argument is derived in more detail in appendix C

growth imply increasing returns in rival factors and knowledge together. Moreover there are increasing returns in all sectors that purchase patents or perform R&D themselves to develop new or improved goods due to the fixed costs associated with knowledge creation. Euler's theorem implies that the production elasticities of a homogenous production function sum to the rate of returns to scale, λ. In the case of constant returns to scale λ equals 1, as does the sum of the factor input shares. However, when economies of scale are increasing, λ will be larger than 1 and factor income shares thus underestimate the factors' output elasticities. As suggested in the value-added example above, researchers typically measure the capital income share as a residual to avoid the difficult measurement of the user cost of capital. Clearly, this underestimates the appropriate weight for capital if economies of scale are present, as the sum of production elasticities will be larger than 1.

Overall, the popular Solow residual, which involves the measurement of production elasticities as income shares assuming that these sum to 1, is in many ways not an appropriate framework to investigate endogenous growth theory. Economies of scale are essential building blocks of models with increasing returns due to externalities and of R&D based growth models, while market power is important in the latter type of models in addition to this. Both features are closely linked to research and development effort. Since the Solow residual is biased when the assumptions of constant returns to scale and perfect competition are violated, it is preferable to use a framework which allows for increasing returns and market-power.

Note that the Solow residual framework can be used to estimate mark-ups and increasing returns to scale. To see this, consider a production function $Y = F(K, L, M, t)$, where output, Y, depends on capital, K, material inputs, M, and labor, L. t denotes time. As outlined above, elasticities will be equal to $\frac{\frac{\partial F}{\partial X_i} X_i}{F} = \mu s_i$ for $i = L, M, K$, if market power is present. Moreover, the partial production elasticities may sum to a number λ different from one, when returns to scale are not constant. So the partial production elasticity of capital may be measured as $\mu s_K = \lambda - \mu s_M - \mu s_L$. The traditional Solow residual for gross output calculated under the assumptions of perfect competition and constant returns to scale data then measures:

$$SR^M = g^M + (\mu - 1)(s_M(\frac{\dot{M}}{M} - \frac{\dot{K}}{K}) + s_L(\frac{\dot{L}}{L} - \frac{\dot{K}}{K})) + (\lambda - 1)\frac{\dot{K}}{K} \quad (3.6)$$

where g^M is the primal productivity growth measure for a gross output production function $g^M = \frac{\dot{Y}}{Y} - \frac{\frac{\partial F}{\partial L}L}{F}\frac{\dot{L}}{L} - \frac{\frac{\partial F}{\partial M}M}{F}\frac{\dot{M}}{M} - \frac{\frac{\partial F}{\partial K}K}{F}\frac{\dot{K}}{K}$. The mark-up and the rate of returns to scale thus become estimable parameters.

Including the R&D capital stock as an additional factor of production at the right hand side of equation (3.6) it would be possible to study mark-ups, economies of scale and the impact of R&D on productivity in a corrected Solow residual framework. For some reason, however, the vast majority of researchers use the conventional Solow residual when estimating the impact of knowledge variables on productivity growth, although R&D based growth models clearly imply that the empirical framework should allow for market power and non-constant returns to scale.

The cost function and factor demand model used in this study to empirically investigate important building blocks of endogenous growth theory has some definite advantages even over the corrected version of the Solow residual (3.6). While the latter is of very limited generality, a flexible functional form can be used for the cost function estimation which is much more general as far as substitutability of factors of production is concerned. When constructing the Solow residual, most researchers assume that factor shares are constant over time. This implies an underlying Cobb-Douglas production function, which may lack sufficient generality, restricting for example the elasticity of substitution among production factors to unity.

Of course, it would be an option to estimate a flexible production function, allowing for both market power and economies of scale, while obtaining estimates of the rate of returns to scale and possibly of the impact of R&D on the production of output. It should be emphasized that this approach would be completely equivalent to estimating a cost function. It is, of course, equally permissible. What is important from the point of view of economic theory is to use a productivity growth measure that, unlike the conventional Solow residual, encompasses market power and economies of scale. One attractive feature of the cost function and factor demand system employed in this dissertation is a particularly elegant possibility to estimate mark-ups within the system. Moreover, in contrast to the Solow residual, the cost function and factor demand model readily encompasses varying capacity utilization. This possibility proves very useful as will become apparent in the presentation of empirical results in chapter 4. The next section develops some duality theory to show that with a cost function and factor demand model it is possible to study most of the more relevant features of R&D based growth models.

3.1.2 The Cost Function Approach

Consider the general production function $F(X,t)$. It is a well-known result of duality theory that there will be a cost function that describes the technology in the exact same manner (for a text-book presentation see Mas-Colell, Whinston & Green (1995)). Given a positive vector of N input prices $P \equiv (P_1, ..., P_N)$, the cost function $\tilde{C}$ that is dual to the production function can be defined as

$$\tilde{C}(P,\ Y,\ t) = \min_X \{P'X : F(X) \geqq Y,\ X \geqq 0\} \tag{3.7}$$

where Y denotes output. It can be shown that $\tilde{C}$ satisfies a number of regularity conditions. It is a positive function *i)* $\tilde{C}(\cdot) \geqq 0$, non-decreasing in output, linearly homogeneous, *ii)* $\tilde{C}(mP,Y,t) = m\tilde{C}(P,Y,t)$, where m is a constant, and concave in prices, so that the N by N matrix of second derivatives, $\nabla^2_{PP}\tilde{C}(P,Y,t)$, will be negative semi-definite, provided that $\tilde{C}$ is twice continuously differentiable (see Mas-Colell et al. (1995), chapter 5).

Moreover, if $\tilde{C}$ is differentiable, Shephard's Lemma implies that factor demand functions can be directly derived from it through differentiation: $\nabla_P\tilde{C}(P,Y,t) = X(P,t)$, where $X(P,t)$ is a vector of factor demand. For empirical work, this is one of the attractive features of the dual approach. Since the cost function is derived from optimization behavior, it is based on sound microfoundations. Moreover, factor demands can be derived from the cost function and estimated in a system along with it to increase efficiency. Thereby, they are treated as endogenous variables. This is certainly more appropriate than in the production function approach where input factors appear as independent variables. Nonetheless, it should be noted that endogeneity problems are not entirely solved in the cost function approach, since output is endogenous, being a function of capital, labor and material inputs.

The primal rate of returns to scale is defined as the increase in output due to a proportional increase in all inputs, which equals

$$\lambda = \sum \frac{\frac{\partial F}{\partial X_i} X_i}{F(X,t)} \tag{3.8}$$

according to Euler's theorem. To see that the primal and the dual measure of the rate of returns to scale coincide, remember the cost minimization condition, $P_i = \mu_L \frac{\partial F}{\partial X_i}$, where μ_L is the Lagrangian multiplier of the minimization problem. The latter is the shadow value of relaxing the minimization constraint in the optimum: $\mu_L = \frac{\partial \tilde{C}}{\partial Y}$. Inserting these two expressions into 3.8, it is possible to prove that λ equals the inverse of the cost elasticity with respect to output $\varepsilon_{\tilde{C}Y} = \frac{\partial \ln \tilde{C}}{\partial \ln Y}$, the dual measure of the rate of returns to scale:

$$\lambda = \sum \frac{\mu_L \frac{\partial F}{\partial X_i} X_i}{\mu_L F(X,t)} = \sum \frac{P_i X_i}{\frac{\partial \tilde{C}}{\partial Y} Y} = \frac{1}{\varepsilon_{\tilde{C}Y}} \tag{3.9}$$

The last equality holds, since $\tilde{C} = \sum_i P_i X_i$.

The primal and dual measures of productivity growth are also closely linked. Total differentiation of the cost function with respect to time and division by $\tilde{C}$ yields, after some rearrangement of terms, $\frac{\dot{\tilde{C}}}{\tilde{C}} = \varepsilon_{\tilde{C}Y} \frac{\dot{Y}}{Y} + \sum_i \frac{P_i X_i}{\tilde{C}} \frac{\dot{P}_i}{P_i} + \varepsilon_{\tilde{C}t}$, where $-\varepsilon_{\tilde{C}t} = -\frac{\partial \ln \tilde{C}}{\partial t}$ is the dual measure of productivity growth. Since $\tilde{C} = \sum_i P_i X_i$, the growth rate of costs can also be expressed as $\frac{\dot{\tilde{C}}}{\tilde{C}} = \sum_i \frac{P_i X_i}{\tilde{C}} \frac{\dot{P}_i}{P_i} + \sum_i \frac{P_i X_i}{\tilde{C}} \frac{\dot{X}_i}{X_i}$. Combining the two expressions for the growth rate of costs yields: $-\varepsilon_{\tilde{C}t} = \varepsilon_{\tilde{C}Y} \frac{\dot{Y}}{Y} - \sum_i \frac{P_i X_i}{\tilde{C}} \frac{\dot{X}_i}{X_i}$. Multiplying numerator and denominator of the weights for factor input growth in equation (3.1) with the Lagrangian multiplier of the cost minimization problem μ_L, using $P_i = \mu_L \frac{\partial F}{\partial X_i}$ and $\mu_L = \frac{\partial \tilde{C}}{\partial Y}$ and rearranging shows that the primal measure of productivity growth can be written as: $g = \frac{\dot{Y}}{Y} - \frac{1}{\varepsilon_{\tilde{C}Y}} \sum_i \frac{P_i X_i}{\tilde{C}} \frac{\dot{X}_i}{X_i}$. Primal and dual measure are therefore related as

$$g = -\frac{\varepsilon_{\tilde{C}t}}{\varepsilon_{\tilde{C}Y}} \tag{3.10}$$

If some factors of production are fixed in the short run due to adjustment costs, variable input demand and thus costs will not depend on the price of these inputs, but on their quantities. The quasi-fix inputs cannot be adjusted to changes of their prices and therefore the variable factors will not be affected either. Short-run total costs are then defined as

$$\tilde{C} = G(P_v, Y, X_k, t) + \sum_i P_{ki} X_{ki} \tag{3.11}$$

where X_k is a vector of quasi-fix inputs, P_v includes only prices of variable inputs and P_k prices of quasi-fixed inputs. Cost are minimized and long-run optimum will be attained when $Z_{ki} = P_{ki}$ holds for all quasi-fix inputs, where $Z_{ki} = -\frac{\partial G}{\partial X_{ki}}$ is the shadow value of factor X_{ki}. If this is higher than its market price due to short-run fixities, then it would pay to use more of the input. Capacity is overutilized. If the market price is higher than the shadow value, in turn, there is excess capacity. Notice that a specification where some factors are modeled as quasi-fix contains the equilibrium model as a special case.

Measures for technological change and economies of scale can be derived in a manner analogous to the equilibrium case. Note that the optimization problem for the short-run cost function involves minimizing variable costs subject to a production function which is a function of both variable and quasi-fix input factors:

$$G(P_v, Y, X_k, t) = \min_{X_v} \{P_v^{'} X_v : F(X_v, X_k, t) \geqq Y, X \geqq 0\}. \tag{3.12}$$

Using a completely analogous argument as above it follows that the rate of returns to scale in variable factors equals the inverse of the elasticity of variable cost with respect to output.

To understand how the dual counterpart of the primal rate of returns to scale in variable and quasi-fix factors can be derived, note that

$$\frac{\partial \ln G}{\partial \ln X_{ki}} = -\frac{\frac{\partial F}{\partial X_{kj}} X_{kj}}{\sum_i \frac{\partial F}{\partial X_{vi}} X_{vi}} \tag{3.13}$$

(Caves, Christensen & Swanson 1981). Some steps are required to show that this result is true: $\frac{\partial \ln G}{\partial \ln X_{ki}} = \frac{\frac{\partial G}{\partial X_{ki}} X_{ki}}{G} = \frac{\frac{\partial G}{\partial X_{ki}} X_{ki}}{\sum_j P_{vj} X_{vj}} = \frac{\frac{\partial G}{\partial X_{ki}} X_{ki}}{\mu_L^v \sum_j \frac{\partial F}{\partial X_{vj}} X_{vj}}$. The last step follows from the first order condition of the cost minimization problem with quasi-fix factors, μ_L^v denoting the Lagrangian multiplier of the minimization problem for variable costs. From the envelope theorem, it follows that $\frac{\partial G}{\partial X_{ki}} = -\mu_L^v \frac{\partial F}{\partial X_{ki}}$. This last step establishes the result. Let ε_{GY} denote the elasticity of variable costs with respect to output and $\varepsilon_{GX_{kj}}$ the elasticity with respect to the jth quasi-fix input. It now follows that the overall rate of returns to scale to variable and quasi-fix factors can be derived from the cost function as:

$$\eta_{vf} = \frac{\sum_i \frac{\partial F}{\partial X_{vi}} X_{vi} + \sum_j \frac{\partial F}{\partial X_{kj}} X_{kj}}{F(\cdot)} = \frac{1 - \sum_j \varepsilon_{GX_{kj}}}{\varepsilon_{GY}} \tag{3.14}$$

Lau (1978) has shown that standard cost function properties are maintained for the variable cost function. Most importantly, Shephard's Lemma still holds for the variable inputs. Regularity conditions require that the cost function be decreasing and convex in the quasi-fix inputs, implying that $\nabla_{X_k X_k} G(P_v, Y, X_k, t)$ should be a positive-semidefinite matrix.

Essentially, to model variable cost functions empirically, prices of quasi-fix inputs only have to be replaced by the corresponding quantities. Since capital is often believed to be fix in the short-run, many researchers in the productivity literature specify variable cost functions (Morrison 1988, Kwon & Park 1995). This framework is often referred to as a dynamic factor demand model. It offers an abundance of possibilities of modelling off-equilibrium dynamics. Adjustment costs may be specified, for example, to derive Euler equations from the cost minimization problem to be estimated along with the factor demand system. An overview over the underlying theory and the applied literature is provided in Nadiri & Prucha (1999).

The cost function may also include behavioral or environmental variables, such as the degree of learning of the firm or externalities, as outlined in McFadden (1978a). In that case, the cost function is the specified as $\tilde{C}(P, Y, S, t)$, or possibly $G(P_v, Y, X_k, S, t)$, where S is a vector of M environmental variables. This possibility is exploited by researchers who employ the cost function approach to investigate the role of R&D externalities (Bernstein & Nadiri 1988, Bernstein & Yan 1997, Morrison Paul & Siegel 1997), or of public infrastructure (Mamuneas & Nadiri 1994, Lynde & Richmond 1992). The characteristics of (2.30) are very well encompassed by a suitable cost function which includes other industries' R&D capital stocks as external variables.

To derive the rate of returns to scale in internal and external factors, it can be established with an analogous argument as above that the elasticity of the variable cost function with respect to the mth external factor is equal to $\varepsilon_{GS_m} = \frac{\partial \ln G}{\partial \ln S_m} = -\frac{\frac{\partial F}{\partial S_m} S_m}{\sum_i \frac{\partial F}{\partial X_{vi}} X_{vi}}$. It thus follows that the rate of returns to scale in private and external factors, $\frac{\sum_i \frac{\partial F}{\partial X_{vi}} X_{vi} + \sum_j \frac{\partial F}{\partial X_{kj}} X_{kj} + \sum_m \frac{\partial F}{\partial S_m} S_m}{F(X_v, X_k, S, t)}$, can be derived from a cost function as

$$\eta = \frac{1 - \sum_j \varepsilon_{GX_{kj}} - \sum_m \varepsilon_{GS_m}}{\varepsilon_{GY}} \tag{3.15}$$

Hence, it is straightforward to derive measures of productivity growth and returns to scale from an estimated cost function that accounts for both varying capacity utilization and externalities.

Note that the definition of the cost function and the derived elasticities to measure economies of scale and productivity growth do not rely on competitive markets at any point. The cost function approach is thus a suitable framework to explore the building blocks of typical growth models. In order to explicitly measure the size of mark-ups, the profit maximization condition, $P_Y = \mu \frac{\partial \tilde{C}}{\partial Y}$, can be appended to the factor demand system, where μ is the mark-up of price over marginal cost. μ may either be estimated as a constant or it can be further modeled and estimated as a time-variable function of other parameters.

The cost function and factor demand model readily encompasses all of the more important features of endogenous growth theory. While allowing for both non-competitive behavior and non-constant returns to scale, the impact of knowledge variables on costs can be assessed, and its implication for the overall rate of returns to scale can be quantified. Because of these attractive features, a cost function approach will be used as an empirical framework in this study. Before presenting the exact empirical model, some theory concerning flexible functional forms will be developed in the next section, which should help to assess the generality of the framework chosen in this study.

3.2 The Empirical Model

3.2.1 The Theory of Flexible Functional Forms

The following reasoning draws heavily on Diewert & Wales (1987). Let $\tilde{C}^+(\ P, Y, t)$ be some cost function with N variable inputs, so $P = (P_1, ..., P_N)$. As outlined above, $\tilde{C}^+$ has to be linearly homogeneous and concave in input prices in order to be a valid cost function .

Let $P^+ >> 0_N$, $Y^+ > 0$ and $t^+ > 0$ and let $\tilde{C}^+$ be twice continuously differentiable with respect to its $N+2$ arguments at (P^+, Y^+, t^+). In that case, the linear homogeneity property of $\tilde{C}^+$ in P together with Euler's Theorem on homogeneous functions imply the following $N+3$ restrictions on the first and second derivatives of $\tilde{C}^+$:

$$P^+\nabla_P\tilde{C}^+(P^+,Y^+,t^+) = \tilde{C}^+(P^+,Y^+,t^+) \tag{3.16}$$

$$P^+\nabla^2_{PP}\tilde{C}^+(P^+,Y^+,t^+) = 0_N^T \tag{3.17}$$

$$P^+\nabla^2_{PY}\tilde{C}^+(P^+,Y^+,t^+) = \nabla_Y\tilde{C}^+(P^+,Y^+,t^+) \tag{3.18}$$

$$P^+\nabla^2_{Pt}\tilde{C}^+(P^+,Y^+,t^+) \quad = \quad \nabla_t\tilde{C}^+(P^+,Y^+,t^+) \tag{3.19}$$

where $\nabla_P\tilde{C}^+(P^+,Y^+,t^+)$ denotes the column vector of first order partial derivatives of $\tilde{C}^+$ with respect to the components of P and $\nabla^2_{PP}\tilde{C}^+(P^+,Y^+,t^+)$ denotes the N by N matrix of second order partial derivatives of $\tilde{C}^+$ with respect to the components of P. $\nabla^2_{PY}\tilde{C}^+(P^+,Y^+,t^+)$ and $\nabla^2_{Pt}\tilde{C}^+(P^+,Y^+,t^+)$ denote second order cross derivatives.

The assumption that $\tilde{C}^+$ is twice continuously differentiable together with Young's theorem in calculus imply the following $(N+2)(N+1)/2$ symmetry restrictions.

$$\nabla^2\tilde{C}^+(P^+,Y^+,t^+) = [\nabla^2\tilde{C}^+(P^+,Y^+,t^+)]^T \tag{3.20}$$

where $[\nabla^2\tilde{C}^+(P^+,Y^+,t^+)]^T$ is the transpose of $\nabla^2\tilde{C}^+(P^+,Y^+,t^+)$, which in turn denotes the $N+2$ by $N+2$ matrix of second order partial derivatives of C^+ with respect to all its $N+2$ arguments. A functional form for a cost function is defined as flexible when it "could provide a second order approximation of an arbitrary twice continuously differentiable cost function $\tilde{C}^+$ that satisfies the homogeneity in prices property" (Diewert (1974), page 113). Thus the flexibility property requires that a candidate functional form of some cost function $\tilde{C}$ at the point (P^+, Y^+, t^+) can satisfy the following $1 + (N+2) + (N+2)^2$ conditions:

$$\begin{aligned} \tilde{C}(P^+,Y^+,t^+) &= \tilde{C}^+(P^+,Y^+,t^+) \\ \nabla\tilde{C}(P^+,Y^+,t^+) &= \nabla\tilde{C}^+(P^+,Y^+,t^+) \text{ and} \\ \nabla^2\tilde{C}(P^+,Y^+,t^+) &= \nabla^2\tilde{C}^+(P^+,Y^+,t^+) \end{aligned} \tag{3.21}$$

In other words, the value of the cost function, the $N+2$ first derivatives and the $(N+2)^2$ second derivatives coincide at point (P^+, Y^+, t^+). Imposing homogeneity in prices on the candidate function $\tilde{C}$ involves the $N+3+(N+2)*(N+1)/2$ restrictions (3.16)-(3.20). This reduces the number of free parameters. It thus follows that in order to be flexible $\tilde{C}$ must contain at least $1+N+2+(N+2)^2-N+3+(N+2)(N+1)/2 = N(N+1)/2+2N+3$ free parameters. Notice that this analysis readily carries over to the case of a variable cost function. Just replace factor prices with the quantities of the quasi-fix factors.

A cost function with three inputs would therefore require 15 free parameters in order to qualify as a flexible functional form. With time series data sets over, say, 20-30 years this may preclude estimation due to a lack of degrees of freedom or computational difficulties in many cases. Thus it may often be desirable to sacrifice some flexibility. Establishing some criteria to choose appropriate functional forms, Fuss, McFadden & Mundlak (1978) point out that parsimony in parameters may be advantageous to avoid problems of multicollinearity. Moreover, it is desirable that the results of the empirical investigation be easy to interpret. Excessively parameter-rich functional forms may contain economically implausible implications which are hidden at first sight.

Flexibility in prices may often be a desirable property to allow for arbitrary substitution properties among different factors of production rather than imposing unitary or constant elasticity of substitution. On the other hand, it may well be sufficient to leave the first derivatives of the factor demands with respect to the sources of productivity growth unconstrained, so that $\tilde{C}$ can satisfy $\nabla^2_{Pt}\tilde{C}(P^+, Y^+, t^+) = \nabla^2_{Pt}\tilde{C}^+(P^+, Y^+, t^+)$, while second order derivatives with respect to t and cross derivatives with other variables could be set to zero. As an example, Diewert & Wales (1992) define a technological progress flexible functional form which is not fully flexible with respect to the trend variable, as its second derivative is set to zero.

This discussion should provide some guidance to judge where reasonable generality is achieved in the empirical implementation, where it is sacrificed and on what grounds. It should be noted, however, that flexible functional forms are of course not confined to cost functions. In principle, studies based on a primal approach could be based on a more general production function than the Cobb-Douglas form. For some reason, however, researchers who choose the primal approach often rely on the Cobb-Douglas form, while empirical researchers who choose a cost function prefer more flexible functional forms.

3.2.2 The McFadden Cost Function

A number of flexible functional forms have been developed and used in the literature (for an extensive overview, see Morrison (1993)). One of the most popular is certainly the translog cost function. Its convenience lies primarily in its logarithmic form which implies that elasticities derived from it are linear in parameters. It may be interpreted as a Taylor series approximation to an arbitrary functional form.

One attractive feature of the translog functional form is the fact that it encompasses the Cobb-Douglas cost function as a special case, which is the dual to the Cobb-Douglas production function. Whether or not it is appropriate to use the latter in empirical research, as is frequently done, may be tested formally when a translog cost function is estimated.

In practice, the translog form often poses many problems, however. It is a common problem that estimated cost functions of a flexible form violate regularity conditions (Diewert & Wales (1987)). In this respect, the translog functional form is a particularly complicated case. Because of the logarithmic form, second order derivatives depend on shares and prices. Therefore, they have to be checked for each period and industry.

In fact, a glance at empirical studies that employ the translog functional form reveals that most researchers have to struggle with curvature conditions. Bernstein & Nadiri (1988) have to retreat to a truncated translog form without squared terms to resolve the problem of violated concavity conditions. For some industries in his sample, Mamuneas (1999) has to set several second order price parameters to zero to avoid that his estimated cost function violates concavity restrictions. In principle, imposition of global concavity is possible for the translog cost function, but that removes most of its flexibility (Diewert & Wales 1987).

To tackle problems concerning the concavity restrictions, an alternative functional form will be used on which global curvature conditions can be imposed much more easily than in the translog case. The symmetric generalized McFadden functional form was originally introduced into the literature by Diewert & Wales (1987) as a slight generalization of a functional form proposed by McFadden (1978*b*). The form has been extended by other authors to include fixed inputs (Rask 1995), or external factors (Bernstein & Yan 1997, Bernstein & Mohnen 1998). The following specification is chosen in this study:

$$\begin{aligned}\tilde{C} &= g(P) * Y + \sum_i b_{ii} * P_i * Y + \sum_i b_i * P_i + \sum_i b_{it} * P_i * t * Y \\ &+ b_t(\sum_i \tilde{\alpha}_i * P_i) * t + b_{YY}(\sum_i \tilde{\beta}_i * P_i) * Y^2 + b_{tt}(\sum_i \tilde{\gamma}_i * P_i) * t^2 * Y \\ &+ b_{RY}(\sum_i \tilde{\phi}_i * P_i) * R * Y + \sum_j b_{Sj}(\sum_i \tilde{\zeta}_i * P_i) * S_j\end{aligned} \tag{3.22}$$

where $g(P) = \frac{1}{2}(\frac{P'\bar{S}P}{\theta P})$. P is a N-dimensional vector containing the prices, $\bar{S}$ a symmetric matrix with elements (s_{ij}), and θ a N-dimensional vector of constants selected by the researcher. For identification purposes, N additional restrictions have to be imposed on $\bar{S} : \sum_j s_{ij} = 0$. Note, that the cost function is homogeneous in prices by construction.

In this study, the cost function includes three different prices, namely the wage rate, P_L, the price of material inputs, P_M, and the user cost of physical capital, P_K, so $i = L, K, M$.

The development of R&D projects takes a long time and is subject to many uncertainties. Thus, it seems reasonable to believe that R&D may not be adjusted optimally in each period. This calls for modelling the R&D capital stock, R, as quasi-fix. However, although (3.22) looks like a variable cost function with R&D as a quasi-fix factor, the interpretation in the empirical investigation presented here is different due to the specifics of the data construction. The rival input factors, labor, capital and material inputs, are not corrected for the inclusion of R&D costs. Therefore, b_{RY} does not measure the impact of the R&D capital stock on variable non-R&D costs. It measures the impact on total costs including R&D. This can be interpreted as an excess return to R&D as will be argued more precisely in section 3.3.2. It should also be noted that because of this, the R&D capital stock does not have to comply with the usual regularity conditions for quasi-fix factors.

Three different spillover variables are considered as external factors, namely spillovers from other domestic industries, S_d, spillovers from the same industry in other countries, S_{fs}, and spillovers from the other industries in foreign countries, S_{fo}, so $j = d, fs, fo$. Note that the form is flexible with respect to prices, income and the time trend, but not with respect to R&D and the spillover variables. Flexibility with respect to R&D capital stocks is sacrificed to avoid both excessive complexity and, what is more, problems concerning multicollinearity, which arise because the time trend and all of the R&D capital stocks involved in the estimation are highly collinear.

In principle, the parameters $\tilde{\alpha}_i, \tilde{\beta}_i, \tilde{\gamma}_i, \tilde{\phi}_i, \tilde{\zeta}_i$ could be estimated, setting b_t, b_{YY}, b_{tt}, b_{RY}, b_{Sj} to 1. However, to preserve degrees of freedom, $\tilde{\alpha}_i, \tilde{\beta}_i, \tilde{\gamma}_i, \tilde{\phi}_i, \tilde{\zeta}_i$ are set equal to θ_i, the corresponding element in θ. b_t, b_{YY}, b_{tt}, b_{RY}, b_{Sj} are then parameters to be estimated. Note that the functional form is still flexible with respect to prices of rival factors and the time trend after this simplification. The criterion established in the last section requires $N(N+1)/2 + 2N + 3$ free parameters for a flexible cost function with N factors of production and a time trend, but no external variables. $N(N+1)/2 + 2N + 3$ is 15 in the case of three factor inputs. Letting R&D and spillover variables aside, the cost function contains exactly 15 free parameters after preselecting $\tilde{\alpha}_i, \tilde{\beta}_i, \tilde{\gamma}_i, \tilde{\phi}_i, \tilde{\zeta}_i$.

The choice of θ is completely arbitrary. Different researchers have experimented with many different values, including a value of one for all elements of θ. In this study, the elements of θ are set equal to the sample midpoint of the ratio of the corresponding input value to costs.

As Diewert & Wales (1987) point out, the cost function will be concave in prices if and only if $\bar{S}$ is negative semi-definite. Concavity can be imposed using a technique developed by Wiley, Schmidt & Bramble (1973). According to this approach, $\bar{S}$ is constrained to be equal to $\bar{S} = -\tilde{Z}\tilde{Z}'$, where $\tilde{Z}$ is a lower triangular matrix. The need for at least N restrictions on $\bar{S}$ remains. Row sums may be chosen to equal 0 as above.

Factor demand equations can again be derived using Shephard's lemma.

$$
\begin{aligned}
x_i &= \frac{\sum_k s_{ik} P_k}{\sum_k \theta_k P_k} * Y - \theta_i \frac{\sum_i \sum_k s_{ki} P_k P_i}{(\sum_k \theta_k P_k)^2} * Y \\
&+ b_{ii} * Y + b_i + b_{it} * t * Y + b_t \theta_i * t + b_{YY} \theta_i * Y^2 + b_{tt} \theta_i * t^2 * Y \\
&+ b_{RY} \theta_i * R * Y + \sum_j b_{Sj} \theta_i * S_j
\end{aligned}
\tag{3.23}
$$

for $i = L, K, M$ and $k = L, K, M$. Profit maximization implies $P_Y = \mu \frac{\partial \tilde{C}}{\partial Y}$, where μ is the mark-up of price over marginal cost. In the case of the McFadden cost function the exact specification for this equation is:

$$
\begin{aligned}
P_Y &= \mu \{ g(P) + \sum_i b_{ii} * P_i + \sum_i b_{it} * P_i * t \\
&+ 2 b_{YY} (\sum_k \theta_k * P_k) * Y + b_{tt} (\sum_k \theta_k * P_k) * t^2 + b_{RY} (\sum_k \theta_k * P_k) * R \}
\end{aligned}
\tag{3.24}
$$

The mark-up μ is then a parameter to be estimated. Clearly, it is only identified when estimating the price equation along with the cost function and factor demand system imposing cross equation restrictions. Measures for the rate of returns to scale, the rate of technical progress and cost elasticities with respect to the different capital stocks can easily be derived from the estimated cost function.

Many studies that use the factor demand framework exploit the possibility to model some factors as quasi-fix, often both physical and R&D capital. Adjustment costs are in many cases modeled explicitly. To accommodate possible short-run deviations from equilibrium in this study an error correction form is chosen instead. This framework allows for temporary deviations from optimal adjustment of all factors of production, even those which are not modelled as being quasi-fix. At the same time, there is no need to model adjustment costs explicitly.

Moreover, the error correction form is apt to handle residual autocorrelation. This problem is frequently encountered when estimating factor demand systems. The error correction form is therefore a particularly attractive way to encompass deviations from equilibrium, since as a side-effect, it also tackles econometric problems that are otherwise difficult to handle.

3.2.3 The Error Correction Form

The motivation for the use of an error correction form is the observation that the actual factor demand may not be optimal in each period, because for some reason adjustment to optimum may be costly.

A very general way to model this phenomenon is outlined in Anderson & Blundell (1982). The error correction mechanism can be derived from a general autoregressive distributed lag model. Let X_t denote the vector of actual factor inputs at time t, which is three-dimensional in the case of a variable cost function with R&D capital as a quasi-fix input and physical capital, material inputs and labor as variable inputs. X_t^* is the vector of equilibrium factor inputs when all variable factors are optimally adjusted. For illustrative purposes, a single lag in the adjustment process is assumed, although the derivation can easily be extended to longer lag structures:

$$X_t = A_x X_t^* + B_x X_{t-1}^* + D_x X_{t-1} \tag{3.25}$$

In equilibrium $X_t = X_t^*$, $X_t^* = X_{t-1}^*$ and $X_t = X_{(t-1)}$, $A_x + B_x + D_x = I^M$ must hold, where I^M is the identity matrix. Thus the mechanism can be represented in error correction form as

$$\Delta X_t = A_x \Delta X_t^* + \Gamma(X_{t-1} - X_{t-1}^*) \tag{3.26}$$

where $\Gamma = -(A_x + B_x)$. Note that the elements in X_t^* are combinations of equilibrium parameters and independent variables as apparent in (3.23). The error correction model therefore requires regressing the first differences of actual factor inputs on the lagged factor inputs as well as first differences and lags of independent variables. In the most general form of the error correction model, the estimated parameters of lagged differences of prices, income and R&D variables are linear combinations of the elements in A_x and the equilibrium parameters. The error correction terms, in turn, are linear combinations of the elements in A_x and B_x.

If the autoregressive distributed lag model has a longer lag structure, the error correction form may also include lagged differences of the actual factor inputs. More specifically:

$$\Delta X_t = \sum_j A_{xj} \Delta X^*_{t-j} + \Gamma(X_{t-1} - X^*_{t-1}) + \sum_j E_{xj} \Delta X_{t-j} + w_{xt} \qquad (3.27)$$

where w_{xt} is a vector of error terms and E_{xj} is a parameter matrix. In the empirical investigation presented below, the matrices Γ as well as A_{xj} and E_{xj} are assumed to be diagonal for all lags j. This is done for the sake of simplicity and to preserve degrees of freedom.

While there is no economic theory underlying the short-run off-equilibrium dynamics in (3.27), the equilibrium factor inputs X^*_t can be derived from a cost function applying Shephard's lemma. It is assumed that the cost function can also be represented in an error correction form, which can be derived from an autoregressive distributed lag model in an analogous fashion as above.

$$\Delta \tilde{C}_t = \sum_j \delta^e_{cj} \Delta \tilde{C}^*_{t-j} + \gamma_c(\tilde{C}_{t-1} - \tilde{C}^*_{(t-1)}) + \sum_j \delta_{cj} \Delta \tilde{C}_{t-j} + w_{ct} \qquad (3.28)$$

$\tilde{C}_t$ denotes actual or observed cost at time period t and $\tilde{C}^*_t$ denotes equilibrium costs as specified in (3.22). γ_c is the error correction parameter and w_{ct} is an error term. The $\delta^e_{cj}s$ are the parameters for the lagged differences of equilibrium costs and the $\delta_{cj}s$ for the lagged differences of actual costs. Accordingly, the error correction representation for the price equation can be represented as:

$$\Delta P_{Yt} = \sum_j \delta^e_{Yj} \Delta P^*_{Yt-j} + \gamma_Y(P_{Y(t-1)} - P^*_{Y(t-1)}) + \sum_j \delta_{Yj} \Delta P_{Yt-j} + w_{Yt} \qquad (3.29)$$

The system (3.27)-(3.29) can then be estimated imposing cross-equation restrictions on equilibrium factor shares, X^*_{t-1}, lagged equilibrium prices, $P^*_{Y(t-1)}$, and lagged equilibrium costs, $\tilde{C}^*_{(t-1)}$, as well as cross equation restrictions among lagged differences of these equilibrium variables. Measures for rate of returns to scale, the rate of technological progress and cost elasticities for the R&D variables can be derived from the estimated equilibrium function as outlined in section 3.1.2.

Not only is the error correction model attractive because it allows for deviations from equilibrium without a need to model the adjustment process explicitly, it is also apt to tackle the problem of autocorrelation in the residuals. This is frequently encountered when estimating factor demand systems. Some researchers recur to the traditional Cochrane-Orcutt method to correct for autocorrelation (Nadiri & Nandi 1999). However, as Mizon (1995) shows, a more general specification, such as the error correction form is preferable, since the Cochrane-Orcutt autocorrelation correction imposes common factor restrictions. If invalid, these may bias estimation results.

The next section presents the data used in the empirical investigation.

3.3 The Data

3.3.1 Prices, Output and Inputs

The cost function is estimated with annual two-digit manufacturing industries data of six major OECD countries: USA, Canada, Japan, Germany, France and Italy. An industry list is provided in the data appendix.

Output, factor inputs and the corresponding price data mostly stem from the OECD STAN database. Earlier versions of this dataset have been used before to investigate mark-ups (Beccarello 1996) and the role of knowledge (Keller 2001, Griffith et al. 2000). However, these studies suffer from the problem that earlier versions of this database do not include gross output in constant prices. Therefore, authors were previously confined to using value-added data. The novel feature of the new STAN database used in this study is the availability of gross output and material inputs. The new STAN database offers for the first time the possibility to study production structure and the role of knowledge for productivity with a detailed international industry data set that is not subject to biases associated with the omission of material inputs. Since R&D based growth theory implies that potential biases associated with the omission of material inputs are likely to materialize, this new feature of the STAN database is a definite advantage over earlier versions.

In the STAN database, German data is available for the unified country only which reduces the sample period to 1991-1998. Since this is not enough for reliable estimation, data for West-German manufacturing industries gathered by the Deutsches Institut für Wirtschaftsforschung (DIW) is used instead (Görzig, Schintke & Schmidt 2000).

Output is gross output in 1995 prices. Table 3.1 shows the relative size of each country in terms of its share in aggregate manufacturing gross output and in aggregate R&D capital of all countries. The table also displays aggregate manufacturing R&D capital growth. Both in terms of its share in output as in R&D, the US is the biggest economy followed by Japan and Germany.

Table 3.1: Relative Size of Manufacturing Sectors in Terms of Output and R&D Capital

Country	Share in R&D Capital	Share in Output	R&D Capital Growth
Canada	1.53	4.50	5.81
France	6.98	8.24	3.65
Germany	12.99	12.20	3.37
Italy	2.94	9.57	5.03
Japan	20.11	21.98	6.73
US	55.45	43.51	3.06

(Average Percentage over 1982-1998)

However, the US share in aggregate R&D capital of all countries is significantly higher than its share in aggregate output. Italy and Canada, on the other hand, are smaller in terms of R&D than in terms of output, while the relative size of the remaining countries is approximately the same regardless of the indicator.

This indicates that different R&D intensities, that is ratios of R&D to output, prevail in these countries. However, the manufacturing R&D capital stock grew relatively fast on average in Canada and Italy, where R&D intensity is lower than in other countries, while the slowest growth occurred in the relatively R&D intensive manufacturing industries of the US.

Prices for gross output and value-added are calculated as the ratio of the nominal output series to its constant price counterpart. 1995 is the baseyear. Material inputs are measured as the difference between gross output and value added. The material inputs price is the ratio of nominal material inputs to the same series in 1995 prices.

The labor input variable is measured as total employment, and the wage rate is the ratio of labor compensation to the number of employees. This assumes implicitly that the self-employed receive the same wage rate as the employees. All prices are normalized to 1 in 1995. Consequently, the labor input variable is multiplied by the wage rate of the baseyear, so that the product of labor input and the wage rate equals labor compensation.

Net capital stocks are available for the US, Italy and France. For Canada, Germany and Japan, they are calculated with the perpetual inventory method. All constant price variables are converted to US dollars using 1995 purchasing power parities. The user cost of capital is calculated as $P_K = \omega_K(r + \delta)$, where ω_K is the investment price deflator, r is the real interest rate and δ is the depreciation rate of physical capital.

The sample period is 1980-1998. However, the data is not always complete. For Italian industries, no data is available for the time before 1982. Canadian data is complete only up until 1996. Japanese data is available only for a few relatively aggregate industries.

A detailed description of data sources and variable construction is provided in the data appendix.

3.3.2 R&D and Productivity

Due to data limitations it is not possible to correct labor, material inputs and capital for R&D expenditures to avoid double counting, To understand what this implies for the interpretation of the estimated effect of R&D, consider a simple Cobb-Douglas production function $Y = AL^{\alpha}K^{\beta}M^{\varsigma}R^{\xi}$. Now, the labor variable may include R&D expenditures, because some of the staff works in research and development. Likewise, some of the material inputs just as well as machinery and equipment are used in the process of acquiring new knowledge. Thus, each of the three "traditional" factors of production includes some R&D expenditure.

Note that there is good reason to treat expenditures on R&D labor, capital or material inputs as a special case. New knowledge has a positive impact on output not only today. Some of it will be maintained and enhance productivity in the future. Therefore, there is good reason to subtract R&D expenditures from the traditional factors and construct a stock variable. In that case α, β and ζ measure the production elasticities of traditional factors only, while ξ measures the full impact of R&D. Results have to be interpreted a little differently when labor, capital and material inputs still include their R&D components. ξ will be positive only if knowledge is indeed different from the traditional production factors, in that for example the work of R&D personnel has a stronger and/or longer lasting effect on output than simple production labor. In that sense ξ can be interpreted as an excess return to R&D capital.

An analogous argument can be raised for a cost function. It is important to note that with double-counting a negative effect of R&D on costs is a stronger result than finding regularity conditions fulfilled. It means that R&D reduces costs **including** R&D expenditures. If this is the case, it is certainly safe to conclude that investment in knowledge-creation enhances productivity.

For later comparison with the dual measure of productivity growth, Table 3.2 presents average productivity growth for each industry in the sample as measured by the Solow residual. It is calculated as a discrete time version of (3.2):

$$SR_t = d(\log(Y_t)) - \bar{s}_{Lt}d(\log(L_t)) - \bar{s}_{Kt}d(\log(K_t)) - \bar{s}_{Mt}d(\log(M_t)) \tag{3.30}$$

where t is a time index, $d(\cdot)$, is the first difference operator, $d(Z_t) = Z_t - Z_{t-1}$. $\bar{s}_{it}$ is the time t average of the income share of factor i over two consecutive years: $\bar{s}_{it} = \frac{1}{2}(s_{it} + s_{i(t-1)})$. The total factor productivity is thus constructed as a Divisia index,

Table 3.2: Average Growth of Total Factor Productivity; 1980-1998; in per cent

Country / Industry	Canada	France	Germany	Italy	Japan	US
Food	-0.21	-0.39	0.33	0.30	-1.21	-0.05
Textiles	0.41	0.47	0.22	0.81	-	0.96
Wood	0.55	-	0.64	1.57	-	-
Publishing	-0.63	0.42	0.50	0.72	-	-
Chemicals	0.94	-	0.80	1.36	-	1.19
Plastics	0.56	-	0.44	0.21	-	1.42
Mineral Prod.	-0.10	1.09	0.03	0.81	-	1.16
Metals	0.50	0.70	0.77	1.14	-0.02	0.71
Machinery	-0.31	0.76	0.82	0.69	0.13	-
Elect. & Opt. Eq.	1.45	1.75	0.67	1.36	2.13	-
Transport	0.26	0.58	0.34	0.83	-0.17	0.57
Man N.E.C.	-0.13	0.26	0.30	0.43	-	-

which is a correct approximation to a translog cost function. This encompasses more flexibility than calculating the weights as the average weight over the sample period, which implicitly implies a Cobb-Douglas cost function.

Overall, productivity growth measured with the Solow residual is rather small. It rarely exceeds 1%. Only in the electrical and optical equipment industry in Japan does it exceed 2%. In general, the Solow residual is highest in the chemical industry and in electrical and optical equipment. It is lowest in the food and tobacco industry, where the average over the sample period is negative for France, Japan, Canada and the US. Negative productivity growth is observed in a number of Canadian industries in addition to this, including the paper and publishing industry, mineral products, the machinery industry and manufacturing n.e.c.. The same holds for the Japanese transport as well as the basic and fabricated metals industry. Negative productivity growth, implying technological regress, is certainly hard to interpret from an economic point of view.

As endogenous growth theory suggests that there is a link between R&D activity, mark-ups and economies of scale, it is useful at this point to take a look at the R&D data used in this study. The lab equipment version of R&D based growth models implies that knowledge stocks can be measured with R&D capital stocks, as apparent in equation

(2.23). Yet, it is generally agreed upon that research and development expenditures are an imperfect measure for innovations, because they are an input rather than an output of the knowledge production process. Not all of the research and development expenditures will be equally successful in generating innovations. However, as innovations are not directly observed, R&D expenditures are widely used as a proxy. It is hoped that by the law of large numbers innovations will on average be proportional to R&D expenditures. Output measures of the innovation process, such as patent counts, are generally not deemed superior. Firstly, many innovations are not patented and, secondly, patents will generally not be of equal quality. The value of patents may differ sharply. Although this is also true for R&D investments, the law of large numbers is more likely to alleviate this problem in the case of R&D expenditures than in the case of patents, mainly because the propensity to patent differs for different kinds of innovations.

R&D investment data provided in the OECD's ANBERD database (OECD 1999) is used to construct R&D capital stocks. This data covers all intramural business enterprise R&D expenditure. The R&D capital stocks are compiled applying the perpetual inventory method to the R&D investment data. The investment series are deflated with the respective country's GDP-Deflator. The depreciation rate δ_r is assumed to be 12% which coincides with Nadiri & Prucha's (1993) estimate of the R&D capital stock depreciation rate for the US total manufacturing sector. All R&D capital stocks are converted to US Dollars using 1995 purchasing power parities.

Since the relative size of countries in terms of output and in terms of R&D differs considerably in some cases, it seems to be the case that R&D intensities vary across countries, as argued in the previous section. To get a more detailed picture, Table 3.3 displays R&D-intensity by industry as measured by the ratio of R&D expenditures to gross output over the period 1980-1998. US and Japanese industries tend to be a little more R&D intensive than those of other countries, while R&D intensity is remarkably low in Italian industries. Overall, the same industry groups tend to be the most R&D intensive across countries, namely chemicals, electrical and optical equipment and transport

Table 3.3: Average Ratio of R&D to Output; 1980-1998; in per cent

Country / Industry	Canada	France	Germany	Italy	Japan	US
Food	0.16	0.22	0.18	0.07	0.57	0.32
Textiles	0.30	0.21	0.32	0.01	0.54	0.19
Wood	0.13	0.11	0.18	0.03	-	0.31
Publishing	0.30	0.10	0.18	0.02	0.31	0.38
Chemicals	1.60	3.58	4.66	2.14	4.84	4.50
Plastics	0.31	1.68	1.01	0.55	6.03	1.08
Mineral Prod.	0.21	0.68	0.85	0.08	1.89	1.04
Metals	0.46	0.57	0.85	0.26	0.99	0.58
Machinery	1.03	1.37	2.22	0.50	1.85	1.57
Elect. & Opt. Eq.	7.55	6.86	6.36	3.29	5.98	8.92
Transport	1.16	4.97	4.60	3.84	2.72	8.25
Man N.E.C.	0.51	0.26	0.51	0.03	-	-

equipment. Only the Canadian chemical industry is not very R&D intensive.

Especially in the case of the electrical and optical equipment and the chemical industry relatively high R&D intensity and relatively high productivity growth seem to coincide. However, the Solow residual used to measure TFP growth displayed in Table 3.2 is biased upward if market power and economies of scale prevail, as should be the case according to R&D based growth theories. Therefore the productivity growth measure derived from the cost function and factor demand model discussed in section 3.2.2 is presented in the next section. This framework does not impose any restrictions as far as competitiveness and returns to scale are concerned. At the same time, the factor demand model is used to obtain estimates of mark-ups and economies of scale to assess how important it is empirically to choose a framework which is robust to the presence of mark-ups and/or economies of scale.

Chapter 4

Productivity, Mark-Ups and Economies of Scale

4.1 Estimation Method

Productivity growth lies at the heart of the growth process according to most models of economic growth. If market power and economies of scale are present as R&D based models of economic growth suggest, it is of crucial importance to measure productivity growth within a framework that is robust to the presence of economies of scale and market power, such as the cost function and factor demand system described in equations (3.22)-(3.24). To concentrate on the empirical importance of mark-ups and economies of scale and on the implications for the measurement of productivity growth, this system is estimated without including R&D capital stocks and spillover variables as a first step.

It is sensible to suspect that there may be important differences between, say, the food industry and the chemical industry in each country. At the same time, the production structure of the chemical industry is very likely to be similar in different industrialized countries. Therefore, each industry is pooled across countries. The cost function is then estimated industry by industry. Unfortunately, complete data for all of the six countries is available only for a few rather aggregate industries. The cost functions for the more disaggregate industries are estimated each with only a subset of the countries.

The system (3.22)-(3.24) is first estimated directly with Seemingly Unrelated Regressions (SUR). The size of the industries sometimes differs significantly across countries. To make the assumption of homoscedasticity more plausible the factors of production and output are normalized by dividing them with the industry's sample average of output. The parameters θ_L, θ_K and θ_M are set equal to the average of the ratio of the corresponding factor to costs. Results are reported in appendix A.1.

Since the production of output is a function of capital, labor and material inputs, it can hardly be regarded as exogenous. Thus an instrumental variable estimation technique would be preferable. Variables such as output, labor, capital and material inputs typically display strong autocorrelation. The same goes for the price variables. In this sense, lagged arguments of the cost function are valid instruments. However, both Durbin-Watson statistics reported in appendix A.1 and Ljung-Box Q-statistics (not reported) indicate that there is strong autocorrelation in the residuals. If output is suspected to be correlated with contemporaneous error terms, which in turn are autocorrelated, then there is no reason to assume that lagged output is uncorrelated with subsequent error terms. Thus, since only bad instruments are available, uninstrumented estimation techniques are preferred, although they may be subject to an endogenous variable bias.

The autocorrelation in the residuals may well be interpreted as evidence that the equilibrium model, which assumes that all factors are adjusted optimally at all times, is not appropriate. The error correction model allows for very general off-equilibrium dynamics. At the same time it is suitable to overcome the problem of autocorrelation in the residuals. Estimation results obtained with the error correction framework are reported in appendix A.2. It is assumed for simplicity that the matrices A_{xj}, E_{xj} and Γ in the factor demand system (3.27) are diagonal. Although this is a strong assumption, including off-diagonal elements in the estimation usually results in insignificant estimates, so the simplifying assumption seems appropriate. The length of the lag structure is decided by the data in the sense that additional lags are included until Ljung-Box Q-

Statistics cannot detect any more autocorrelation in the residuals.

It seems natural to assume that once the problem of autocorrelation is solved, instrumental variable estimation can be applied. However, with the error correction form including first differences of all dependent and independent variables another problem arises. While output, inputs and prices in levels are all strongly autocorrelated, this is not true for the first differences of these variables. The correlation of the differenced variables with their own lags are extremely small, regardless of whether the lags are in differences or in levels. Thus, at least for the differences in the error correction equations no valid instruments are available.

As research on the properties of instrumental variable estimators in small sample shows (Nelson & Startz 1990), the instrumental variable bias may in fact be worse than the OLS bias when the instruments are only weakly correlated with the instrumented variables. Staiger & Stock (1997) point out that the instrumental variable estimator has to be treated with caution when first stage F-statistics are below 10. For the differenced variables, the first stage F-statistic is almost invariably below 2. For this reason, SUR is the preferred estimation method for the cost function in the error correction form. Unfortunately, the endogeneity problem remains unsolved. While many authors who investigate dynamic factor demand models use three-stage least squares or other instrumental variable methods, their data is very likely subject to the same problems discussed here. Most authors simply do not seem to consider problems concerning residual autocorrelation and the validity of the instruments they use.

Country-industry specific effects are captured by estimating the constants of the factor demand equations b_M, b_L and b_K and the mark-up μ with industry-country-dummies. All other parameters are assumed to be the same across industries in different countries. For some industries the estimation in levels imply a Hessian matrix, $\bar{S}$, that has one eigenvalue slightly larger than zero, thus violating regularity conditions. However, imposing concavity changes parameter estimates only very little. It is not tested whether the positive eigenvalues are significant, because the problem disappears completely when the error correction specification is applied. Accounting for short-run deviations from equilibrium results in estimates which imply a concave cost function without any exception. It is thus concluded that the positive eigenvalues implied by some of the direct estimates, if anything, are a result of specification error. In what follows, the discussion is based solely on results obtained with the error correction form. However, it should be noted that the similarity of the direct and the error correction estimates underlines the robustness of the results.

Although Durbin-Watson statistics are reported in the tables, they are not valid test-statistics when lagged dependent variables enter the estimation equation. Therefore, Ljung-Box Q-statistics are used to decide how many lags have to be included to remove the autocorrelation structure in the residuals. It is interesting to note that while for the material inputs demand one lag is often enough, it is not rare that up to three lags have to be included in the capital inputs equation to obtain residuals that look like white noise. This supports the view that material inputs can be adjusted rather quickly, while adjustment costs for capital seem to be high and thus adjustment to changes in exogenous variables is slow. The labor demand equation also requires a number of lags in most cases. This suggests that the common specification in dynamic factor demand models, where capital is assumed to be quasi-fix, but labor and material inputs are variable, may not be adequate. The generality of the error correction model, which allows for short-run deviations from equilibrium for all factors of production, thus appears as a definite advantage over dynamic factor demand models, where the researcher has to decide beforehand which factors of production are variable and which are not.

To test whether unit roots in the data may cause problems, Im, Pesaran & Shin's (1995) test for heterogenous panels is applied to the variables entering the cost function. This test is based on the t-statistic of Dickey-Fuller tests averaged over all cross sections. Im et al. (1995) show that their panel unit root test substantially increases the power of the conventional Dickey-Fuller test, while allowing for heterogeneity in that the estimated coefficients as well as residual serial correlation are allowed to differ across groups. The test is conducted with a panel including all of the 56 cross-sections (12 industries with a differing number of countries up to 6) for which data is complete. To take account of autocorrelation in the residuals augmented Dickey-Fuller tests with one lagged difference are performed for each variable in levels. Since all variables are trending a trend term is included in all of the regressions. The t-bar statistics are reported in Table 4.1 The

Table 4.1: Im-Pesaran-Shin-Test for a Unit Root in Heterogeneous Panels

K	L	M	Y	P_L	P_K	P_M	P_Y
-3.342**	-2.81**	-2.47**	-2.44*	-2.01	-2.18	-2.99**	-2.69**

Table shows average T-Statistic of an Augmented Dickey-Fuller Test with 1 Lag
Critical Values (Im et al. (1995), Table 4): -2.46 (1%); -2.38 (5%); −2.33 (10%)
**Null Hypothesis of a Unit Root can be rejected at a 1% Level of Significance
*Null Hypothesis of a Unit Root can be rejected at a 5% Level of Significance

critical values for the t-bar statistics containing a trend with 20 time periods and 50 cross sections reported in Im et al.'s (1995) Table 4 are -2.46 (1%), -2.38 (5%) and -2.33 (10%). This setup is closest to the panel investigated in this study with 56 cross sections and 19 time periods. As can be seen in Table 4.1, the null hypothesis that all cross sections contain a unit root can be rejected at a 1% level of significance for all variables but the wage rate and the user cost of capital. For the latter two variables the null hypothesis cannot be rejected even at a 10% level of significance. However, Im et al.'s (1995) Monte Carlo simulations reveal that the power of their test, although higher than for the Dickey-Fuller test for single times series, is very low especially with short panels as the one investigated in this study. While the possibility that some of the variables may contain a unit root cannot be completely dismissed, it may just as well be the case that all of the variables are trend stationary. The statistical tools available at present to test for unit roots in short panels do not seem to be powerful enough to draw any unequivocal conclusions.

Since the possibility of unit roots governing the time series properties of some of the variables cannot be completely dismissed, it is useful to take a look at the error corrections terms which are all significantly negative and thus indicate reversion to equilibrium.

Indeed, the majority of error correction terms are significant enough to pass the Banerjee, Dolado & Mestre (1996) test for cointegration. This cannot be viewed as an exact cointegration test for the cost function and factor demand system estimated in this study, because it is designed for single-equation frameworks without the complicated multiplicative terms of independent variables which appear in cost functions of the flexible functional form. Nevertheless, the test can serve as a guideline to judge whether the estimated cost and factor demand functions can be viewed as cointegrating relationships should some of the variables be non-stationary.

Table 4.2: T-Statistics of the Error Correction Terms

Industry	Cost	Labor	Capital	Mat. Inputs.	Price
Food	-3.775	-5.903	-3.532	-6.402	-5.403
Textiles	-3.639	-7.522	-4.107	-5.218	-3.270
Wood	-3.628	-3.916	-3.797	-2.674	-5.967
Publishing	-4.317	-4.195	-3.066	-4.188	-6.616
Chemicals	-6.934	-4.626	-4.055	-8.418	-4.530
Rubber	-6.547	-7.672	-5.239	-7.297	-3.638
Mineral Prod.	-2.448	-7.789	-5.108	-3.165	-4.798
Metals	-4.896	-6.583	-4.713	-3.874	-5.991
Machinery	-4.935	-6.860	-5.314	-5.953	-1.462
Elect. & Opt Eq.	-6.044	-7.718	-3.144	-5.205	-5.993
Transport	-5.113	-6.248	-4.355	-6.258	-3.928
Man., N.E.C.	-9.489	-10.460	-4.768	-11.211	-2.269

T-statistic of the EC- term for the Cost Function,
the Factor Demands and the Price Equation

The test is based on the conventional t-statistics for the error correction term. If it is large enough in absolute value, the null hypothesis of no cointegration can be rejected. The critical values for a sample size of fifty with five independent variables are -4.6 for the 5% significance level, -4.19 for the 10% significance level and -3.53 for the 25% significance level. Unfortunately, critical values for estimation equations involving more than five independent variables are not reported in Banerjee et al.'s (1996) paper. The t-statistics for the error correction terms of the estimated cost, factor demand and price functions are reported in Table 4.2. The majority of the statistics exceed the 5%-critical value. In most industries the error correction term for one of the equations - in some cases for two - is not significant enough to reject the null hypothesis of no cointegration at a 10% significance level. However, the t-statistics of the remaining error correction terms often exceed the 5-percent critical value by far. Since all of the equations in the factor demand system are derived from the same cost function, it is certainly permissible to argue that if statistical tests suggest that the majority of the equations in the system are cointegrating relationships, it follows from theory that all equations in the system must be cointegrating relationships. The only industry which looks critical is the wood industry, where four out of five error correction terms are not significant enough to reject the null hypothesis of no cointegration. Again it has to be kept in mind that this test as well has low power against the alternative.

Since the McFadden form is a second order approximation to a completely general cost function and factor demand system, theory clearly implies that it should be possible to fit the data to such a system. While it would be easier to analyze unit root and cointegration problems with a simpler functional form, it is highly questionable based on statistical tests whether unit roots are present at all. Moreover, the available statistical evidence points towards unit root problems being under control, should they be present at all. The cost function framework employed in this study has many advantages, including its generality and the possibility to accommodate varying capacity utilization. Since it is extremely hard to analyze unit roots in short panels in any case, economic theory should be emphasized more strongly as a basis for the analysis than unit root econometrics. Therefore, the advantages of the cost function and factor demand system are deemed more important than the disadvantage that unit root problems are particularly difficult to handle in this framework, should they be present.

4.2 Productivity Growth

In the majority of growth models discussed in chapter 2, technological change is the driving force of economic growth. Therefore, it is useful to start the investigation taking a look at the productivity growth measure derived from the cost function estimation. It is particularly interesting to compare this measure with the Solow residual, because this is a first stepping stone to distinguish whether endogenous theory is better supported by the data than the neoclassical theory. The Solow residual is biased upwards as a productivity growth measure, if economies of scale and/or market power are present Therefore, the dual measure, which does not hinge on the assumptions of competitive markets and constant returns to scale, should be systematically smaller than the Solow residual, if endogenous growth theory is relevant. In contrast, the primal and dual measure of productivity growth should be equal if the neoclassical model explains the growth process well.

The average productivity growth as estimated by the cost elasticity with respect to the trend term is negative in five industries as can be verified in Table 4.3. Standard errors of the elasticity computed with the delta method (Greene (1997), chapter 6) indicate that this is significant, implying the presence of technological regress, which is certainly hard to interpret economically. Productivity growth is indistinguishable from zero in the non-metallic mineral products industry. Only in the electrical and optical equipment industry is it as high as 1% per annum. Significantly positive productivity growth can be found only in this industry, in basic and fabricated metals and in the textiles industry.

However, in most industries a majority of the parameters associated with the trend term is insignificant as can be verified in appendix A.2. This holds especially for the squared trend term, which is extremely small in all industries and in most cases insignificant. The electrical and optical equipment industry is the only case, where all the trend parameters are significant. While it is a priori desirable to chose a very general specification of productivity growth as in the cost function (3.22), the insignificance of many of the trend-term parameters suggests that an easier specification may be preferable.

Table 4.3: Average Productivity Growth; 1980-1998; Flexible Specification

Industry	US	Italy	Japan	Germany	Canada	France
Food	-0.52	-0.45	-0.5	-0.49	-0.60	-0.52
	(0.15)	(0.14)	(0.16)	(0.14)	(0.17)	(0.15)
Textiles	0.68	0.65	-	0.63	0.68	0.63
	(0.11)	(0.11)	-	(0.11)	(0.12)	(0.11)
Wood	-	-0.51	-	-0.51	-0.57	-
	-	(0.17)	-	(0.18)	(0.19)	
Publishing	-	-0.95	-	-1.06	-1.22	-1.12
	-	(0.35)	-	(0.32)	(0.37)	(0.32)
Chemicals	0.07	0.11	-	0.07	0.001	-
	(0.13)	(0.12)	-	(0.12)	(0.15)	-
Plastics	-0.38	-0.32	-	-0.45	-0.53	-
	(0.14)	(0.15)	-	(0.16)	(0.18)	-
Mineral Prod.	0.04	0.02	-	0.01	0.03	-
	(0.14)	(0.13)	-	(0.15)	(0.16)	-
Metals	0.36	0.35	0.29	0.33	0.38	0.034
	(0.12)	(0.12)	(0.12)	(0.12)	(0.046)	(0.012)
Machinery	-	0.33	0.33	0.36	0.47	0.37
	-	(0.20)	(0.21)	(0.23)	(0.24)	(0.22)
Elect.& Opt Eq.	-	1.01	1.00	1.00	1.12	0.96
	-	(0.21)	(0.22)	(0.21)	(0.23)	(0.32)
Transport	0.10	0.10	0.10	0.13	0.19	0.14
	(0.17)	(0.16)	(0.16)	(0.17)	(0.05)	(0.18)
Man. N.E.C.	-	-0.31	-	-0.46	-0.69	-0.64
	-	(0.11)		(0.13)	(0.16)	(0.15)

(Standard Errors in Parentheses)

Therefore, the cost function is reestimated setting all trend parameters but b_t to zero. This is done for all industries but electrical and optical equipment, where the flexible specification of productivity growth seems to be appropriate. The resulting estimate of productivity growth is presented in Table 4.4. Results seem a lot more convincing than with the flexible specification. While the estimates are still well below 1 percent in all of the investigated industries, they are now significant in almost all of the industries where the estimate of average productivity growth is positive. Only in the food industry is the estimate still significantly negative. The negative estimate in the wood and the paper and publishing industry is now insignificant, while estimated productivity growth even becomes significantly positive in manufacturing n.e.c.

Table 4.4: Average Productivity Growth; 1980-1998; Simple Specification I**

Industry	US	Italy	Japan	Germany	Canada	France
Food	-0.23	-0.22	-0.25	-0.22	-0.24	-0.22
	(0.11)	(0.11)	(0.12)	(0.11)	(0.12)	(0.11)
Textiles^{+}	0.68	0.65	-	0.64	0.66	0.63
	(0.09)	(0.09)	-	(0.09)	(0.09)	(0.09)
Wood	-	-0.08	-	-0.09	-0.09	-
	-	(0.16)	-	(0.18)	(0.18)	-
Publishing	-	-0.20	-	-0.21	-0.22	-0.20
	-	(0.31)	-	(0.32)	(0.33)	(0.31)
Chemicals	0.43	0.40	-	0.40	0.45	-
	(0.11)	(0.99)	-	(0.09)	(0.11)	-
Mineral Prod.	0.32	0.29	-	0.32	0.34	0.32
	(0.16)	(0.14)	-	(0.16)	(0.17)	(0.16)
Metals	0.21	0.21	0.20	0.21	0.22	0.22
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Machinery	-	0.31	0.33	0.34	0.35	0.32
	-	(0.20)	(0.21)	(0.22)	(0.22)	(0.21)
Transport	0.28	0.27	0.26	0.28	0.30	0.29
	(0.17)	(0.16)	(0.16)	(0.17)	(0.18)	(0.18)
Man N.E.C.	-	0.26	-	0.27	0.29	0.31
	-	(0.12)	-	(0.12)	(0.13)	(0.14)

**Only b_t measures the impact of the trend term
(Standard Errors in Parentheses)
$^{+}b_{Lt}$ not set to zero

Results are not reported for the rubber and plastics product industry, as the simple specification results in a violation of concavity conditions. This also holds for the textiles industry. In this case, it is enough to allow not only b_t but also b_{Lt} to be different from zero to obtain estimates that comply with regularity restrictions. As can be verified in appendix A.2, this is the only trend term parameter that is significant in the cost function estimation with the flexible specification of productivity growth. Both b_t and b_{Lt} are significantly negative, when all the other insignificant trend term parameters are set to zero. Therefore, this seems to be an appropriate specification for the textiles industry. Indeed, comparing Tables 4.3 and 4.4 it turns out that the productivity estimate hardly changes when the insignificant trend term parameters are set to zero.

For a number of industries, Table 4.5 reports average productivity growth estimates obtained with a specification where b_{Lt}, b_{Mt} and b_{Kt} are estimated, while b_t is set to zero. This is deemed suitable as an alternative specification for those industries where b_t is insignificant, while b_{Lt}, b_{Mt} and b_{Kt} or at least two of them are significant in the estimation with the fully flexible trend term specification.

The estimated productivity growth for the machinery industry is slightly lower than before, but it is estimated more accurately, standard errors being lower than in the specification in which only b_t measures the influence of the trend term. In the basic and fabricated metal industry, neither the size of the estimate nor the standard errors change much. In the transport equipment industry, the estimate of the average productivity growth is negative with this alternative specification, although insignificant. In all of these industries, b_{Lt}, b_{Kt} and b_{Mt} are significant without exception. b_{Kt} is barely significant at a 10%-percent significance level, but it is included in the estimation for the paper and publishing industry. In contrast, only b_{Mt} and b_{Kt} are significant in the estimation for the wood and the chemical industry, so b_{Lt} is set to zero.

With the alternative simple trend term specification, the estimated productivity growth is lower but still significantly positive for the chemical industry. Unfortunately, it is again significantly negative for the wood industry and the paper and publishing industry in all countries. Estimates are not reported for industries, where only one out of the three remaining trend term parameters is significant (food and other non-metallic mineral products), or where this specification results in estimates which do no comply with concavity restrictions (manufacturing industries n.e.c.).

Both of the two simpler specifications of the trend term yield significantly positive estimates for all industries for which the productivity growth estimate is positive but insignificant with the flexible specification. Yet, the finding of technological regress cannot be completely dismissed for the five industries, which display significantly negative productivity growth in the estimation with the fully flexible trend term specification.

Table 4.5: Average Productivity Growth; 1980-1998; Simple Specification II**

Industry+	US	Italy	Japan	Germany	Canada	France
Wood	-	-0.46	-	-0.44	-0.52	-
	-	(0.11)	-	(0.12)	(0.13)	-
Publishing	-	-0.30	-	-0.36	-0.34	-0.40
	-	(0.13)	-	(0.12)	(0.15)	(0.13)
Chemicals	0.17	0.17	-	0.15	0.17	-
	(0.007)	(0.006)	-	(0.006)	(0.007)	-
Plastics	-0.13	-0.01	-	-0.18	-0.15	-
	(0.09)	(0.10)	-	(0.10)	(0.10)	-
Metals	0.29	0.27	0.21	0.25	0.30	0.26
	(0.05)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)
Machinery	-	0.31	0.27	0.29	0.35	0.28
	-	(0.13)	(0.14)	(0.15)	(0.14)	(0.14)
Transport	-0.16	-0.11	-0.15	-0.13	-0.15	-0.16
	(0.10)	(0.10)	(0.10)	(0.10)	(0.11)	(0.10)

(Standard Errors in Parentheses)

**Only b_{Lt}, b_{Mt} and b_{Kt} measure the impact of the trend term

Results are mixed for the wood and the paper and publishing industries, as the negative estimate is insignificant in the first specification with only b_t, but significant with the alternative simple specification.

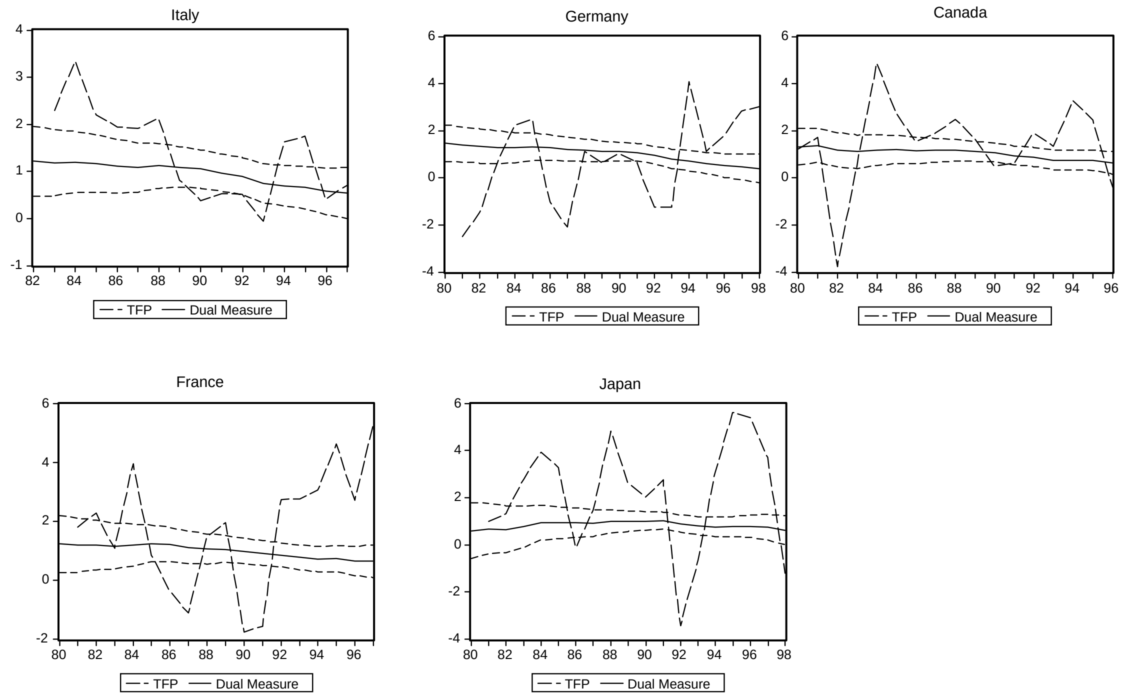
While a negative estimate of productivity growth is by no means uncommon in cost function estimations (see for example Kwon & Park (1995)), it is certainly hard to interpret. One explanation could be that the labor, capital and material inputs variables include R&D expenditures in this dissertation as well as in many other studies. Productivity growth is equivalent to downward shifts of the cost function. Clearly, it would be desirable to measure downward shifts of - non-R&D - production costs, which R&D based growth theories would attribute to technological change due to innovations. R&D expenditures should not be included in the measure of production costs, because they are investments in technological change rather than the result of it according to these theories. Yet, production costs do include R&D expenditures because of data limitations. Thus the downward shifts of the cost function measured by the trend term is very likely to understate technological change in the production of manufacturing output, because increased R&D effort of course raises R&D costs, even if it results in lower production costs due to successful innovations.

Rather than interpreting the negative productivity growth estimates for some industries as technological regress, it seems more convincing to conclude that technological progress as a result of R&D activity in these industries is very small. In fact, no R&D variable has a significant impact on the costs of production in the food, wood or paper and publishing industry, as will be discussed in the next chapter. The same holds for manufacturing n.e.c.. In the rubber and plastics industry only some international intra-industry knowledge spillovers can be found. Due to double counting, the small productivity gains that may be there are probably underestimated. On top of this, there may be a deterioration of framework conditions in these industries which compensates any technological change due to innovations that may be present.

It certainly seems useful to give up some flexibility concerning the productivity growth specification. With the exception of the electrical and optical equipment industry, where the flexible specification seems to work well, only a few of the trend term parameters are significant in all of the investigated industries. In what follows, the presented results are based on the estimation with the fully flexible specification of the trend term only for electrical and optical equipment. Instead, the specification with b_{Lt}, b_{Kt} and b_{Mt} is chosen for all industries considered in Table 4.5. This can very well be justified based on the results obtained with the fully flexible specification, since b_t is insignificant for all of these industries, while often two or more of the parameters b_{Lt}, b_{Kt} and b_{Mt} are significant, at least in the industries where the estimated average productivity growth is positive. The alternative specification, where only b_t measures the impact of the trend term is chosen for non-metallic mineral products and the food industry, because in each case only one of the trend term parameters b_{Lt}, b_{Kt} and b_{Mt} is significant. In manufacturing n.e.c., the specification with only b_t is chosen because the alternative simple specification yields estimates which do not comply with the concavity restrictions.

A more difficult case is the chemical industry, because estimated productivity growth

Figure 4-1: Productivity Growth: TFP vs. Dual Measure; Elect. and Opt. Eq.



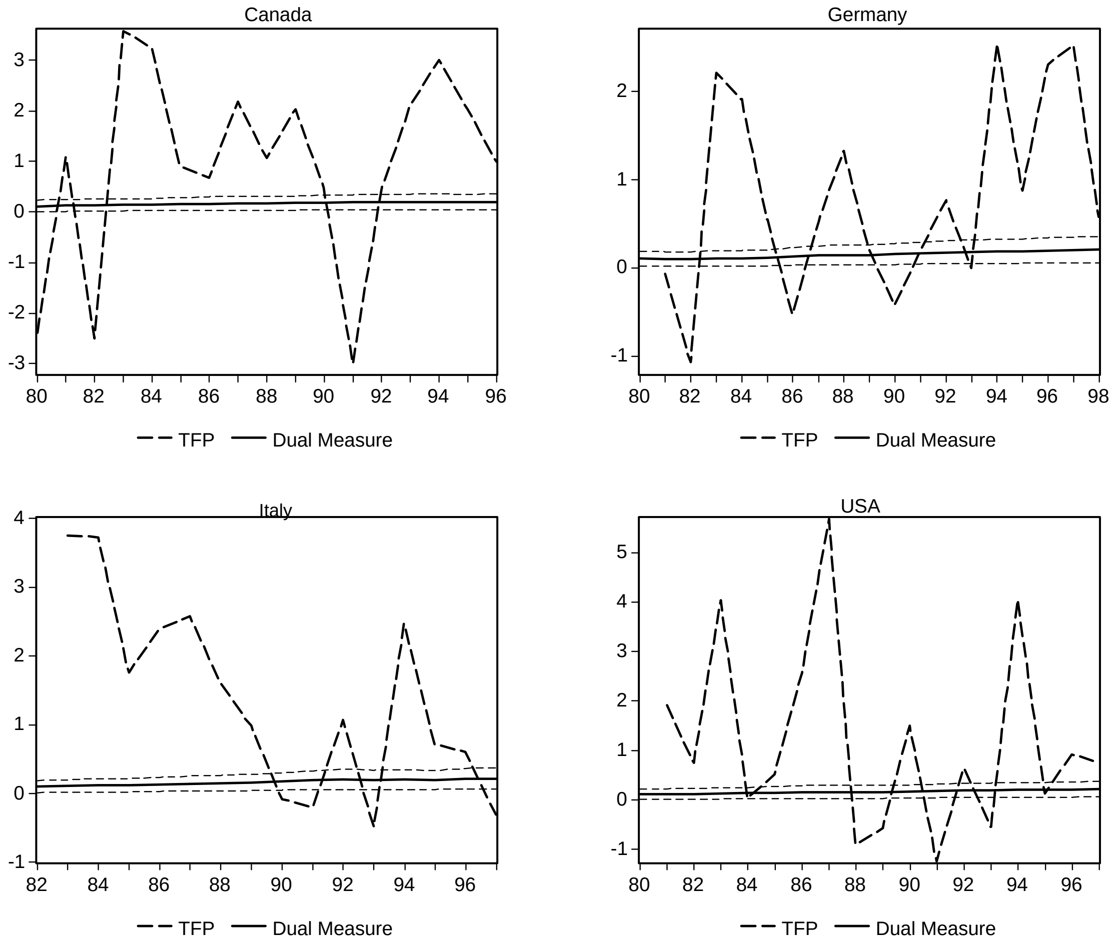
changes somewhat depending on the specification. However, Ljung-Box Q-statistics indicate first order serial correlation in the specification where only b_t measures the impact of the trend term, so the specification with b_{Kt} and b_{Mt} is chosen instead. While estimated productivity growth is somewhat lower with the alternative specification, none of the other estimates changes noticeably. Results with the preferred trend term specification for each industry are presented in appendix A.3. All of the results presented in the following sections are based on these estimates.

Regardless of the specification of the trend term, estimated productivity growth is by all means very small for all of the investigated industries. As outlined in chapter 3, R&D based models of growth imply that the Solow residual is likely to overstate the real productivity growth, because both economies of scale and mark-ups cause an upward bias of this productivity growth measure. On these grounds, it is to be expected that the dual measure should be smaller than the Solow residual if R&D based growth theories are relevant. In fact, comparing Tables 4.3 to 4.5 with Table 3.2 in chapter 3, it turns out that the average dual measure is decisively lower than the total factor productivity growth measure for almost all industries and countries. The only exception is the textiles industry where the dual measure is bigger than the Solow residual for the Canada, France and Germany. In the German electrical and optical equipment industry the dual measure is bigger than the Solow residual, as well.

To get a clearer image of the time series properties of the primal and dual productivity growth measures over time, Figures 4-1 and 4-2 plot total factor productivity and the dual productivity growth measure along with a 95%-confidence interval for the electrical and optical equipment industry and for the chemical industry as two examples. In the electrical and optical equipment industry, the difference between average TFP and the average dual measure of productivity growth is relatively small. As can be seen in Figure 4-1, the Solow residual is smaller than the dual measure in all countries during several subperiods due to particularly high cyclical variation in the primal productivity growth measure. This also holds for the chemical industry, although the Solow residual is quite a bit higher than the dual productivity measure during most subperiods in this industry.

In both industries the Solow residual has a strong cyclical component, while the dual measure of productivity growth is much smoother. The cyclical component of the primal measure may very well be a figment of unobserved cyclical variation in the utilization of labor and capital. The capital stock and employment as a measure of labor input are likely to underestimate the use of these factors in booms and overestimate it in slumps, because they measure capacity rather than actual factor utilization. Clearly, this creates a spurious cyclical component in the primal measure of productivity. Hours would be preferable as a measure for labor input to capture the cyclical variation of the use of this factor, but unfortunately only employment is available. As far as capital is concerned, it is highly difficult to measure the actual use of capital services rather than the production capacity that is measured with the capital stock. Capacity utilization measures to correct

Figure 4-2: Productivity Growth: TFP vs. Dual Measure; Chemical Industry



the capital stock are seldom available, especially on more disaggregate data levels, and in many cases their reliability may be questionable (Shapiro 1989).

Evidence that the primal TFP measure presented in this chapter is likely to contain a spurious cyclical element is provided by Paquet & Roubidoux (2001). They are able to adjust their capital stock series with a newly available aggregate capacity utilization measure when measuring total factor productivity with aggregate Canadian data. Comparing the Solow residual, which is unadjusted for varying capacity utilization, with the adjusted measure, it turns out that the latter is lot less volatile, containing fewer data points that indicate technology decline.

There is considerable evidence that in addition to concerns regarding the assumptions of constant returns to scale and perfect competition, the data should by all means somehow be adjusted for varying capacity utilization, if the Solow residual is used as a measure of productivity growth. In contrast, the error correction form used to estimate the cost function does accommodate changes in capacity utilization, because it encompasses short-run deviations from equilibrium. This results in much smoother estimates of productivity growth. With the cost function estimation it seems to be possible to avoid adding spurious cyclical variation to the productivity growth measure. Since it is in most cases extremely difficult to adjust the data for varying capacity utilization, the possibility to accommodate short-run deviations from equilibrium within the cost function approach is an additional reason why this framework appears more suitable to investigate the determinants of productivity growth.

In the next sections it is investigated whether the estimation results imply the presence of economies of scale and market power. This might be responsible for the fact that total factor productivity growth is systematically higher than the dual measure of productivity growth.

4.3 Economies of Scale

By a standard replication argument, returns to scale should in general be expected to be constant in the rival factors capital, labor and material inputs. Based on the growth theories with increasing returns due to externalities presented in section 2.2, economies of scale in the rival factors could be increasing instead, if non-rival knowledge is accumulated as a side effect of the production of some of the rival goods, such as physical capital in Romer's (1986) or human capital in Lucas's (1988) model. Since the two-digit industry level is already fairly aggregate, it should be possible to detect some economies of scale, if these models are relevant.

Table 4.6 displays the implied average rate of returns to scale over the sample period along with standard errors calculated with the delta method. The estimates imply increasing returns to scale for nearly all of the industries.

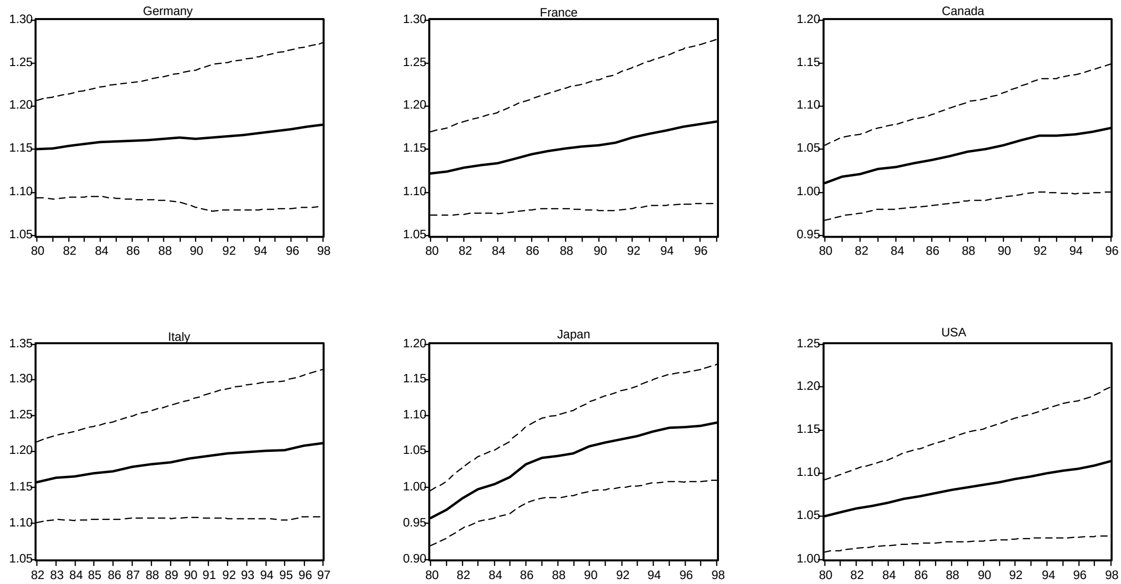
Table 4.6: Average Rate of Returns to Scale; 1980-1998

Industry	US	Italy	Japan	Germany	Canada	France
Food	1.083	1.188	1.043	1.162	1.046	1.152
	(0.057)	(0.067)	(0.054)	(0.062)	(0.055)	(0.062)
Textiles	1.144	1.175	-	1.133	1.131	1.130
	(0.030)	(0.032)	-	(0.029)	(0.029)	(0.028)
Wood	-	1.266	-	1.183	1.138	-
	-	(0.090)	-	(0.075)	(0.073)	-
Publishing	-	1.217	-	1.145	1.110	1.169
	-	(0.065)	-	(0.059)	(0.055)	(0.064)
Chemicals	1.129	1.214	-	1.186	1.136	-
	(0.030)	(0.030)	-	(0.028)	(0.030)	-
Plastics	1.261	1.178	-	1.166	1.177	-
	(0.055)	(0.039)	-	(0.038)	(0.039)	-
Mineral Prod.	1.327	1.483	-	1.332	1.282	1.317
	(0.078)	(0.083)	-	(0.071)	(0.067)	(0.067)
Metals	1.217	1.240	1.229	1.198	1.210	1.180
	(0.048)	(0.050)	(0.048)	(0.045)	(0.047)	(0.043)
Machinery	-	1.292	1.188	1.134	1.174	1.212
	-	(0.051)	(0.046)	(0.040)	(0.042)	(0.040)
Elect. & Opt Eq.	-	1.187	1.122	1.167	1.214	1.096
	-	(0.037)	(0.032)	(0.036)	(0.042)	(0.032)
Transport	1.184	1.277	1.271	1.206	1.177	1.217
	(0.048)	(0.055)	(0.055)	(0.048)	(0.045)	(0.048)
Man. N.E.C.	-	1.201	-	1.145	1.121	0.962
	-	(0.035)	-	(0.036)	(0.032)	(0.028)

(Standard Errors in Parentheses)

Only in the Japanese and the Canadian food industries and in manufacturing industries n.e.c. in France is the estimated average rate of returns to scale not significantly different from one. In general, the size of the estimates is very uniform. The average rate of returns to scale varies between 1.1 and 1.3 for almost all of the investigated industries. Figure 4-3 plots the rate of returns to scale for the food industry along with the 95%-confidence interval for the estimated elasticity. This includes 1 in Japan and Canada over the whole sample period, so the hypothesis of constant returns to scale cannot be rejected for these two countries. For all other countries even the lower bound of the confidence interval is bigger than one over the entire sample period.

Figure 4-3: Economies of Scale in the Food Industry

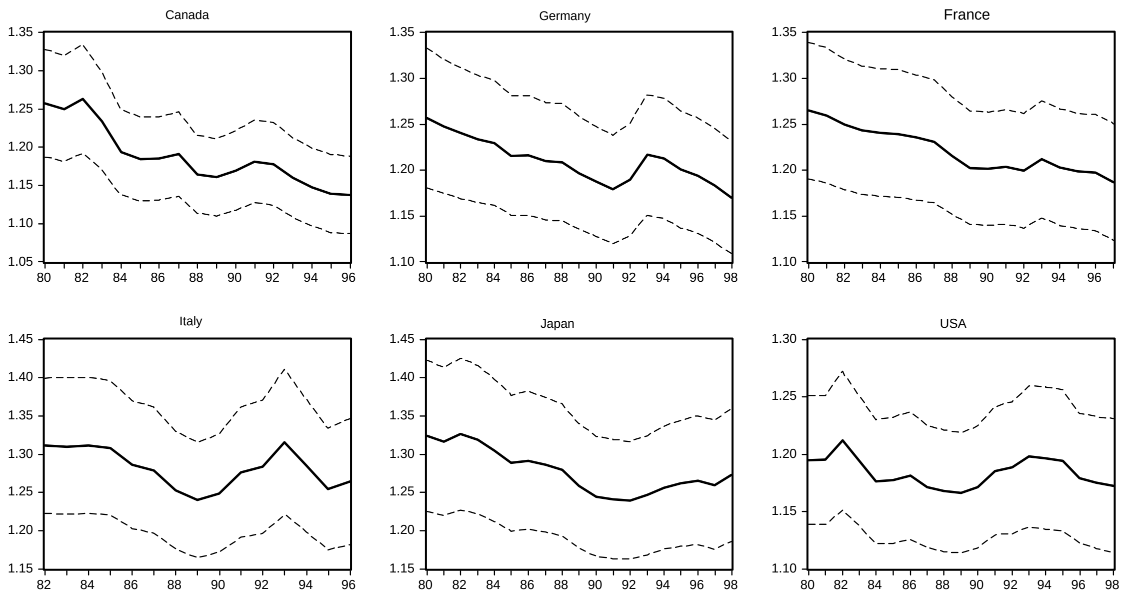


To visualize an alternative example of an industry with relatively high economies of scale, Figure 4-4 displays the implied rate of returns to scale for the transport equipment industry, where even the lower bound of the 95-%-confidence interval is well above 1.1 for all countries. More so than in the food industry the rate of returns to scale seems to have quite a pronounced cyclical component. The plot of the time series looks as if there was a slight downward trend in the transport equipment industry of Canada and Germany, while the rate of returns to scale seems to be upward trending in the food industry. These seeming trends should be attributed to the short sample period. It would certainly be very surprising if there was a long-run trend in the rate of returns to scale.

While growth models with externalities can accommodate economies of scale in rival factors, because knowledge is accumulated in direct proportion to one of them, R&D

based growth theories suggest in principle that returns to rival factors should be constant. However, theory does suggest that there may be economies of scale even if only the rival factors are considered, because there are fixed costs associated with investments in R&D. Moreover, returns to scale are increasing in rival factors and knowledge together. Based on the latter argument, it may seem surprising to detect economies of scale in a cost function estimation where R&D capital stocks have not been included. However, as pointed out in the data description, it is not possible to correct labor, capital and material inputs for the inclusion of R&D capital stocks. Therefore, it is very likely that at least some of the effect of R&D on overall economies of scale is captured by the cost elasticity with respect to output.

Figure 4-4: Economies of Scale in the Transport Equipment Industry



Since knowledge is the source of economies of scale according to R&D based growth models, it would be interesting to see whether it is possible to detect a relationship between knowledge variables and the estimated rate of returns to scale. As the size of the average rate of returns to scale is very uniform across industries, it is hardly possible to detect such a relationship by mere inspection of Table 4.6. Most industries displaying relatively high economies of scale are also relatively R&D-intensive, while R&D-intensity is low in manufacturing not elsewhere classified, the food and the textiles industry, where returns to scale are close to constant. On the other hand, the highly R&D-intensive chemical and electrical and optical equipment industries hold middle positions when it comes to economies of scale.

To get a clearer image whether economies of scale might be related to R&D, the estimated excess returns to scale, the rate of returns to scale minus one, is regressed first on R&D-intensity and then on the R&D-capital stock in a pooled regression with fixed industry effects. To avoid heterogeneity due to different size, the R&D capital stocks are introduced into the regression as indices taking a value of one in 1995.

Table 4.7: Results of Panel Regression of Returns to Scale on different R&D Variables

$SE_{it} = f_{it}^{RIo} + b_{RI} * RDY_{it} + u_{it}^{RIo}$			$SE_{it} = f_{it}^{Ro} + b_{KR}R_{it} + u_{it}^{Ro}$		
b_{RI}	2.453	(0.316)	b_{KR}	0.024	(0.006)
R^2	0.827		R^2	0.813	
$D.W$	0.141		$D.W.$	0.143	

(Standard Errors in Parentheses)

In Tables 4.7, 4.8 and 4.9 $SE_{it} = \frac{1}{\varepsilon_{\tilde{C}Y\,it}} - 1$ denotes the excess returns to scale, RDY_{it} is the R&D-intensity, R_{it} the R&D capital stock, f_{it}^{j} is an industry specific constant and u_{it}^{j} is an error term for $j = RIo$, Ro, $RIec$, $\mathrm{Re}c$. i is an industry index and t is a time index. Both the estimated parameter of the R&D-intensity and of the R&D capital stock are positive and significant However, the Durbin Watson statistic indicates strong autocorrelation in the residuals, so the estimated standard errors are likely to be severely distorted. Moreover, since the rate of returns to scale is a function of the prices, output and input data, the parameter estimates may primarily capture a common cyclical component in the data, while it is of course the long-run relationship between knowledge creation and economies of scale that is interesting in the present context. Since the investigated time span is rather short, it is by no means easy to uncover this. However, estimating the relationship between economies of scale in an error correction model may be more appropriate, because this framework helps deal with the autocorrelation and it is more likely to capture a long-run relationship between the variables.

Table 4.8 reports results of the estimated relation between returns to scale and R&D-intensity. Differences turn out to be significant up to lag two. The coefficient γ_{RI} is the error correction term, while $h_{RI} = -\frac{b_{RI}}{\gamma_{RI}}$ measures the implied long-run relationship between the R&D-intensity and the estimated rate of returns to scale. Again, the equation is estimated with industry-country fixed effects, while all slope coefficients are assumed to be the same across all industries and countries. The implied parameter measuring the long-run relationship between R&D-intensity and economies of scale is h_{RI} =3.467. It is significant and in a reasonably similar range as the corresponding parameter estimated with OLS.

Table 4.8: Relation between R&D Intensity and Economies of Scale; Error Correction Form

$$\Delta SE_{it} = f_{it}^{RIec} + \gamma_{RI} SE_{it-1} + b_{RI} * RDY_{it-1} + \sum_j d_{RIj} \Delta SE_{it-j} + \sum_j e_{RIj} \Delta RI_{it-j} + u_{it}^{RIec}$$

γ_{RI}	b_{RI}	e_{RI0}	e_{RI1}	e_{RI2}	d_{RI1}	d_{RI2}	R^2	$D.W.$	$t.stat.$
-0.107	0.371	0.65	-0.709	-0.531	0.251	-0.162	0.465	1.895	-8.885
(0.012)	(0.127)	(0.21)	(0.204)	(0.202)	(0.30)	0.030)			

(Standard Errors in Parentheses)

The t-statistic of the error correction term, denoted "t.stat." in Table 4.8 is highly significant indicating reversion to equilibrium. Similar results emerge when estimating the relationship between the R&D capital stock and the rate of returns to scale in the error correction form. Results of this estimation are reported in Table 4.9. The implied long-run parameter measuring the relationship between the R&D capital stock and economies of scale is 0.065. It is significant and positive and not too far from the parameter obtained with the direct estimation of this relationship. The t-statistic of the error correction term is again highly significant.

Overall the estimation results indicate that there seems to be some positive relationship between economies of scale and knowledge variables, so R&D activity may be a source of economies of scale as suggested by R&D based models of growth. Yet, the results should not be overvalued. The estimation of the relationship between economies of scale and R&D-variables is of course completely ad hoc. The exercise is simply meant to uncover whether it is possible to detect any positive relationship at all. This approach seems useful from a pragmatic point of view, because it is difficult to distinguish an unequivocal relationship just by inspecting the estimated average rate of returns to scale summarized in Table 4.6 taking into account the industries' R&D-intensities. It is true that, since the input data is not corrected for the inclusion of R&D, and because of the fixed cost associated with R&D investments, the cost elasticity with respect to output should be expected to capture at least part of the economies to scale that can be traced to R&D. Nevertheless, results should be treated with caution, because theory does not provide any guidance as to how strong the relationship between R&D variables and economies of scale should be and what precise form it should take.

Table 4.9: Relation between R&D Capital and Economies of Scale; Error Correction Form

$\Delta SE_{it} = f_{it}^{\mathrm{Re}\,c} + \gamma_R SE_{it-1} + b_R R_{it-1} + \sum_j d_{Rj} \Delta SE_{it-j} + \sum_j e_{Rj} \Delta R_{it-j} + u_{it}^{\mathrm{Re}\,c}$

γ_R	b_R	e_{R0}	e_{R1}	e_{R2}	d_{R1}	d_{R2}	R^2	$D.W.$	$t.stat.$
-0.109	0.007	-0.014	0.031	-0.008	0.214	-0.190	0.417	1.884	-9.090
(0.012)	(0.002)	(0.015)	(0.017)	(0.0016)	(0.030)	(0.030)			

(Standard Errors in Parentheses)

The important bottomline from the point of view of growth theory is that significant economies of scale are found in all of the investigated industries. This empirical result supports the endogenous growth theories discussed in chapter 2. According to Romer's (1986) and Lucas's (1988) models with externalities, the aggregate production function may display increasing returns to scale, because productive knowledge is accumulated as a side effect of investments in physical or human capital. In R&D based models of growth, knowledge created as a result of investments in R&D is the source of economies of scale. Although some ad hoc regressions of the time series measuring the rate of returns to scale on different R&D variables reveal that there does seem to be a positive relationship, these results should be interpreted with caution, because these regressions are not well structured by theory. The safest conclusion that can be drawn from the results is that there is indeed considerable evidence of the presence of economies of scale.

In this sense the results support endogenous growth theories as opposed to neoclassical growth theory, which is unambiguously based on a constant returns to scale technology.

A way to distinguish whether the results support R&D based growth theories rather than models with increasing returns due to externalities is to take a look at what the results imply concerning the presence of market-power. While the externality models are based on the assumption of competitive markets, R&D based growth models have to rely on market power to explain knowledge creation as a response to market incentives.

4.4 Market Power

R&D based models of economic growth suggest that each industry which conducts research and development should be able to charge a mark-up of price over marginal cost to cover the fixed cost associated with knowledge creation. In fact, estimated mark-ups are significantly bigger than one in all industries but rubber and plastics products, where the hypothesis of competitive pricing cannot be rejected at the 5%-significance level for the US and Italy. This can be verified in Table 4.10.

Based on theory mark-ups may be expected to be higher in industries where the R&D-intensity is relatively high, because these industries bear higher fixed costs in relation to their output. For this reason, one might expect a positive relationship between R&D-intensity and the size of the mark-up. Yet, for most industries estimated mark-ups vary between 1.2 and 1.3. This seems to be rather uniform, whether or not the industries are R&D-intensive.

Figure 4-5 plots the estimated mark-ups against the average R&D-intensities of the different industries. It certainly does not look as if there was any relationship. In fact, the fitted regression line stemming from an ordinary least squares regression of mark-ups on average R&D-intensities can be seen to be a straight line in Figure 4-5.

However, market-power and the size of mark-ups can be related to many other things than a patent or technological knowledge that can effectively be hidden from other pro-

Table 4.10: Estimates of the Mark-up of Price over Marginal Cost

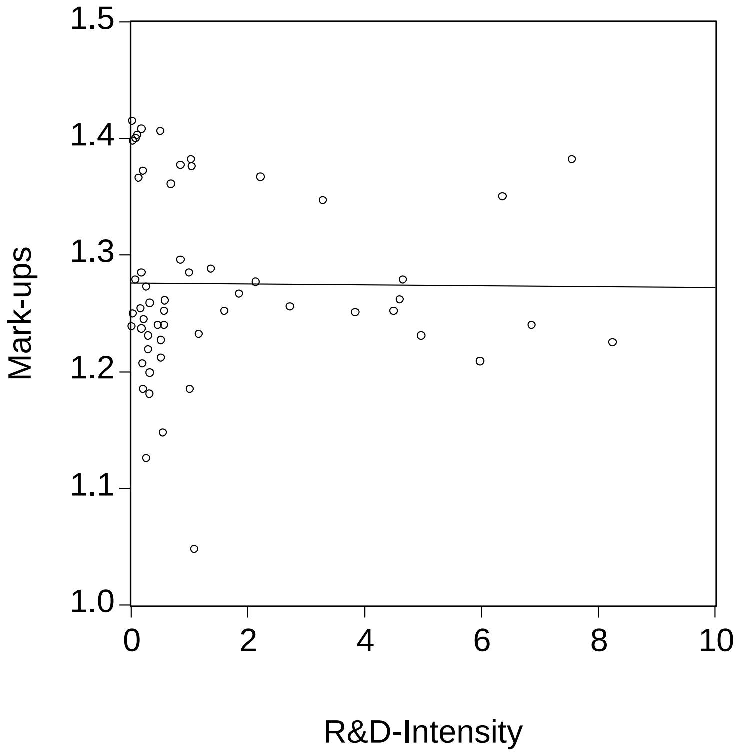
Industry	US	Italy	Japan	Germany	Canada	France
Food	1.259	1.279	1.240	1.237	1.254	1.245
	(0.074)	(0.074)	(0.072)	(0.070)	(0.076)	(0.073)
Textiles	1.207	1.239	-	1.199	1.219	1.185
	(0.026)	(0.029)		(0.026)	(0.028)	(0.027)
Wood	-	1.398	-	1.285	1.366	-
	-	(0.075)	-	(0.069)	(0.072)	-
Publishing	-	1.415	-	1.408	1.231	1.403
	-	(0.080)	-	(0.079)	(0.070)	(0.079)
Chemicals	1.252	1.277	-	1.279	1.252	-
	(0.033)	(0.034)	-	(0.032)	(0.034)	-
Plastics	1.048	1.148	-	1.185	1.181	-
	(0.151)	(0.086)	-	(0.078)	(0.080)	-
Mineral Prod.	1.376	1.400	-	1.377	1.372	1.361
	(0.062)	(0.067)	-	(0.059)	(0.061)	(0.059)
Metals	1.261	1.273	1.285	1.296	1.240	1.252
	(0.037)	(0.038)	(0.036)	(0.037)	(0.038)	(0.036)
Machinery	-	1.406	1.267	1.367	1.382	1.288
	-	(0.135)	(0.066)	(0.126)	(0.149)	(0.074)
Elect. & Opt. Eq.	-	1.347	1.209	1.350	1.382	1.240
	-	(0.051)	(0.037)	(0.044)	(0.050)	(0.040)
Transport	1.225	1.251	1.256	1.262	1.232	1.231
	(0.033)	(0.039)	(0.031)	(0.033)	(0.036)	(0.033)
Man., N.E.C.	-	1.250	-	1.212	1.227	1.126
	-	(0.052)		(0.049)	(0.053)	(0.040)

(Standard Errors in Parentheses)

ducers. It may be due to monopoly rights granted by the government or the level of protection from international trade. Moreover, the size of the mark-up also depends on the price elasticity of market demand, which is unrelated to market-power. These factors may obscure the relationship between R&D-intensity and the size of mark-ups in some industries. To capture this possibility, it is tested whether industry dummies are significant in the regression of mark-ups on R&D.

As it turns out, dummies are significant for the wood and the publishing and printing industry, where mark-ups are remarkably high, while the R&D-intensity is very low compared with other industries. The rubber and plastics industry dummy is also signif-

Figure 4-5: Mark-ups and Average R&D-Intensity; 1980-1998



icant, as well as the dummy of other non-metallic mineral products and the machinery industry. The first industry has the lowest mark-ups of all industries, while mark-ups are particularly high in the latter two industries. The significance of country dummies is tested as well. Only the dummy for Italy is significant. Since the R&D-intensity in Italian industries is remarkably low compared with other countries, this is not very surprising. Table 4.11 presents the results of a regression of mark-ups on R&D-intensity with all significant dummies included in the estimation.

b_0 is a constant, b_{RDI} is the coefficient of the R&D-intensity and the $d_i s$ denote the dummies, where the suffix I stands for Italy, while the numbers denote ISIC industry codes which are explained in the data appendix. When all significant industry and country dummies are included in the regression, the coefficient of R&D-intensity becomes

Table 4.11: Regression of Mark-ups on R&D-Intensity

b_0	b_{RDI}	d_{20}	d_{21}	d_{25}	d_{26}	d_{29}	d_I	R^2
1.227	0.007	0.107	0.125	-0.103	0.137	0.096	0.043	0.692
(0.011)	(0.003)	(0.029)	(0.025)	(0.025)	(0.023)	(0.022)	(0.008)	

(Standard Errors in Parentheses)

positive and significant. Hence, there is some, albeit weak, evidence in favor of the notion, that a high amount of R&D activity is associated with higher mark-ups, although this relationship seems to be obscured by other factors influencing the size of mark-ups in a number of industries.

It seems intuitive to assume that high mark-ups should be observed in industries where a lot of R&D is performed, because the fixed cost associated with knowledge creation are high. Yet, the only clear implication from R&D based growth models is that some positive mark-ups should exist in all industries that perform R&D. This is clearly supported by the data, as mark-ups are positive in nearly all of the investigated industries. This result is clear evidence in favor of R&D based models of growth, distinguishing it from alternative growth theories.

Overall the results reported so far support endogenous growth theory, particularly R&D based models. The presence of mark-ups and economies of scale is confirmed for nearly all of the investigated industries. There is also some - although rather weak - evidence, that both mark-ups and economies of scale are linked to the amount of R&D activity. The next section explores how these findings compare to earlier results.

4.5 Comparison with the Existing Literature

Although earlier studies typically did not aim at investigating mark-ups, economies of scale and the role of knowledge in an integrated approach to study the relationship between these features, many researchers have investigated either mark-ups or economies of scale separately.

One of the earliest and most prominent examples of a test for market-power in the

Solow residual framework is Hall's (1988) analysis. He regresses the share-weighted factor income growth on output growth to estimate the inverse of the mark-up with two-stage least squares. Estimated mark-ups are substantial for most industries, ranging between 1.86 in the services sector and 3.8 in trade. In an estimation with further industry detail, most estimates of the mark-ups range between 1.5 and 3. A caveat applies to these results, though, as Hall does not include material inputs in his regression, using value added rather than gross output as his output measure. This is likely to result in an upward bias of the estimated mark-up as he shows in his paper. This suspicion is confirmed in Domowitz, Hubbard & Petersen's (1988) study who use highly disaggregated US manufacturing gross output data to verify Hall's result. The estimated size of the mark-up is much smaller than in Hall's study, varying between 1.38 in the primary metals industry and 2.05 in the publishing and printing industry. Most estimates are considerably below 2.

Beccarello (1996) uses an earlier version of the STAN database to investigate mark-ups in OECD industries. His mark-up estimates vary in a wider range and are generally higher than the estimates presented in the previous section. The average of the industry mark-up across countries ranges from 1.07 in Germany to 1.89 in Japan. Many estimates for individual industries are well above 2. The difference in results can easily be explained as Beccarello employs an earlier version of the STAN database, which forces him to use value-added data. As outlined before, this is likely to cause an upward bias in the estimates.

It is a general observation that mark-up estimates are higher and vary more when value-added data is used. This phenomenon is also revealed when comparing Roeger's (1995) and Oliveira Martins, Pilat & Scarpetta's (1996) results, who make use of the nominal version of the Solow residual to develop a framework that allows them to estimate without instruments. This is an advantage, because appropriate instruments are very difficult to find. Roeger, who uses Hall's value-added dataset, finds mark-ups varying between 1.3 and 3.14 in different industries, although most estimates are below 2. Oliveira

Martins, Pilat & Scarpetta's estimates obtained with nominal OECD industry gross output data are lower, varying between 1.03 and 1.8.

Classifying the industries in their sample with respect to relative establishment size and R&D intensity, Oliveira Martins, Pilat & Scarpetta find that mark-ups tend to be higher in industries with low average establishment size. Within the group of low and high average establishment size respectively, mark-ups tend to be higher in industries with high R&D-intensity. This result, of course, is particularly interesting from the point of view of endogenous growth theory which predicts that market-power should be associated with R&D activity.

The only study that does not unequivocally point towards positive mark-ups is Paquet & Roubidoux's (2001) investigation with aggregate Canadian data. They obtain an estimate of μ that is significantly larger than 1 with unadjusted data. Yet, while the point estimate is still 1.377 when the capital stock series is adjusted for varying capacity utilization, the estimate is so imprecise that the hypothesis of constant returns cannot be rejected. It should be noted, however, that the authors estimate a value added version of (3.6) conjecturing - similar to Hall (1988) - that returns to scale are constant, so that the last term in the equation disappears. Yet, it is very likely that increasing returns and market power come together. First, market power is necessary in order not to incur losses with an increasing returns to scale technology. Secondly, fixed costs and other sources of increasing returns are likely candidates to prevent factors from earning their marginal products.

When using the dual framework to estimate mark-ups, researchers often append an inverse output demand function to their factor demand system. The mark-up in the profit maximization condition is then calculated as $\mu = \frac{1}{1+\varepsilon_{PY}}$ (see for example Kim & Nadiri (1996*b*), Nadiri & Nandi (1999), Morrison (1990) and Kwon & Park (1995)), where ε_{PY} denotes the price elasticity of market demand. In all of these studies mark-ups are found to be positive. However, this approach implicitly assumes a monopolistic market-structure. To avoid this, Bernstein & Mohnen (1991) develop a cost function and factor demand system which allows them to estimate the market elasticity of demand and the conjectural elasticity of oligopolistic firms jointly. The conjectural elasticity is the percentage change of market output due to a one percent change of firm $i's$ output. Applying their model to three Canadian industries the authors find significant mark-ups ranging from 1.2 in the chemical industry to 1.8 in the electrical machinery industry.

Alternatively, some authors estimate only the mark-up, and not the price elasticity of market demand, using a specification similar to the one used in this study. Flaig & Steiner (1990) model their mark-up term in a quite general way to allow for both a trend and cyclical variation. The estimates obtained with German industry data are fairly stable over time. The average estimate of the mark-up ranges between 1.05 in the food industry and 1.498 in the chemical products industry. Mamuneas (1999) estimates mark-ups for US high-tech industries that are conjectured to be constant. His estimates imply mark-ups that range between 1.01 for chemical products and 2.69 in the electrical industry.

In general, estimates obtained within the primal and the dual approach respectively do not seem to differ much. The crucial factor when estimating mark-ups appears to be the definition of output. It can be shown that the use of value-added data biases results upwards. In fact, estimates obtained with gross output data are generally lower than those obtained with value-added data. Regardless of the output definition used in prior investigations, mark-up estimates obtained in this study are in general more homogeneous and lower. Mostly ranging around 1.2 and being well below 1.5 for every industry, they seem in fact much more realistic than many estimates presented before. This encouraging finding could be due to the empirical framework, which allows both for considerable flexibility as far as the functional form is concerned and for very general short-term deviations from equilibrium.

From the point of view of R&D based growth theories, the important bottom-line is that the presence of market-power in most industries is a very robust result in the empirical literature. Mark-ups that are significantly greater than one are found with many different datasets and estimation methods.

As far as economies of scale are concerned, the finding of moderately increasing returns to scale is a very common result of work based on the cost function approach. Studies with results in a similar range as those presented in the previous section include Flaig & Steiner (1993), Kwon & Park (1995), Mamuneas (1999), Kim & Nadiri (1996*b*), Morrison Paul & Siegel (1997), Morrison Paul & Siegel (1999) and Nadiri & Nandi (1999). In contrast, results obtained with the Solow residual approach are much more mixed and controversial.

Using an extension of his framework to investigate mark-ups, Hall (1990) finds significant increasing returns to scale in all industries he investigates. His estimates are particularly high. Only for three out of 23 industries is the estimate below 1.3. In 13 cases it is above 2. Hall's method, however, has been criticized, because he estimates the inverse of the rate of returns to scale rather than estimating it directly. Bartelsmann (1995) points out that the estimate of the inverse of a parameter is not equal to the inverse of its estimate, and that this problem cannot be overcome by instrumental variable estimation. Using Hall's data, he finds that the direct estimate of rate of returns to scale is much smaller than its size implied by the estimate of its inverse.

Basu and Fernald also question Hall's choice of instruments as being only weakly correlated with the explanatory variables. Arguing that Hall' s instruments are not only weak but even bad, in the sense that they are correlated with the errors, Basu and Fernald conclude that the result of large increasing returns to scale is due to a considerable bias. Employing value-added data similar to Hall's, they even find evidence of decreasing returns to scale in the average manufacturing industry. A similar result is obtained with gross output data.

In fact, it is not uncommon in studies based on the primal approach to find constant or even decreasing returns to scale. The difficulty of obtaining convincing estimates of the rate of returns to scale in production function estimations is related to a well known puzzle: Capital often appears to play no role in production function estimations. This finding has been stressed by Lucas (1970) and Bernanke & Parkinson (1991), among others. Although their studies differ with respect to data sets, sample periods and estimation methods, they all arrive at the same conclusion: capital enters the estimated production function either with the wrong sign or not at all. This result, which is certainly not compatible with theory by any means, also implies a downward bias in the estimated rate of returns to scale, since this is measured by the sum of the factors' production elasticities.

Implausible estimates obtained with the Solow residual approach are often attributed to a failure to account for varying capacity utilization. Burnside, Eichenbaum & Rebelo (1995) try to overcome this problem by correcting the capital input data for cyclical variation. With different US gross output data sets and instruments, their results uniformly imply constant returns to scale. Burnside (1996) finds similar results across different data and instrument sets. While finding increasing returns with unadjusted data, Paquet & Roubidoux (2001) obtain a point estimate of the rate of returns to scale that is even smaller than one after adjusting their capital stock series with a capacity utilization measure, although they cannot reject the hypothesis of constant returns.

With aggregate US data Basu & Fernald (1997) find evidence for increasing returns, while they find even decreasing returns with industry data. This is similar to the results of Caballero & Lyons (1992) who find a higher rate of returns to scale with aggregate US data than with industry data. Caballero and Lyons interpret this as evidence for productive spillovers or "thick-market" externalities. They suspect an external source of economies of scale. In fact, when including aggregate production in the regression they find a positive impact on industry output which they view as a confirmation for their interpretation. In their work on European industries (Caballero & Lyons 1990), they use aggregate input growth rather than output growth to account for productive spillovers. The estimate of their spillover variable is positive and significant for most industries.

However, Basu & Fernald (1995) argue that this evidence for productive spillovers is due to specification error, namely the omission of material inputs. They show theoretically that material inputs influence value added directly when market power is present. This is true, because income shares, which are used to deduct material inputs from gross output to obtain value added, do not measure the productive contribution of material inputs correctly, when prices do not equal marginal costs. Since both input and output growth may proxy material inputs, the evidence for productive spillovers might be due to an omitted variable bias.[1]

Basu & Fernald (1997) show that aggregation may bias the estimate of the rate of returns to scale in either direction. This is viewed as an explanation why the estimate of the rate of returns to scale differs sometimes depending on the level of aggregation and for the - theoretically puzzling, but empirically not uncommon - finding of decreasing returns to scale at the industry level.

Nevertheless, Bartelsman, Caballero & Lyons (1994) find evidence for productive externalities with US gross output data at the four-digit level. Most of their estimates imply moderate internal increasing returns to scale. Using the same dataset, Morrison Paul & Siegel (1997) confirm evidence for both internal and external economies of scale with a dynamic cost function framework including material inputs and allowing for varying capacity utilization or quasi-fixity of some of the factors. Since the data used in these two studies is quite disaggregate and does include material inputs, Basu & Fernald's (1995) critique is hardly applicable. Overall, there seems to be at least some reliable evidence in favor of slightly increasing returns to scale due to internal and possibly to external returns to scale.

Results on economies of scale obtained within the primal approach are much more contradictory and debated than those obtained with cost function estimations. Yet, it is not difficult to argue that results obtained with a cost function are likely to be more reliable. First, most of the production function estimations and the construction of the Solow residual in studies discussed in this section are based on the Cobb-Douglas function. In contrast, the cost function studies typically rely on flexible functional forms, which are much more general. Moreover, a number of researchers who use the Hall/Solow residual framework attempt to correct their data for factors such as varying capital utilization

[1] Their argument is presented in more detail in appendix C

(Basu 1996, Burnside 1996) and labor hoarding (Burnside, Eichenbaum & Rebelo 1993), because a failure to account for this is frequently believed to bias results. The dual framework, in contrast, readily encompasses varying capacity utilization without a need to recur to correction of the data. In fact, the possibility to model slow adjustment of the capital stock to equilibrium is exploited in all of the dual studies presented in this section.

The difficulty to estimate production elasticities and thus economies of scale correctly is also revealed by the observation, that the estimated output elasticity of physical capital tends to be lower in studies that stress the time-dimension rather than the cross-section dimension of the data. Both Mairesse & Sassenou (1991) and Nadiri (1993) point to this fact in their overview articles discussing studies that try to assess the impact of R&D on productivity. Mairesse & Sassenou (1991) attribute this phenomenon to collinearity of both physical and R&D capital with a time trend. Moreover, they point out that biases due to random measurement errors or omission of variables capturing short-term adjustments to business-cycles are likely to be stronger in time-series than in cross-section data. There seem to be a number of reasons why estimates of the production elasticity of capital may be suspected to be downward biased in a primal framework. Of course, an estimate of the output elasticity of physical capital which is biased downward directly results in a downward bias of the estimated rate of returns to scale.

Taking the numerous problems associated with the primal approach into consideration, there is enough reason to conclude that overall the existing empirical literature points towards slightly increasing returns to scale.

4.6 Implications for Growth Theory and Empirics

So far, the Solow residual has been highly popular in empirical work on R&D based growth models. Yet, relying on the assumptions of perfect competition and constant returns to scale, it may not be the best framework to investigate the role of knowledge for economic growth, since R&D based models of growth imply the presence of economies of scale and market power. In that case, the Solow residual is biased upward as a measure of productivity growth.

Results presented in this chapter indeed suggest the presence of both economies of scale and market power. This implies that endogenous growth theory seems to be empirically more relevant than the neoclassical growth model which relies on constant returns to scale and perfect competition. While economies of scale may be interpreted as evidence in favor of growth models with externalities or R&D based growth models, market power is a building block of the latter class of growth theories alone. There is also some evidence that both mark-ups and economies of scale are linked to the amount of R&D activity an industry performs. However, although these results are certainly interesting from the point of view of R&D based growth models, they are derived from ad hoc regressions based on very little theory, so they should be interpreted with some caution.

As theory would suggest in the presence of market power and economies of scale, the dual measure of productivity growth derived from the cost function and factor demand system estimation implies slower technological change than the Solow residual, which is upward biased when the assumptions of perfect competition and constant returns to scale do not hold. Another interesting result of this chapter is that total factor productivity as measured by the Solow residual displays much higher cyclical variation than the dual measure of productivity growth, which is rather smooth. This characteristic of the primal measure of productivity growth is likely to be a figment of unobserved cyclical variation in factor utilization. In contrast to the Solow residual, the factor demand system in the error correction form does account for varying capacity utilization allowing for very general deviations from equilibrium in the short run. The possibility to derive a productivity growth measure that does not suffer from a spurious cyclical component appears as a definite advantage over the primal approach.

The results concerning the presence of market power and economies of scale also seem to fit well into the existing literature. In many respects, the estimates presented in this chapter seem more reliable than many of the results presented before. The size of the mark-up estimates is lower and in effect more realistic than in many earlier studies. This may very well be due to the empirical framework chosen in this study, which is both flexible, as far as the functional form is concerned, and allows for very general forms of varying capacity utilization. A failure to account for unobserved variation in capacity utilization may also be one among many other reasons why prior studies investigating economies of scale based on production function estimations or the Solow residual come up with so many conflicting results, while estimates based on the cost function approach unanimously suggest the presence of economies of scale.

Overall, the framework used in this study seems to resolve many of the problems associated with the Solow residual framework. Since it also opens the possibility to investigate all of the more relevant features of R&D based growth models in an integrated approach, it appears a particularly well suited framework to investigate this type of theories. Suggesting the presence of market power and economies of scale, the empirical evidence presented in this chapter is very much in favor of R&D based growth theories. At the same time, both the theory presented in the second chapter and the empirical evidence call for a framework to estimate productivity growth that does not hinge on the assumptions of constant returns to scale and perfect competition when investigating the impact of R&D on technical change.

Chapter 5

The Role of Knowledge

5.1 R&D Capital and Productivity

According to R&D based models of growth, research and development is the driving force of technological change. Productivity growth is proportional to the resources devoted to R&D both in the lab equipment specification and in version (2.12) of the knowledge production function. As outlined in the presentation of the theoretical models, the lab equipment version of the knowledge production function is a little more realistic, assuming that both capital and labor are inputs to the knowledge production process. In contrast, in the knowledge production process described in (2.12) labor - frequently interpreted as human capital - is the only production input. The lab equipment version of the knowledge production process is the rationale to assume that an industry's stock of knowledge A should be proportional to its R&D capital stock, as apparent in equation (2.23). In what follows, the term "own R&D" is used to describe the effect of each industry's research and development effort on its productivity as opposed to R&D spillovers from other industries.

Technological change, that is growth in A, is reflected in downward shifts of the cost function. Any technological change is attributed to knowledge production in R&D based models of growth. Thus the impact of R&D on costs is expected to be negative, and there should be no role for the trend term to explain downward shifts of the cost function once R&D capital stocks are accounted for in the estimation. In reality, there may be sources of technological change other than innovations, such as organizational changes or changes in government policy, some of which may even have adverse effects on productivity growth.

If R&D capital stocks are not included in the estimation, as in the previous chapter, it is hoped that the trend term captures both the productivity growth that is due to R&D and technological change stemming from other sources. As soon as R&D capital stocks are included in the estimation, they should capture that part of productivity that is a result of market driven knowledge creation, while the trend should measure only productivity growth that is due to other sources.

In the present context at least two problems are likely to arise when trying to measure and source technological change correctly. One is that the trend term and R&D capital stocks are highly collinear. Therefore, it will be very difficult to get precise estimates of their respective impact on costs and to attribute the observed technological change correctly to R&D and non-R&D sources. The other problem has already been discussed in section 4.2. It is related to the double-counting due to the fact that it is not possible to correct the rival factors of production for the inclusion of R&D. Therefore, the estimated impact of R&D capital on costs is likely to underestimate technological change reflected in decreases of non-R&D production costs due to innovations, because what is really measured are decreases in total costs including R&D.

Keeping this problem in mind, the system (3.22)-(3.24) in the error correction form is estimated again, this time including each industry's R&D capital stock in the estimation, to see whether at least some productivity enhancing effect can be detected. Considering the previous discussion it is not very surprising that a significant impact of the R&D capital stock on costs can be found only in a handful of industries. As can be verified in appendix A.4 the estimated impact of R&D is clearly significant in the transport equipment and in the machinery industry, while it is just significant at the 5% level of significance in the electrical and optical equipment industry. In the basic and fabricated metals industry it is only barely significant even at the 10% level of significance. It is significantly positive in the manufacturing industries n.e.c. and - at a 10% level of significance - in the wood industry. Yet, in both cases the inclusion of the R&D capital stocks in the cost function estimation results in parameter estimates that violate concavity restrictions. Therefore, the results are not deemed reliable and are not presented in appendix A.4. In all of the other industries, no significant impact of R&D can be found.

The finding that there is no significant impact of R&D on costs in half of the industries does not imply that R&D has no impact at all. It simply means that there is no excess return to R&D in these industries. The impact of R&D-labor on output, as an example, is not significantly higher than the impact of ordinary production labor. When instead R&D is significant, this implies that the impact of R&D on output is above normal. There are excess returns to R&D. This may occur because investment in R&D leads to innovations which enhance the efficiency of the production process in significant ways. A complementary interpretation is that there may be intra-industry spillovers between the firms in the investigated industry. Both interpretations are very much in the spirit of endogenous growth theory.

Elementary economic reasoning suggests that investment in R&D should be high where its return is high. Therefore, it does not come as a surprise that almost all the industries that earn an excess return on R&D are relatively R&D-intensive. The chemicals industry is the only R&D-intensive industry where the impact is insignificant.

It is indeed a general finding that including R&D in the cost function lowers the productivity growth that is captured by the trend term. This can be verified in Table 5.1, which reports the average productivity growth implied by the estimation without knowledge variables,$-\varepsilon_{CT}$, and with own R&D, $-\varepsilon_{CT}^{R\&D}$, respectively.

Only in the basic and fabricated metals industry is this effect very small. The drop in productivity growth estimated by the trend term is more noticeable in the electrical and optical equipment industry. In the machinery industry estimated productivity

Table 5.1: Influence of R&D Capital Stocks on the Productivity Growth Estimate

Industry^{+}	R&D	US	Italy	Japan	Germany	Canada	France
Metals	$-\varepsilon_{CT}$	0.29	0.27	0.21	0.25	0.30	0.26
		(0.05)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)
	$-\varepsilon_{CT}^{R\&D}$	0.252	0.23	0.17	0.21	0.26	0.22
		(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)
Machinery	$-\varepsilon_{CT}$		0.31	0.27	0.29	0.35	0.28
			(0.13)	(0.14)	(015)	(0.14)	(0.14)
	$-\varepsilon_{CT}^{R\&D}$		-0.06	-0.12	-0.11	-0.04	-0.10
			(0.16)	(0.16)	(0.17)	(0.17)	(0.16)
Elect. &Optical Eq.	$-\varepsilon_{CT}$	-	1.01	1.00	1.00	1.12	0.96
			(0.21)	(0.22)	(0.21)	(0.23)	(0.32)
	$-\varepsilon_{CT}^{R\&D}$	-	0.69	0.62	0.73	0.76	0.66
			(0.28)	(0.30)	(0.29)	(0.32)	(0.32)
Transport	$-\varepsilon_{CT}$	-0.16	-0.11	-0.15	-0.13	-0.15	-0.16
		(0.10)	(0.10)	(0.10)	(0.10)	(0.11)	(0.10)
	$-\varepsilon_{CT}^{R\&D}$	-0.35	-0.28	-0.33	-0.32	-0.35	-0.35
		(0.12)	(0.11)	(0.12)	(0.12)	(0.12)	(0.13)

$-\varepsilon_{CT}$: Average Productivity Growth in the Estimation without R&D
$-\varepsilon_{CT}^{R\&D}$: Average Productivity Growth in the Estimation with R&D
(Standard Errors in Parentheses)

becomes negative and insignificant once excess returns to R&D are accounted for. In the transport equipment industry taking account of excess returns to R&D results in a significantly negative estimate of productivity growth that is captured by the trend term, suggesting that non-R&D sources of technological change possibly have adverse effects on productivity growth.

The impact of R&D is insignificant in all the industries where productivity growth is estimated to be negative when R&D is not included in the estimation. These observations suggest that excess returns to R&D can indeed explain a good part of the observed productivity growth. When R&D is not included in the estimation, the unspecific trend term seems to pick some of its impact. This finding supports the viewpoint of endogenous growth theory that technological change is a result of deliberate investments in research and development.

Table 5.2 shows the costs elasticities with respect to R&D for the industries where the impact of R&D is significant. Note that this elasticity is considerably higher in absolute value than the cost elasticity with respect to the time trend in the estimation without R&D.[1] This suggests that while the time trend seems to pick up some of the effect of R&D on productivity growth when R&D capital stocks are not included in the regression, it may not capture all of it.

Table 5.2: Average Cost Elasticities with Respect to R&D Capital

Industry	R&D	US	Italy	Japan	Germany	Canada	France
Metals	ε_{CR}	-0.020	-0.007	-0.031	-0.029	-0.013	-0.017
		(0.006)	(0.004)	(0.019)	(0.017)	(0.008)	(0.010)
Machinery	ε_{CR}	-	-0.029	-0.126	-0.174	-0.070	-0.101
		-	(0.006)	(0.028)	(0.038)	(0.016)	(0.022)
Elect. & Opt. Eq.	ε_{CR}	-	-0.029	-0.054	-0.070	-0.051	-0.073
		-	(0.015)	(0.028)	(0.037)	(0.027)	(0.038)
Transport	ε_{CR}	-0.092	-0.035	-0.026	-0.044	-0.010	-0.052
		(0.038)	(0.015)	(0.011)	(0.019)	(0.004)	(0.022)

ε_{CR} : Cost Elasticity w.r.t. R&D
(Standard Errors in Parentheses)

According to R&D based models of economic growth, knowledge is the source of economies of scale. When R&D is not included in the estimation the cost elasticity with respect to output may pick up some of the effect of R&D on overall returns to scale. A similar idea is implicit in Morrison Paul & Siegel's (1997) interpretation of their results of a cost function estimation for US manufacturing industries. They find that their estimate of the rate of returns to scale measured with the inverse of the cost elasticity with respect to output decreases when R&D is included in the estimation. This is interpreted as evidence that at least some of the observed economies of scale can be traced to knowledge as R&D based models of economic growth would suggest.

Such a systematic decrease of the estimated rate of returns to scale after the inclusion of R&D capital stocks is not found in this study, as can be verified quickly comparing Tables 5.3 and 4.6. The latter reports the rate of return to rival factors, $\frac{1}{\varepsilon_{CY}}$, derived

[1]The cost elasticity with respect to the time trend in tables 4.3 to 4.5 is multiplied by 100, to obtain productivity growth in percent.

from the cost function estimation with R&D capital. It is a little bit higher than in the estimation without R&D in some industries and a little bit lower in others, but overall the estimate is hardly changed. It does not seem to be the case that the estimate of the rate of returns to scale picks up that part of the scale effect of R&D that is due to excess returns when R&D is not accounted for in the estimation. Yet, in industries with an excess return to R&D the rate of returns to scale is higher than this, because the impact of R&D on output is stronger than the output elasticities of labor, capital and material inputs suggest. Table 5.3 also reports the measure of the rate of return, η_{vf}, which includes the effect of excess returns to R&D.

Table 5.3: Internal Economies of Scale with and without R&D

Industry	R&D	US	Italy	Japan	Germany	Canada	France
Metals	$\frac{1}{\varepsilon_{CY}}$	1.208	1.215	1.253	1.214	1.192	1.171
		(0.048)	(0.050)	(0.053)	(0.048)	(0.047)	(0.043)
	η_{vf}	1.227	1.222	1.282	1.241	1.204	1.188
		(0.049)	(0.049)	(0.061)	(0.055)	(0.046)	(0.044)
Machinery	$\frac{1}{\varepsilon_{CY}}$	-	1.150	1.243	1.266	1.136	1.231
		-	(0.041)	(0.053)	(0.058)	(0.039)	(0.040)
	η_{vf}	-	1.178	1.364	1.429	1.205	1.327
		-	(0.038)	(0.065)	(0.082)	(0.039)	(0.169)
Elect. & Opt. Eq.	$\frac{1}{\varepsilon_{CY}}$	-	1.132	1.118	1.178	1.194	1.118
		-	(0.045)	(0.034)	(0.040)	(0.044)	(0.036)
	η_{vf}	-	1.160	1.171	1.246	1.248	1.191
		-	(0.037)	(0.043)	(0.058)	(0.049)	(0.060)
Transport	$\frac{1}{\varepsilon_{CY}}$	1.292	1.279	1.255	1.228	1.126	1.254
		(0.076)	(0.055)	(0.053)	(0.051)	(0.043)	(0.054)
	η_{vf}	1.378	1.311	1.280	1.270	1.136	1.304
		(0.102)	(0.057)	(0.053)	(0.058)	(0.042)	(0.063)

(Standard Errors in Parentheses)

In most cases taking into account the excess return to R&D raises the measured rate of returns to scale only by a relatively moderate amount. One exception to this rule is the machinery industry, where the difference between $\frac{1}{\varepsilon_{CY}}$ and η_{vf} is quite substantial for Germany.

Overall, these results are in line with R&D based models of growth. In some particularly R&D-intensive industries returns to investments in knowledge creation are found to be above normal. These excess returns to R&D seem to explain a part of the observed productivity growth and in line with the theory they are a source of increasing returns.

The R&D based models presented in chapter 2 not only imply that each industry's R&D effort should enhance its own productivity. Knowledge may also spill over to other industries and have a beneficial effect on their productivity growth. The following sections therefore examine whether knowledge spillovers can be found in the OECD industries investigated in this dissertation.

5.2 Modelling Spillovers

5.2.1 Alternative Strategies

The R&D based models of growth presented in chapter 2 suggest that innovations as a result of research and development effort in each industry i enhance its productivity growth. Moreover, industry i may benefit from knowledge created in other industries that spills over through trade in intermediate inputs which embody technological change. As suggested in equation (2.30), this can be modelled empirically by including other industries' R&D capital stocks as an input in the production function of industry i. By the duality of the cost and the production function describing a production technology the R&D capital stocks from external sources would also appear in the industry's cost function as external variables. Additionally, a trend variable may be included in the cost or production function to capture sources of productivity growth that are exogenous to the model, such as government regulation or changes in organization.

Ideally, the impact of each different source of productivity growth should be estimated separately to assess its relative importance. The cost or production function of an industry i would than include its own R&D capital stock and that of all other industries. Especially when working with many cross-sections, though, degrees of freedom may not be the only limit to the inclusion of all potential spillover sources as a separate variable.

Since R&D capital stocks are typically trended, these variables are more often than not highly collinear. Due to this multicollinearity problem, it will be more than difficult to pin down the magnitude of the individual impacts of different R&D capital stocks and the time trend on costs or productivity.

Basant & Fikkert (1996) report their problems when trying to include spillover variables along with own R&D and time dummies in their estimation equation of a production function for Indian industries. Whenever they include time dummies, this lowers the statistical significance of the R&D variables dramatically. In their overview article about studies concerning the impact of R&D on productivity Mairesse & Sassenou (1991) confirm that most researchers encounter severe problems with multicollinearity when trying to investigate R&D and other sources of productivity growth in an integrated approach.

The high degree of multicollinearity may well be the reason why many researchers consider only some combination of variables that capture sources of productivity, rather than all of them together. Mohnen, Nadiri & Prucha (1986) include only own R&D, Nadiri & Prucha (1996) and Nadiri & Nandi (1999) combine own R&D and a trend term, Bernstein & Nadiri (1988), Bernstein & Yan (1997) and Bernstein & Mohnen (1998) investigate own R&D and international spillovers jointly, without including a trend. Morrison Paul & Siegel (1999), in turn, investigate the impact of R&D spillovers and a trend term without own R&D.

Clearly, multicollinearity will not only make it difficult to differentiate between the impact of own R&D, R&D spillovers and the trend term. It is even more difficult to assess the relative importance of different spillover sources. The final production function (2.30) suggests to take account of each industry's R&D capital stock as a separate variable. Of course, this will most certainly aggravate multicollinearity problems. Bernstein & Nadiri (1988) are one of the very few examples of a study that succeeds in estimating spillovers from several different industries individually with data from some US high-tech industries. It goes without saying that this approach becomes more and more difficult the larger the number of industries included in the sample.

In most studies, R&D capital stocks from outside industries or countries are aggregated to somehow measure a joint spillover effect. As an example, Morrison Paul & Siegel (1999) estimate a cost function with US industry data at the two-digit Standard Industrial Classification (SIC) level. They include R&D at one level of aggregation higher to capture the external nature of some of the knowledge production.

Alternatively, researchers aggregate the R&D capital stocks with weights which are intended to capture a specific transmission mechanism for knowledge spillovers. As outlined above, knowledge embodied in new or improved products may spill over through trade. Country-level studies that intend to stress this technological transfer mechanism often use import shares to weight R&D capital stocks that originated in other countries. A prominent example for this approach is the study by Coe & Helpman (1995). Kim & Nadiri (1996a) use the same approach within a cost function framework with OECD country level data, while Keller (2001) constructs import shares at the industry level.

To capture technological transfer through trade between different industries in one country, input-output coefficients are used in many studies. Terleckyj (1974) as well as Nadiri & Wolff (1993) and - in the more recent literature - Keller (2001) use this method to stress R&D spillovers due to customer-supplier relations.

It should be noted, however, that technology may also flow from the upstream to the downstream industry. Mansfield (1984) points to evidence that the supplier may also benefit from research and development conducted by the costumer. Moreover, technology may spill over through many other channels than trade. Therefore, alternative weighting schemes have been used in the literature to capture different spillover channels. Lichtenberg & van Pottelsberghe de la Potterie (1996), for example, rely both on trade and on foreign direct investment to construct weights.

Scherer (1984) creates a technology flow matrix by determining the industry of origin and the industry of use for US patents. Branstetter (2001) relies on foreign patenting. Jaffe (1986) constructs measures of technological closeness. According to this approach, the weights should be proportional to the similarity in the firm's patent portfolio. The firms are positioned in the "technological space" through vectors containing the distribution of patents over different classes. Technological closeness between two firms is then measured as the uncentered correlation of those vectors.

At the industry level a technology flow matrix based on technological closeness, known as the Yale concordance, has been developed by Evenson, Putnam & Kortum (1989). Vectors containing probabilities that industries use patents from a particular patent class are employed to locate industries in the technology space. The Yale concordance has been used by Keller (2001) and Los & Verspagen (2000) to construct weights for their spillover variables.

Patents and innovations are indicators of the technology status of industries or firms. Since spillovers due to technological proximity are likely to occur on a purely intellectual level, externalities that are captured using patent data may be viewed as being of the disembodied kind. In contrast, spillovers that are captured using trade or input-output data are embodied in goods.

While none of the weighting schemes discussed above is superior, in that they simply stress different transmission channels, each has its own shortcomings. The use of patent data requires the drastic assumption that the value of patents does not differ for various producers, within and across countries and over time.

On the other hand, Keller (1998) repeats Coe & Helpman's (1995) regressions with a spillover variable whose weights are randomly generated. Finding even larger spillovers than Coe and Helpman, he concludes that their shares may not be appropriate to capture knowledge spillovers that occur due to international trade. His technique to generate trade shares is criticized by Coe & Hoffmaister (1999) for not being random in contrast to what Keller claims. Using random trade shares generated with an alternative technique, they find no significant impact on productivity. Nevertheless, Keller's study appears to show that the Coe and Helpman results are not dependent on having found weights that capture the spillover channel correctly. Since there are many ways for knowledge to spill over, a perfect strategy to mirror spillover channels empirically does not exist.

Although it is by no means easy to tackle the problem of multicollinearity between R&D capital stocks, spillover variables and the trend term, each of these variables captures a different aspect of technological change. Estimates may actually pick up some combined effects from all of these, if some variables that source technological growth are omitted. It is therefore desirable to try and find a way to cope with the problem of multicollinearity to untangle the different sources of productivity growth.

However, with a large number of cross-sections, it is impossible to estimate the impact of each knowledge stock from other industries individually. The next section outlines an aggregation approach for spillover variables in a multi-country, multi-industry setting. The proposed weighting scheme draws heavily on Keller (2001).

5.2.2 Spillovers in a Multi-Country Multi-Industry Setting

To reduce the number of collinear variables to be included in the estimation, this study will focus on three different spillover sources: Each industry may benefit from spillovers of other industries in the same country, from international intra-industry spillovers and from inter-industry spillovers.

The weighting schemes used for aggregating the R&D capital stocks focuses on capturing trade as a spillover channel. This is in line with the models presented in chapter 2 which provide a theory on how knowledge may spill over through trade of input factors between different sectors.

To capture spillovers from other industries in the same country, input-output coefficients are used to weight their R&D capital stocks. Hence, the domestic spillover variable for industry i in country k is constructed as

$$S_d^{ki} = \sum_{j \neq i} \omega_{ij} R_j \tag{5.1}$$

where ω_{ij} denotes the input-output coefficients of intermediate goods flowing from industry i to industry j. More specifically, ω_{ij} is industry j's sales to industry i as a percentage of industry j's total sales to the entire economy.

Stressing trade as a transmission channel at the international level involves using import shares as weights. These are conceptually equivalent to the input-output coefficients that capture domestic trade relations.

Let m_{kvi} be the bilateral import share of country k from country v for goods from industry i. For a given country k and sector i the effect of R&D conducted in the same sector in foreign countries is then:

$$S_{fs}^{ki} = \sum_{v \neq k} m_{kvi} R_{vi} \tag{5.2}$$

Using 5.2 to calculate the intra-industry spillover variable, it is implicitly assumed that country k's import share of goods from country v that can be assigned to industry i captures the channel of intra-industry spillovers appropriately, although, of course, not all imports from industry i abroad will go to that same industry. Some US imports from Japan's fabricated metal industry may go to the transport industry rather than to the US fabricated metal industry. From a theoretical point of view, it would be desirable to have a more precise breakdown of industries that actually receive goods from industry i. Empirically, assigning imports to industries according to the type of good that is traded is the best that one can do. To the best of my knowledge, international trade data that contains information about buying and selling industries does not exist.

Industry i can also benefit from R&D that is conducted in foreign sectors $m \neq j$. This is referred to as inter-industry spillovers. To construct weights, input-output matrices for imports are used. For each industry the matrices display the use of intermediate inputs which are produced in foreign countries.

For a specific country k let v_{mi} denote the share of industry $i's$ imports of intermediates from the m industry. S_{fo}^{ki} may then be defined as:

$$S_{fo}^{ki} = \sum_{m \neq i} v_{mi} S_{fs}^{km} \tag{5.3}$$

This aggregation scheme reduces the number of spillover effects to be estimated to three. It thus preserves degrees of freedom and alleviates multicollinearity problems.

The weights for the domestic spillover variable, ω_{ij}, are measured with input-output coefficients. Input-output tables measuring domestic intermediate goods flows for each of the countries in the sample are provided by the OECD (OECD 1995).

Since in the model spillovers can be associated with trade in capital goods, it may seem desirable to use capital goods flow matrices to construct the weights. Although the OECD does provide input-output matrices for capital goods, these are very incomplete. Therefore, intermediate goods flow matrices are used instead.

Qualitatively, matrices are quite similar across countries. Not surprisingly, for example, both the fabricated metal industry and the machinery industry retrieve the bulk of their intermediate inputs from the basic metal industry, as does the transport equipment industry. In general, the food and tobacco industries do not provide a large quantity of intermediate inputs for other manufacturing industries. Quantitatively, however, there are important differences between the input-output coefficients of France and Germany and the remaining countries, especially for fabricated metal products. This indicates that accuracy is gained, when using input-output data from each individual country rather than assuming that input-output structures can be approximated well with data from the US only, as in Keller (2001).

Table 5.4: Average Import Shares in Transport Equipment; 1980-97; in per cent

$\frac{to}{from}$	Canada	USA	Japan	France	Germany	Italy
Canada	0	42.04	1.15	0.41	0.91	2.38
USA	86.53	0	59.47	9.66	18.26	8.14
Japan	9.59	41.73	0	6.36	25.12	3.22
France	1.46	3.26	4.87	0	37.29	33.02
Germany	2.18	11.32	32.19	66.37	0	56.38
Italy	0.24	1.65	2.34	17.19	18.42	0

The intra-industry spillover variables are constructed using import shares as weights. These are conceptually equivalent to the input-output coefficients capturing domestic trade relations. The import shares are constructed drawing on Feenstra's (2000) data of import flows over the period 1980-1997. Time-invariant import-shares are constructed averaging the import-shares over 1980-1997. As an example, the bilateral import share matrix for transport equipment is shown in Table 5.4.

Average import shares over all industries are shown in Table 5.5. As can be seen in these tables, import shares are different across world regions. They are certainly related to geography. While Canada and Japan receive most of their imports from the US, European countries trade more among each other and tend to receive their largest import share from Germany. The US receive most of their imports from Canada and Japan, while their biggest European trade partner is Germany.

Table 5.5: Average Bilateral Import Shares over all Industries; 1980-1997; in per cent

$\frac{to}{from}$	Canada	USA	Japan	France	Germany	Italy
Canada	0	39.33	8.17	1.67	2.55	2.26
USA	84.98	0	66.18	14.37	19.40	15.21
Japan	6.48	33.51	0	6.95	13.92	5.50
France	2.79	7.32	5.71	0	33.03	30.77
Germany	2.95	11.04	13.38	47.15	0	46.25
Italy	0.28	8.79	6.55	29.85	31.09	0

Import input-output matrices provided by the OECD are used to construct weights for the inter-industry spillover variable. The coefficients are calculated in a manner completely analogous to the input-output coefficients for the domestic spillover variable. Again, there are some similar patterns across countries, but significant quantitative differences remain, so constructing weights individually for each country is advantageous. A more detailed description of the construction of spillover weights is provided in the data appendix.

The next section presents estimation results concerning the impact of spillover variables on the costs of production.

5.3 Spillovers in OECD Industries

According to R&D based models of growth, R&D may not only enhance productivity growth in the firm that invests in it. Other economic agents can benefit from this investment through knowledge spillovers. There are essentially two different types of spillover channels implicit in the models described in chapter 2. First, industry i may benefit from innovations developed elsewhere, because they are embodied in intermediate capital or material inputs that it buys from other industries. Thus, it does not have to invent these new or improved products itself to benefit from the innovation. These type of spillovers are very well modelled with the weighting scheme described in the previous section.

Both the Aghion & Howitt (1998a) model and the Romer (1990) model imply that there may be disembodied spillovers associated with the knowledge production process in addition to this. Industries aspiring to develop innovations may benefit from research and development conducted before in other industries, because this allows them to build on previously developed knowledge. More precisely, new ideas may be exchanged e.g. at scientific conferences, due to the movement of engineers between different industries and/or countries or because foreign direct investment allows research and development personnel in the country, where the investment is made, to build on knowledge created in the investor's country. One could certainly think of many other channels for disembodied spillovers.

Even though trade related weights are chosen to construct spillover variables, it is hoped that these would also capture at least some of the disembodied spillovers associated with the knowledge production process, should that be of empirical importance. Since an ideal weighting scheme does not exist, one among the many possibilities has to be chosen arbitrarily. The models presented in chapter 2 provide clear guidance as to how to weight spillovers embodied in intermediate inputs, while it is difficult to derive a weighting scheme for disembodied spillovers. Therefore, trade weights are chosen in this study.

To see whether it is possible to pin down knowledge externalities empirically, the spillover variables described in the previous section are included in the cost function as external factors. From a theoretical point of view it is certainly desirable to include the three different spillover variables simultaneously to pin down their individual impact. This would ensure that an individual spillover variable does not pick up the impact of another variable that was excluded. Unfortunately, this approach proves infeasible because of multicollinearity between the different spillover variables. As more and more R&D variables are included in the estimation, estimates change sometimes dramatically and standard errors rise. Therefore, an alternative strategy is pursued. The impact of each spillover variable is investigated individually. It is then tested whether the result, that the impact is significant, is robust to excluding own R&D and the trend term from the regression and to employing a more flexible trend term specification. Estimation results with spillover variables that prove to have a significant impact on costs are reported in appendix A.5, if this result is robust in the sense just defined.

In four industries, food, wood, publishing and printing and manufacturing not elsewhere classified, none of the spillover variables has a significant impact. Since "exogenous" technological change is negative in the estimation without R&D variables for the three industries mentioned first, this result is not surprising. There just is no productivity growth to be explained, at least in the sample period considered here. In the manufacturing industries not elsewhere classified, in turn, there is some positive productivity growth, which however seems to have a different source than investment in R&D or knowledge spillovers.

As an overall picture, knowledge created in the same industry abroad seems to be the most important source of spillovers. If a significant impact of any of the spillover variables can be found at all, the intra-industry spillover variable is among it for almost all the industries. The only exception is the non-metallic mineral products industry, where only domestic spillovers have a significant impact. Consequently, the specification with own R&D and domestic spillovers is reported for non-metallic mineral products in appendix A.5. For all other industries the intra-industry spillover variable is chosen instead. If both the R&D variable and the intra-industry spillover variable are significant, both are included in the estimation. If, instead, only the spillover variable is significant, it is included alone. This is the case for the chemical and the rubber and plastics industry.

In the textiles industry and in the chemical industry international inter-industry spillovers also have a significantly negative impact on costs. This finding is robust to the exclusion of own R&D and the trend term. The well-known signs of multicollinearity appear, however, when both international spillover variables are included together: the estimated impact changes and standard errors rise dramatically. It is impossible to pin down empirically which one of the two variables is really relevant and what is their relative importance. The estimation results with the intra-industry spillover variable are reported for two reasons. First, the fact that it is significant in so many industries suggests that it is the most important among the spillover sources considered here. Second, it is somewhat implausible that an industry should benefit from knowledge created in foreign industries other than itself, while knowledge created in those same industries located at home has no impact on its productivity. Therefore, the estimated impact of the intra-industry spillover is deemed more reliable.

Moreover, in the textiles industry the impact of own R&D becomes significant along with the spillover variable, as soon as the trend term is excluded from the estimation. Since productivity growth estimated with the trend term is significant even after the inclusion of knowledge variables in the estimation, appendix A.5 reports results of the specification with the trend term parameters b_{Lt} and b_t and the intra-industry spillovers, but without its own R&D capital stock.

International intra- and inter-industry spillovers are also significant in the electrical and optical equipment industry, as long as own R&D is not included in the estimation. Since, these results are not robust in the sense defined above, they are not reported. However, it should be noted that for this industry it is not only hard to distinguish the influence of different spillover sources. It is also difficult, if not impossible, to differentiate between the influence of the industry's own R&D investments and spillovers.

The difficulty to choose the right sources of productivity growth for the industries discussed in the previous paragraphs is certainly a symptom of the more general problem that different multicollinear variables are conjectured to enter the estimation equation. In such a case it is very difficult to decide empirically, which variable is relevant in reality.

Table 5.6: Influence of Spillover Variables on the Productivity Growth Estimates

Industry	Prod.	US	Italy	Japan	Germany	Canada	France
Textiles	$-\varepsilon_{CT}$	0.68	0.65	-	0.64	0.66	0.63
		(0.09)	(0.09)		(0.09)	(0.09)	(0.09)
	$-\varepsilon_{CT}^{b_{sfs}}$	0.54	0.52		0.51	0.52	(0.50)
		(0.09)	(0.09)		(0.10)	(0.09)	(0.10)
Chemicals	$-\varepsilon_{CT}$	0.17	0.17	-	0.15	0.17	-
		(0.01)	(0.06)		(0.01)	(0.01)	
	$-\varepsilon_{CT}^{b_{sfs}}$	0.08	0.09		0.08	0.08	0.10
		(0.07)	(0.07)		(0.06)	(0.08)	(0.10)
Plastics	$-\varepsilon_{CT}$	-0.13	-0.01	-	-0.18	-0.15	
		(0.09)	(0.10)		(0.10)	(0.10)	
	$-\varepsilon_{CT}^{b_{sfs}}$	-0.22	-0.18		-0.29	-0.25	
		(0.10)	(0.11)		(0.11)	(0.10)	
Mineral Prod.	$-\varepsilon_{CT}$	0.32	0.29	-	0.32	0.34	0.32
		(0.16)	(0.14)		(0.16)	(0.17)	(0.16)
	$-\varepsilon_{CT}^{b_{sd}}$	-0.0001	-0.0002		-0.0001	-0.0001	
		(0.002)	(0.002)		(0.002)	(0.002)	
Metals	$-\varepsilon_{CT}$	0.29	0.27	0.21	0.25	0.30	0.26
		(0.05)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)
	$-\varepsilon_{CT}^{b_{sfs}}$	0.28	0.27	0.20	0.24	0.28	0.24
		(0.08)	(0.07)	(0.07)	(0.07)	(0.27)	(0.07)
Machinery	$-\varepsilon_{CT}$		0.31	0.27	0.29	0.35	0.28
			(0.13)	(0.14)	(015)	(0.14)	(0.14)
	$-\varepsilon_{CT}^{b_{sfs}}$		-0.64	-0.70	-0.74	-0.64	-0.66
			(0.19)	(0.19)	(0.20)	(0.19)	(0.18)

(Standard Errors in Parentheses)

As R&D based growth theory would suggest, the spillover variables apparently explain a portion of the observed productivity growth. Table 5.6 reports productivity growth estimates obtained with and without spillover variables included in the estimation. $-\varepsilon_{CT}^{b_{sfs}}$ is the cost elasticity with respect to the trend term obtained from the estimation including intra-industry spillovers, while $-\varepsilon_{CT}^{b_{sd}}$ is obtained from the estimation including the domestic spillover variable. This spillover variable is significant only in the cost function for the mineral products industry.

Including spillover variables lowers the dual measure of technological change in all of the investigated industries. The only exception is the basic and fabricated metals industry, where the implied productivity growth decreases only slightly, even if both the industry's own R&D capital stock and the significant intra-industry spillover variable are included in the estimation.

The decrease is also quite small in the textiles industry, where significantly positive productivity growth is still estimated even after the inclusion of the spillover variable into the estimation equation. This suggests that there seem to be other sources than knowledge creation as a result of research and development effort that are important for productivity growth in this industry.

In the chemicals industry the small but significant productivity growth that is measured when estimating the cost function without R&D variables becomes even smaller and insignificant once the intra-industry spillover variable is included in the estimation. Likewise, in the mineral products industry even the point estimate of productivity growth is virtually zero once the domestic spillover variable is included in the estimation, while it is significantly positive when R&D variables are not included. In these two industries, the trend term seems to capture productivity growth due to knowledge spillovers when these are not explicitly taken into account.

In the machinery industry the productivity growth estimate measured with the trend term even becomes significantly negative once both the industry's own R&D effort and international intra-industry spillovers are accounted for. This is an indication that sources of technological change other than knowledge creation, such as organizational changes or government policies, have adverse effects on productivity growth. This also seems to hold for the rubber and plastics industry, where estimated productivity growth is negative but insignificant in the estimation without R&D variables. With intra-industry

Table 5.7: Average Cost Elasticities with Respect to Spillover Variables

Industry	R&D	US	Italy	Japan	Germany	Canada	France
Textiles	ε_{Csfs}	-0.005	-0.010	-	-0.010	-0.127	-0.010
		(0.001)	(0.003)		(0.001)	(0.041)	(0.004)
Chemicals	ε_{Csfs}	-0.003	-0.023	-	-0.013	-0.128	–0.180
		(0.001)	(0.007)		(0.004)	(0.039)	(0.066)
Plastics	ε_{Csfs}	-0.005	-0.021	-	-0.016	-0.184	-
		(0.002)	(0.011)	-	(0.008)	(0.093)	-
Mineral Prod.	ε_{Csd}	-0.162	-0.026		-0.125	-0.037	-0.099
		(0.067)	(0.011)		(0.053)	(0.016)	(0.041)
Metals	ε_{CR}	-0.027	-0.001	-0.041	-0.038	-0.017	-0.022
		(0.012)	(0.004)	(0.019)	(0.018)	(0.008)	(0.010)
	ε_{Csfs}	-0.027	-0.088	-0.065	-0.062	-0.500	-0.117
		(0.013)	(0.026)	(0.020)	(0.018)	(0.145)	(0.035)
Machinery	ε_{CR}	-	-0.035	-0.154	-0.215	-0.085	-0.120
		-	(0.007)	(0.09)	(0.041)	(0.016)	(0.023)
	ε_{Csfs}	-	-0.033	-0.015	-0.014	-0.325	-0.054
		-	(0.010)	(0.005)	(0.004)	(0.099)	(0.016)

ε_{Csfs}: Cost Elasticity w.r.t. the Intra-Industry Spillover Variable
ε_{Csd}: Cost Elasticity w.r.t. the Domestic Spillover Variable
(Standard Errors in Parentheses)

spillovers included in the estimation, the estimate of technological regress rises enough in absolute value so that it becomes significantly negative.

Overall these results seem to suggest that in line with the R&D based theories of growth presented in chapter 2 market driven knowledge creation can account for most of the observed productivity growth. While results differ considerably across industries, both excess returns to investments in R&D and spillovers from other industries are found to explain some of the technological change that is measured when R&D variables are not accounted for in the estimation. Since productivity growth estimated with the trend term becomes insignificant or even negative in the majority of industries, it can be concluded that sources of technological change other than innovations more often than not seem to have adverse effects on R&D.

In all of the industries where spillovers are found to have a significant impact on costs this effect is found to be negative. This can be verified in Table 5.7, which reports average cost elasticities with respect to own R&D and with respect to the spillover variable. ε_{CR} denotes the cost elasticity with respect to the industry's own R&D capital stock, ε_{Csfs} is the cost elasticity with respect to the international intra-industry variable, while ε_{Csd} denotes the cost elasticity with respect to the domestic inter-industry spillover variable.

Since the impact of R&D and spillover variables is negative, these variables shift the cost function downwards, implying that they are a source of technological progress, as R&D based models of growth would suggest. Similar as the cost elasticities with respect to the industries' own R&D capital stocks, the elasticities with respect to spillover variables tend to be larger in absolute value than the productivity growth estimated with the trend term in the estimation without R&D variables. As discussed in section 5.1, this seems to suggest that the trend term picks up some of the productivity growth due to knowledge creation, but not all of it, when R&D variables are not accounted for in the estimation. This also fits into the interpretation outlined before, that some of the sources of technological change other than innovations seem to have adverse effects on productivity growth.

It is a somewhat relieving finding that in spite of the multicollinearity between different R&D variables, including spillover variables in the estimation hardly seems to change the cost elasticity with respect to R&D in most industries. This can be verified comparing Tables 5.7 and 5.2.

R&D based models of growth suggest that the economy's stock of knowledge is a source of increasing returns. This may apply to knowledge created in the industry where it contributes to economies of scale as well as to spillovers. To assess the importance of this effect in the investigated industries, the rate of returns to scale including the effect of excess returns to the industries' own R&D capital as well as the effect of spillovers is reported in Table 5.8. η captures both internal and external economies of scale which are due to spillovers. For those industries for which no significant impact of spillover variables could be found η of course equals η_{vf} in Table 5.3

Table 5.8: Average Economies of Scale in Rival Factors, R&D Capital and Spillovers

Industry	R&D	US	Italy	Japan	Germany	Canada	France
Textiles	η	1.160	1.195	-	1.148	1.295	1.152
		(0.031)	(0.033)	-	(0.031)	(0.064)	(0.030)
Chemicals	η	1.122	1.232	-	1.196	1.302	-
		(0.030)	(0.032)	-	(0.029)	(0.062)	-
Plastics	η	1.276	1.210	-	1.191	1.410	-
		(0.046)	(0.042)	-	(0.041)	(0.127)	-
Mineral Prod.	η	1.584	1.498	-	1.499	1.327	1.449
		(0.138)	(0.081)	-	(0.107)	(0.069)	(0.092)
Metals	η	1.240	1.315	1.379	1.328	1.816	1.327
		(0.053)	(0.069)	(0.073)	(0.066)	(0.212)	(0.074)
Machinery	η	-	1.196	1.436	1.505	1.602	1.386
		-	(0.041)	(0.070)	(0.091)	(0.138)	(0.055)
Elect. &Opt. Eq.	η	-	1.160	1.171	1.246	1.248	1.191
		-	(0.037)	(0.040)	(0.058)	(0.049)	(0.060)
Transport	η	1.378	1.311	1.280	1.270	1.136	1.304
		(0.102)	(0.057)	(0.053)	(0.058)	(0.042)	(0.063)

(Standard Errors in Parentheses)

As in the estimation with own R&D, the estimated internal rate of returns to scale is quite robust to the inclusion of further knowledge variables. Only in the chemical industry does it decrease somewhat. This is also the reason why η is slightly lower than the estimate of internal economies of scale presented in Table 4.6 for the US chemical industry. Since this effect is observed for only one industry it does not seem wise to draw any conclusions from this. Rather, the inverse of the cost elasticity with respect to output seems to capture the internal rate of returns to scale quite accurately in most industries, whether or not knowledge variables are included in the estimation.

However, overall returns to scale in traditional factors, own R&D and knowledge spillovers are higher than internal economies of scale alone for almost all industries and countries. For some industries, most notably non-metallic mineral products, the machinery industry and to some extent the basic and fabricated metal industry, the difference is substantial. In the first two industries, internal and external economies of scale together imply a rate of returns to scale that is close to 1.5 and higher in many countries In accordance with the theoretical model, the empirical results imply that knowledge is a source of economies of scale.

Overall, the results presented in this section and in section 5.1 are very much in line with the R&D based models of growth presented in the second chapter. Either the industries' own R&D capital stocks or spillovers or both are found to be sources of productivity growth in the majority of the investigated industries. These knowledge variables cause downward shifts of the industries' cost functions. Since productivity growth estimated with the trend term decreases once knowledge variables are included in the estimation, it can be concluded that the trend term picks up some of the effect of R&D as long as it is not accounted for explicitly in the estimation. As R&D based models of growth would suggest, both the industries' own R&D capital stocks and/or spillovers from other industries are shown to be a source of economies of scale.

At the same time, the results presented in this chapter suggest that it is very revealing to choose a more disaggregate estimation level and to differentiate between industries. The estimated impact of the different industries' research and development activity for their own technological advancements as well for productivity growth in other sectors differs considerably across industries. In fact, in a number of industries neither significant productivity gains nor any role for knowledge as a driving force for them can be found. On the contrary, there seem to be effects other than knowledge creation and innovations that adversely affect the industries' productivity.

It is also important to note that different knowledge variables and the trend are highly collinear, so that it is extremely difficult to get precise estimates of the impact of different sources of technological change and to assess their relative importance. Yet, the results presented in this section are carefully checked for their robustness. For this reason they can be considered quite reliable. Most notably it seems safe enough to draw the conclusion that for the industries investigated in this study, international intra-industry spillovers seem to be most important among the three different spillover sources that are taken into account.

The next section describes how the results presented in this chapter compare with existing results concerning the impact of R&D and spillovers on productivity.

5.4 Knowledge and Productivity - Existing Results

Coe & Helpman's (1995) investigation is one of the earliest and most prominent country-level studies explicitly aimed at testing the empirical relevance of endogenous growth models. The authors regress the domestic and foreign trade weighted R&D capital stocks on the log of total factor productivity using trade shares to weight the spillover variable. With a panel of 22 advanced economies over 1971-1990, they find that R&D is indeed shared across national borders. Both domestic and foreign import-share-weighted R&D capital stocks are found to foster total factor productivity.

Table 5.9: Estimates of Output Elasticities of R&D Capital at the Country Level

Study	CRS and PC imposed*	Direct Elasticity	Indirect Elasticity	Sample Period	Obs.
Coe & Helpman (1995)	yes	0.078-0.234	0.03-0.15	1971-90	440
Engelbrecht (1997)	yes	0.055-0.072	0.061-0.087	1971-85	315
Kao, Chiang & Chen (1999)	yes	0.091 (0.02)	0.044 (0.03)	1971-90	440
Lichtenberg & Pottelsberghe (1996)	yes	0.017 (0.008)	0.044 (0.005)	1971-90	440

*CRS: Constant Returns to Scale; PC: Perfect Competition
(Standard Errors in Parentheses)

The Coe and Helpman study has led a number of researchers to extend the framework, using essentially the same data. Engelbrecht (1997) adds human capital to the Coe-Helpman specification. While identifying an important role of human capital as an additional engine of productivity growth, he confirms Coe & Helpman's (1995) results concerning the impact of R&D on productivity. To account more appropriately for unit roots in the data Kao et al. (1999) repeat Coe & Helpman's (1995) investigation using

Dynamic OLS and Fully-Modified OLS. The authors confirm the qualitative result that both domestic R&D and international spillovers have an important impact on productivity. Lichtenberg & van Pottelsberghe de la Potterie (1996) find that the trade-share weighted spillover variable becomes insignificant, once an additional FDI-weighted variable is included in the estimation. While this could be interpreted as a sign that FDI is more important as a channel of productivity spillovers than trade, it is much more likely to be simply a problem of multicollinearity. Given that the spillover variables differ only in their weights, they are more than likely to be highly collinear.

Hoping to gain further insight into different spillover sources, Keller (2001) constructs a domestic spillover variable, an international intra-industry and an inter-industry spillover variable using the weighting scheme described in section 5.2.2. Table 5.10 reports estimation results of the specification with input-output weights with all of the spillover variables included in the estimation. The reported indirect elasticity concerns the domestic spillover variable. The estimates vary largely depending on which spillover variables he includes, and standard errors rise as more and more R&D variables enter the estimation equation. While Keller's results do confirm that R&D matters as an engine of productivity growth, care should be taken when drawing conclusions from the relative size of estimated R&D parameters. Because of the multicollinearity problem, it seems rather unlikely that it is possible to precisely pin down the relative effect of different spillover variables.

Table 5.10: Estimates of Output Elasticities of R&D Capital at the Industry Level

Study	CRS and PC imposed*	Direct Elasticity	Indirect Elasticity	Sample Period	Obs.
Keller (2001)	CRS: yes			1970-	2288
	PC: no	0.607	0.571	91	
		(0.119)	(0.558)		
Verspagen (1997)	no	0.077	0.095	1972-	5852
		(0.009)	(0.011)	92	

*CRS: Constant Returns to Scale; PC: Perfect Competition
(Standard Errors in Parentheses)

Using an earlier version of the STAN database Keller is confined to value-added data, which is likely to cause problems, when the market for material inputs is not competitive as discussed extensively in section 3.1.1 and in appendix C. In the light of the empirical results of this dissertation, it may also appear problematic that Keller assumes the impact of R&D and knowledge variables to be the same across all industries. Results presented in the previous section suggest that there are important differences between industries. In fact, in some of the industries none of the knowledge variables seem to have a significant impact at all.

With a similar international industry dataset from the OECD, Verspagen (1997) estimates a Cobb-Douglas production function augmented with own R&D capital stocks and domestic as well as an international spillover variables. Generally, both the industry's own R&D variable as well as the spillover variables have a significantly positive impact in most specifications. There is an interesting difference between the "within"-estimates, stressing the time dimension of the panel, and the "between"-estimates, which stress the cross section dimension instead. The rate of returns to scale in all private factors including R&D, which is implied by the "within"-estimates is significantly smaller than one in most cases. In contrast, it is bigger than one, although not significantly, in most estimations for which the between-estimator is applied. This is primarily due to the fact, that the estimated elasticity of physical capital is systematically lower, when the within-estimator is applied. A similar phenomenon is observed in Los & Verspagen's (2000) study with US firm level data. This is in line with Mairesse & Sassenou's (1991) and Nadiri's (1993) observation discussed before, that the estimated elasticity of physical and R&D capital tend to be lower in time series than in cross section estimations.

As an alternative to the TFP regression in levels, estimating the impact of R&D on productivity in growth rates is also popular in the applied literature. In these studies it is common to use the ratio of R&D expenditures over output as an explanatory variable. The coefficient is often interpreted as the rate of return to R&D (Jones & Williams 1998).

Most industry studies that aim at measuring the rate of return to R&D directly, con-

Table 5.11: Estimates of the Rate of Return of R&D at the Industry Level

Study	CRS and PC Imposed*	Direct Rates of Return	Indirect Rates of Return	Sample Period	Obs.
US					
Terleckyj (1980)		0.25	0.82	1948	20
		(0.08)	(0.21)	-66	
Sveiskauskas (1981)	yes	0.171		1959	144
		(0.559)		-69	
Scherer (1982)	CRS: yes	0.29	0.74	1973-	87
	PC: no	(0.144)	(0.391)	78	
Griliches & Mairesse (1983)	PC: no	0.23		CSD++	60
	CRS: yes	(0.12)			
Japan	yes	0.255	0.8	CSD++	50
Goto & Suzuki (1989)		(0.140)	(0.417)		
France					
Griliches & Mairesse (1983)	PC: no	0.33	CSD++		60
	CRS: yes	(0.14)			
International					
Grifffith, Redding	yes	0.207-0.446		1970	2478
& van Reenen (2000)		(0.170)-(0.178)		-92	

*CRS=Constant Returns to Scale; PC=Perfect Competition
++CSD:Cross-Section Data; (Standard Errors in Parentheses)

firm the result that knowledge has a significantly positive effect on productivity growth. As can be verified with a glance at Table 5.11, in most cases even the size of the different estimates is quite close to each other, although sample periods, estimation techniques, investigated countries, the definition and measurement of output and inputs and the weighting scheme for the spillover variables differ widely among the studies.

In addition to estimating the direct effect of R&D on productivity, Griffith et al. (2000) also try to asses whether R&D enhances the absorptive capacity of an industry. To this end, they develop a technology gap variable measuring each industry's productivity relative to that of the technology leader. To capture the role of knowledge creation as an enhancement of absorptive capacity they interact the ratio of R&D expenditures to output with this technology gap term and introduce this as an explanatory variable into their estimation equation. Their result that R&D has a significant direct effect on productivity and enhances productivity catch-up with the technology leader remains robust to several adjustments to TFP, such as allowing for mark-ups and varying capacity utilization or accounting for heterogeneity of skills in the labor force.

Table 5.12: Estimates of Elasticities with respect to R&D at the Firm Level

Study	CRS and PC imposed	Direct Elasticity	Indirect Elasticity	Sample Period	Obs.
US					
Schankerman (1981)	no	0.232		CSD^{++}	101
		(0.029)		1963	
Griliches (1986)	no	0.126		1972	491
		(0.019)		CSD^{++}	
Branstetter (2001)	no	0.362	0.831	CSD^{++}	209
		(0.130)	(0.443)	1983-89	
Los & Verspagen (2000)	no	0.0073	0.432	1974-	2475
		(0.027)	(0.061)	1993	
Hall & Mairesse (1996)	no	0.039		1985-	2210
		(0.048)		89	
Japan					
Branstetter (2001)	no	0.013	0.703	CSD^{++}	205
		(0.049)	(0.346)	1983-89	
France					
Hall & Mairesse (1996)	no	-0.138		1985-	1905
		(0.044)		89	

*CRS=Constant Returns to Scale; PC=Perfect Competition
$^{++}$CSD:Cross-Section Data; (Standard Errors in Parentheses)

To show that a positive impact of R&D and spillovers on productivity has also been found in several firm level studies for different countries, different data sets and different sample periods Table 5.12 displays some representative results. An overview over firm level studies is provided in Mairesse & Sassenou (1991).

From the point of view of this dissertation Schankerman's (1981) results are particularly interesting. Adjusting his data for double-counting, the author is able to show that a failure to do so results indeed in downward biased estimates.

In conflict with the theory they investigate, many researchers employing the primal approach to estimate the impact of knowledge on productivity impose constant returns to scale and perfect competition. While the investigation of the role of knowledge in the primal approach typically relies on the Cobb-Douglas function, functional forms chosen in cost function studies are much more general. Moreover, most researchers who employ a dual approach typically exploit the possibility to allow for varying capacity utilization and economies of scale. For this reason, the cost function framework seems more appropriate than the more limited Solow residual framework.

Bernstein & Nadiri (1988) estimate a translog cost function system to explore spillovers among five US high-tech industries. Rather than precalculating weights to construct an aggregate spillover variable, the impact of each R&D capital stock from other industries is estimated individually. Bönte (1997) replicates this study with German data. Like Bernstein and Nadiri he is able to find spillover relations between some, but not all of the industries.

Morrison Paul & Siegel (1997) estimate a generalized Leontief cost function for US two-digit manufacturing industries. R&D, information technology and human capital are introduced as external factors at a higher aggregation level to capture their external nature. All of the external capital factors are found to be productivity enhancing. Cost elasticities with respect to R&D capital stocks are also summarized in Table 5.13.

Table 5.13: Cost Elasticities with Respect to R&D Capital

Study	Direct Elasticity	Indirect Elasticity	Sample Period	Obs.
Bernstein & Nadiri (1988)		-0.059 - 0.208	1958-81	24 each
Bönte (1996)		-0.56 - 1.93	1972-89	18 each
Kim & Nadiri (1996a)	-0.015 - 0.043	-0.007 - 0.059	1964-91	196
Kim & Nadiri (1996b)	-0.091		1974-90	51
Morrison Paul & Siegel (1997)		-0.02 - 0.294	1958-89	450 ind.
Bernstein & Yan (1997)		-0.001 - 0.866	1962-88	60 each
Mamuneas (1999)		-0.105 - 0.508	1949-91	43 each

Bernstein & Mohnen (1998) investigate the effect of own R&D and of bilateral spillovers for the US and Japanese R&D-intensive industries, which are aggregated into one. The authors find spillovers from the US to Japan, but not the other way around. The cost function also includes a significant trend term. This implies that own R&D and spillovers between these two countries only do not fully explain all of the observed productivity growth.

Nadiri and Kim use a translog function to estimate the role of economies of scale, mark-ups and the impact of private R&D (Kim & Nadiri 1996*b*) for the manufacturing sectors of Japan, Korea and the US. In a second study (Kim & Nadiri 1996*a*) they investigate the role of private R&D and spillovers with manufacturing sector data for the G7 countries, imposing constant returns to scale and perfect competition. Thus, while the two studies together encompass all the relevant features of endogenous growth theory, they are investigated separately.

Bernstein & Yan (1997) estimate domestic and bilateral inter-industry spillovers for Canadian and Japanese industries. The data is pooled across countries and estimated industry by industry. International spillovers from Canada to Japan are found for all industries, but chemical products. Yet, spillovers from Japan to Canada are significant in electrical products, food and beverages and primary metals only. Domestic spillovers reduce costs in four out of ten Canadian, and in eight out of ten Japanese industries.

Overall the prediction of R&D based models of growth that knowledge is a driving force of productivity growth is a very well established empirical result. A positive influence of both own R&D and knowledge spillovers on productivity growth has been found both in the primal and in the dual framework, with many different data sets, different levels of data aggregation, for different time periods and different countries, with many alternative estimation methods and different definitions of the spillover variables.

If anything, the result that R&D is productivity enhancing appears more unambiguous in the previous literature than in this dissertation. While for a number of industries no significant impact of any of the knowledge variables can be found, such phenomena are reported only in a few studies conducted before. This may well be due to the fact that only some researchers actually differentiate between different countries, industries or firms. Yet, the empirical results of this dissertation and some other studies, such as Bernstein & Mohnen (1998) and Bernstein & Nadiri (1988), suggest that it can be very revealing to allow for heterogeneity. Of course this approach is not without its limits, because there may not be enough observations to estimate a different parameter for each cross section. Yet, the problem should be kept in mind when interpreting empirical results.

Another problem that is carefully taken into account in this dissertation, but often not in the previous literature, is the multicollinearity between different knowledge variables and the trend term. Researchers who enter several knowledge variables into their estimation equation usually present their results as if both the sign of their parameter estimates as well as their size was very reliable. Some researchers, such as Keller (2001), even draw conclusions about the relative importance of different spillover variables. Given the finding discussed in the previous section, that results often change dramatically when entering additional knowledge variables, any study trying to source productivity growth precisely should be treated with caution.

Studies employing the primal approach are frequently based on the Solow residual framework relying on the assumptions of constant returns to scale and perfect competition. Some researchers, such as Keller (2001), use cost shares as weights to allow for market power. A few others estimate the production elasticities, an approach that allows for both market power and economies of scale. Cost function studies generally encompass these important features of R&D based growth theory. Yet, none of the studies discussed in this section aims at estimating mark-ups, economies of scale and the impact of knowledge in an integrated approach. In fact, to the best of my knowledge such an attempt has not been made before.

Chapter 6

Conclusions

The Solow residual framework, which relies on the assumptions of constant returns to scale and prefect competition, is highly popular among empirical researchers investigating R&D based models of growth. Yet, theory calls for a framework that encompasses market power and non-constant returns to scale when investigating these models. In the theoretical part of this dissertation it is shown that economies of scale and market-power are inextricably linked to knowledge as an engine of productivity growth, if innovations are assumed to be created as a result of market incentives. In consequence, all R&D based growth models encompass market power and economies of scale in the aggregate production function.

The Solow residual is an appropriate measure of productivity growth, if the neoclassical growth model is chosen as a theoretical background, because this theory does indeed rely on the assumptions of perfect competition and constant returns to scale. In contrast, according to endogenous growth models with externalities, there may be economies of scale as a result of the spillovers, although these models still allow for a perfect competition equilibrium. R&D based models of growth imply that market power has to be present, so that innovators can recover their costs of knowledge creation. These models, unlike any other growth theory, predict that market power, economies of scale and a productivity enhancing role for knowledge should be found in the data. Thus, investigating these phenomena empirically provides a possibility to judge the relevance of R&D based growth models in comparison with competing theories.

It is shown in the third chapter of the dissertation that the Solow residual is a biased measure of productivity growth when the assumptions of perfect competition and constant returns do not hold. In contrast, the cost function framework chosen in this dissertation readily encompasses economies of scale and market-power. This characteristic makes it a much more suitable framework to study R&D based growth theory empirically. Based on the theory it may not only be desirable to choose a productivity growth measure that is unbiased in the presence of market power and economies of scale. Since these features distinguish R&D based models from other growth theories, it appears desirable to test whether they can indeed be found in the data. The cost function and factor demand model chosen in this dissertation provides a framework to estimate mark-ups, the rate of returns to scale and the impact of knowledge in an integrated approach and to study possible links between these features.

An empirical investigation with a new international industry data set from the OECD reveals, in fact, the presence of both market-power and economies of scale in all of the investigated industries. Thus, both theoretical reasoning and empirical results suggest that the popular Solow residual framework is not appropriate to investigate the role of knowledge for economic growth, because it is biased upwards as a measure of productivity growth. A comparison of the Solow residual with the productivity growth measure obtained from the cost function estimation reveals, in fact, that the latter is much lower for all of the investigated industries.

Moreover, the Solow residual displays a strong cyclical component, while the dual productivity growth measure is very smooth. This is likely to be due to the fact that the error correction framework chosen for the cost function estimation encompasses very general short run deviations from equilibrium or in other words varying capacity utilization. The Solow residual, in contrast, assumes that equilibrium is attained at all times. Especially the capital stock is much more likely to measure capacity, rather than actual use of capital services, which would thus be underestimated in booms and overestimated in slumps adding a spurious cyclical component to the productivity growth measure. For this reason it seems to be a definite advantage of the empirical framework chosen in this study that it accounts appropriately for varying capacity utilization.

The finding of economies of scale alone would support different classes of endogenous growth theories, including models with increasing returns due to externalities. Yet, market power and economies of scale together clearly favor R&D based growth models over competing theories. Of course, this is not a proof that R&D based growth theories are right, because market-power and economies of scale may well be due to other factors than the mechanisms described in those models. Yet the finding that mark-ups are positive and that returns to scale are increasing does imply that among competing growth theories the data fits R&D based models best.

Some ad hoc regressions reveal that the estimated size of mark-ups and of the rate of returns to scale seem to be related to the amount of R&D activity that the industries perform. This could be interpreted as further evidence in favor of R&D based growth theory. Yet, the regressions are based on very little theory, so any conclusions drawn from them should be very cautious.

Both theory and the econometric results suggest that the cost function framework is much more suitable to investigate the impact of R&D on productivity, because mark-ups and economies of scale are likely to bias the Solow residual as a productivity growth measure. Moreover, it seems to be important to account for varying capacity utilization. Therefore the cost function in the error correction form is used to estimate the impact of knowledge variables on the costs of production and on productivity.

According to R&D based growth theories, investments in research and development may not only enhance the productivity of the investor, but knowledge may also spill over to other producers, because it is embodied in intermediate inputs traded among different industries. Moreover there may be disembodied spillovers because researchers in one industry can build on knowledge that has been previously created elsewhere. Therefore, the impact of the industries' own R&D capital stock is investigated. In addition to this, externalities from three different sources are considered: domestic spillovers from other industries, international intra-industry spillovers and international inter-industry spillovers.

A significant impact of the industries' R&D capital stock on their own productivity is found only in four relatively R&D-intensive industries. Yet, because labor, material inputs and the capital stocks are not corrected for the inclusion of R&D expenditures, the estimated impact of R&D capital on costs measures excess returns to R&D rather than the full impact of knowledge on productivity. Excess returns to R&D could be interpreted as intra-industry spillovers. Alternatively, it may be concluded that knowledge is particularly productive in these industries, having a much stronger and/or longer lasting effect than the rival factors of production.

Spillovers are found to enhance productivity in six industries, two of which also benefit from excess returns to R&D. Only in four out of twelve industries no significant impact of any of the knowledge variables can be found at all. In three of these the dual measure of productivity growth is negative. So it simply seems to be the case that there is little technological change to be explained with innovative activity in these industries, at least over the investigated sample period. R&D-intensity is particularly low in all of the four industries where no significant impact of knowledge variables can be found. It is thus not too surprising that there should not be a very important role for knowledge variables in these industries.

The productivity growth measured with the trend term is found to decrease in all industries, once knowledge variables with a significant impact are included in the estimation. In most cases it becomes insignificant or even significantly negative, indicating that sources of technological change other than innovations, such as government policies or organizational changes, may even have adverse effects on productivity growth. In any case, this finding suggests that knowledge creation does indeed explain a good part of the observed productivity growth, as theory suggests.

According to R&D based growth models, there should be economies of scale in rival factors and knowledge together. In accordance with this prediction, the knowledge variables are found to be a source of economies of scale in all industries where they have a significant impact.

While it is a well established result of this study that spillovers matter in many industries, it also turns out that attributing them to a specific source is highly difficult. Because of strong multicollinearity among all of the different knowledge variables and the trend term it is hardly possible to decide which are really the sources of productivity growth. It is even more difficult to asses their relative importance precisely, if more than one knowledge variable is found to be significant. Therefore, careful robustness checks are performed. Although the multicollinearity problem is strong, it seems safe to conclude from the results that international intra-industry spillovers are the most important source of externalities in the investigated industries.

The econometric results imply important differences among the different industries. Both the estimated productivity growth and the impact of different knowledge variables are found to vary considerably across industries. The results confirm both the theory and earlier empirical findings in that in many industries investments in R&D seem to both enhance the productivity of the investor and spill over to ease technological advancements elsewhere. At the same time, the results imply that much of the prior research has not taken multicollinearity problems into account appropriately, nor did it allow for heterogeneity as much as the available data would have allowed for. Yet, both issues seem to be very important. Because both problems can be solved only imperfectly, it does not seem wise to draw strong conclusions from any empirical results that involve R&D capital stocks. The qualitative result that knowledge seems to be important for productivity growth is well established. Any stronger conclusion, such as the exact size of the impact and the relative importance of different sources of knowledge externalities, should always be treated with caution.

The link between market power, economies of scale and market driven innovative activity as a source of productivity growth, which is implied by R&D based growth theories, has been much overlooked in the empirical literature. Yet these features are necessarily interrelated, once it is agreed upon that innovations as a response to market incentives are at the heart of economic growth. Therefore, it is pervasive to investigate simultaneously whether market power, economies of scale and a productivity enhancing role for knowledge can be found in the data. The empirical investigation in this dissertation suggests, that R&D based growth models seem to pass this empirical test very well.

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Appendix A

Estimation Results

A.1 Direct Results

The meaning of the parameters is described in section 3.2.2. Those parameters that are estimated with country dummies, namely the constants of the factor demand equations, b_L, b_K and b_M, and the mark-up, μ, are reported with an additional index denoting the country. US stands for the US, I for Italy, JP for Japan, D for Germany, C for Canada and F for France. $\mathrm{R}^2 s$ and the Durbin Watson Statistic, D.W., are reported separately for the cost function, the three factor demand equations, labor, capital and material inputs and the price equation.

Table A.1: Estimation Results for the Food and Beverages Industry (15-16)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.129	-1.496	0.432	0.354	-1.120	1.165
(0.027)	(0.323)	(0.079)	(0.047)	(0.279)	(0.118)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.050	0.088	0.102	0.032	0.071	0.096
(0.016)	(0.016)	(0.017)	(0.017)	(0.016)	(0.017)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.108	0.200	0.155	0.205	0.059	0.227
(0.059)	(0.060)	(0.063)	(0.063)	(0.058)	(0.062)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.012	0.040	-0.108	0.069	-0.019	-0.019
(0.017)	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
0.0005	0.008	0.009	-0.003	-0.062	-0.002
(0.0005)	(0.001)	(0.001)	(0.006)	(0.014)	($0.4*10^{-4}$)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.237	1.267	1.204	1.232	1.233	1.216
(0.044)	(0.044)	(0.042)	(0.043)	(0.045)	(0.043)

	Cost	Labor	Capital	Material	Price
R^2	0.990	0.861	0.912	0.985	0.977
D.W.	0.386	0.174	0.215	0.756	0.381
Obs.	107	107	107	107	107

(Standard Errors in Parentheses)

Table A.2: Estimation Results for the Textiles Industry (17-19)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.504	-2.078	0.923	0.789	-1.474	1.046
(0.047)	(0.250)	(0.095)	(0.053)	(0.208)	(0.087)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.047	0.035	-	-0.003	0.068	0.041
(0.012)	(0.012)	-	-0.003	(0.012)	(0.012)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.256	0.0356	-	0.418	0.181	0.247
(0.028)	(0.028)	-	(0.027)	(0.029)	(0.028)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.046	0.035	-	0.048	0.003	0.018
(0.019)	(0.018)	-	(0.018)	(0.019)	)0.018)
b_{LT}	b_{KT}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.007	-0.008	0.001	-0.0009	-0.03	$5*10^{-5}$
(0.0007)	(0.002)	(0.0007)	(0.0004)	(0.007)	$(2*10^{-5})$
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.219	1.224	-	1.213	1.211	1.175
(0.017)	(0.018)	-	(0.018)	(0.017)	(0.018)

	Cost	Labor	Capital	Material	Price
R^2	0.994	0.979	0.951	0.908	0.985
D.W.	0.470	0.572	0.321	0.266	0.342
Obs.	88	88	88	88	88

(Standard Errors in Parentheses)

Table A.3: Estimation Results for the Wood Industry (20)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.135	0.125	0.011	0.135	0.080	0.676
(0.060)	(0.349)	(0.137)	(0.069)	(0.289)	(0.099)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.242	-	0.169	0.181	-
-	(0.020)	-	(0.021)	(0.021)	-
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	1.021	-	0.575	0.345	-
-	(0.050)	-	(0.051)	(0.053)	-
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	-0.045	-	-0.052	-0.048	-
-	(0.027)	-	(0.028)	(0.027)	-
b_{LT}	b_{KT}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.001	0.004	-0.001	-0.006	-0.034	-0.002
(0.001)	(0.002)	(0.001)	(0.001)	(0.015)	($6*10^5$)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.327	-		1.239	1.263
-	(0.062)	-		(0.060)	(0.059)
	Cost	Labor	Capital	Material	Price
R^2	0.990	0.841	0.980	0.958	0.977
D.W.	0.528	0.288	0.273	0.388	0.809
Obs.	52	52	52	52	52

(Standard Errors in Parentheses)

Table A.4: Estimation Results for the Paper and Publishing Industry (21-22)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.012	0.769	-0.168	0.093	0.550	0.424
(0.065)	(0.085)	(0.151)	(0.072)	(0.314)	(0.102)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.173	-	0.158	0.147	0.206
-	(0.012)	-	(0.013)	(0.013)	(0.013)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	0.333	-	0.555	0.439	0.339
-	(0.047)	-	(0.051)	(0.051)	(0.051)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	-0.025	-	-0.067	-0.135	-0.067
-	(0.014)	-	(0.015)	(0.015)	(0.015)
b_{LT}	b_{KT}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.001	0.019	0.003	-0.002	-0.030	$-4*10^{-5}$
(0.0009)	(0.002)	(0.001)	(0.0008)	(0.012)	$(6*10^{-4})$
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.321	-	1.293	1.162	1.286
-	(0.041)	-	(0.039)	(0.037)	(0.039)

	Cost	Labor	Capital	Material	Price
R^2	0.995	0.854	0.919	0.990	0.981
D.W.	0.417	0.363	0.336	0.670	0.874
Obs.	69	69	69	69	69

(Standard Errors in Parentheses)

Table A.5: Estimation Results for the Chemical Industry (24)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.114	-0.614	0.150	0.082	-0.670	0.909
(0.040)	(0.233)	(0.089)	(0.050)	(0.195)	(0.077)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.184	0.166	-	0.191	0.139	-
(0.016)	(0.015)	-	(0.016)	(0.016)	-
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.584	0.666	-	0.596	0.672	-
(0.059)	(0.060)	-	(0.063)	(0.058)	-
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-0.089	0.018	-	-0.004	-0.060	-
(0.030)	(0.029)	-	(0.030)	(0.030)	-
b_{LT}	b_{KT}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.001	0.011	-0.0003	-0.004	0.047	-0.0001
(0.0009)	(0.003)	(0.001)	(0.001)	(0.020)	($5*10^{-5}$)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.182	1.216	-	1.201	1.184	-
(0.057)	(0.058)	-	(0.058)	(0.057)	-

	Cost	Labor	Capital	Material	Price
R^2	0.993	0.886	0.783	0.960	0.984
D.W.	0.561	0.354	0.348	0.492	0.772
Obs.	70	70	70	70	70

(Standard Errors in Parentheses)

Table A.6: Estimation Results for Rubber and Plastics Products (25)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.202	-0.237	0.323	0.448	-0.204	0.540
(0.079)	(0.493)	(0.193)	(0.092)	(0.383)	(0.120)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.092	0.021	-	0.070	0.079	-
(0.013)	(0.013)	-	(0.013)	(0.013)	-
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.334	0.513	-	0.484	0.337	-
(0.032)	(0.038)	-	(0.036)	(0.030)	-
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.054	0.009	-	-0.035	-0.006	-
(0.017)	(0.017)	-	(0.017)	(0.017)	-
b_{LT}	b_{KT}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.002	0.012	0.006	-0.0005	-0.069	$-8*10^{-5}$
(0.001)	(0.002)	(0.001)	(0.001)	(0.012)	$(5*10^{-5})$
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.404	1.303	-	1.361	1.340	-
(0.045)	(0.041)	-	(0.043)	(0.043)	-

	Cost	Labor	Capital	Material	Price
R^2	0.998	0.948	0.973	0.992	0.974
D.W.	0.672	0.549	0.429	0.505	0.429
Obs.	70	70	70	70	70

(Standard Errors in Parentheses)

Table A.7: Estimation Results for Other Non-Metallic Mineral Products (26)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.726	-1.769	1.084	0.792	-1.393	0.744
(0.077)	(0.343)	(0.143)	(0.072)	(0.308)	(0.105)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.138	0.102	-	0.079	0.095	0.117
(0.034)	(0.014)	-	(0.014)	(0.014)	(0.014)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.560	0.722	-	0.550	0.544	0.544
(0.044)	(0.044)	-	(0.445)	(0.046)	(0.046)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.040	0.062	-	0.008	0.020	0.018
(0.017)	(0.017)	-	(0.018)	(0.017)	(0.017)
b_{LT}	b_{KT}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.004	-0.009	-0.0001	-0.002	-0.007	0.0001
(0.0007)	(0.0002)	(0.0008)	(0.0005)	(0.010)	$(4*10^{-5})$
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.292	1.321	-	1.271	1.259	1.270
(0.036)	(0.037)	-	(0.036)	(0.036)	(0.036)

	Cost	Labor	Capital	Material	Price
R^2	0.987	0.920	0.920	0.929	0.977
D.W.	0.697	0.591	0.554	0.650	0.543
Obs.	88	88	88	88	88

(Standard Errors in Parentheses)

Table A.8: Estimation Results for the Basic and Fabricated Metals Industries (27-28)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.276	0.216	0.314	0.400	0.399	0.293
(0.056)	(0.385)	(0.142)	(0.076)	(0.374)	(0.116)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.160	0.153	0.093	0.169	0.121	0.177
(0.014	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.487	0.574	0.851	0.616	0.304	0.451
(0.061)	(0.058)	(0.058)	(0.058)	(0.066)	(0.062)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.009	0.028	0.034	-0.027	0.066	-0.009
(0.015)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
b_{LT}	b_{KT}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.003	-0.004	0.0006	-0.002	0.008	$4*10^{-4}$
(0.0006)	(0.002)	(0.0006)	(0.0005)	(0.008)	$(3*10^{-4})$
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.256	1.266	1.256	1.269	1.252	1.247
(0.027)	(0.027)	(0.025)	(0.026)	(0.027)	(0.026)

	Cost	Labor	Capital	Material	Price
R^2	0.995	0.864	0.898	0.971	0.992
D.W.	0.881	0.374	0.377	0.591	0.747
Obs.	107	107	107	107	107

(Standard Errors in Parentheses)

Table A.9: Estimation Results for the Machinery Industry (29)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.339	-0.015	0.224	0.359	0.217	0.480
(0.071)	(0.340)	(0.146)	(0.077)	(0.263)	(0.099)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.093	0.094	0.118	0.113	0.147
-	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	0.266	0.227	0.093	-0.014	0.140
-	(0.044)	(0.047)	(0.048)	(0.045)	(0.046)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	0.058	0.022	0.021	-0.025	0.048
-	(0.014)	(0.015)	(0.015)	(0.014)	(0.014)
b_{LT}	b_{KT}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.001	-0.001	0.001	-0.001	-0.034	0.0002
(0.001)	(0.002)	(0.001)	(0.001)	(0.010)	(0.00)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.324	1.323	1.246	1.267	1.361
-	(0.032)	(0.031)	(0.029)	(0.031)	(0.032)

	Cost	Labor	Capital	Material	Price
R^2	0.990	0.748	0.853	0.974	0.968
D.W.	0.464	0.276	0.214	0.447	0.301
Obs.	89	89	89	89	89

(Standard Errors in Parentheses)

Table A.10: Estimation Results for the Electrical and Optical Equipment Industry (30-33)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
0.449	2.478	-0.934	-0.040	2.11	-0.072
(0.097)	(0.466)	(0.08)	(0.099)	(0.354)	(0.106)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.136	0.159	0.146	0.098	0.199
-	(0.0132)	(0.015)	(0.013)	(0.013)	(0.014)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	0.280	0.130	0.333	-0.139	0.179
-	(0.039)	(0.042)	(0.039)	(0.041)	(0.041)
b_{KUS}	b_{MUS}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	0.046	0.067	0.009	0.156	0.016
-	(0.049)	(0.009)	(0.010)	(0.010)	(0.010)
b_{LT}	b_{KT}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.015	0.016	0.003	0.004	-0.055	$2*10^{-5}$
(0.001)	(0.003)	(0.001)	(0.0009)	(0.008)	$(6*10^{-5})$
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.563	1.706	1.641	1.625	1.546
-.	(0.047)	(0.046)	(0.049)	(0.050)	(0.044)

	Cost	Labor	Capital	Material	Price
R^2	0.995	0.834	0.936	0.931	0.976
D.W.	0.612	0.538	0.286	0.733	0.399
Obs.	89	89	89	89	89

(Standard Errors in Parentheses)

Table A.11: Estimation Results for the Transport Equipment Industry (34-35)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.1512	0.466	0.072	0.246	0.369	0.431
(0.060)	(0.618)	(0.178)	(0.082)	(0.480)	(0.192)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.171	0.146	0.121	0.114	0.065	0.089
(0.013)	(0.012)	(0.013)	(0.013)	(0.012)	(0.013)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.242	0.478	0.425	0.373	0.145	0.268
(0.046)	(0.046)	(0.054)	(0.048)	(0.043)	(0.026)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-0.059	-0.015	-0.011	-0.031	0.029	0.036
(0.012)	(0.011)	(0.012)	(0.012)	(0.011)	(0.012)
b_{LT}	b_{KT}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.004	0.011	0.002	0.0007	-0.023	$6*10^{-5}$
(0.0008)	(0.002)	(0.001)	(0.0006)	(0.007)	$(4*10^{-5})$
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.211	1.248	1.263	1.263	1.263	1.230
(0.021)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)

	Cost	Labor	Capital	Material	Price
R^2	0.997	0.877	0.904	0.989	0.984
D.W.	0.858	0.375	0.399	0.588	0.324
Obs.	107	107	107	107	107

(Standard Errors in Parentheses)

Table A.12: Estimation Results for Manufacturing Industries N.E.C., Recycling (36-37)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.608	-0.630	0.550	0.494	-0.332	0.665
(0.066)	(0.312)	(0.137)	(0.065)	(0.226)	(0.071)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.067	-	0.074	0.162	0.096
-	(0.015)	-	(0.014)	(0.015)	(0.014)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	0.374	-	0.202	0.079	0.396
-	(0.033)	-	(0.032)	(0.028)	(0.031)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	-0.016	-	-0.042	-0.124	-0.130
-	(0.015)	-	(0.015)	(0.015)	(0.015)
b_{LT}	b_{KT}	b_{Mt}	b_t	b_{YY}	b_{tt}
0.004	0.001	0.002	-0.002	-0.020	-0.0003
(0.0008)	(0.001)	(0.0008)	(0.0004)	(0.008)	($4*10^{-5}$)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.139	-	1.107	1.104	1.079
-	(0.026)	-	(0.025)	(0.025)	(0.024)

	Cost	Labor	Capital	Material	Price
R^2	0.994	0.912	0.984	0.982	0.990
D.W.	0.661	0.595	0.640	0.941	0.869
Obs.	70	70	70	70	70

(Standard Errors in Parentheses)

A.2 Results of the Error Correction Form

As outlined in the previous section, the meaning of most parameters is described in section 3.2.2. The $\gamma_i s$ denote the error correction terms for $i = C, L, M, K, Y$, where C stands for the cost function, L for labor, K for capital, M for material inputs and Y for the price equation. The a_is denote parameters for lagged differences of optimal costs, factor demands and prices respectively, while $c_i s$ are parameters for lagged differences of their actual counterparts. Numbers following a or c indicate how many times the difference is lagged. "t.stat." denotes the t-statistic of the error correction term for each equation entering the cost function and factor demand system and "Obs." denotes the number of observations.

Table A.13: Estimation Results for the Food and Beverages Industry (15-16)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.146	-1.017	0.296	0.284	-0.126	0.240
(0.054)	(0.370)	(0.131)	(0.087)	(0.348)	(0.112)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.021	0.061	0.085	0.002	0.041	0.061
(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-0.356	-0.156	-0.063	-0.249	-0.394	-0.115
(0.170)	(0.164)	(0.157)	(0.174)	(0.165)	(0.162)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.063	0.082	-0.047	0.131	0.022	-0.0003
(0.030)	(0.032)	(0.031)	(0.030)	(0.030)	($7*10^{-5}$)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
0.001	0.0009	0.009	-0.0002	-0.067	$1*10^{-6}$
(0.0007)	(0.003)	(0.002)	(0.001)	(0.015)	($6*10^{-7}$)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.282	1.303	1.279	1.285	1.260	1.272
(0.070)	(0.072)	(0.070)	(0.071)	(0.079)	(0.070)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a1_M$
0.976	0.739	0.072	1.151	0.992	1.151
(0.015)	(0.131)	(0.035)	(0.052)	(0.071)	(0.052)
$a2_L$	$c1_L$	$c1_K$	$c1_Y$	$c2_K$	$c2_Y$
-0.159	0.085	0.899	0.065	-0.403	0.073
(0.058)	(0.040)	(0.086)	(0.036)	(0.087)	(0.035)
γ_C	γ_L	γ_K	γ_M	γ_Y	
-0.077	-0.121	-0.032	-0.126	-0.211	
(0.020)	(0.020)	(0.009)	(0.020)	(0.039)	

	Cost	Labor:	Capital	Material	Price
R^2	0.875	0.429	0.800	0.708	0.880
D.W.	2.382	1.844	1.686	2.324	1.911
t.stat.	-3.775	-5.903	-3.532	-6.402	-5.403
Obs.	93	93	93	93	93

(Standard Errors in Parentheses)

Table A.14: Estimation Results for the Textiles Industry (17-19)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.162	-0.161	0.087	0.301	0.214	0.666
(0.068)	(0.265)	(0.123)	(0.070)	(0.242)	(0.081)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.119	0.099	-	0.047	0.145	0.109
(0.019)	(0.019)	-	(0.018)	(0.019)	(0.018)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.005	0.167	-	0.113	-0.050	0.035
(0.111)	(0.105)	-	(0.120)	(0.106)	(0.105)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.014	0.041	-	0.062	-0.008	0.020
(0.026)	(0.026)	-	(0.023)	(0.025)	(0.024)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.007	-0.001	0.0007	-0.002	-0.001	$5*10^{-5}$
(0.001)	(0.002)	(0.002)	(0.001)	(0.008)	$(7*10^{-5})$
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.190	1.215	-	1.188	1.210	1.182
(0.031)	(0.038)	-	(0.030)	(0.031)	(0.030)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
0.939	0.849	0.108	1.015	0.844	-0.165
(0.010)	(0.040)	(0.043)	(0.030)	(0.048)	(0.046)
$a2_L$	$a2_K$	$a2_M$	$c1_C$	$c1_L$	$c1_K$
0.008	0.073	-0.214	0.211	0.176	0.579
(0.055)	(0.042)	(0.049)	(0.047)	(0.076)	(0.064)
$c1_M$	$c1_Y$	γ_C	γ_L	γ_K	γ_M
0.190	0.230	-0.080	-0.161	-0.045	-0.109
(0.045)	(0.042)	(0.022)	(0.021)	(0.011)	(0.021)
γ_C					
-0.140					
(0.043)					

	Cost	Labor	Capital	Material	Price
R^2	0.976	0.771	0.829	0.949	0.935
D.W.	2.277	2.180	1.650	1.880	2.395
t.-stat	-3.639	-7.522	-4.107	-5.218	-3.270
Obs.	82	82	82	82	82

(Standard Errors in Parentheses)

Table A.15: Estimation Results for the Wood Industry (20)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.028	-0.430	0.095	0.043	0.368	0.701
(0.020)	(0.350)	(0.083)	(0.028)	(0.322)	(0.130)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.185	-	0.170	0.194	-
-	(0.030)	-	(0.023)	(0.024)	-
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	0.249	-	-0.013	-0.068	-
-	(0.198)	-	(0.037)	(0.041)	-
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	-0.036	-	-0.052	0.0003	-
-	(0.042)	-	(0.043)	(0.038)	-
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-5*10^{-5}	-0.008	0.005	0.0005	-0.006	-2*10^{-7}
(3*10^{-4})	(0.005)	(0.001)	(0.001)	(0.009)	(1*10^{-5})
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.423	-	1.310	1.393	-
-	(0.076)	-	(0.070)	(0.074)	-
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_M$	$a1_Y$
1.182	13.972	0.050	1.155	1.222	1.461
(0.055)	(15.420)	(0.034)	(0.058)	(0.135)	(0.166)
$a2_K$	$c1_C$	$c1_L$	$c1_K$	$c1_Y$	γ_C
0.102	0.071	0.289	0.683	0.291	-0.115
(0.044)	(0.012)	(0.050)	(0.092)	(0.067)	(0.032)
γ_L	γ_K	γ_M	γ_Y		
-0.074	-0.060	-0.115	-0.555		
(0.019)	(0.022)	(0.030)	(0.093)		

	Cost	Labor	Material	Capital	Price
R^2	0.964	0.871	0.948	0.700	0.800
t.-stat.	-3.628	-3.916	-3.797	-2.674	-5.967
D.W.	2.204	2.395	2.006	1.689	2.020
Obs.	48	48	48	48	48

(Standard Errors in Parentheses)

Table A.16: Estimation Results for the Paper and Publishing Industry (21-22)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.013	-0.036	-0.009	0.138	-0.091	0.704
(0.030)	(0.156)	(0.064)	(0.050)	(0.118)	(0.061)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.134	-	0.117	0.118	0.161
-	(0.030)	-	(0.031)	(0.029)	(0.033)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	0.134	-	0.323	0.303	0.150
-	(0.089)	-	(0.086)	(0.081)	(0.083)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	-0.104	-	-0.149	-0.211	-0.136
-	(0.041)	-	(0.038)	(0.037)	(0.039)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
0.002	0.021	0.010	0.002	-0.067	-0.0004
(0.002)	(0.003)	(0.002)	(0.002)	(0.014)	($1*10^{-4}$)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.392	-	1.376	1.216	1.369
-	(0.071)	-	(0.069)	(0.062)	(0.069)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
1.066	0.800	0.579	1.098	1.397	-0.117
(0.033)	(0.233)	(0.421)	(0.065)	(0.094)	(0.072)
$a2_L$	$a2_K$	$a2_Y$	$c1_C$	$c1_L$	$c1_K$
0.567	1.338	-0.922	0.175	0.181	0.961
(0.241)	(0.624)	(0.168)	(0.065)	(0.078)	(0.099)
$c1_Y$	$c2_K$	γ_C	γ_K	γ_L	γ_M
0.760	-0.281	-0.112	-0.125	-0.196	-0.154
(0.118)	(0.121)	(0.026)	(0.041)	(0.047)	(0.037)
γ_Y					
-0.638					
(0.096)					

	Cost	Labor	Capital	Material	Price
R^2	0.980	0.730	0.803	0.907	0.932
D.W.	2.045	1.498	2.407	2.016	2.509
t.stat.	-4.317	-4.195	-3.066	-4.188	-6.616
Obs.	58	58	58	58	58

(Standard Deviations in Parentheses)

Table A.17: Estimation Results for the Chemical Industry (24)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.052	-0.097	0.046	0.064	-0.019	0.739
(0.017)	(0.078)	(0.031)	(0.024)	(0.079)	(0.038)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.189	0.167	-	0.191	0.139	-
(0.017)	(0.017)	-	(0.017)	(0.016)	-
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.549	0.625	-	0.581	0.607	-
(0.033)	(0.035)	-	(0.032)	(0.033)	-
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-0.131	-0.047	-	-0.057	-0.109	-
(0.024)	(0.022)	-	(0.022)	(0.024)	-
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
0.0007	0.012	0.006	-0.003	-0.0006	-0.0003
(0.001)	(0.003)	(0.002)	(0.001)	(0.016)	(0.0001)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.242	1.257	-	1.263	1.239	-
(0.026)	(0.035)	-	(0.034)	(0.035)	-
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
1.001	0.765	2.385	1.005	1.142	-0.471
(0.011)	(0.138)	(0.680)	(0.014)	(0.063)	(0.053)
$a2_C$	$a2_L$	$a2_M$	$a2_Y$	$c1_C$	$c1_L$
-0.470	0.367	-0.451	-0.175	0.489	0.353
(0.053)	(0.171)	(0.053)	(0.123)	(0.052)	(0.054)
$c1_K$	$c1_M$	$c1_Y$	$c2_L$	$c2_K$	γ_C
0.717	0.440	0.186	-0.090	-0.146	-0.183
(0.085)	(0.048)	(0.105)	(0.037)	(0.087)	(0.026)
γ_L	γ_K	γ_M	γ_Y		
-0.155	-0.174	-0.202	-0.370		
(0.034)	(0.043)	(0.024)	(0.082)		

	Cost	Labor	Capital	Material	Price
R^2	0.936	0.419	0.725	0.885	0.868
D.W.	2.505	1.723	1.703	2.407	1.990
t.stat.	-6.934	-4.626	-4.055	-8.418	-4.530
Obs.	60	60	60	60	60

(Standard Errors in Parentheses)

Table A.18: Estimation Results for Rubber and Plastics Products (25)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.209	-0.948	0.414	0.410	-0.479	0.658
(0.081)	(0.374)	(0.161)	(0.083)	(0.302)	(0.094)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.100	0.025	-	0.075	0.087	-
(0.017)	(0.017)	-	(0.017)	(0.017)	-
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.098	0.299	-	0.235	0.130	-
(0.072)	(0.071)	-	(0.072)	(0.069)	-
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.112	0.100	-	0.045	0.044	-
(0.025)	(0.024)	-	(0.025)	(0.025)	-
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
0.0005	0.006	0.013	-0.001	0.002	-0.0004
(0.002)	(0.005)	(0.313)	(0.003)	(0.010)	(0.0001)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.099	1.167	-	1.181	1.174	-
(0.102)	(0.084)	-	(0.078)	(0.080)	-
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
0.997	0.775	-0.015	1.175	-0.103	-0.175
(0.013)	(0.063)	(0.054)	(0.035)	(0.028)	(0.048)
$a2_M$	$a2_Y$	$c1_C$	$c1_L$	$c1_K$	$c1_M$
-0.291	0.250	0.185	0.189	0.516	0.195
(0.064)	(0.051)	(0.047)	(0.040)	(0.069)	(0.044)
γ_C	γ_L	γ_K	γ_M	γ_Y	
-0.233	-0.351	-0.164	-0.239	-0.103	
(0.036)	(0.046)	(0.031)	(0.033)	(0.028)	

	Cost	Labor	Capital	Material	Price
R^2	0.955	0.728	0.693	0.889	0.901
D.W.	2.165	1.919	1.729	2.092	1.886
t.stat.	-6.547	-7.672	-5.239	-7.297	-3.638
Obs.	64	64	64	64	64

(Standard Errors in Parentheses)

Table A.19: Estimation Results for Other Non-Metallic Mineral Products (26)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.232	-1.060	0.398	0.397	-0.379	0.637
(0.095)	(0.295)	(0.154)	(0.086)	(0.311)	(0.080)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.142	0.100	-	0.069	0.103	0.109
(0.018)	(0.020)	-	(0.020)	(0.019)	(0.020)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.032	0.240	-	0.222	-0.012	0.034
(0.135)	(0.128)	-	(0.131)	(0.140)	(0.130)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.065	0.167	-	0.107	0.062	0.098
(0.040)	(0.038)	-	(0.033)	(0.033)	(0.029)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.006	-0.002	0.0004	0.003	0.020	$3*10^{-5}$
(0.001)	(0.003)	(0.001)	(0.001)	(0.009)	$(7*10^{-5})$
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.577	1.649	-	1.572	1.555	1.562
(0.076)	(0.084)	-	(0.077)	(0.076)	(0.077)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_L$
1.063	0.837	0.053	1.399	0.854	0.127
(0.050)	(0.068)	(0.033)	(0.119)	(0.090)	(0.026)
$c1_C$	$c1_K$	$c1_Y$	$c2_K$	$c2_Y$	γ_C
0.048	0.595	0.444	-0.108	-0.227	-0.049
(0.008)	(0.073)	(0.066)	(0.076)	(0.061)	(0.020)
γ_L	γ_K	γ_M	γ_Y		
-0.171	-0.118	-0.062	-0.229		
(0.022)	(0.023)	(0.020)	(0.048)		

	Cost	Labor	Capital	Material	Price
R^2	0.904	0.757	0.665	0.898	0.845
D.W.	2.248	1.780	1.812	2.398	1.605
t.stat.	-2.448	-7.789	-5.108	-3.165	-4.798
Obs.	77	77	77	77	77

(Standard Errors in Parentheses)

Table A.20: Estimation Results for Basic and Fabricated Metals (27-28)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.089	-0.455	0.161	0.220	0.216	0.703
(0.060)	(0.307)	(0.127)	(0.080)	(0.335)	(0.091)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.170	0.144	0.112	0.168	0.136	0.136
(0.024)	(0.024)	(0.025)	(0.024)	(0.025)	(0.025)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.057	0.083	0.553	0.104	-0.052	0.034
(0.161)	(0.164)	(0.169)	(0.166)	(0.161)	(0.166)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.022	0.059	0.044	0.015	0.063	0.006
(0.024)	(0.024)	(0.023)	(0.024)	(0.025)	(0.024)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.003	-0.005	0.0008	-0.001	0.012	$1*10^{-6}$
(0.001)	(0.003)	(0.0001)	(0.001)	(0.008)	$(1*10^{-5})$
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.252	1.264	1.274	1..284	1.242	1.187
(0.040)	(0.041)	(0.040)	(0.041)	(0.040)	(0.053)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
1.015	0.840	-0.002	1.205	1.187	-0.235
(0.018)	(0.133)	(0.026)	(0.044)	(0.053)	(0.049)
$a2_L$	$a2_K$	$a2_M$	$a2_Y$	$c1_C$	$c1_L$
0.276	0.061	-0.329	-0.049	0.246	0.198
(0.097)	(0.033)	(0.061)	(0.028)	(0.047)	(0.045)
$c1_K$	$c1_M$	$c1_Y$	$c2_K$	$c2_Y$	γc
0.872	0.205	0.340	-0.344	-0.049	-0.135
(0.080)	(0.047)	(0.088)	(0.077)	(0.028)	(0.028)
γ_L	γ_K	γ_M	γ_Y		
-0.156	-0.046	-0.088	-0.444		
(0.024)	(0.001)	(0.023)	(0.074)		

	Cost	Labor	Capital	Material	Price
R^2	0.973	0.767	0.815	0.938	0.957
D.W.	2.318	1.657	1.583	2.496	1.916
t.stat.	-4.896	-6.583	-4.713	-3.874	-5.991
Obs.	92	92	92	92	92

(Standard Errors in Parentheses)

Table A.21: Estimation Results for the Machinery Industry (29)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.272	-0.918	0.449	0.487	-0.043	0.690
(0.083)	(0.267)	(0.144)	(0.084)	(0.245)	(0.066)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.090	0.123	0.109	0.130	0.117
-	(0.027)	(0.026)	(0.025)	(0.028)	(0.026)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	-0.072	-0.007	-0.402	-0.300	-0.211
-	(0.105)	(0.103)	(0.118)	(0.102)	(0.108)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	0.152	0.036	0.051	0.052	0.091
-	(0.034)	(0.030)	(0.029)	(0.028)	(0.023)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.009	-0.012	-0.003	0.002	0.0003	0.0003
(0.002)	(0.003)	(0.002)	(0.003)	(0.007)	(0.008)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.479	1. 344	1.439	1.460	1.366
-	(0.191)	(0.098)	(0.184)	(0.209)	(0.099)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
0.973	0.765	0.046	1.181	0.862	-0.261
(0.021)	(0.061)	(0.014)	(0.050)	(0.082)	(0.034)
$a2_M$	$c1_C$	$c1_L$	$c1_K$	$c1_Y$	$c2_K$
-0.359	0.299	0.267	0.609	0.226	-0.150
(0.056)	(0.034)	(0.030)	(0.100)	(0.059)	(0.088)
γ_C	γ_L	γ_K	γ_M	γ_Y	
-0.078	-0.102	-0.054	-0.095	-0.050	
(0.016)	(0.015)	(0.010)	(0.016)	(0.034)	

	Cost	Labor	Capital	Material	Price
R^2	0.964	0.837	0.821	0.955	0.830
D.W.	2.081	1.919	1.561	2.275	1.980
t.stat.	-4.935	-6.860	-5.314	-5.953	-1.462
Obs.	78	78	78	78	78

(Standard Errors in Parentheses)

Table A.22: Estimation Results for the Electrical and Optical Equipment Industry (30-33)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.052	-0.049	0.041	0.320	0.134	0.873
(0.041)	(0.161)	(0.072)	(0.050)	(0.124)	(0.054)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.143	0.138	0.150	0.096	0.174
-	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	0.474	0.324	0.504	0.113	0.309
-	(0.076)	(0.074)	(0.069)	(0.061)	(0.070)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	-0.151	-0.130	-0.175	-0.040	-0.190
-	(0.024)	(0.021)	(0.023)	(0.022)	(0.020)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.014	-0.008	-0.015	0.007	-0.032	0.0005
(0.002)	(0.003)	(0.003)	(0.003)	(0.012)	(0.0001)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.347	1.209	1.350	1.382	1.240
-	(0.051)	(0.037)	(0.044)	(0.050)	(0.040)
$a1_C$	$a1_L$	$a1_M$	$a1_Y$	$a2_C$	$a2_L$
0.978	0.922	1.002	0.699	-0.372	-0.131
(0.016)	(0.074)	(0.026)	(0.060)	(0.049)	(0.074)
$a2_K$	$a2_M$	$a2_Y$	$c1_C$	$c1_L$	$c1_K$
0.655	-0.378	-0.169	0.373	0.338	0.824
(0.425)	(0.055)	(0.083)	(0.050)	(0.047)	(0.085)
$c1_M$	$c1_Y$	$c2_L$	$c2_K$	$c2_Y$	γ_C
0.334	0.327	0.046	-0.104	-0.168	-0.121
(0.055)	(0.093)	(0.017)	(0.078)	(0.058)	(0.020)
γ_L	γ_K	γ_M	γ_Y		
-0.180	-0.029	-0.111	-0.184		
(0.023)	(0.009)	(0.021)	(0.031)		

	Cost	Labor	Capital	Material	Price
R^2	0.938	0.742	0.803	0.932	0.911
D.W.	1.645	1.786	1.684	1.797	1.944
t.stat.	−6.044	-7.718	-3.144	-5.205	-5.993
Obs.	76	76	76	76	76

(Standard Errors in Parentheses)

Table A.23: Estimation Results for the Transport Equipment Industry (34-35)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.152	-0.700	0.252	0.299	-0.162	0.844
(0.064)	(0.403)	(0.403)	(0.081)	(0.323)	(0.118)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.167	0.113	0.127	0.110	0.060	0.058
(0.021)	(0.019)	(0.020)	(0.020)	(0.021)	(0.019)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-0.041	0.323	0.382	0.237	0.006	0.073
(0.103)	(0.095)	(0.104)	(0.097)	(0.093)	(0.099)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-0.010	0.055	0.046	0.025	0.068	0.089
(0.025)	(0.025)	(0.025)	(0.025)	(0.022)	(0.022)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.006	0.002	-0.004	0.0005	-0.013	0.003
(0.001)	(0.003)	(0.002)	(0.001)	(0.007)	(0.001)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.233	1.280	1.254	1.275	1.246	1.239
(0.038)	(0.044)	(0.035)	(0.038)	(0.040)	(0.038)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_L$
0.984	0.683	0.011	1.124	0.800	0.130
(0.017)	(0.084)	(0.026)	(0.032)	(0.064)	(0.050)
$a2_Y$	$c1_L$	$c1_K$	$c1_M$	$c1_Y$	$c2_K$
-0.180	0.053	0.675	-0.016	0.343	-0.258
(0.097)	(0.029)	(0.081)	(0.007)	(0.081)	(0.070)
γ_C	γ_L	γ_K	γ_M	γ_Y	
-0.109	-0.137	-0.053	-0.133	-0.162	
(0.021)	(0.021)	(0.012)	(0.021)	(0.041)	

	Cost	Labor	Capital	Material	Price
R^2	0.957	0.719	0.688	0.956	0.853
D.W.	2.123	1.656	1.779	2.215	2.173
t.stat.	-5.113	-6.258	-4.355	-6.258	-3.928
Obs.	94	94	94	94	94

(Standard Errors of Parentheses)

Table A.24: Estimation Results for Manufacturing Industries N.E.C., Recycling (36-37)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.156	-0.123	0.033	0.190	0.039	0.639
(0.068)	(0.311)	(0.129)	(0.065)	(0.227)	(0.084)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.065	-	0.070	0.180	0.114
-	(0.019)	-	(0.018)	(0.018)	(0.019)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	0.304	-	0.127	0.008	0.300
-	(0.059)	-	(0.061)	(0.055)	(0.061)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	0.011	-	-0.030	-0.110	-0.123
-	(0.025)	-	(0.025)	(0.024)	(0.023)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
0.006	0.013	0.018	-0.0007	-0.022	-0.0009
(0.016)	(0.003)	(0.002)	(0.002)	(0.014)	(0.001)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.245	-	1.199	1.254	1.167
-	(0.053)	-	(0.043)	(0.063)	(0.038)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
0.959	0.897	0.085	1.015	0.839	-0.135
(0.010)	(0.043)	(0.066)	(0.018)	(0.064)	(0.033)
$a2_K$	$a2_M$	$a2_Y$	$c1_C$	$c1_L$	$c1_M$
0.220	-0.151	-0.325	0.180	0.156	0.163
(0.110)	(0.040)	(0.101)	(0.036)	(0.029)	(0.034)
$c1_Y$	γc	γ_L	γ_K	γ_M	γ_Y
0.356	-0.275	-0.273	-0.097	-0.292	-0.143
(0.104)	(0.029)	(0.026)	(0.020)	(0.026)	(0.062)

	Cost	Labor	Capital	Material	Price
R^2	0.953	0.738	0.707	0.911	0.738
D.W.	1.823	1.718	1.738	1.953	1.718
t.stat.	-9.489	-10.460	-4.743	-11.211	−2.297
Obs.	62	62	62	62	62

(Standard Errors in Parentheses)

A.3 Results with Simple Trend Term Specification

Table A.25: Estimation Results for the Food and Beverages Industry (15-16)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}	b_{LUS}
-0.156	-0.913	0.291	0.291	-0.306	0.985	0.015
(0.046)	(0.338)	(0.115)	(0.081)	(0.354)	(0.113)	(0.022)
b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}	b_{KUS}	b_{KI}
0.059	0.078	-0.004	0.036	0.054	-0.124	0.061
(0.023)	(0.022)	(0.023)	(0.022)	(0.023)	(0.132)	(0.132)
b_{KJP}	b_{KD}	b_{KC}	b_{KF}	b_{MUS}	b_{MI}	b_{MJP}
0.129	-0.011	-0.167	0.101	0.007	0.029	-0.107
(0.135)	(0.135)	(0.130)	(0.135)	(0.029)	(0.030)	(0.030)
b_{MD}	b_{MC}	b_{MF}	b_t	b_{YY}	μ_{US}	μ_I
0.072	-0.033	-0.04	0.002	-0.042	1.258	1.279
(0.029)	(0.029)	(0.030)	(0.001)	(0.018)	(0.075)	(0.078)
μ_{JP}	μ_D	μ_C	μ_F	$a1_C$	$a1_L$	$a1_K$
1.240	1.237	1.254	1.245	0.962	0.722	0.089
(0.072)	(0.070)	(0.076)	(0.073)	(0.012)	(0.111)	(0.047)
$a1_M$	$a1_Y$	$a1_M$	$a2_L$	$c1_L$	$c1_K$	$c1_Y$
1.074	0.878	1.074	-0.165	0.097	0.874	0.071
(0.025)	(0.056)	(0.025)	(0.057)	(0.042)	(0.084)	(0.037)
$c2_K$	$c2_Y$	γ_C	γ_L	γ_K	γ_M	γ_Y
-0.371	0.028	-0.095	-0.122	-0.039	-0.146	-0.118
(0.085)	(0.035)	(0.021)	(0.022)	(0.010)	(0.022)	(0.026)

	Cost	Labor:	Capital	Material	Price
R^2	0.876	0.414	0.795	0.717	0.871
D.W.	2.341	1.793	1.616	2.320	2.030
t.stat.	-4.418	-5.455	-3.910	-6.540	-4.571
Obs.	93	93	93	93	93

(Standard Errors in Parentheses)

Table A.26: Estimation Results for the Textiles Industry (17-19)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.178	-0.140	0.071	0.276	0.196	0.703
(0.049)	(0.243)	(0.094)	(0.053)	(0.232)	(0.081)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.124	0.101	-	0.049	0.149	0.110
(0.019)	(0.018)	-	(0.017)	(0.017)	(0.016)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.032	0.193	-	0.140	-0.024	0.060
(0.106)	(0.101)	-	(0.115)	(0.103)	(0.101)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-0.002	0.026	-	0.048	-0.025	0.004
(0.025)	(0.025)	-	(0.022)	(0.024)	(0.023)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.005	-	-	-0.002	-0.017	-
(0.001)	-	-	(0.001)	(0.008)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.207	1.239	-	1.199	1.219	1.185
(0.027)	(0.029)	-	(0.026)	(0.028)	(0.027)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
0.933	0.876	0.116	0.988	0.808	-0.167
(0.010)	(0.037)	(0.049)	(0.025)	(0.044)	(0.046)
$a2_L$	$a2_K$	$a2_M$	$c1_C$	$c1_L$	$c1_K$
-0.010	0.081	-0.207	0.217	0.177	0.566
(0.055)	(0.049)	(0.047)	(0.047)	(0.046)	(0.064)
$c1_M$	$c1_Y$	γ_C	γ_L	γ_K	γ_M
0.196	0.189	-0.077	-0.163	-0.047	-0.108
(0.045)	(0.040)	(0.022)	(0.020)	(0.011)	(0.021)
γ_C					
-0.077					
(0.022)					

	Cost	Labor	Capital	Material	Price
R^2	0.976	0.771	0.829	0.949	0.935
D.W.	2.277	2.180	1.650	1.880	2.395
t.-stat	-3.487	-7.986	-4.301	-5.205	-4.373
Obs.	82	82	82	82	82

(Standard Errors in Parentheses)

Table A.27: Estimation Results for the Wood Industry (20)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.034	-0.549	0.119	0.054	0.268	0.756
(0.020)	(0.368)	(0.090)	(0.028)	(0.322)	(0.131)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.190	-	0.175	0.200	-
-	(0.027)	-	(0.021)	(0.022)	-
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	0.284	-	-0.234	-0.082	-
-	(0.189)	-	(0.160)	(0.171)	-
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	-0.046	-	-0.025	0.083	-
-	(0.041)	-	(0.036)	(0.039)	-
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-	-0.008	0.005	-	-0.010	-
-	(0.004)	(0.001)	-	(0.010)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.398	-	1.285	1.366	-
-	(0.075)	-	(0.069)	(0.072)	-
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a1_K$
1.167	10.619	0.056	1.102	1.429	0.056
(0.055)	(10.221)	(0.036)	(0.084)	(0.160)	(0.036)
$a2_K$	$c1_C$	$c1_L$	$c1_K$	$c1_Y$	γ_C
0.101	0.071	0.288	0.699	0.296	-0.118
(0.044)	(0.012)	(0.048)	(0.094)	(0.067)	(0.032)
γ_L	γ_K	γ_M	γ_Y		
-0.074	-0.071	-0.108	-0.550		
(0.019)	(0.024)	(0.028)	(0.093)		

	Cost	Labor	Material	Capital	Price
R^2	0.964	0.871	0.948	0.700	0.799
t.-stat.	-3.628	-3.882	-3.880	-2.989	-5.929
D.W.	2.174	2.414	1.993	1.758	2.040
Obs.	48	48	48	48	48

(Standard Errors in Parentheses)

Table A.28: Estimation Results for the Paper and Publishing Industry (21-22)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.010	-0.043	0.007	0.240	-0.018	0.628
(0.018)	(0.083)	(0.030)	(0.048)	(0.086)	(0.056)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.086	-	0.063	0.082	0.102
-	(0.037)	-	(0.039)	(0.036)	(0.041)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	0.096	-	0.296	0.267	0.115
-	(0.117)	-	(0.110)	(0.111)	(0.111)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	-0.017	-	-0.064	-0.124	-0.055
-	(0.042)	-	(0.039)	(0.037)	(0.040)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.004	0.008	0.005	-	-0.058	-
(0.001)	(0.005)	(0.001)	-	(0.013)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.415	-	1.407	1.231	1.403
-	(0.079)	-	(0.079)	(0.069)	(0.079)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
1.109	0.572	1.465	1.247	1.522	-0.162
(0.047)	(0.152)	(1.509)	(0.097)	(0.115)	(0.078)
$a2_L$	$a2_K$	$a2_Y$	$c1_C$	$c1_L$	$c1_K$
0.322	3.205	-0.962	0.202	0.153	1.003
(0.129)	(3.225)	(0.185)	(0.068)	(0.072)	(0.102)
$c1_Y$	$c2_K$	γ_C	γ_K	γ_L	γ_M
0.713	-0.273	-0.054	-0.114	-0.106	-0.115
(0.114)	(0.120)	(0.022)	(0.036)	(0.036)	(0.039)
γ_Y					
-0.571					
(0.085)					

	Cost	Labor	Capital	Material	Price
R^2	0.978	0.696	0.795	0.911	0.924
D.W.	2.082	1.411	2.511	2.104	2.382
t.stat.	-2.448	-2.953	-3.143	-2.959	-6.703
Obs.	58	58	58	58	58

(Standard Deviations in Parentheses)

Table A.29: Estimation Results for the Chemical Industry (24)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.049	-0.060	0.035	0.084	-0.164	0.677
(0.018)	(0.082)	(0.034)	(0.030)	(0.080)	(0.033)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.166	0.148	-	0.171	0.118	-
(0.019)	(0.019)	-	(0.020)	(0.018)	-
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.583	0.665	-	0.616	0.642	-
(0.032)	(0.032)	-	(0.031)	(0.030)	-
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-0.093	-0.016	-	-0.024	-0.070	-
(0.024)	(0.022)	-	(0.022)	(0.023)	-
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.002	0.004	-	-	0.034	-
(0.006)	(0.002)	-	-	(0.013)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.253	1.277	-	1.280	1.252	-
(0.033)	(0.034)	-	(0.033)	(0.034)	-
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
1.002	0.643	2.352	1.028	1.143	-0.482
(0.011)	(0.119)	(1.196)	(0.017)	(0.065)	(0.053)
$a2_C$	$a2_L$	$a2_M$	$a2_Y$	$c1_C$	$c1_L$
-0.482	0.238	-0.463	-0.051	0.496	0.367
(0.053)	(0.103)	(0.054)	(0.127)	(0.052)	(0.053)
$c1_K$	$c1_M$	$c1_Y$	$c2_L$	$c2_K$	γ_C
0.694	0.438	0.070	-0.079	-0.108	-0.177
(0.088)	(0.049)	(0.106)	(0.034)	(0.089)	(0.025)
γ_L	γ_K	γ_M	γ_Y		
-0.154	-0.196	-0.183	-0.342		
(0.033)	(0.043)	(0.024)	(0.081)		

	Cost	Labor	Capital	Material	Price
R^2	0.933	0.406	0.709	0.881	0.849
D.W.	2.392	1.637	1.611	2.360	1.870
t.stat.	-7.207	-4.720	-4.553	-7.669	-4.218
Obs.	60	60	60	60	60

(Standard Errors in Parentheses)

Table A.30: Estimation Results for Rubber and Plastics Products (25)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.144	-0.744	0.302	0.419	-0.239	0.636
(0.081)	(0.369)	(0.163)	(0.083)	(0.325)	(0.089)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.065	-0.012	-	0.038	0.053	-
(0.015)	(0.016)	-	(0.015)	(0.014)	-
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.058	0.271	-	0.198	0.086	-
(0.042)	(0.034)	-	(0.042)	(0.043)	-
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.137	0.118	-	0.068	0.068	-
(0.021)	(0.020)	-	(0.021)	(0.020)	-
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.005	-	0.006	-	0.002	-
(0.001)	-	(0.001)	-	(0.010)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.048	1.147	-	1.186	1.181	-
(0.151)	(0.087)	-	(0.078)	(0.080)	-
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
1.002	0.690	-0.001	1.243	1.123	-0.178
(0.014)	(0.048)	(0.046)	(0.034)	(0.062)	(0.050)
$a2_M$	$c1_C$	$c1_L$	$c1_K$	$c1_M$	$c1_Y$
-0.336	0.187	0.193	0.520	0.211	0.163
(0.068)	(0.048)	(0.041)	(0.070)	(0.045)	(0.043)
γ_C	γ_L	γ_K	γ_M	γ_Y	
-0.241	-0.392	-0.139	-0.262	-0.064	
(0.034)	(0.047)	(0.027)	(0.032)	(0.043)	

	Cost	Labor	Capital	Material	Price
R^2	0.952	0.726	0.678	0.884	0.893
D.W.	2.032	1.760	1.697	2.028	2.069
t.stat.	-7.070	-8.356	-5.180	-8.081	-2.001
Obs.	64	64	64	64	64

(Standard Errors in Parentheses)

Table A.31: Estimation Results for Other Non-Metallic Mineral Products (26)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.393	-0.964	0.503	0.419	-0.294	0.602
(0.067)	(0.294)	(0.125)	(0.073)	(0.316)	(0.095)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.160	0.121	-	0.090	0.125	0.127
(0.018)	(0.019)	-	(0.018)	(0.018)	(0.019)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.077	0.293	-	0.287	0.040	0.084
(0.135)	(0.128)	-	(0.131)	(0.138)	(0.130)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.117	0.233	-	0.159	0.118	0.140
(0.040)	(0.039)	-	(0.036)	(0.036)	(0.032)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-	-	-	-0.003	0.014	-
-	-	-	(0.001)	(0.009)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.376	1.400	-	1.377	1.372	1.361
(0.062)	(0.067)	-	(0.059)	(0.061)	(0.059)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_L$
0.959	0.864	0.045	1.179	0.856	0.091
(0.025)	(0.067)	(0.034)	(0.052)	(0.082)	(0.027)
$c1_C$	$c1_K$	$c1_Y$	$c2_K$	$c2_Y$	γ_C
0.038	0.568	0.511	-0.107	-0.158	-0.080
(0.008)	(0.075)	(0.071)	(0.078)	(0.062)	(0.026)
γ_L	γ_K	γ_M	γ_Y		
-0.179	-0.132	-0.081	-0.229		
(0.024)	(0.025)	(0.024)	(0.048)		

	Cost	Labor	Capital	Material	Price
R^2	0.904	0.757	0.665	0.898	0.845
D.W.	2.248	1.780	1.812	2.398	1.605
t.stat.	-3.014	-7.516	-5.209	-3.402	-2.768
Obs.	77	77	77	77	77

(Standard Errors in Parentheses)

Table A.32: Estimation Results for Basic and Fabricated Metals (27-28)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.102	-0.489	0.187	0.242	0.168	0.690
(0.063)	(0.316)	(0.132)	(0.081)	(0.343)	(0.089)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.159	0.133	0.102	0.157	0.125	0.165
(0.022)	(0.022)	(0.023)	(0.022)	(0.023)	(0.023)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.072	0.097	0.561	0.121	-0.039	0.048
(0.158)	(0.160)	(0.165)	(0.163)	(0.158)	(0.163)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.026	0.064	0.049	0.021	0.067	0.010
(0.024)	(0.024)	(0.022)	(0.023)	(0.024)	(0.023)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.003	-0.005	0.0009	-	0.013	-
(0.001)	(0.003)	(0.0001)	-	(0.008)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.261	1.274	1.285	1.296	1.240	1.252
(0.037)	(0.038)	(0.036)	(0.037)	(0.038)	(0.038)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
1.018	0.806	-0.002	1.217	1.201	-0.236
(0.016)	(0.121)	(0.026)	(0.040)	(0.050)	(0.049)
$a2_L$	$a2_K$	$a2_M$	$a2_Y$	$c1_C$	$c1_L$
0.255	0.064	-0.336	-0.341	0.246	0.197
(0.089)	(0.034)	(0.059)	(0.111)	(0.047)	(0.045)
$c1_K$	$c1_M$	$c1_Y$	$c2_K$	$c2_Y$	γc
0.868	0.337	0.345	-0.343	-0.049	-0.133
(0.080)	(0.059)	(0.087)	(0.076)	(0.027)	(0.026)
γ_L	γ_K	γ_M	γ_Y		
-0.160	-0.048	-0.097	-0.451		
(0.023)	(0.010)	(0.022)	(0.072)		

	Cost	Labor	Capital	Material	Price
R^2	0.973	0.767	0.814	0.938	0.957
D.W.	2.313	1.655	1.575	2.501	1.916
t.stat.	-5.119	-6.872	-4.726	-4.423	-6.240
Obs.	92	92	92	92	92

(Standard Errors in Parentheses)

Table A.33: Estimation Results for the Machinery Industry (29)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.313	-1.082	0.528	0.498	-0.188	0.700
(0.084)	(0.266)	(0.144)	(0.084)	(0.246)	(0.067)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.089	0.128	0.111	0.128	0.118
-	(0.022)	(0.022)	(0.021)	(0.023)	(0.022)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	-0.062	0.014	-0.386	-0.277	-0.193
-	(0.104)	(0.101)	(0.117)	(0.101)	(0.106)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	0.156	0.041	0.060	0.065	0.093
-	(0.029)	(0.027)	(0.024)	(0.024)	(0.020)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.004	-0.010	-0.002	-	0.002	-
(0.002)	(0.003)	(0.001)	-	(0.008)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.406	1. 267	1.367	1.382	1.288
-	(0.135)	(0.066)	(0.126)	(0.150)	(0.074)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
0.977	0.790	0.049	1.176	0.857	-0.244
(0.019)	(0.063)	(0.014)	(0.048)	(0.080)	(0.035)
$a2_M$	$c1_C$	$c1_L$	$c1_K$	$c1_Y$	$c2_K$
-0.329	0.288	0.251	0.593	0.218	-0.150
(0.057)	(0.036)	(0.031)	(0.101)	(0.057)	(0.089)
γ_C	γ_L	γ_K	γ_M	γ_Y	
-0.076	-0.100	-0.056	-0.093	-0.050	
(0.016)	(0.015)	(0.010)	(0.016)	(0.036)	

	Cost	Labor	Capital	Material	Price
R^2	0.965	0.833	0.819	0.955	0.825
D.W.	2.033	1.923	1.549	2.263	1.951
t.stat.	-4.814	-6.738	-5.296	-5.936	-1.417
Obs.	78	78	78	78	78

(Standard Errors in Parentheses)

Table A.34: Estimation Results for the Electrical and Optical Equipment Industry (30-33)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.052	-0.049	0.041	0.320	0.134	0.873
(0.041)	(0.161)	(0.072)	(0.050)	(0.124)	(0.054)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.143	0.138	0.150	0.096	0.174
-	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	0.474	0.324	0.504	0.113	0.309
-	(0.076)	(0.074)	(0.069)	(0.061)	(0.070)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	-0.151	-0.130	-0.175	-0.040	-0.190
-	(0.024)	(0.021)	(0.023)	(0.022)	(0.020)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.014	-0.008	-0.015	0.007	-0.032	0.0005
(0.002)	(0.003)	(0.003)	(0.003)	(0.012)	(0.0001)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.347	1.209	1.350	1.382	1.240
-	(0.051)	(0.037)	(0.044)	(0.050)	(0.040)
$a1_C$	$a1_L$	$a1_M$	$a1_Y$	$a2_C$	$a2_L$
0.978	0.922	1.002	0.699	-0.372	-0.131
(0.016)	(0.074)	(0.026)	(0.060)	(0.049)	(0.074)
$a2_K$	$a2_M$	$a2_Y$	$c1_C$	$c1_L$	$c1_K$
0.655	-0.378	-0.169	0.373	0.338	0.824
(0.425)	(0.055)	(0.083)	(0.050)	(0.047)	(0.085)
$c1_M$	$c1_Y$	$c2_L$	$c2_K$	$c2_Y$	γ_C
0.334	0.327	0.046	-0.104	-0.168	-0.121
(0.055)	(0.093)	(0.017)	(0.078)	(0.058)	(0.020)
γ_L	γ_K	γ_M	γ_Y		
-0.180	-0.029	-0.111	-0.184		
(0.023)	(0.009)	(0.021)	(0.031)		

	Cost	Labor	Capital	Material	Price
R^2	0.938	0.742	0.803	0.932	0.911
D.W.	1.645	1.786	1.684	1.797	1.944
t.stat.	–6.044	-7.718	-3.144	-5.205	-5.993
Obs.	76	76	76	76	76

(Standard Errors in Parentheses)

Table A.35: Estimation Results for the Transport Equipment Industry (34-35)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.137	-0.678	0.227	0.266	-0.206	0.810
(0.060)	(0.390)	(0.135)	(0.074)	(0.313)	(0.117)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.169	0.113	0.125	0.109	0.059	0.063
(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-0.010	0.341	0.385	0.261	0.039	0.104
(0.095)	(0.091)	(0.096)	(0.091)	(0.087)	(0.092)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-0.009	0.051	0.048	0.014	0.061	0.087
(0.026)	(0.023)	(0.024)	(0.025)	(0.021)	(0.022)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.003	0.005	-0.004	-	-0.013	-
(0.001)	(0.003)	(0.001)	-	(0.007)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.225	1.251	1.256	1.262	1.233	1.231
(0.033)	(0.039)	(0.031)	(0.033)	(0.036)	(0.033)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_L$
0.990	0.688	0.007	1.124	0.804	0.142
(0.014)	(0.077)	(0.028)	(0.029)	(0.065)	(0.053)
$a2_Y$	$c1_L$	$c1_K$	$c1_M$	$c1_Y$	$c2_K$
-0.152	0.045	0.668	-0.019	0.381	-0.259
(0.099)	(0.029)	(0.082)	(0.007)	(0.083)	(0.072)
γ_C	γ_L	γ_K	γ_M	γ_Y	
-0.120	-0.154	-0.059	-0.131	-0.145	
(0.022)	(0.022)	(0.012)	(0.022)	(0.040)	

	Cost	Labor	Capital	Material	Price
R^2	0.958	0.717	0.689	0.958	0.852
D.W.	2.284	1.614	1.766	2.284	2.263
t.stat.	-5.334	-7.103	-4.741	-5.891	-3.589
Obs.	94	94	94	94	94

(Standard Errors of Parentheses)

Table A.36: Estimation Results for Manufacturing Industries N.E.C., Recycling (36-37)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.171	-0.076	0.045	0.227	-0.072	0.736
(0.036)	(0.100)	(0.044)	(0.032)	(0.101)	(0.048)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.085	-	0.064	0.180	0.079
-	(0.022)	-	(0.022)	(0.018)	(0.020)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	0.379	-	0.230	0.235	0.543
-	(0.129)	-	(0.124)	(0.097)	(0.108)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	0.041	-	0.031	-0.115	-0.165
-	(0.027)	-	(0.031)	(0.026)	(0.023)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-	-	-	-0.002	-0.022	-
-	-	-	(0.001)	(0.012)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.250	-	1.212	1.227	1.126
-	(0.052)	-	(0.049)	(0.053)	(0.040)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
0.950	0.885	-0.518	0.947	0.844	-0.137
(0.027)	(0.070)	(0.521)	(0.044)	(0.065)	(0.036)
$a2_K$	$a2_M$	$a2_Y$	$c1_C$	$c1_L$	$c1_M$
-1.626	-0.146	-0.309	0.187	0.156	0.163
(1.523)	(0.043)	(0.091)	(0.039)	(0.034)	(0.039)
$c1_Y$	γ_C	γ_L	γ_K	γ_M	γ_Y
0.371	-0.047	-0.101	-0.020	-0.057	-0.141
(0.085)	(0.015)	(0.014)	(0.001)	(0.019)	(0.055)

	Cost	Labor	Capital	Material	Price
R^2	0.937	0.711	0.696	0.889	0.776
D.W.	1.710	1.570	1.898	2.168	1.889
t.stat.	-3.012	-7.004	-2.219	-3.019	–2.548
Obs.	62	62	62	62	62

(Standard Errors in Parentheses)

A.4 Results with R&D

Table A.37: Estimation Results for Basic and Fabricated Metals (27-28)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}	b_{LUS}
-0.110	-0.546	0.209	0.267	0.187	0.699	0.152
(0.064)	(0.321)	(0.135)	(0.084)	(0.349)	(0.089)	(0.023)
b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}	b_{KUS}	b_{KI}
0.123	0.102	0.156	0.116	0.158	0.014	0.031
(0.022)	-(0.023)	(0.023)	(0.023)	(0.023)	(0.163)	(0.168)
b_{KJP}	b_{KD}	b_{KC}	b_{KF}	b_{MUS}	b_{MI}	b_{MJP}
0.512	0.067	0.099	-0.013	0.035	0.066	0.071
(0.170)	(0.169)	(0.164)	(0.169)	(0.024)	(0.024)	(0.024)
b_{MD}	b_{MC}	b_{MF}	b_{Lt}	b_{Kt}	b_{Mt}	b_{YY}
0.040	0.073	0.018	-0.003	-0.006	0.001	0.014
(0.024)	(0.024)	(0.023)	(0.001)	(0.003)	(0.001)	(0.008)
b_{RY}	μ_{US}	μ_I	μ_D	μ_C	μ_F	$a1_C$
-0.354	1.254	1.246	1.306	1.310	1.221	1.018
(0.215)	(0.037)	(0.039)	(0.040)	(0.040)	(0.038)	(0.017)
$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_L$	$a2_C$	$a2_K$
0.784	-0.003	1.241	1.218	0.234	-0.232	0.052
(0.111)	(0.025)	(0.044)	(0.053)	(0.082)	(0.049)	(0.030)
$a2_M$	$a2_Y$	$c1_C$	$c1_L$	$c1_K$	$c2_K$	$c1_M$
-0.346	-0.332	0.241	-0.199	0.836	-0.318	0.210
(0.060)	(0.112)	(0.047)	(0.045)	(0.080)	(0.075)	(0.046)
$c1_Y$	$c2_Y$	γ_C	γ_L	γ_K	γ_M	γ_Y
0.337	-0.052	-0.124	-0.160	-0.048	-0.097	-0.404
(0.086)	(0.027)	(0.025)	(0.023)	(0.010)	(0.021)	(0.071)

	Cost	Labor	Capital	Material	Price
R^2	0.973	0.761	0.810	0.940	0.955
D.W.	2.259	1.646	1.509	2.491	1.895
t.stat.	-5.059	-6.974	-4.784	-4.589	-5.666
Obs.	92	92	92	92	92

(Standard Errors in Parentheses)

Table A.38: Estimation Results for the Machinery Industry (29)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.327	-1.018	0.524	0.502	-0.054	0.692
(0.084)	(0.251)	(0.142)	(0.082)	(0.223)	(0.061)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.066	0.145	0.148	0.123	0.130
-	(0.022)	(0.021)	(0.021)	(0.022)	(0.020)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	-0.135	-0.0001	-0.420	-0.330	-0.235
-	(0.097)	(0.099)	(0.108)	(0.095)	(0.101)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	0.110	0.086	0.140	0.073	0.122
-	(0.031)	(0.027)	(0.027)	(0.024)	(0.019)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.002	-0.008	-0.006	-	-0.004	-
(0.001)	(0.003)	(0.001)	-	(0.007)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.105	1.321	1.424	1.198	1.284
-	(0.082)	(0.058)	(0.081)	(0.065)	(0.058)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
0.973	0.823	0.043	1.178	0.930	-0.199
(0.021)	(0.059)	(0.013)	(0.045)	(0.080)	(0.035)
$a2_M$	$c1_C$	$c1_L$	$c1_K$	$c1_Y$	$c2_K$
-0.252	0.243	0.220	0.610	0.213	-0.186
(0.056)	(0.035)	(0.030)	(0.102)	(0.054)	(0.090)
γc	γ_L	γ_K	γ_M	γ_Y	b_{RY}
-0.079	-0.102	-0.049	-0.084	-0.075	-0.890
(0.015)	(0.013)	(0.001)	(0.016)	(0.041)	(0.190)

	Cost	Labor	Capital	Material	Price
R^2	0.963	0.813	0.824	0.956	0.827
D.W.	1.879	1.774	1.603	2.210	2.00
t.stat.	-5.236	-6.828	-5.285	-5.233	-1.854
Obs.	78	78	78	78	78

(Standard Errors in Parentheses)

Table A.39: Estimation Results for the Electrical and Optical Equipment Industry (30-33)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.048	-0.058	0.043	0.340	0.176	0.871
(0.049)	(0.199)	(0.089)	(0.056)	(0.156)	(0.063)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.123	0.132	0.145	0.088	0.173
-	(0.022)	(0.020)	(0.020)	(0.020)	(0.020)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	0.453	0.329	0.491	0.096	0.319
-	(0.082)	(0.086)	(0.074)	(0.067)	(0.080)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	-0.170	-0.127	-0.158	-0.037	-0.171
-	(0.028)	(0.021)	(0.024)	(0.022)	(0.020)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.013	-0.007	-0.012	0.007	-0.032	0.0004
(0.002)	(0.003)	(0.004)	(0.002)	(0.012)	(0.0003)
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.283	1.208	1.360	1.366	1.258
-	(0.056)	(0.038)	(0.047)	(0.051)	(0.044)
$a1_C$	$a1_L$	$a1_M$	$a1_Y$	$a2_C$	$a2_L$
0.981	0.889	1.017	0.713	-0.348	-0.129
(0.016)	(0.066)	(0.027)	(0.060)	(0.048)	(0.059)
$a2_K$	$a2_M$	$a2_Y$	$c1_C$	$c1_L$	$c1_K$
0.458	-0.354	-0.161	0.348	0.322	0.806
(0.311)	(0.056)	(0.085)	(0.050)	(0.047)	(0.087)
$c1_M$	$c1_Y$	$c2_L$	$c2_K$	$c2_Y$	γ_C
0.309	0.307	0.040	-0..091	-0.171	-0.131
(0.054)	(0.092)	(0.018)	(0.079)	(0.057)	(0.021)
γ_L	γ_K	γ_M	γ_Y	b_{RY}	
-0.184	-0.029	-0.117	-0.196	-0.120	
(0.025)	(0.009)	(0.023)	(0.032)	(0.061)	

	Cost	Labor	Capital	Material	Price
R^2	0.938	0.736	0.800	0.933	0.913
D.W.	1.599	1.764	1.657	1.760	2.007
t.stat.	–6.240	-7.412	-3.041	-5.168	-6.157
Obs.	76	76	76	76	76

(Standard Errors in Parentheses)

Table A.40: Estimation Results for the Transport Equipment Industry (34-35)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.163	-0.815	0.285	0.306	-0.319	0.845
(0.062)	(0.388)	(0.138)	(0.075)	(0.313)	(0.115)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.180	0.109	0.117	0.108	0.044	0.064
(0.017)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-0.020	0.337	0.368	0.264	0.028	0.115
(0.089)	(0.084)	(0.087)	(0.085)	(0.080)	(0.086)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.047	0.054	0.046	0.029	0.040	0.107
(0.032)	(0.022)	(0.023)	(0.024)	(0.023)	(0.022)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.003	0.006	0.005	-	-0.014	-
(0.001)	(0.003)	(0.001)	-	(0.007)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.328	1.251	1.245	1.283	1.186	1.266
(0.058)	(0.039)	(0.030)	(0.035)	(0.039)	(0.037)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_L$
0.990	0.666	0.003	1.129	0.822	0.121
(0.013)	(0.068)	(0.029)	(0.028)	(0.065)	(0.048)
$a2_Y$	$c1_L$	$c1_K$	$c1_M$	$c1_Y$	$c2_K$
-0.126	0.048	0.653	-0.016	0.353	-0.250
(0.098)	(0.029)	(0.082)	(0.007)	(0.083)	(0.071)
γ_C	γ_L	γ_K	γ_M	γ_Y	b_{RY}
-0.133	-0.165	-0.064	-0.144	-0.146	-0.128
(0.022)	(0.021)	(0.012)	(0.021)	(0.039)	(0.054)

	Cost	Labor	Capital	Material	Price
R^2	0.961	0.713	0.688	0.959	0.854
D.W.	2.120	1.604	1.751	2.226	2.249
t.stat.	-5.925	-7.726	-5.164	-6.883	-3.769
Obs.	94	94	94	94	94

(Standard Errors of Parentheses)

A.5 Results with Spillover Variables

Table A.41: Estimation Results for the Textiles Industry (17-19)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}	b_{LUS}
-0.156	-0.133	0.040	0.252	0.165	0.726	0.130
(0.050)	(0.234)	(0.094)	(0.055)	(0.229)	(0.081)	(0.018)
b_{LI}	b_{LD}	b_{LC}	b_{LF}	b_{KUS}	b_{KI}	b_{KD}
0.105	0.051	0.190	0.115	0.056	0.232	0.155
(0.018)	(0.017)	(0.022)	(0.016)	(0.118)	(0.112)	(0.132)
b_{KC}	b_{KF}	b_{MUS}	b_{MI}	b_{MD}	b_{MC}	b_{MF}
0.080	0.108	-0.012	0.019	0.043	0.049	-0.002
(0.118)	(0.112)	(0.025)	(0.025)	(0.022)	(0.035)	(0.023)
μ_{US}	μ_I	μ_D	μ_C	μ_F	$a1_C$	$a1_L$
1.220	1.253	1.210	1.227	1.198	0.934	0.891
(0.028)	(0.030)	(0.025)	(0.029)	(0.028)	(0.010)	(0.041)
$a1_K$	$a1_M$	$a1_Y$	$a2_C$	$a2_L$	$a2_K$	$a2_M$
0.136	0.978	0.813	-0.170	-0.011	0.096	-0.205
(0.068)	(0.026)	(0.044)	(0.045)	(0.056)	(0.063)	(0.045)
$c1_C$	$c1_L$	$c1_K$	$c1_M$	$c1_Y$	γ_C	γ_L
0.221	0.169	0.594	0.199	0.188	-0.060	-0.149
(0.046)	(0.045)	(0.067)	(0.044)	(0.040)	(0.021)	(0.018)
γ_K	γ_M	γ_Y	b_{Lt}	b_t	b_{Sfs}	b_{YY}
-0.036	-0.097	-0.184	-0.005	-0.0003	-0.873	-0.019
(0.010)	(0.019)	(0.045)	(0.001)	(0.001)	(0.284)	(0.008)

	Cost	Labor	Capital	Material	Price
R^2	0.976	0.757	0.832	0.948	0.938
D.W.	2.297	2.048	1.692	1.966	2.310
t.-stat	-2.896	-8.095	-3.518	-4.982	-4.120
Obs.	82	82	82	82	82

(Standard Errors in Parentheses)

Table A.42: Estimation Results for the Chemical Industry (24)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.068	-0.089	0.050	0.103	-0.196	0.704
(0.026)	(0.138)	(0.055)	(0.037)	(0.125)	(0.043)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.151	0.137	-	0.159	0.133	-
(0.020)	(0.020)	-	(0.020)	(0.021)	-
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.589	0.686	-	0.629	0.746	-
(0.038)	(0.038)	-	(0.037)	(0.044)	-
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-0.103	-0.011	-	-0.025	0.011	-
(0.024)	(0.022)	-	(0.021)	(0.032)	-
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
0.002	-0.006	-	-	-0.0004	-
(0.001)	(0.002)	-	-	(0.016)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.247	1.270	-	1.276	1.238	-
(0.032)	(0.033)	-	(0.032)	(0.034)	-
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_L$
0.995	0.555	1.356	1.027	1.162	0.352
(0.010)	(0.095)	(0.578)	(0.017)	(0.064)	(0.053)
$a2_M$	$a2_Y$	$c1_C$	$c1_L$	$c1_K$	$c1_M$
-0.434	-0.094	0.471	0.352	0.628	0.414
(0.053)	(0.125)	(0.052)	(0.053)	(0.086)	(0.048)
$c1_Y$	$c2_L$	$c2_K$	$c3_K$	$c3_L$	γ_C
0.101	0.352	0.628	-0.105	-0.114	-0.175
(0.103)	(0.053)	(0.086)	(0.083)	(0.035)	(0.029)
γ_L	γ_K	γ_M	γ_Y	b_{Sfs}	
-0.142	-0.204	-0.184	-0.346	-0.029	
(0.031)	(0.043)	(0.027)	(0.078)	(0.009)	

	Cost	Labor	Capital	Material	Price
R^2	0.934	0.373	0.718	0.885	0.850
D.W.	2.388	2.417	1.615	2.417	1.828
t.stat.	-6.266	-4.530	-4.749	-6.788	-4.447
Obs.	60	60	60	60	60

Table A.43: Estimation Results for Rubber and Plastics Products (25)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.164	-0.841	0.348	0.438	-0.314	0.641
(0.078)	(0.362)	(0.157)	(0.081)	(0.318)	(0.088)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.069	-0.004	-	0.044	0.101	-
(0.014)	(0.016)	-	(0.015)	(0.027)	-
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.057	0.272	-	0.200	0.170	-
(0.040)	(0.033)	-	(0.041)	(0.058)	-
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.143	0.133	-	0.081	0.182	-
(0.021)	(0.021)	-	(0.022)	(0.061)	-
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.004	-	0.006	-	-0.002	-
(0.001)	-	(0.001)	-	(0.010)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
0.977	1.113	-	1.146	1.173	-
(0.203)	(0.110)	-	(0.106)	(0.096)	-
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
1.006	0.698	-0.015	1.294	1.133	-0.165
(0.013)	(0.048)	(0.045)	(0.032)	(0.062)	(0.050)
$a2_M$	$a2_Y$	$c1_C$	$c1_L$	$c1_K$	$c1_M$
-0.325	0.163	0.173	0.177	0.502	0.202
(0.069)	(0.044)	(0.049)	(0.040)	(0.069)	(0.045)
γ_C	γ_L	γ_K	γ_M	γ_Y	b_{Sfs}
-0.237	-0.395	-0.145	-0.259	-0.055	-0.132
(0.034)	(0.048)	(0.027)	(0.033)	(0.029)	(0.067)

	Cost	Labor	Capital	Material	Price
R^2	0.952	0.721	0.687	0.885	0.893
D.W.	2.085	1.683	1.695	2.115	2.074
t.stat.	-6.944	-8.288	-5.451	-7.955	-1.880
Obs.	64	64	64	64	64

(Standard Errors in Parentheses)

Table A.44: Estimation Results for Other Non-Metallic Mineral Products Industry (26)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.397	-0.941	0.502	0.421	-0.307	0.589
(0.063)	(0.280)	(0.119)	(0.069)	(0.295)	(0.089)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.206	0.115	-	0.121	0.125	0.149
(0.025)	(0.018)	-	(0.021)	(0.017)	(0.020)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.199	0.318	-	0.383	0.082	0.157
(0.121)	(0.111)	-	(0.116)	(0.120)	(0.114)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.210	0.214	-	0.206	0.117	0.174
(0.052)	(0.037)	-	(0.040)	(0.034)	(0.034)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-	-	-	0.0001	0.015	-
-	-	-	(0.002)	(0.010)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.380	1.410	-	1.386	1.388	1.370
(0.062)	(0.069)	-	(0.058)	(0.061)	(0.059)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_L$
0.968	0.863	0.052	1.184	0.858	0.092
(0.022)	(0.062)	(0.036)	(0.046)	(0.082)	(0.028)
$c1_C$	$c1_K$	$c1_Y$	$c2_K$	$c2_Y$	γ_C
0.043	0.544	0.501	-0.079	-0.153	-0.097
(0.008)	(0.074)	(0.071)	(0.078)	(0.063)	(0.030)
γ_L	γ_K	γ_M	γ_Y	b_{Sd}	
-0.192	-0.146	-0.096	-0.102	-1.100	
(0.026)	(0.026)	(0.026)	(0.041)	(0.045)	

	Cost	Labor	Capital	Material	Price
R^2	0.915	0.784	0.745	0.879	0.877
D.W.	2.495	2.152	1.780	2.477	2.162
t.stat.	-3.247	-7.415	-5.707	-3.673	-2.462
Obs.	77	77	77	77	77

(standrad Errors in Parentheses)

Table A.45: Estimation Results for Basic and Fabricated Metals (27-28)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.110	-0.464	0.196	0.293	0.226	0.674
(0.067)	(0.335)	(0.141)	(0.081)	(0.337)	(0.091)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
0.139	0.129	0.105	0.156	0.242	0.176
(0.020)	(0.021)	(0.020)	(0.020)	(0.043)	(0.023)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
0.035	0.120	0.571	0.150	0.219	0.070
(0.153)	(0.156)	(0.159)	(0.158)	(0.185)	(0.160)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
0.058	0.133	0.137	0.098	0.416	0.108
(0.025)	(0.028)	(0.028)	(0.025)	(0.092)	(0.031)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.004	-0.004	0.001	-	0.016	-
(0.001)	(0.003)	(0.001)	-	(0.008)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
1.213	1.200	1.276	1..278	1.181	1.206
(0.034)	(0.036)	(0.038)	(0.037)	(0.035)	(0.034)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
0.990	0.693	-0.0009	1.214	1.192	-0.198
(0.014)	(0.068)	(0.026)	(0.041)	(0.052)	(0.046)
$a2_L$	$a2_K$	$a2_M$	$a2_Y$	$c1_C$	$c1_L$
0.205	0.048	-0.344	-0.327	0.205	0.177
(0.063)	(0.031)	(0.056)	(0.106)	(0.046)	(0.043)
$c1_K$	$c1_M$	$c1_Y$	$c2_K$	$c2_Y$	γc
0.765	0.204	0.340	-0.263	-0.052	-0.100
(0.023)	(0.043)	(0.083)	(0.071)	(0.027)	(0.021)
γ_L	γ_K	γ_M	γ_Y	b_{RY}	b_{Sfs}
-0.161	-0.055	-0.108	-0.392	-0.486	-1.189
(0.023)	(0.011)	(0.021)	(0.068)	(0.226)	(0.325)

	Cost	Labor	Capital	Material	Price
R^2	0.973	0.767	0.800	0.942	0.952
D.W.	2.172	1.655	1.387	2.423	1.886
t.stat.	-4.688	-6.998	-4.933	-5.079	-5.760
Obs.	92	92	92	92	92

(Standard Errors in Parentheses)

Table A.46: Estimation Results for the Machinery Industry (29)

s_{LL}	s_{KK}	s_{LK}	b_{LL}	b_{KK}	b_{MM}
-0.292	-0.834	0.449	0.474	0.074	0.617
(0.082)	(0.251)	(0.139)	(0.080)	(0.214)	(0.060)
b_{LUS}	b_{LI}	b_{LJP}	b_{LD}	b_{LC}	b_{LF}
-	0.051	0.133	0.133	0.216	0.137
-	(0.021)	(0.020)	(0.020)	(0.038)	(0.022)
b_{KUS}	b_{KI}	b_{KJP}	b_{KD}	b_{KC}	b_{KF}
-	-0.128	-0.010	-0.410	-0.243	-0.226
-	(0.087)	(0.096)	(0.097)	(0.093)	(0.093)
b_{MUS}	b_{MI}	b_{MJP}	b_{MD}	b_{MC}	b_{MF}
-	0.105	0.097	0.142	0.248	0.168
-	(0.030)	(0.024)	(0.024)	(0.056)	(0.020)
b_{Lt}	b_{Kt}	b_{Mt}	b_t	b_{YY}	b_{tt}
-0.001	-0.006	-0.008	-	-0.0005	-
(0.001)	(0.003)	(0.001)	-	(0.006)	-
μ_{US}	μ_I	μ_{JP}	μ_D	μ_C	μ_F
-	1.036	1.359	1.442	1.153	1.300
-	(0.085)	(0.057)	(0.068)	(0.058)	(0.059)
$a1_C$	$a1_L$	$a1_K$	$a1_M$	$a1_Y$	$a2_C$
0.993	0.809	0.038	1.219	1.021	-0.177
(0.017)	(0.060)	(0.013)	(0.047)	(0.082)	(0.048)
$a2_M$	$c1_C$	$c1_L$	$c1_K$	$c1_Y$	$c2_K$
-0.224	0.213	0.199	0.651	0.164	-0.179
(0.064)	(0.048)	(0.045)	(0.102)	(0.092)	(0.096)
γ_C	γ_L	γ_K	γ_M	γ_Y	b_{RY}
-0.087	-0.120	-0.045	-0.101	-0.093	-1.058
(0.016)	(0.017)	(0.010)	(0.018)	(0.039)	(0.186)
b_{Sfs}					
-0.112					
(0.033)					

	Cost	Labor	Capital	Material	Price
R^2	0.960	0.806	0.828	0.957	0.826
D.W.	1.854	1.665	1.674	2.285	1.940
t.stat.	-5.305	-7.201	-4.485	-5.583	-2.401
Obs.	78	78	78	78	78

(Standard Errors in Parentheses)

Appendix B

Distribution of Relative Productivity

The following proof can be found in Aghion & Howitt (1998*b*), chapter 3. It shows that the distribution of relative productivity parameters in the Aghion & Howitt (1998*a*) model remains constant over time.

$\Psi(.,t)$ is the cumulative distribution of the absolute productivity parameters A across sectors at any arbitrarily given date t. Pick any $A > 0$ that was the leading edge parameter at some date $t_0 \geq 0$ and define $\Phi(t) \equiv \Psi(A,t)$. Then

$$\Phi(t_0) = 1 \tag{B.1}$$

because at time t_0 no sector has a productivity parameter larger than the leading edge parameter A, and

$$\frac{d\Phi(t_0)}{dt} = -\Phi(t)\psi i^R \text{ for all } t \geqq t_0 \tag{B.2}$$

After t_0 the rate at which the mass of sectors behind A falls is the overall flow of innovations occurring in sectors currently behind A. There are $\Phi(t)$ such sectors, each innovating with a Poisson arrival rate ψi^R. Together (B.1) and (B.2) define a differential equation that $\Phi(t)$ must obey. This is uniquely solved as

$$\Phi(t) = e^{-\psi \int_{t_0}^{t} i^R(s)ds} \tag{B.3}$$

also because $\frac{dA^{\max}}{dt}(t) \equiv A^{\max}(t)\psi i^R(t)\ln\gamma$, and $A = A^{\max}(t_0)$

$$A^{\max}(t) = Ae^{\psi \ln\gamma \int_{t_0}^{t} i^R(s)ds} \tag{B.4}$$

Together the last two equations imply

$$\Phi(t) = (\frac{A}{A^{\max}(t)})^{\frac{1}{\ln\gamma}} \tag{B.5}$$

$\Phi(t)$ is the fraction of sectors at time t for which the relative productivity is smaller than $a = \frac{A}{A^{\max}(t)}$. Equation (B.5) establishes that this fraction is indeed given by $H(a) = a^{\frac{1}{\ln\gamma}}$ at date t, if a is the relative productivity at t of any sector that innovated on or after date 0. If t is large enough, this will include almost all values $a \in [0, 1]$.

Appendix C

Value Added with Imperfect Competition

Basu & Fernald's (1995) argument that using value added data may bias estimation results concerning economies of scale and spillovers is based on the assumption that the value added measure is derived from gross output as a Divisia index, as in the data prepared by Jorgenson, Fraumeni & Gollop (1987) and extended in subsequent years. Yet, the analysis readily carries over to value added obtained with double deflation, the most commonly used method to obtain a current price value added measure. This will be shown further below.

When a Divisia index is used to construct a value added measure, value added Y^{vd} is implicitly defined as

$$\frac{\dot{Y}}{Y} = (1 - s_M)\frac{\dot{Y}^{vd}}{Y^{vd}} + s_M\frac{\dot{M}}{M} \tag{C.1}$$

where s_M is the income share of material inputs. This equation can be rearranged to give

$$\frac{\dot{Y}^{vd}}{Y^{vd}} = \frac{\frac{\dot{Y}}{Y} - s_M\frac{\dot{M}}{M}}{1 - s_M} \tag{C.2}$$

In order to show that the rate of returns to scale estimates is likely to be biased when value added data is used, it is useful to derive the most frequently used estimation equation to estimate the rate of returns to scale in the primal framework. Remember that the rate of returns to scale equals $\lambda = \mu(s_L + s_M + s_K)$ when both economies of scale and mark-ups are present in a gross output production function. Multiplying both sides of this equation with factor i's cost share $c_i = \frac{P_i X_i}{P_L L + P_K K + P_M M}$, it turns out that $\lambda c_i = \mu s_i$. Therefore, taking into account the derivation of equation (3.5), it can be quickly verified that the relation of output and input growth rates can be written as

$$\frac{\dot{Y}}{Y} = \lambda \frac{\dot{Z}^M}{Z^M} + g \tag{C.3}$$

where $\frac{\dot{Z}^M}{Z^M} = (c_L \frac{\dot{L}}{L} + c_K \frac{\dot{K}}{K} + c_M \frac{\dot{M}}{M})$ denotes the cost share weighted factor input growth. Substituting this into (C.2) yields

$$\frac{\dot{Y}^{vd}}{Y^{vd}} = \frac{\lambda(1 - c_M)}{1 - s_M} \frac{\dot{Z}^{vd}}{Z^{vd}} + \frac{\lambda c_M - s_M}{1 - s_M} \frac{\dot{M}}{M} + \frac{g}{1 - s_M} \tag{C.4}$$

where $\frac{\dot{Z}^{vd}}{Z^{vd}} = \frac{c_L}{c_L + c_K} \frac{\dot{L}}{L} + \frac{c_K}{c_L + c_K} \frac{\dot{K}}{K}$ is the value added equivalent of $\frac{\dot{Z}^M}{Z^M}$. Since $\lambda c_i = \mu s_i$

$$\frac{\dot{Y}^{vd}}{Y^{vd}} = \frac{\lambda(1 - c_M)}{1 - s_M} \frac{\dot{Z}^{vd}}{Z^{vd}} + (\mu - 1) \frac{s_M}{1 - s_M} \frac{\dot{M}}{M} + \frac{g}{1 - s_M} \tag{C.5}$$

This equation implies that, unless mark-ups are 1, value added will depend directly on material input growth. Value added is computed from gross output by substracting the contribution of material inputs assuming that their production elasticity equals their income share. Yet, this will not be the case in the presence of market power. This is likely to cause an omitted variable bias, if value added growth is regressed on cost share weighted factor input growth to estimate the rate of returns to scale λ. The second misspecification is that the coefficient of $\frac{\dot{Z}^{vd}}{Z^{vd}}$ will not in general equal the true rate of returns to scale, unless there is perfect competition, so that $s_M = c_M$. Otherwise the divisor will be too large, causing a downward bias in the estimated rate of returns to scale.

Caballero & Lyons (1990) and Caballero & Lyons (1992) employ industry value added data to estimate an equation like $\frac{\dot{Y}_i^{vd}}{Y_i^{vd}} = \lambda_0 + \lambda_1 \frac{\dot{Z}_i^{vd}}{Z_i^{vd}} + \lambda_2 \frac{\dot{A}c}{Ac} + \varepsilon_i$, where $\frac{\dot{A}c}{Ac}$ is an aggregate activity measure, such as aggregate input or aggregate output, while the variables with index i are industry variables. ε_i is an error term. $\frac{\dot{A}c}{Ac}$ is included in the estimation equation to capture productive spillovers. Yet, Basu & Fernald (1995) argue that these are likely to proxy the omitted material inputs growth. Thus, the finding of positive productive spillovers may be nothing but a figment of specification error.

To see that the analysis carries over to value added measures obtained with double deflation, observe that double-deflated value added equals

$$Y^v = Y - M \tag{C.6}$$

where Y^v is constant price value added, Y is constant price gross output and M is constant price material inputs. The right hand side variables are deflated each with their own price index, which is why the method is called double deflation. Differentiating this equation, diving by Y^v and rearranging yields

$$\frac{\dot{Y}^v}{Y^v} = \frac{\dot{Y}}{Y} - \frac{m_y}{1 - m_y}(\frac{\dot{M}}{M} - \frac{\dot{Y}}{Y}) \tag{C.7}$$

where $m_y = \frac{M}{Y}$ is the constant price share of material inputs in gross output. The difference between the Divisia index and the double deflated index used to construct value added is the weights used to substract material inputs growth from output growth. Constant price weights are used in the double deflation method, whereas the Divisia index is calculated with current price weights. To compare the two measures, it is useful to rewrite equation (C.2) as

$$\frac{\dot{Y}^{vd}}{Y^{vd}} = \frac{\dot{Y}}{Y} - \frac{s_M}{1 - s_M}(\frac{\dot{M}}{M} - \frac{\dot{Y}}{Y}) \tag{C.8}$$

Combining (C.7) and (C.8), the growth rate of double deflated output can be rewritten as

$$\frac{\dot{Y}^v}{Y^v} = \frac{\dot{Y}^{vd}}{Y^{vd}} - \frac{m_y}{(1-m_y)(1-s_M)}(1-\frac{P_M}{P_Y})(\frac{\dot{M}}{M} - \frac{\dot{Y}}{Y}) \tag{C.9}$$

where the second term on the right hand side represents the double deflation bias. This disappears in two cases: When gross output always grows at the same rate as material inputs, and if the price of output, P_Y, and the price of material inputs, P_M, is always the same (Bruno & Sachs 1985).

From (C.9) it should be clear that double deflated value added growth is subject to the same biases as the Divisia index, potentially with a double deflation bias in addition to this.

Appendix D

The Data

The OECD STAN database provides input and output data for industries in OECD member countries. The newest version (OECD 2000b), based on the ISIC, Rev. 3 industry classification includes several service sectors in addition to manufacturing industries.

Although sometimes incomplete, the new STAN edition improves upon earlier versions in many aspects. It provides volume measures of gross fixed capital formation and capital stocks for some countries. In the older version only gross fixed capital formation in current prices was available. Very importantly, the newer version includes a volume measure of gross output, while no gross output deflator was available before. With both gross output and value added in constant prices at hand a measure of material inputs in constant prices can be constructed as the difference between the two output measures.

The sample of countries in this study includes Canada, France, Germany, Italy, Japan and the US. The data is taken from the STAN database for all countries but Germany. Although the new STAN database does include some service sectors, this study focuses on manufacturing sectors, because this is where the bulk of research and development is performed. Table D.1 gives an overview over the ISIC, Rev. 3 industry classification on which the new STAN database relies.

Output: Prices of gross output and value added are calculated as the ratio of the nominal output series to their volume index. 1995 values are normalized to one. Constant

Table D.1: The ISIC, Rev. 3 Industry Classification

ISIC-Code	Industry
15-16	Food Products, Beverages and Tobacco
17-19	Textiles, Textile Products, Leather and Footwear
20	Wood and Products of Wood and Cork
21-22	Pulp, Paper, Publishing and Printing
23-25	Chemical, Rubber, Plastics and Fuel Products
23	Coke, Refined Petroleum Products And Nuclear Fuel
24	Chemicals and Chemical Products
25	Rubber and Plastics Products
26	Other Non-Metallic Mineral Products
27	Basic Metals
28	Fabricated Metal Products
27-28	Basic Metals and Fabricated Metal Products
29-33	Machinery and Equipment
29	Machinery and Equipment N.E.C.
30-33	Electrical and Optical Equipment
30	Office, Accounting and Computing Machinery
31	Electrical Machinery and Apparatus N.E.C
32	Radio, Television and Communication Equipment
33	Medical, Precision and Optical Instruments
34-35	Transport Equipment
34	Motor Vehicles, Trailers and Semi-Trailers
35	Other Transport Euipment
36-37	Manufacturing N.E.C., Recycling

price output series are then calculated by dividing the current price series with this deflator.

For Canada a volume index for gross output is not available in the STAN database. Industrial product price indices provided by Statistics Canada are used instead as deflators for gross output. The deflators are converted to ISIC, Rev. 3 with a conversion scheme provided by the OECD. When the deflators have to be aggregated to match industry groups, gross output shares are used as weights.

Value added and gross output volume indices are not available for years earlier than 1991 for many French industries. To estimate the missing data it is assumed that the lacking price indices grew at the same rate as the corresponding price index of the manufacturing sector.

Material Inputs: Material inputs are measured as the difference between gross output and value added. The ratio of the difference of the current price series to the constant price series is the price of material inputs.

Labor Input: When available total employment at full time equivalents is used as a measure of labor income. However, full time equivalents are available for France, Italy and the US only. The simple total employment measure has to be used for Japan, Canada and Germany. The wage rate is calculated as labor compensation divided by the number of employees. It is normalized to one in 1995. Labor compensation is adjusted for the labor income of the self-employed assuming that the wage rate of the self-employed is the same as for the employees. The labor input variable is multiplied by the wage rate of the base year, so that the product of the normalized wage rate and labor input equals labor compensation.

In the case of France employment at full time equivalents is not available for several industries before 1990. For the chemical industry (ISIC 24) and the rubber and plastics industry (ISIC 25) the number of employees as a percentage of employees of the industry group 23-25 is almost exactly the same as the corresponding percentage of total employment after 1990. Therefore, the number of employees is estimated assuming that this holds also in the years before. That is, the number of employees in each industry is calculated as the number of employees of industry group 23-25 multiplied by the industry's share in total employment of the aggregate industry group 23-25.

For industries 27 to 33 the number of employees is estimated making use of information contained in the number of employees of those industries as a percentage of employees in the entire manufacturing sector after 1990. In some industries the level of this percentage is slightly different from the corresponding percentage of total employment after 1990, while the movement of the percentages is completely parallel. To correct for the difference in levels, the estimated share of employees of these industries before 1990 is calculated as the industry's share of total employment in manufacturing employment minus the average difference between the employees' share and the share of total employment of the industry after 1990.

For Canada, the number of employees for industries 27-33 is not available. These series are estimated assuming that the number of employees as a percentage of total employment is the same in each of these industries as in the aggregate industry group 27-33.

Capital: In the STAN database net capital stocks are available for Italy only. As the OECD does not provide capital stocks for the US, net capital stocks from the Bureau of Economic Analysis are used. For France net capital stocks at a fairly aggregate level are obtained from the French National Statistical Office, INSEE. The STAN database does contain gross capital stocks for France, Italy, Canada and Japan. For Japan, Canada and Germany, I construct net capital stock series using the perpetual inventory method.

$$K_{i(t+1)} = I_{it} + (1-\delta)K_{it} \tag{D.1}$$

where I_{it} is industry $i's$ period t investment in physical capital at constant prices, K_{it} is the physical capital stock and δ is the depreciation rate of physical capital. Assuming a constant growth rate of investments, as well as constant depreciation rates for both gross and net capital stocks it can be shown after solving the difference equation (D.1), that the ratio of net capital stock to gross capital stock will converge to a constant. In fact, in the case of France and Italy, where both gross and net capital stocks are at hand, the ratios are close to constant, between 0.52 and 0.62 depending on the industry. For the construction of net capital stocks for Japan, France and Germany, I assume a starting value for the net capital stock that equals 55% of the gross capital stock for the corresponding year. The depreciation rate is assumed to equal 9%.

For Canada, investment at constant prices is provided in the STAN database, so the net capital stocks can easily be computed using (D.1). This is trickier in the case of Japan, for which current price investment is not provided in the STAN database. Since investment at constant prices is provided as an index, with a value of 100 in 1995, the level of investment in prices of 1995 is unknown. Assuming a depreciation rate of 4% for the gross capital stock, it turns out that for each industry an artificial investment series deduced with the help of (D.1), as $I_{it} = K_{i(t+1)} - (1-\delta)K_{it}$ has almost exactly the same shape as the volume index of investment provided in the STAN database. Therefore, the level of the investment series is chosen by setting the 1995 value of the STAN volume index equal to the investment series calculated from the gross capital stock series as explained above and multiplying all other observations with the same constant.

German data is taken from a different database provided by the Deutsches Institut für Wirtschaftsforschung (DIW) described below, which includes no investment data at all. Investment data is taken from an older version of the STAN database instead, which provides current price gross fixed capital formation (OECD 1998). The investment price deflator is calculated as the ratio of current to constant price investment in the manufacturing sector which I obtain from the Statistisches Bundesamt. It should be noted that the investment series thus deflated match very well the movement of an investment series obtained from the gross capital stock series as $I_{it} = K_{it+1} - K_{it} + \delta K_{it}$, with δ assumed to equal 4%. Since the STAN series only reaches 1994, I augment the series using D.1 to deduce investment series from the gross capital stock after 1994. For δ I use the average depreciation rate from 1980-1994 that results when assuming that the gross capital stocks of the DIW were calculated with the STAN-98-investment series.

The user cost of capital is calculated as $p_K = \omega_K(\rho + \delta)$, where ω_K is the investment price deflator, ρ is the real interest rate and δ is the depreciation rate. For Canada, France, Italy and the US gross capital formation data is provided in the STAN database, so implicit investment price deflators can be calculated from these series. For Japan, there are no investment price deflators by industry. Instead, gross capital formation series in current and constant prices for the entire Japanese economy are taken from the OECD National Accounts to construct an implicit price deflator. It is assumed to be the same in each industry.

Gross capital formation series for the West-German manufacturing sector are taken from the Statistisches Bundesamt to construct investment price deflators for German industries. The data is augmented with series for unified Germany in the nineties.

The real interest rate is defined as the average of the difference between the long-term government bond yield taken from the IMF's International Financial Statistics and the inflation rate. The inflation rate is calculated from GDP deflators. For the US the GDP deflator is constructed with GDP series from the Bureau of Economic Analysis. For Italy and Japan the data is taken from the OECD National Accounts. The implicit GDP price deflator is directly taken from the OECD national accounts for Canada. German GDP data is taken from the OECD National Accounts as well. West-German data lacking, the German GDP deflator has to be calculated with data for the unified country for the nineties. The series calculated with data from the OECD National Accounts is augmented with a deflator calculated with GDP series taken from the Statistisches Bundesamt for 1998. For France the GDP deflator is taken from the French National Statistical Office, INSEE.

German data: Data for Germany is available for the unified country only which obviously reduces the sample period to 1991-1998. Since this is not enough for reliable estimation, data for West-German manufacturing industries gathered by the Deutsches Institut für Wirtschaftsforschung (DIW) is used instead (Görzig et al. 2000). The DIW has converted data from the Federal Statistical Office's monthly reports from the old German WZ79 classification to ISIC, Rev. 3 to obtain the series. Unlike in the national accounts firms that are legally one company but produce different products may be assigned to different industries in the monthly reports. Therefore, there are some differences to national accounts data, but the available variables should serve as reasonable proxies.

Gross output not being available, it has to be proxied by the turnover variable provided by the DIW. Value added at 1995 prices is evaluated at factor costs. Total employment is used as the measure for labor input, while gross capital stocks at 1995 prices serve as the capital input measure. Labor compensation includes the employee's, but not the employer's contribution to social security.

Neither a deflator for value added nor for gross output is available through the DIW. A value-added deflator is constructed by converting the ratio of current to constant price value-added from the old STAN database from the ISIC, Rev. 2 industry classification to ISIC, Rev. 3 using an approximate conversion scheme provided by the OECD. When several ISIC, Rev. 2 industries have to be aggregated to match an ISIC, Rev. 3 industry, shares in the constant price value-added of the aggregate industry are used as weights. The data is augmented with series from the German Federal Statistical Office for the unified country.

A gross output deflator not being available through the OECD, producer price indices from the Federal Statistical Office are used instead. Since each industry might additionally produce goods other than its main product, it would be desirable to combine the corresponding price indices, weighting them with data from output tables. However, a comparison of the "raw" prices with weighted indices from Bönte (1997) shows that they are very similar. Their correlation after detrending by regressing each series on a constant and a trend is higher than 0.99 for all series but one, for which it is 0.98. With this justification unweighted producer price indices are used instead.

Unfortunately, the conversion from the German WZ79 industry classification to ISIC, Rev. 2 is rather crude, as the conversion scheme provided by the Federal Statistical Office only indicates whether a particular WZ70 industry enters into a particular ISIC, Rev. 2 industry without providing a percentage. Therefore, the price index of some WZ79-industries are included into the price indices of several different ISIC, Rev. 2 industries. Due to the lack of gross output at constant prices, shares in current price gross output of the aggregate industry are used as weights. The data is augmented with gross output deflators implicit in gross output data for unified Germany provided by the Federal Statistical Office.

For Germany only total employment is available, so the number of self-employed has to be estimated. This is done by using the average share of the self-employed in total employment as apparent in the STAN data for all of Germany based on ISIC, Rev. 3. Assuming that this percentage was approximately the same in West-Germany even before 1991 and that it was constant over time, the share can be used to calculate the number of self-employed with the total employment series provided by the DIW. Although these may seem to be arbitrary assumptions, it turns out that the TFP growth measure changes only slightly when the labor share is corrected for the estimated income of the self-employed. Moreover, although data from the Federal Statistical Office has not been used, because for many industries the conversion from WZ79 to ISIC3 seems too rough, the estimate described above proves to be quite close for those industries for which there is a one-to-one match.

The German data does not include the recycling industry. Data from industry 36 is assumed to be a reasonable proxy for 36-37, since the recycling industry is typically rather small.

Research and Development Data A convenient feature of the STAN databases both old and new is that they are completely compatible with the OECD ANBERD and ANSRE databases (OECD 1999) which cover intramural business expenditure on research and development and R&D personnel respectively. The research and development expenditure data based on the ISIC, Rev. 3 industry classification is available for the time span 1987-1996/7 only. However, at least the series for manufacturing industries can be expanded with data on research and development expenditure based on the ISIC, Rev. 2 industry classification which covers 1970-1997. Using a conversion scheme provided by the OECD it turns out that the ISIC, Rev. 2 series match the ISIC, Rev. 3 series one-to-one for most industries and countries. The ANBERD 2000 database is used to expand the series to 1998 (OECD 2000*a*). It should be noted that the Italian data provided by the OECD includes extramural R&D expenditure while every other country reports intramural R&D expenditure only.

R&D capital stocks are calculated using the perpetual inventory method:

$$R_{i(t+1)} = I_{it}^{R} + (1 - \delta_r)R_{it} \tag{D.2}$$

where I_{it}^{R} is period t research and development expenditure in industry i,and R_{it} is the R&D capital stock of industry i in period t. The investment series are deflated with the respective country's GDP-Deflator and the depreciation rate δ_r is assumed to be 12%. The initial capital stock is calculated as $R_0 = \frac{I_{i0}^{R}}{\bar{g}^{R}+\delta_r}$ where $\bar{g}^{R}$ is the average growth rate of R&D-expenditures over the sample period.

While the conversion of R&D data in ISIC, Rev. 2 proves to be a perfect match to ISIC, Rev. 3 data in most cases, occasional difficulties have to be overcome for some industries. Separate R&D data for the US wood industry is not available in the Anberd 2000 data based on ISIC, Rev. 3. Instead, data for the wood and the paper and publishing and printing industry is reported as an aggregate. Disaggregated data for two industries is estimated by converting the ANBERD 1999 data based on ISIC, Rev. 2 with an OECD conversion scheme to ISIC, Rev. 3. The 1997 value for the paper and publishing industry is calculated as the R&D investment of the aggregate industry as apparent in the ISIC, Rev. 3 data of ANBERD 2000 minus the average difference between the R&D investment in this industry aggregate and the R&D investment of the paper and publishing industry in previous years. The R&D investment in the wood industry for this year is the residual.

Converting Japanese ISIC, Rev. 2 data for industry group 36-37, it turns out that the converted R&D investment is much higher than the data provided directly in ISIC, Rev. 3. This is certainly due to the fact, that the OECD conversion scheme is only approximate. The converted series is corrected with its average difference over 1987-1993 to the corresponding R&D investment series provided in ANBERD data based on ISIC, Rev. 3 to obtain data for the years before 1987.

For Germany ANBERD data based on ISIC, Rev. 3 (ANBERD 3) is available for the unified country only, while ANBERD data based on ISIC, Rev. 2 (ANBERD 2) for West-Germany and unified Germany can be compared for 1991 to 1993. It should be noted that only a small fraction of Germany's research and development is conducted in the East-

German Länder, although the percentage has increased some from 3.78 % in 1991 to 5.99 % in 1997 (Stifterverband für die deutsche Wissenschaft 1999). In principle, the difference between data for Germany and West-German data could be neglected, and ANBERD 3 data could be used to approximate the R&D investment of West-German industries. Not only does the size of East-German R&D investment seem to be negligeable, but it is also very difficult to assign research and development expenditures to a specific German region. In fact, when comparing West-German and German data provided in ANBERD 2, it turns out that the West-German R&D investment is higher for several industries according to the data, in the case of the food industry in 1994 this difference even amounts to more than 20%. Therefore, it does not seem useful to use the information contained in this data to correct the R&D expenditure of later years for the inclusion of East-German R&D. Rather, ANBERD 3 data from ANBERD 1999 and ANBERD 2000 for each industry is corrected with the percentage difference of East- and West-German R&D as evidenced in the Stifterverband für die deutsche Wissenschaft's (1999) data. Since the Stifterverband collects data for odd years only, I use linear interpolation to estimate percentage differences for 1994 and 1996. I assume that the growth rate of the percentage difference is the same in 1998 as it was in 1997 to obtain an estimate for 1998.

Spillover Variables: For the construction of weights for the **domestic spillover variable**, input-output tables measuring intermediate goods flows for each of the countries in the sample are provided by the OECD (OECD 1995). In addition to total intermediate goods flows, tables with imported intermediate goods and domestically traded goods only are available. Input-output tables for domestic goods flows are employed to calculate the weights. The OECD tables are based on ISIC, Rev. 2 so they have to be converted to match the R&D capital stocks. This is done using a conversion scheme provided by the OECD.

The OECD does not currently update its input-output tables, so the tables are never more recent than 1991. Germany provides data for 1986, 1988 and 1991, Canada for 1981, 1986, 1990, France and Japan for 1980, 1985 and 1990, and the US for 1982, 1985 and 1990, while for Italy an input-output table for 1985 only is available. For each of these countries, input-output coefficients for all of these years are constructed. The average of the coefficients in the three different years is used to calculate ω_{ij}. When available, input-output tables in constant prices are used. However, for Italy and the US input-output tables are available in current prices only.

The diagonal of each input-output coefficient matrix is set to zero, since each industry's R&D capital stock enters its cost function as a separate variable. Therefore, it should not be included additionally in the domestic spillover variable. In the case of Germany, the radio, television and communication equipment industry is lacking in the input-output tables. Due to a lack of a better alternative to tackle this problem, it is assumed that no spillovers stem from this industry.

Since some industries are aggregated in the empirical analysis due to data limitations, the corresponding spillover variables have to be aggregated as well. This is done by weighting each spillover variable with the ratio of material inputs used in this industry to material inputs of the aggregate industry. These weights take account of the relative size of inter-industry trade as a transmission channel for each industry to be aggregated.

Intra-Industry Spillovers: The import shares are constructed drawing on Feenstra's (2000) data of import flows over the period 1980-1997. This database is based on the Standard International Trade Classification (SITC) of the United Nations. It quantifies imports of different kinds of goods. However, it is possible to assign each type of good to a particular industry. In fact, the Feenstra database also includes tables based on the US Standard Industry Classification. A conversion scheme provided by the OECD is used to convert this data to ISIC, Rev. 3.

Time-invariant import-shares are constructed averaging the import-shares over 1980-1997.

Inter-Industry Spillovers: Import input-output matrices provided by the OECD (OECD 1995) are used to construct weights for the inter-industry spillover variable. The coefficients are calculated in a manner completely analogous to the input-output coefficients for the domestic spillover variable. Time-invariant coefficients are obtained by averaging over all years in the sample period 1980-1998, for which input-output tables are available. Data availability is the same as for the domestic spillover variable. Again, input-output tables in current prices have to be used for Italy and the US. The diagonal of each input-output coefficient matrix is set to zero to avoid double-counting.

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