R&D-Based Endogenous Growth in Finland

A Comparative Study on the Semi-Endogenous and the Schumpeterian Growth Models

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Tiivistelmä Referat – Abstract

Theories of endogenous growth aim at finding the sources of productivity growth inside an economy. According to R&D-based endogenous growth theories, total factor productivity (TFP) growth is driven by innovations that improve existing technologies.

This thesis studies Finnish TFP growth from 1955 to 2008 by concentrating on two recent theories of R&D-based growth. In the semi-endogenous theory, a steady growth rate of R&D input is required for a sustained TFP growth rate. In the second generation model, also called the Schumpeterian model, a steady level of R&D intensity defined as R&D input adjusted with a measure of product variety, is required for steady TFP growth.

These two frameworks are used to analyse a dataset that has been collected and combined from various sources. A nonstationary multivariate time series model (VECM) is used to study the two models in a nested framework which enables the comparison of the models in a robust manner. As far as we know, the nested model approach has not been conducted before in similar empirical studies.

The findings of this thesis are that R&D input, using seven different measures, and TFP are cointegrated as suggested by the semi-endogenous model. However, the product variety assumption presented by the Schumpeterian model is not fully rejected although the steady state assumption of strict proportionality between R&D input and product variety is firmly rejected.

These findings are in accordance with empirical studies supporting R&D-induced growth in a wider sense. However, they are contradictory with articles that compare semi-endogenous and Schumpeterian models, which have found support for the latter but not for the former.

In conclusion, this thesis argues that Finnish TFP has in fact been affected by R&D already when Finland was still lagging behind the world's high technology frontier.

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Tiivistelmä Referat – Abstract

Endogeeniset kasvuteoriat pyrkivät selittämään tuottavuuden kasvua talouden sisällä. T&k-perusteisten kasvuteorioiden mukaan tuottavuuden kasvu syntyy olemassa olevaa teknologiaa parantavista innovaatioista.

Tässä tutkimuksessa tarkastellaan Suomen tuottavuuden kasvua vuosina 1955-2008 kahden viimeaikaisen t&k-perusteisen kasvumallin avulla. Semi-endogeenisessa kasvuteoriassa tasaisen tuottavuuden kasvun edellytys steady state -tilanteessa on t&k-panoksen tasainen kasvu. Toisen sukupolven kasvumallissa, jota kutsutaan myös Schumpeteriläiseksi malliksi, tasainen t&k-intensiteetti, eli t&k panos korjattuna tuotteiden moninaisuutta taloudessa kuvaavalla muuttujalla, on edellytys kestävälle tuottavuuden kasvulle.

Näitä kahta mallia käytetään analysoitaessa aineistoa, joka on kerätty ja koottu useista lähteistä. Mallien vertailussa käytetään epästationaarista moniuloitteista aikasarjamallia (VECM), joka mahdollistaa kasvumallien vertailun saman aikasarjamallin sisäkkäisinä versioina. Tällaista sisäkkäistä tarkastelua ei ole tiettävästi käytetty aikaisemmin kyseisten kasvumallien vertailussa.

Tutkimuksen tulokset osoittavat, että t&k-panos seitsemällä eri muuttujalla mitattuna ja kokonaistuottavuus ovat yhteisintegroituneita semi-endogeenisen mallin osoittamalla tavalla. Tutkimus ei kuitenkaan pysty hylkäämään Schumpeteriläisessä mallissa esiintyvää tuotteiden moninaisuutta kuvaavaa muuttujaa, vaikkakin steady state -oletus t&k-menojen ja tuotteiden moninaisuutta kuvaavan muuttujan välisestä suorasta relaatiosta voidaan hylätä selvästi.

Tutkimustulokset ovat yhdenmukaisia t&k-perusteisten kasvumallien empiirisen tutkimuksen kanssa sen laajassa merkityksessä. Ne ovat kuitenkin ristiriidassa semi-endogeenista ja Schumpeteriläistä kasvumallia vertailevien tutkimusten kanssa, joiden tulokset puoltavat Schumpeteriläistä teoriaa.

Kaiken kaikkiaan tutkimus osoittaa, että t&k-panoksella on ollut vaikutusta suomalaiseen tuottavuuteen jo pitkän aikaa ennen kuin Suomesta tuli korkean teknologian edelläkävijä.

Avainsanat – Nyckelord – Keywords
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Contents

List of Figures

List of Tables

Chapter 1

Introduction

In the classical growth model by Solow (1956), technology is "manna from heaven" and enters the production function as an exogenous variable; growth resulting from other factors than capital or labour is unexplained. Endogenous growth theory aims to represent technology as an endogenous variable in the production function, so that one can understand exactly how technology is invented.

In this study we show that R&D and TFP have had a strong relation in Finland already since the 1950's. Our study is motivated by an article by Jalava et al. (2002), "Technology and Structural Change: Productivity in the Finnish Manufacturing Industries, 1925–2000". The authors leave an important question to be answered by future research: "Why has the TFP growth been so strong in the Finnish manufacturing industries?" This thesis studies Finnish TFP as an aggregate, but surely a great part of the growth can be traced down to the manufacturing sector.[1] It is clear that technological change particularly in ICT has been the driver of growth in Finland from the 1990's, but it is not so evident what kind of role research and development has played earlier.

This study suggests that for the period 1955–2008, research and development, measured with several different indicators, has had an impact on the growth of

[1] Over 50% of Finnish productivity growth resulted from the manufacturing sector during 2000–2005 (OECD 2006).

Finnish TFP. We have studied two front-line theories of endogenous growth, the semi-endogenous and the Schumpeterian growth models, to study two possible explanations of the nature of the relation between R&D and TFP.

Contradictory to the findings of several prominent articles,[2] we found out that the semi-endogenous model describes well the Finnish economy. The semi-endogenous theory claims that a steady growth rate of R&D input is required for a sustained TFP growth rate. Indeed, Finnish R&D input and TFP growth are cointegrated and move "hand-in-hand", even though TFP growth has been much faster than the growth of any of the R&D inputs studied.

The Schumpeterian model states that a steady level of R&D *intensity*, defined as R&D input adjusted with a measure of product variety, is required for steady TFP growth. We cannot reject the hypothesis that product variety –the notion that as the economy grows, innovations are diluted over a larger number of sectors– plays some kind of role in Finnish TFP growth. Nevertheless, the steady state property of product variety, namely that R&D input and product variety grow strictly proportionately together, is firmly rejected.

In this study, a generalized version of a productivity-growth function presented by Ha & Howitt (2007), is estimated inside a nonstationary multivariate time series model. Contradictory to previous studies that have estimated two separately defined models,[3] in this study the semi-endogenous and Schumpeterian models are estimated as *nested* models inside a VECM-framework. This sort of statistical specification of the models gives formally comparable results, since in addition to setting the hypothesis for the validation of the model in question, also the hypothesis of rejecting the competing model can be tested simultaneously.

Our dataset has been collected and combined from various resources, also partly from non-digital sources. The time span of the study, 1955–2008, is longer than in many other studies of Finnish productivity which mostly concentrate on the ICT

[2]For example Ha & Howitt (2007), Madsen (2008), Madsen et al. (2010), Zachariadis (2003) and Zachariadis (2004).

[3]For example Ha & Howitt (2007) and Madsen et al. (2010).

-era. Therefore this study provides valuable insight to the Finnish success story already after World War II, finding out that not only has R&D been important for the new Nokia -economy, but that it already played a significant role during the times when Finland was in European terms a backward economy, growth was driven by Soviet trade, wood, paper and metal being the cornerstones of the economy (Hjerppe 2008).

Empirical studies on endogenous growth have generally concentrated on large economic entities, such as the U.S. and G5 countries (Jones 1995a; Ha & Howitt 2007) or OECD countries (Coe et al. 2009), since endogenous growth theories are typically seen as describing a larger entity than a national economy, due to the nonrival nature of ideas. However, as a recent study by Pessoa (2010) shows, the relation between R&D and economic growth differs largely from country to country. Therefore, we regard that a country-level setting, when the effects of foreign R&D are also taken into consideration, presents a fresh way of using the R&D-based growth theories. We are not the first to collaborate this idea though; a study on India by Madsen et al. (2010) finds positive results on the effects of both foreign and domestic R&D to TFP growth.

The thesis is constructed as follows: The theoretical frameworks are presented in chapter 2 starting with the microeconomic foundations of endogenous growth theory in chapter 2.1. The R&D-based growth models are discussed in chapter 2.2. We follow the theoretical framework by Ha & Howitt (2007), presenting the models in historical order. First we study the first generation fully endogenous growth models by Romer (1990), Aghion & Howitt (1992) and Grossman & Helpman (1991), then the semi-endogenous growth models by Jones (1995b), Kortum (1997), and Segerström (1998) and finally, the second-generation or Schumpeterian fully endogenous growth models by Aghion & Howitt (1998), Howitt (1999), Dinopoulos & Thompson (1998) and Young (1998).

In the empirical part of the study chapter 3 describes the collecting and combining of the data and some observations concerning it. The methods of multivariate time series analysis are presented in chapter 4, and finally the estimation of the models is done in chapter 5, where in section 5.5 we discuss our results comparing them with previous research. Lastly, chapter 6 concludes and presents ideas for further research.

Chapter 2

R&D-Based Endogenous Growth Theory

In this chapter we first present the microeconomic foundations of endogenous growth models on a general level, including a short side-step to the endogenous growth models that build on capital instead of R&D. Then we move onto the macroeconomic models studying the first generation, the semi-endogenous and the second generation growth models. Finally, we take a short look on how technology transfers affect TFP growth.

2.1 Microeconomic Foundations

Research and development is about producing ideas and inventions. Firstly, in order to understand the special nature of producing ideas or knowledge, we introduce the concepts of rivalry and excludability following Romer (1990). Secondly, we briefly describe some endogenous models that are not based on R&D, but which connect productivity with capital accumulation.

Finally, we move towards to the R&D-based macroeconomic models. The model introduced by Romer (1990) is regarded as being the foundation stone for all the

R&D based growth models, not least because of its solid microeconomic framework. We briefly describe the model as an example on how an optimal R&D input is derived inside a microeconomic framework.

2.1.1 Rivalry and Excludability

According to Romer (1990) "a purely rival good has the property that its use by one firm or person precludes its use by another; a purely nonrival good has the property that its use by one firm or person in no way limits its use by another".

Ideas are thus nonrival: the use of an idea in a certain activity does not limit the use of the same idea in another activity. A good example of a perfectly nonrival good is calculus. Romer defines rivalry and excludability as technological attributes of goods, but excludability can also be achieved through the legal system. Excludability means that the owner of a good can exclude others from using it (Romer 1990). In idea-based products an excludable good could be a satellite-tv and an nonexcludable good the results of basic research.

Conventional economic goods that can be privately owned and traded in competitive markets are both rivalrous and excludable (Romer 1990). Nonexcludable goods that are also nonrival are called public goods (for example national defense and scientific research). The degree of excludability can be expressed as an externality. Nonexcludable goods that have positive externalities are often publicly produced and a perfectly nonexcludable good cannot be privately traded in markets (Romer 1990).

Rivalry and excludability are linked: a rival good generally is also excludable since owning a rival product means that one can exclude others from using it (Romer 1990). An exception to the rule is a good that suffers from "tragedy of the commons" problem, from the inability to define the ownership of the good. For instance fish in the sea are indeed rival but still nonexcludable.

However, excludability does not imply rivalry. Technology as a nonrival good can be excludable: for example a design produced in a private, profit-maximizing company is rival, but the firm can control its copying and therefore the firm can also sell the idea.

Romer also highlights the difference between human capital and "ideas" as goods that can be nonrival and nonexcludable: A piece of human capital, say the knowledge of calculus, is tied to a human body and thus it can only be used once at a time which makes the knowledge of calculus both rival an nonexcludable, whereas calculus itself is a nonrival and nonexcludable good. Human capital can therefore be traded in competitive markets whereas the underlying nonrival and nonexcludable ideas cannot.

Perfect nonrivalry is an idealization, since the idea is itself tied to something physical, like on a computer. Thus its copying is not free, but the marginal costs are much smaller than the fixed costs that are related to producing the idea in the first place. Hence there are increasing returns to scale in the production of ideas or "idea-intensive" goods (that can be rival), that use nonrival goods as inputs. By doubling the costs of production (the input) of a certain amount of goods more than doubles the amount of final goods produced (the output). Because of the fixed costs, also labour productivity rises with the scale of production of the final good (Romer 1990).

Formally, a production function F that uses a nonrival input A and a rival input X cannot be concave because $F(\lambda A, \lambda X) > \lambda F(A, X)$. More generally, since $F(A, X) = X\frac{dF}{dX}(A, X)$, it follows that $F(A, X) < A\frac{dF}{dA}(A, X) + \frac{dF}{dX}(A, X)$. If all inputs are paid their value marginal product, the firm suffers losses (Romer 1990). Since in perfect competition the price of the final product will be equal to marginal cost, the firm will make a loss equal to the fixed costs (Romer 1990).

This result means that in a market where inputs used are nonrival, perfect competition is impossible and imperfect competition is a necessary condition for this market to exist. A monopolist producer can reduce production and set the price to be equal to the marginal revenue.

The monopoly power can be guaranteed by giving a right (a patent for instance) that makes competition impossible. From the point of view of the social optimum, the result is similar to any other monopoly market: the product is underused and there is a dead weight loss (Romer 1990).

2.1.2 Endogenous Growth Theory with "Learning by Doing" and the AK-model

The common idea in the "learning by doing" and the AK-models is that capital accumulation –whether it is physical or intangible capital– results in productivity growth. The "learning by doing" model of Arrow (1962) formulates this so that extra physical capital necessarily leads to an equiproportionate increase in knowledge when workers learn to use the new capital. In the AK-models by Romer (1986), Romer (1987), Lucas (1988) and Rebelo (1991), investment in broadly defined capital has a positive long-run effect on growth. For instance Lucas (1988) formulates a model where the production of human capital generates knowledge, which is a nonrival, nonexcludable good.

Arrow (1962) formulates the issue of "learning by doing" through an individual company that takes extra capital into use (taking it as given). Solving the model yields constant returns at the firm level, but increasing returns to scale at the aggregate level. The growth at the aggregate level comes not just from the direct effect of having additional aggregate capital, but moreover from workers having to learn to use the new capital and thus becoming more sophisticated. The firm that has increased its capital stock does not collect the profits, since other firms will imitate it and workers will spread the knowledge in the long run by changing their employer. Thus there is an externality: "a knowledge spillover" that results in technological advancement.

In the AK-model there is also an externality from additional capital, so that capital enters the production function as technology.[4] In the AK-model there is an

[4] A simple generalization of the AK-model describes well the idea: Technology is now defined as $A_t = K_t^{\phi} = K_t$, where $\phi = 1$. The aggregate production function becomes $Y_t = K_t^{\alpha}(K_t L_t)^{1-\alpha} =$

infinite or very long time for convergence to the steady state. As in learning by doing, there are increasing returns to scale in capital at the aggregate level.

The important result arising from the AK-model is that a higher savings rate (or rate of accumulation of human capital) gives rise to a *permanently* higher growth rate of GDP. However, an increasing population also affects the growth rate of output positively, meaning there is a scale effect that is contradictory to empirical findings (the scale effect is discussed in detail in chapter 2.2).

Romer (1990) criticizes "learning by doing" because of the "strict proportionality between knowledge and physical capital or knowledge and education as an unexplained and exogenously given feature of the technology", and because it neglects the possibility that firms intentionally make investments in R&D. In "learning by doing" the production of a nonrival, nonexcludable good is only an *unintentional* side effect of the production of a conventional good.

By studying investment shares, Jones (1995a) concludes that the AK-models do not provide a good description of the driving forces behind growth in developed countries. The evidence suggests that there are effects from the increasing savings rate, but that they are transitory, not permanent like the AK-model suggests. A percentage point increase in the investment rate results in growth increasing for five to eight years.

However limiting might these theories might seem, they are still valid to some extinct. Bernanke & Gürkaynak (2001) present evidence that the rate of investment in human capital is a statistically significant factor in explaining labour productivity growth. Also Jones (1995a) claims that the evidence against the AK-model is not as strong as the evidence against the first generation models (presented in chapter 2.2.1).

$K_t L_t^{1-\alpha}$ where now $L_t^{1-\alpha}$ is denoted by A, which is a constant. This is inconvenient, but it explains where the name "AK-model" comes from.

2.1.3 From Ideas to Technology

The Romer model is a good example on how endogenous growth models are usually connected to microeconomic theory. Romer (1990) presents a model which has three sectors in the economy. The research sector uses human capital and the existing stock of knowledge to produce –as Romer puts it– *designs*, meaning new knowledge or ideas, for new producer durables (intermediate goods). An intermediate-goods sector uses these designs to produce the producer durables that are available for use in final goods production. A final goods sector uses these producer durables as well as labour and human capital to produce final output. The monopolistic competition enters the model so that the research sector obtains a patent on the use of the design in the production of the intermediate good that the design supports, and then transfers the patent (by leasing or selling) to the intermediate sector. The market for each design is a monopoly where the supplier sets the price (Romer 1990). Inside this microeconomic framework, the optimal share of the labour force working for the R&D -sector (research share) that maximizes the growth rate of GDP per worker, can be derived.

Note that technology is productive in two ways, in the final goods sector that uses the intermediate goods produced with the new designs, and also in the research sector where the *existing stock of knowledge* is used in producing new designs. This means that even though there is a patent related to all the designs, the knowledge embodied in the design may be detectable and of use in the whole research sector. In this way the nonrival nature of ideas is present in the model (Romer 1990).

In several theories of R&D-based growth, a model with multiple sectors (one being the R&D sector) is introduced in a similar manner and an optimal R&D input, or share of R&D workforce, is derived. For example Aghion & Howitt (1992), Grossman & Helpman (1991), Jones (1995b) and Howitt (1999) all present their own variety of this kind of sectoral framework.

The fact that all these articles explicitly state that they are building on a similar framework introduced by Romer (1990) is the reason why we have chosen to introduce specifically the Romer-model to describe this microeconomic framework.

2.2 Models of R&D-Based Endogenous Growth

The underlying idea in R&D-based endogenous growth theories is that R&D has an impact on TFP growth. Productivity can thus be influenced by economic policy: institutions and regulations create incentives to innovate which result in new technologies (Ha & Howitt 2007). There are several theories which aim at explaining how productivity and technology are affected by R&D. Ha & Howitt (2007) present a general form of productivity-growth function, which can be used to separate between different theories of R&D-based endogenous growth. These can be grouped in to three categories which are (in historical order) first generation fully endogenous growth models, semi-endogenous growth models and second generation fully endogenous growth models (which Ha & Howitt refer to as the Schumpeterian model).

Like Ha & Howitt (2007), we also estimate only the most recent models, the semi-endogenous and the second generation models. The first generation models are left out of estimation since there already exists substantial evidence refuting them, and since the later theories are particularly developed in order to respond to these inaccuracies.

However, first generation models are, like the name suggests, the first attempts to explain growth arising from R&D. Thus they lay the foundation for the succeeding theories, a reason why we still include them in the theoretical part of the thesis. We discuss the empirical evidence against the first generation models together with the theory in chapter 2.2.1, but the empirical evidence of the semi-endogenous and the second generation model is left to the discussion in chapter 5.5, in order to compare the literature with our results.

Ha & Howitt (2007) define the general form of a productivity-growth function as

$$g_A = \lambda \left(\frac{X}{Q} \right)^{\sigma} A^{\phi - 1}, \tag{2.1}$$

where in steady state

$$Q \propto L^{\beta}. \tag{2.2}$$

Then equivalently, the "ideas production function" or knowledge creation function is defined as[5]

$$\dot{A} = \lambda \left(\frac{X}{Q} \right)^{\sigma} A^{\phi}. \tag{2.3}$$

X is defined as R&D input (or productivity adjusted R&D input), A is technology (TFP) and Q is product variety.

Parameter σ defines the effect of R&D input ($\sigma > 0$)[6] (Ha & Howitt 2007). The economic interpretation of the parameter is that if $\sigma < 1$ there will be duplication of ideas or "stepping on toes" -effect, which affects negatively the production of technology. This means that there is a negative externality from the use of R&D input, meaning that the more firms there is at the R&D -sector, the more probable it is that their work overlaps resulting from not having perfect knowledge on each other's results. If $\sigma = 1$, there is no effect like this. Empirically R&D input X is often measured by the number of researchers in the R&D sector, real expenditures in R&D or the number of patents. It is also very common to use the share of labour force working for the R&D sector as R&D input.

[5]since $g_A = \dot{A}/A$

[6]By imposing restriction $\sigma = 0$ we get TFP growth of the neo-classical model, where there is no R&D input. We do not study this case.

Parameter ϕ defines the returns to scale in knowledge ($\phi \leq 1$).[7] If $\phi > 0$, the more there are ideas produced in the past, the more productive are the new ideas.[8] This is called the "standing on shoulders" -effect and it is often claimed that the right value for ϕ is either close to one or smaller than one. If $\phi < 0$, then it is more and more difficult to produce new ideas, because the easiest ideas are already invented. This is called the "fishing out" -effect.[9] The case of $\phi = 0$ means that the effects are equally big; productivity of ideas is independent of its history (Jones 1995b).

In steady state, product variety Q is proportional to the size of the labour force. L^β is thus empirically used for approximating product variety, parameter β is defined as product proliferation ($\beta = 0$ or $\beta = 1$).[10]

Using the share of labour working in research and development as R&D input has been very common in the literature of R&D-based endogenous growth. Ha & Howitt (2007) study equation 2.1 also in this special case so that $X = N = \nu L$, where N is the number of workers in R&D expressed as fraction ν of labour, which is assumed to be constant in steady state and as previously, $Q = L^\beta$.

With this specification equation 2.1 becomes[11]

$$g_A = \lambda \left(\nu L^{1-\beta}\right)^\sigma A^{\phi-1}. \tag{2.4}$$

This special case has important implications to growth in the three different models and will be discussed later in this chapter.

[7] For instance, if ideas are produced by R&D workers L_A at a rate $\overline{\lambda}$ (and there is no product variety in the model), the knowledge creation function is $\dot{A} = \overline{\lambda} L_A^\sigma$ where $\overline{\lambda} = \lambda A^\phi$ so the rate $\overline{\lambda}$ depends on the stock of ideas already invented (Jones 1995b). By combining these two equations the production function for ideas can be expressed as $\dot{A} = \lambda A^\phi L_A^\sigma$.

[8] $\overline{\lambda}$ is increasing in A.

[9] $\overline{\lambda}$ is decreasing in A.

[10] Product variety Q and parameter β are only present in the Schumpeterian model which is explained more thoroughly in chapter 2.2.3.

[11] By replacing X with νL and Q with L^β we get $g_A = \lambda \left(\nu L / L^\beta\right)^\sigma A^{\phi-1}$.

2.2.1 First generation fully endogenous growth models

The first R&D-based endogenous growth models were developed by Aghion & Howitt (1992), Grossman & Helpman (1991) and Romer (1990). Ha & Howitt (2007) generalize the productivity-growth function in these models to be

$$g_A = \lambda X^{\sigma}, \tag{2.5}$$

where parameters are restricted so that $\phi = 1$, $0 < \sigma \leq 1$ and $\beta = 0$ (so that both A and Q vanish from the equation 2.1). Parameter σ is slightly more restricted in these models than in the semi-endogenous and Schumpeterian models, but as Ha & Howitt (2007) state, the restriction is not crucial in distinguishing between the models.

Equivalently, the knowledge-creation function or ideas production function is

$$\dot{A} = \delta X^{\sigma} A. \tag{2.6}$$

In Ha & Howitt (2007), the R&D input X is specified as either the flow of R&D labour N, or the productivity-adjusted flow R/A of R&D expenditure. However, in the original models of Aghion & Howitt (1992), Grossman & Helpman (1991) and Romer (1990), R&D labour was regarded as the most important input in R&D, since research is labour intensive work. This however resulted in a scale effect, a distinctive feature of all the first generation theories, implying that a larger population should result in higher GDP growth, thus the scale of the population matters for growth. This result is contradictory to empirics, since the development in the 20th century has been of a declining population growth with a steady growth in GDP.

The scale effect can be seen by modifying equation 2.4. For the first generation models with parameter restrictions defined above, this reduces to

$$g_A = \lambda (\nu L)^{\sigma}. \tag{2.7}$$

Thus growth depends on the level of both the research share ν and labour L (Ha & Howitt 2007).

In an original model by Romer (1990) (which can also be regarded as presenting an AK-model as previously noted), human capital is the R&D input.[12] The scale effect is therefore present in this model, since human capital is tied to labour force.

Romer (1990) explains the scale effect so that a larger population means a larger market for ideas. Due to the nonrival and nonexcludable nature of ideas, the production of ideas has increasing returns to scale and therefore ideas can easily cross borders. Romer (1990) sees that therefore also the benefits can be taken into use in a larger area with relatively very little costs. As Romer puts it, "increases in the size of the market have effects not only on the level of income and welfare, but also on the rate of growth. Larger markets induce more research and faster growth".

The parameter restriction $\phi = 1$ in equation 2.6 is a feature that distinguishes the first generation models from the semi-endogenous models. This assumption imposes constant returns to knowledge in the production of new knowledge. In Aghion & Howitt (1992), where they present a very similar ideas production function as Ha & Howitt (2007), this follows from the assumption that each innovation produces a fixed proportional quality improvement. In the product-variety model of Romer (1990), constant returns arise from a special assumption on the knowledge spillover according to which an increase in the number of existing varieties facilitates the generation of new varieties. In Grossman & Helpman (1991) constant returns in

[12] The ideas production function of Romer is very similar $\dot{A} = \lambda H_A A$, where H_A is total human capital employed in research and λ is the productivity parameter. Having the exponent of H_A fixed to 1 is not a crucial assumption, but Romer claims that it imposes linearity in H_A, because weakening this assumption would require a more detailed specification of how income in the research sector is allocated to the participants. Romer claims that it is not important for the dynamic properties of the model (Romer 1990).

innovative activity is present in modelling the growth of consumers' utility. According to Ha & Howitt (2007), constant returns is what allows sustained, non-explosive growth.

What is distinctive in Grossman & Helpman (1991) is the notion of product innovation being horizontal and vertical, horizontal meaning differentiated products (increasing the product variety) and vertical meaning the quality improvement of an already existing product. Thus they take into account the "increasing complexity" through horizontal differentiation.[13]

The microfoundations are quite similar in the models of Romer (1990) and Aghion & Howitt (1992). However, a completely novel factor in Aghion & Howitt (1992) is the notion of "creative destruction". In Aghion & Howitt (1992), creative destruction means that there is a factor of *obsolescence*: when new products arrive they render previous products obsolete. This progress creates both gains and losses in growth. The underlying idea of creative destruction comes from Schumpeter (1942):

The fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumers' goods, the new methods of production or transportation, the new markets,.... [This process] incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one. This process of Creative Destruction is the essential fact about capitalism.

Based on this idea, Aghion & Howitt (1992) assume that individual innovations can be powerful enough to affect the entire economy. The length of innovating time is random due to the innovations arrival rate being a stochastic process, but the relationship between the amount of research in two successive periods can be modelled as deterministic.

In the model of Aghion & Howitt (1992) there are two effects arising from the notion of creative destruction, through which the amount of research this period

[13] It is not formally analogous to the way in which in the second generation model (Ha & Howitt 2007) deflate X by L, but it has a similar underlying idea.

depends negatively upon the expected amount of research next period. The first one is that the pay-off from research this period is the prospect of monopoly rents next period, which will last until the next innovation arrives. The mechanism behind this idea is that research is assumed to produce a random sequence of innovations. The arrival rate of innovations is a Poisson-process which has the property that each innovation occurs independently of the time since the last occurrence. The expected present value of the rent depends negatively on the Poisson arrival rate of the next innovation. This Poisson arrival rate (or the rate of creative destruction) of innovations in the economy at any given moment is defined as

$$\lambda\phi(n_{t+1}). \tag{2.8}$$

Here λ is the arrival parameter, ϕ a constant-returns, concave production function and n is the flow of researchers (the input in innovation production). Technology of research determines parameters λ and ϕ, thus the arrival rate depends only upon the current flow of inputs to research.

The second effect of creative destruction is connected with the labour market equilibrium. The result is that higher expected research next period is connected with less innovative activity today. The rational is that since labour can be allocated either to research or to some other activity, the expectation of more research next period corresponds to a higher demand of researchers in the next period, and therefore higher real wage of researchers. This decreases monopoly rents and therefore discourages research this period.

Finally, GDP growth in this model is a function of the size of innovations, the amount of researchers, and the productivity of research as measured by a parameter indicating the effect of research on the Poisson arrival rate of innovations.

As noted before, the first generation model models suggest that a larger number of R&D workers or a larger share of R&D workers of the labour force results in an increasing growth rate of TFP. However, on the long run, the research share has had a positive growth trend, but the output growth as well as TFP growth rates have been stationary and trendless (Jones 1995a; 1995b). Jones argues that increasing levels of the number of researchers and engineers and certain other policy variables (Jones refers to for example human capital -related variables, export shares, property rights etc.) has not resulted in an increase in output nor TFP growth. Jones claims that the movements of explanatory variables have been large and persistent during the postwar era whereas movements in output and TFP growth have little or no persistent increase. In fact, according to Jones (1995a), the growth rates of 14 OECD countries and the U.S. have all been stationary. Simultaneously however, the number of R&D workers as well as their share of the labour force has grown significantly, for instance in the U.S. the share of scientists and engineers of the labour force grew threefold from 1950 to 1988, from 0.25% to nearly 0.8%. This evidence clearly speaks in favour of refuting the first generation models.

2.2.2 The Semi-Endogenous Growth Model

The semi-endogenous growth model was first introduced by Jones (1995b) and continued by Kortum (1997) and Segerström (1998). The growth rate of TFP in the semi-endogenous model is

$$g_A = \lambda A^{\phi-1} X^{\sigma} \tag{2.9}$$

(Ha & Howitt 2007; Jones 1995b), where $\sigma < 1$ and $\phi < 1$. We can see that when A_t goes to infinity, $A_t^{\phi-1}$ approaches zero and the growth rate has to fall. Note that there is no product variety variable Q in the model, parameter β in equation 2.2 is set to zero.

Even though Ha & Howitt (2007) generalize the first generation articles to have $\sigma < 1$, Jones (1995b) as a matter of fact sees that $\sigma = 1$ is a common feature in the first generation models.[14] As we noted previously, Romer (1990) has made this restriction and in fact, also Aghion & Howitt (1992) assume constant returns production function for the flow of R&D input, which means that TFP growth is proportional to the share of R&D workers, meaning proportional to the size of the labour force in steady state. In his article, Jones (1995b) introduces, to his view for the first time, the possibility of $\sigma < 1$, in order to have decreasing returns to scale in research input.

Whatever is the right way to generalize first generation models, it is true that the semi-endogenous model has $\sigma < 1$ in the production function of ideas. In fact, the true novelty of the theory lies in another parameter restriction, in the semi-endogenous model it is assumed that $\phi < 1$, which introduces a new way of thinking how the arrival rate of innovations depends less strongly on the existing stock of knowledge.

Therefore what is common to the models of Jones (1995b), Kortum (1997) and Segerström (1998) is the thought that the most obvious ideas are discovered first, so that the probability that a person engaged in R&D discovers a new idea is decreasing in the level of knowledge.

Kortum (1997) and Segerström (1998) are very sure on this "fishing out" -effect to exist in knowledge production ($\phi < 0$), but Jones (1995b) allows, in his view, for both decreasing and increasing returns to scale, ($\phi < 1$) since he sees that $\phi > 0$, represents increasing returns to scale in knowledge production. Therefore he regards as $\phi = 0$ a benchmark of constant returns to scale (zero external returns) in which *the arrival rate of new ideas is independent of the stock of knowledge.*

This is contradictory to how the first and the second generation theorists see this parametrization, as they regard the case $\phi = 1$ implying constant returns to knowledge. Jones considers that already having previous discoveries in the ideas pro-

[14] Jones calls this group of models "Romer/Grossman-Helpman/Aghion-Howitt -models" referring to Romer (1990), Aghion & Howitt (1992) and Grossman & Helpman (1991a, 1991b and 1991c). So Jones refers to very much the same literature that Ha & Howitt (2007) which they call the first generation.

duction function refers to increasing returns ($\phi > 0$) and first and second generation theorists see it as a natural input in the production function.[15]

It is noteworthy that the effect of ϕ is external to the scientist; it measures the degree of externalities across time in the R&D process. As a matter of fact, Jones (1995b) argues that the question of the returns to scale in innovation is rather a philosophical question. Jones criticizes the first generation theorists from imposing too strict restrictions by setting $\phi = 1$, and claims that it represents a very arbitrary degree of increasing returns. In fact, the benefit of this parametrization is that it produces a model that is "fully endogenous" which is often seen as an end itself. In spite of having criticized the first-generation theorists for setting arbitrary parameter restrictions, Jones (1995b) does the same by imposing the restriction $\phi < 1$, which, albeit being less restrictive, has also the purely theoretical advantage that it allows the economy to move towards a balanced growth path. So when ϕ really is close to one, then the speed of convergence to the steady state becomes slower.

Another common feature of the semi-endogenous models (Jones 1995b; Kortum 1997; Segerström 1998) is that they suffer from the scale effect; growth in steady state is ultimately tied to population growth. Ha & Howitt (2007) explain this problem by studying the change of the growth rate in equation 2.9. By taking logs and differentiating with respect to time, the growth equation becomes[16]

$$\frac{\dot{g}_A}{g_A} = (1-\phi)\left(\left(\frac{\sigma}{1-\phi}\right)g_X - g_A\right), \tag{2.10}$$

where g_X is the growth rate of R&D input.[17]

[15] In these articles the discussion of the returns to scale is rarely formulated mathematically so it is not always clear whether the authors speak of the knowledge production function as a whole or only the returns to scale to the existing stock of knowledge. To our view the increasing returns to production as a whole would mean that $\sigma + \phi > 1$ and increasing returns to only the existing stock of knowledge A would mean $\phi > 1$.

[16] Using the approximation that for a certain variable a, the growth rate can be defined as $g_a = \Delta \ln a_t = \ln a_t - \ln a_{t-1} \approx d \ln a_t / dt$.

[17] By taking logs the equation 2.9 becomes $\ln g_A = \ln \lambda + \sigma \ln X_t + (\phi - 1) \ln A_t$ and then by

In balanced growth the change of the growth rate of A is zero (growth is constant). Therefore by replacing this to the left-hand-side of equation 2.10, we get $\sigma g_X - (1-\phi)g_A = 0$, so in steady state

$$g_A = \frac{\sigma}{1-\phi} g_X. \tag{2.11}$$

Thus with time, productivity growth rate approaches the growth rate of R&D input (if g_X is constant or approaches a constant).

The scale effect rising from this result can be seen more explicitly if we study the share of R&D workers as the research input. By replacing X with νL in equation 2.9, the growth rate becomes

$$g_A = \lambda \left(\nu L\right)^{\sigma} A^{\phi-1}. \tag{2.12}$$

If we assume like Ha & Howitt (2007), that in a balanced growth path the growth of ν cannot exceed population growth n, we can say that in this setting the growth rate g_A will converge to $(\frac{\sigma}{1-\phi})n$. Then in the balanced growth path the fraction of resources devoted to R&D does not matter, policies to stimulate R&D has mostly transitory effects. Jones (1995b) sees that the scale effect means that when the *world* population grows, the number of researcher grows and these researchers produce more ideas, which raise incomes around the world (Jones 1995a).

Jones (2002) presents some empirical evidence to support his theory of semi-endogenous growth. Contradicting the conventional view that the steady growth rate of the U.S. output over a period of 125 years has indicated the economy being close to its long-run steady-state balanced growth, Jones claims instead that the economy has been in a period of transitional growth, but that this growth has been

taking a time derivative using the approximation the equation becomes $d \ln g_{At}/dt = \sigma(\ln X_t - \ln X_{t-1}) + (\phi - 1)(\ln A_t - \ln A_{t-1})$ which can be formulated as equation 2.10.

constant. Jones calls it the *constant growth path*.

Jones (2002) presents two changes that have occurred during the last 50 years to justify his claim. First, time spent accumulating skills through education (human-capital investment) has increased substantially and second, the research share of R&D workers of total labour force has increased. In theory, these kinds of changes should generate transition dynamics in the short run, creating a temporary rise in the growth rate, and "level effects" in the long run, referring to a permanently higher level of output in the new steady state.

According to Jones (2002), the growth rate can be constant even outside the balanced growth path, since the accumulation of human capital and increase in research share have been steady for the last 50 years.

Through a growth accounting exercise of the growth rate of U.S. output over the period 1950 to 1993, Jones (2002) suggests that more than 80 percent of growth was associated with transition dynamics: The rising level of educational attainment accounts for over one-third of growth and increasing share of R&D workforce in the G5 countries accounts for about 50 percent of growth. Only 10 to 20 percent is due to the long-run component, which in the semi-endogenous model is the increasing population (Jones uses the population of G5 countries as a measure).

Jones claims that the relevant scale variable is the population of the collection of countries that are sufficiently close to the world's technological frontier, that they can contribute to the discovery of new ideas (Jones considers population of the G5 countries a good proxy). So for an individual country, it is the scale of *world* research effort that matters for the economic performance.

Jones (2002) also argues that the semi-endogenous theory is not contradicting cross-country growth regressions that generally have found a negative correlation between per capita output growth and population growth. This is true in the model's steady state, but outside the steady state (in the constant growth path); a higher population growth rate reduces the steady-state capital-output ratio because more investment must go simply to maintain the existing capital-output ratio of the growing population.

Jones (2002) acknowledges the fact that inside his model the growth cannot continue forever. If human capital accumulation and the increase in the research share cease, the growth rate will fall. According to Ha & Howitt (2007), the result that R&D policies do not affect the steady state growth rate, is a crucial flaw in the model.

2.2.3 Second Generation Fully Endogenous Growth Model or Schumpeterian Growth Model

The common feature to pre-second generation R&D-based endogenous growth models is the fact that as the population rises, so do the rate of technological progress and the growth rate of output per person. This is a result from the scale effect caused by the nonrival and nonexcludable nature of innovations (favouring a large market) and from the larger supply of potential R&D workers (Howitt 1999). The second generation fully endogenous growth theories by Aghion & Howitt (1998, ch. 12), Howitt (1999), Dinopoulos & Thompson (1998) and Peretto & Smulders (2002) try to respond to this problem.

Ha & Howitt (2007) generalize the TFP growth rate of the second generation models to be

$$g_A = \lambda \left(\frac{X}{Q}\right)^{\sigma}, \tag{2.13}$$

where in steady state

$$Q \propto L^{\beta}. \tag{2.14}$$

Parameters are here restricted so that $\beta = 1$, $\phi > 1$ and $\sigma > 1$, so A vanishes from equation 2.1.

The new feature of the model is the product variety variable Q. Parameter β is defined as product proliferation and is simply fixed as one. The practical result of the product variety in the model is that it takes away the scale effect caused by the increasing population that is present in the first generation models. The economic interpretation of the model is that as population grows, there are more people who can enter an industry with a new product, thus resulting in more horizontal innovations. This dilutes R&D expenditure over a larger number of separate projects. The restriction $\beta = 1$ comes from the idea that in the long run, R&D input X and product variety Q grow at the same rate and thus the growth-enhancing effect is offset by the deleterious effect of the increasing product variety (Ha & Howitt 2007; Dinopoulos & Thompson 1998).

We can see how the scale effect vanishes from the model by studying the share of R&D workers as the R&D input. By replacing X with νL in equation 2.13, TFP growth rate becomes[18]

$$g_A = \lambda \nu^{\sigma}. \tag{2.15}$$

So now the population effect in the balanced growth path of TFP reduces only to the *fraction* of workers in the R&D -sector (and population as a whole has no effect).

R&D input divided by horizontal product variety X/Q, is defined as "research intensity". Empirically in the Schumpeterian model same data can be used for X as in the semi-endogenous model, such as R&D expenditures, R&D labour force or patents. Since the model assumes that product variety grows at the same rate than population (in steady state), in empirical study one can use labour L as a proxy for product variety or as well any variable that grows in the long run at the same rate

[18] L vanishes from the equation since the exponent becomes 0.

as population. One can use for instance human capital (per person) adjusted labour hL, or output Y, which is a measure of aggregate purchasing power. Ha & Howitt (2007) use X/Q equal to N/L, N/hL, R/AL, R/AhL, or R/Y.

Ha & Howitt (2007) call the model Schumpeterian because in Aghion & Howitt (1998, ch. 12) and Howitt (1999) it embodies the idea of creative destruction presented by Schumpeter (1942). However, naming the model "Schumpeterian" as a synonym for "second generation", as Ha & Howitt (2007) do, is slightly misleading since the models do not incorporate any aspect of creative destruction that did not already exist in the first generation model of Aghion & Howitt (1992). In fact, the second generation Schumpeterian model is just an improved version of the model in Aghion & Howitt (1992) with the only novel aspect being the absence of the scale effect. So when it comes to the parameter denoting creative destruction, the loss of the monopoly rents, the idea is the same in these models as in the first generation models. The naming "augmented Schumpeterian" used by Aghion & Howitt (1998, ch. 12) is more functional but Ha & Howitt (2007) have dropped the prefix off.

Second generation theories stem from Young (1998), who introduces a model where growth can be decomposed into two effects arising from innovative activity. Firstly, innovations can be produced vertically meaning that the quality of already existing innovations increase. In Young's model vertical innovation production has a long-run effect to growth which is independent of the scale of the economy. Secondly, horizontal production of innovations results from R&D aimed at creating new products. The increase in the amount of horizontal innovations results in a growing product variety, which is influenced by changes in scale: as the economy grows the product variety increases. In Young's model the scale effect has only transitory effects on growth.

Thus in the models of Aghion & Howitt (1998, ch. 12) and Howitt (1999), the idea of Young (1998) is incorporated in to the endogenous growth models of Aghion & Howitt (1992) without changing any of its applications to growth, except of course that of the scale effect.

The model of Dinopoulos & Thompson (1998) has very similar implications to long-run growth. The novelty of the model lies in the analysis of welfare implications and transitional dynamics within the Schumpeterian model. The steady-state equilibrium has the following features: R&D expenditures are a constant fraction of the labour force; quality growth is independent of the size of the economy; and the number of product lines is proportional to the size of the economy. That is, size has level effects but not growth effects on welfare.

In the models of Aghion & Howitt (1998, ch. 12) and Howitt (1999), vertical innovations are targeted at specific (intermediate) products so that each innovation creates an improved version of the existing product. This allows the innovator to replace an incumbent monopolist until the next innovation arrives to the sector.

Now the Poisson arrival rate of innovations is connected to the vertical innovations. A slight modification to Aghion & Howitt (1992) presented by equation 2.8 is made, the Poisson arrival rate is now expressed as

$$\phi = \lambda n \qquad \lambda > 0, \tag{2.16}$$

where λ is a parameter indicating the productivity of vertical R&D and n is the productivity-adjusted expenditure on vertical R&D in each sector

$$n = \frac{N_v}{Q} A^{max}, \tag{2.17}$$

where N_v is vertical R&D expenditures, $A^{max} \equiv max\{A_i; i \in [0, Q]\}$ is the "leading-edge productivity parameter" that represents the generation of *vertical* innovations and Q denotes the number of sectors. In each sector the expected pay-off in introducing a new innovation is the same, thus the same amount is spent on vertical R&D in each (intermediate) sector. A^{max} grows at a rate proportional to the aggregate rate of vertical innovations. Howitt (1999) deflates R&D expenditures by A^{max} to "take into account the force of increasing complexity; as technology advances, the resource cost of further advances increases proportionally".

Horizontal innovations are *newly created* (intermediate) products that can be monopolized by the innovator until the first vertical innovation, an improvement to this new product, arrives. So they result only from R&D aimed at creating new products (Howitt 1999). Aghion & Howitt (1998, ch. 12) claim that the number of products grows in the model not because of deliberate innovation but only as a result of "serendipitous imitation". It is noteworthy that vertical R&D is subject to constant returns whereas horizontal innovation is subject to diminishing returns. The diminishing returns arise from the assumption of differences in abilities among R&D workers.

The rate of horizontal innovation is defined as

$$\dot{Q} = \frac{\Psi(N_{ht}, Y_t)}{A_t^{max}}, \tag{2.18}$$

where N_h is horizontal R&D expenditures and Ψ is a concave constant returns production function with positive marginal products. The average product $\dot{Q}\big/N_h$ is a decreasing function of the fraction $h = N_h/Y$ of gross domestic product allocated to horizontal R&D.

The factor of proportionality, which is a measure of the marginal impact of each innovation on the stock of knowledge, is assumed to equal

$$\frac{\sigma}{Q} > 0, \tag{2.19}$$

where σ is the size of vertical innovations.

The result of the model is that the economy has to allocate a larger number of workers to the innovation process in order to maintain a constant rate of productivity growth because those workers must improve a larger number of products. Thus with a larger economy an innovation with respect to any given product will have a smaller impact on the aggregate economy (Howitt 1999). The steady state growth rate of output per person and TFP depend positively on the productivity of vertical R&D, λ, and the size of vertical innovations, σ. Even though the scale effect of population is eliminated from this model, growth still depends also on the population growth rate. Note however, that this is not the only determinant of steady-state growth as in the semi-endogenous model.

The model predicts that during a period of steady growth in output per person or TFP, the fraction $N_v + N_h/Y = n/y + h$ of GDP allocated to R&D should remain constant. h denotes horizontal R&D intensity.

As Ha & Howitt (2007) observe, the share of R&D expenditures relative to GDP has in fact been relatively close to constant since mid-60's, however during 1953–65 the share increased significantly.

Aghion & Howitt (1998, ch. 12) see that the augmented model is robust to Jones' critique since in steady state total input to R&D must grow at the same rate as GDP, while the growth rates of productivity and output per person are constant. This result stems from two ideas. Firstly, increasing complexity makes it necessary to raise R&D over time just to keep the innovation rate constant for each product. Secondly, as the number of products increases, an innovation in any one product affects directly a smaller proportion of the economy and hence has a smaller proportional spillover effect on the aggregate stock of knowledge (Aghion & Howitt 1998, ch. 12).

Aghion & Howitt (1998, ch. 12) claim that one more key difference between the Schumpeterian model and Jones' model is that the Schumpeterian model takes into account both capital and labour in knowledge production whereas Jones only has labour as an input.[19]

Despite these improvements to the first generation Schumpeterian model, criti-

[19]In Aghion & Howitt (1998, ch. 12) capital as R&D input has been studied more closely but we will here skip the details of the model.

cism continues.[20] Jones (1999) criticizes the parameter restriction $\beta = 1$ as being a "knife-edge" assumption. Jones (1999) claims that growth is no more fully endogenous if this assumption is relaxed, since the scale effect is not then eliminated.

In the case $\beta < 1$, the number of sectors grows less than proportionately with population. The size of each sector grows with time but since productivity growth in each sector is proportional to its size, the model exhibits again scale effects on growth.

In the case $\beta > 1$ the number of sectors in the economy grows more than proportionately with population. The size of each sector declines with time and so does productivity growth. The model exhibits a negative scale effect in growth, productivity growth in each sector approaches zero and population growth is once again the driver of growth. In this case the model has a balanced growth path. Jones therefore discusses about a "hybrid" semi-endogenous model with partial product-proliferation defining the parameter restrictions as $\phi < 1$ and $0 < \beta < 1$.[21]

Peretto & Smulders (2002) respond to this critique by building a model where the scale effect may be positive or negative, but always vanishes asymptotically, thus β is one in the steady state. Therefore they do not see the parameter restriction as simply an assumption, but as a result arising from specific microeconomic mechanisms in the externalities of knowledge production.

2.3 Technology Transfers

The smaller the country, the more important is foreign technology as an engine of growth; this is why we have included data of high technology imports in our study of Finland.

In endogenous growth models, the size of the economy in question is somewhat

[20] Jones (1999) includes in the group of second-generation models Aghion & Howitt (1998, ch. 12), Dinopoulos & Thompson (1998), Peretto (1998) and Young (1998).

[21] Also Young (1998) studies cases where the product proliferation parameter β is different from one and draws the conclusion that the model could then generate both positive and negative scale effects on growth.

unclear. Like noted before, there exists a problematic scale effect in the pre-second generation models rising from the implication that a larger population would induce higher TFP growth. Also the nonrivalry and nonexcludable nature of ideas indicates that R&D can easily cross borders and therefore including the effects of foreign R&D to the empirical studies of R&D-based endogenous growth in one way or another, is indeed reasonable.

In the most theoretically oriented studies that aim at justifying an underlying theoretical framework (for instance Ha & Howitt 2007; Jones 2002), the data is from the U.S. or the G5 as a whole, so only countries on the high technology frontier are included. This implies that the U.S. or G5 are regarded as constituting such an entity that corresponds to the one that the theoretical literature refers to. However, in more practically oriented studies (Coe & Helpman 1995; Coe et al. 2009; Madsen et al. 2010) on the effects of R&D to productivity, which also include countries that are not on the high technology frontier, some kind of measure of foreign R&D is used.

Finland also, albeit being on the front edge of high technology in the 21st century, is a small country that depends very much on trade. Also it is noteworthy that our study starts from as early as 1955, a year in which Finland was a relatively poor and backward economy on European measures.

An evident fact is also that many of the innovations used in Finland are surely not developed in the Finnish R&D sector and thus including some kind of measure of foreign R&D is indeed important in the Finnish case.

The measure that is used in cross-country settings, developed by Coe & Helpman (1995) and used by Coe et al. (2009), Madsen (2008) and Madsen et al. (2010), is an import-ratio weighting scheme

$$X_{it}^{f} = \sum_{n} \frac{m_{ijt}}{m_{it}} \bar{X}_{jt}^{d}, \qquad \text{Semi-endogenous growth theory} \tag{2.20}$$

$$\left(\frac{X}{Q}\right)_{it}^{f} = \sum_{n} \frac{m_{ijt}}{m_{it}} \left(\frac{X}{Q}\right)_{jt}^{d} \qquad \text{Schumpeterian growth theory,} \tag{2.21}$$

which presents how foreign R&D from countries j, ($j \in [1, n]$) is counted for country i through its high technological products imports. Now f denotes foreign and d domestic (and they also correspond to an index of innovative activity which is equal to one in the starting year of the study for each individual country to ensure that large countries do not have a higher weight in the index than smaller countries). m_{ij} is imports of high technology products of country j, m_i is total high technology imports for country i and $\bar{X}_j^d$ is the real (domestic) R&D for country j.

In our study, a measure like this would have been an ideal way of studying the impact of foreign R&D to Finnish productivity because it takes into account the level of R&D of the importing country. However, since our time series was partly manually constructed this sort of measure would have been too a heavy workload. Chapter 3 will continue the discussion of how the measure of foreign high technology was constructed in our dataset.

Chapter 3

Data

In this chapter we first present how the data has been collected and constructed from different sources. Then we study more closely the variables used in both the semi-endogenous and Schumpeterian model. List of empirical variables is given in appendix A for the convenience of the reader.

3.1 Output, Labour and Total Factor Productivity

Data on GDP, labour, measured as hours worked, and total factor productivity have been obtained from Jalava et al. (2006) for the years 1955–1974 and continued with Statistics Finland data for the years 1975–2008. In an article "Biased Technical Change and Capital-Labour Substitution in Finland, 1902–2003" Jalava et al. (2006) estimated the form of the Finnish production function for post-World War II times (1945–2003) studying both the CES production function and the Cobb-Douglas production function. The variables for GDP and hours worked were thus readily available from the dataset of Jalava et al. (2006), but TFP was calculated as the Solow residual.

Jalava et al. (2006) have constructed the dataset so that it reflects the non-residential market sector of the Finnish economy meaning that housing services are excluded from the data. The reason for limiting the data in such way is the fact that housing services cannot be seen as producing anything new, but they are rather just reallocating existing assets. Therefore housing services are irrelevant for long-term growth. GDP is measured at basic prices. We will therefore follow this approach, and so the data on GDP and labour that has been obtained from Statistics Finland for the years 1975–2008 has also been treated to correspond to the non-residential market sector and GDP is at basic prices.

Figure 3.1 shows the logarithmized and indexed series of GDP and hours worked. GDP seems to have been growing rather steadily, but the number of hours worked has decreased from late 50's. A sharp decrease was experienced during the severe depression in the early 90's resulting in severe unemployment of which the recovery has been really slow.

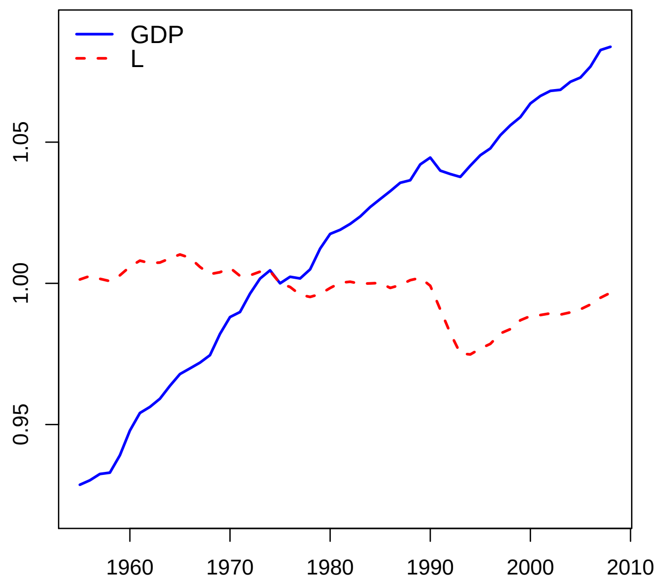

Figure 3.1: GDP and labour (indexed)

We calculated a total of seven measures for total factor productivity for the years 1955–1974 as a Solow residual, from both CES and Cobb-Douglas production functions with several parameter values that Jalava et al. (2006) used in their article.

First, the CES production function is defined as

$$Y_t = A_t[\delta K_t^{-\rho} + (1-\delta)L_t^{-\rho}]^{-\frac{1}{\rho}}. \tag{3.1}$$

By taking logs and rearranging we can calculate total factor productivity, denoted by A, as what is left unexplained from capital and labour

$$\ln A_t = \ln Y_t + \frac{1}{\rho}\left[\ln \delta K_t^{-\rho} + (1-\delta)L_t^{-\rho}\right]. \tag{3.2}$$

Jalava et al. (2006) obtained four plausible values for ρ: 0.389, 0.851 (twice) and 0.854. We also used the average of them all, 0.687.[22]

With these four different values we constructed four TFP-series to see which one gave the most compatible result with the Statistics Finland data. Parameter δ was fixed to 0.5 in all the cases. Since Statistic Finland uses Cobb-Douglas production function in calculating their TFP index we also examined three possible variations of the Cobb-Douglas production function

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}, \tag{3.3}$$

from which we calculated A by taking logs and subtracting

$$\ln A_t = \ln Y_t - [\alpha \ln K_t + (1-\alpha)\ln L_t]. \tag{3.4}$$

[22]In fact they estimated parameter $\sigma = 1/1+\rho$ which gave the values 0.72, 0.57 and twice 0.54. We also used the average of them all, 0.593.

We constructed three series with different values of α: 0.5, 0.4 and 0.3.

So finally we had a total of seven different TFP-series. We inspected the overlapping period, 1975–2003, of each of the seven series and the Statistics Finland dataset. The data used in the estimations was chosen by graphically inspecting the datasets and by studying the stationarity of the difference of the datasets. The variable that gave the "best-fitting" result with the Statistics Finland data was TFP calculated with CES production function with the choice of ρ being 0.687.

Figure 3.2 shows the level of productivity (log) and its growth rate. Total factor productivity has been growing rather steadily since 1955.

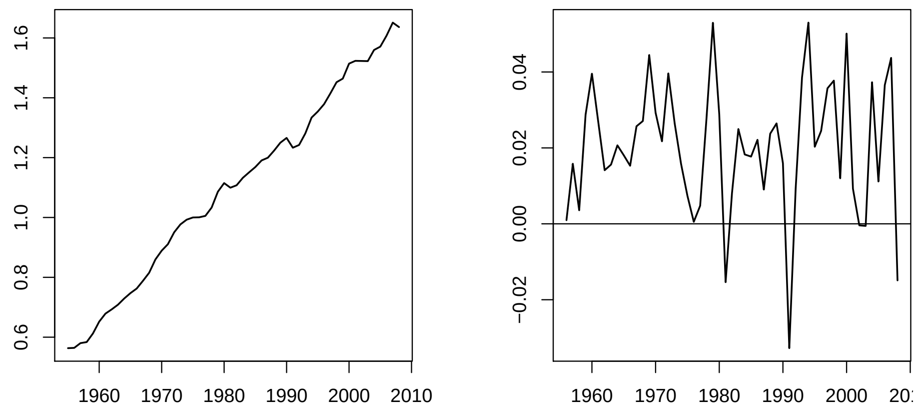

Figure 3.2: Left: TFP (log), right: TFP growth rate.

There does not appear to be a trend in the growth rate, it seems to be fluctuating around a positive mean value near 2 percent, thus there is resemblance in the Finnish and U.S. TFP developments.

3.2 R&D Input Variables

Data on R&D input has also been gathered from separate sources. Data on R&D expenditures R and workforce N as well as person-years N_y are from Statistics Finland for the years 1971–2008. For the years 1955–1970, R&D expenditures are obtained from Saarinen (2005). In the Statistics Finland data there are some individual missing values that we treated with linear interpolation. Saarinen (2005) reports only 5-year averages (for years 1955–1970) expressed as percentage of GDP. We used the GDP data from Jalava et al. (2006) to calculate the real values of R&D expenditures and set the three five year -average values given by Saarinen (2005) to correspond the expenditures in 1957, 1962 and 1967 and used linear interpolation to derive the remaining values during for 1955–1970. The Statistics Finland data on R&D expenditures has been deflated with the same GDP deflator used by Jalava et al. (2006).

The patent data is from The World Intellectual Property Organization (WIPO), we denote total number of patent applications by PA and total number of patent grants by PG. The data has been constructed using two different time series, for years 1955–1994 we have used patent applications by patent office Finland (PRH)[23] and for years 1996–2008 we have used patent applications by country of origin (1995–2008). The country of origin -series are only available since 1995. The criterion for allocating patent applications to a particular country of origin is residency of the first-named applicant. Resident applications in Finland include all applications received by the PRH with a first-named applicant residing in Finland. For Finland, applications filed abroad include all applications filed with other patent offices around the world with a first-named applicant residing in Finland (WIPO 2010).

The reason for WIPO to have constructed a new series is because an increasing amount of patent applications are sent to some international patent offices. Finland joined the European Patent Office (EPO) in 1995 and since then an increasing amount of Finnish patents have been filed through EPO and the number of patents filed through the Finnish patent office PRH, has been decreasing significantly. Therefore combining these series at the date when Finland joined EPO gives

[23]The statistic can be broken down by resident and non-resident. Resident filing refers to an application filed at an Office of or acting for the State in which the first-named applicant in the application concerned has residence. Non-resident filing refers to an application filed at an Office of or acting for the State in which the first-named applicant in the application concerned does not have residence (WIPO 2011). Here we use the total count.

a much more realistic view on the development of the number of Finnish patents than using the old series. The two datasets have nearly the same value for year 1995, and the small difference can be explained since the data of origin be incomplete (WIPO 2011).[24] Figure 3.3 describes how the datasets have been combined.

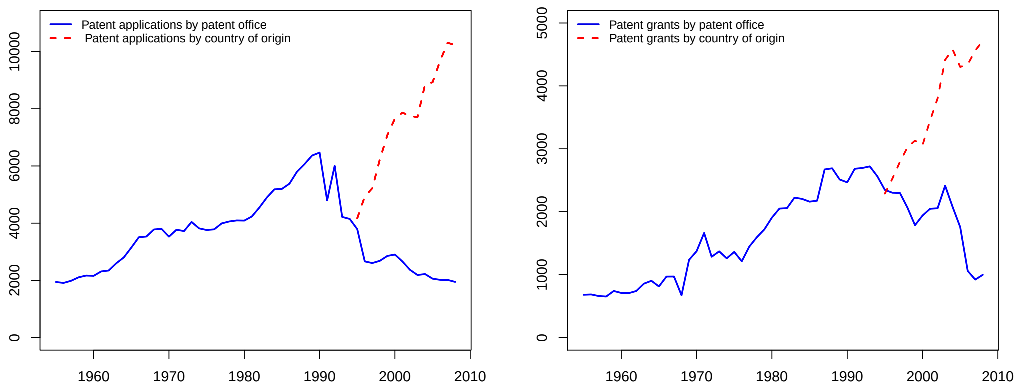

Figure 3.3: Combining the patent data up left: solid: Number of patent applications by office, dash: Number of patent applications by country of origin. Up right: solid: Number of patent grants by office, dash: Number of patent grants by country of origin.

The benefit of the data on the number of patents is that it is easily available as a long time series. However, even though it has been used very widely as an indicator of innovative activity it is becoming less common in recent literature.[25] Trajtenberg (1990) criticizes the use of patents counts since the value of patents varies largely, and therefore he proposes a citations-weighted measure of patents to correct for this flaw. However, this would not be a problem if the average value of patents had been approximately constant over time but as Caballero & Jaffe (1993) claim, even the citations-based measures of the average value of patents have been changing over time. Another problem is that the propensity of patenting might have also changed over time, for instance Griliches (1990) finds indirect evidence of the costs

[24]WIPO (2010) reported that it was not able to determine the country of origin for around 7 percent of total patent applications filed in 2008.

[25]For instance Ha & Howitt (2007), and Jones (2002) have no patent data, Coe et al. (2009) use an index of the strength of patent protection.

of patenting having increased over time. Nevertheless, as Madsen (2008) points out, patent counts still have the advantage that informal R&D is also patented.

Data on high technology imports (denoted as I) is gathered from the Customs Information Service Archives statistical yearbooks for years 1955–1986 and from Uljas database for years 1987–2008. The series has been weighted with the GDP deflator by Jalava et al. (2006). The Standard international Trade Classification (SITC) has been used in choosing the products that can be understood as high technology. The SITC subgroups chosen for high technology has been reported in Appendix D.

Variables used in estimations are all logarithmized. Note that the variables R, A, I, PA and PG are from years 1955–2008, whereas N and N_y are only available for 1971–2008.

3.3 Variables Indicating Semi-endogenous R&D Input

The semi-endogenous growth theory suggests that having total factor productivity growth without a trend would indicate that there should be no trend in the *growth rate* of R&D input either (Ha & Howitt 2007). The growth rate of TFP has not had a statistically significant linear trend, which is also apparent from figure 3.2.[26]

Another result suggested by the semi-endogenous growth theory is that there exists a cointegrating relation between TFP and R&D input. We will study this more closely in chapter 5, but roughly put this would mean that there is a linear dependency between TFP and R&D input that prevents them from diverging too much from each other. The graphical implication of this would be that in an ideal case, the two series move "hand-in-hand".

[26]We estimated a deterministic linear trend by using OLS with heteroscedasticity and autocorrelation consistent (HAC) standard errors. Trend annual change is the OLS-estimator β from the equation $g_X = \alpha + \beta \times YEAR$.

Now we will take a closer look to the R&D input variables. The variable indicating R&D input for the semi-endogenous model is the one that we refer to as X. As empirical counterparts we use seven variables (all logs): R&D expenditures (R), productivity adjusted R&D expenditures (R/A), high technology imports (I), number of R&D workers (N), number of person-years in R&D (N_y), (in a similar manner as Ha & Howitt) patent applications (PA) and patent grants (PG) (as Madsen et al.).[27]

The levels of R&D input -variables are presented together with TFP in figure 3.4. Like TFP, also the R&D variables have been increasing rather linearly over the years. However, growth in TFP has been much faster than growth in any of these R&D input variables. Only the growth rate of R&D expenditures is almost as rapid as the growth rate of TFP. This result does not however hold for the productivity adjusted R&D expenditures, since the adjustment starts slowing down growth significantly after the 70's. At this point it seems that there might be a cointegrating relation with a trend present in most of the models.

Since the semi-endogenous growth theory implies that given a trendless growth rate in TFP, also the growth rate of R&D input should be trendless, we have also plotted the growth rates of R&D input in figure 3.5.

Growth of high technology imports has no statistically significant linear trend and neither do the growth rates of patent variables, which have been fluctuating near zero, although it is noteworthy that both of them have significant volatility peaks. However, both R&D expenditure -variables have a statistically significant downward trend at the 95% level. A similar trend is apparent also in R&D workforce variables, however none of these trends are statistically significant at the 95% level. In R&D expenditures -variables and in the number of R&D person-years the growth has been smoothest.

Like the U.S., also Finland has experienced trendless TFP growth. However, Ha & Howitt (2007) found that the growth rates of R&D input have been declining,

[27] A table of the empirical variables is presented in Appendix A.

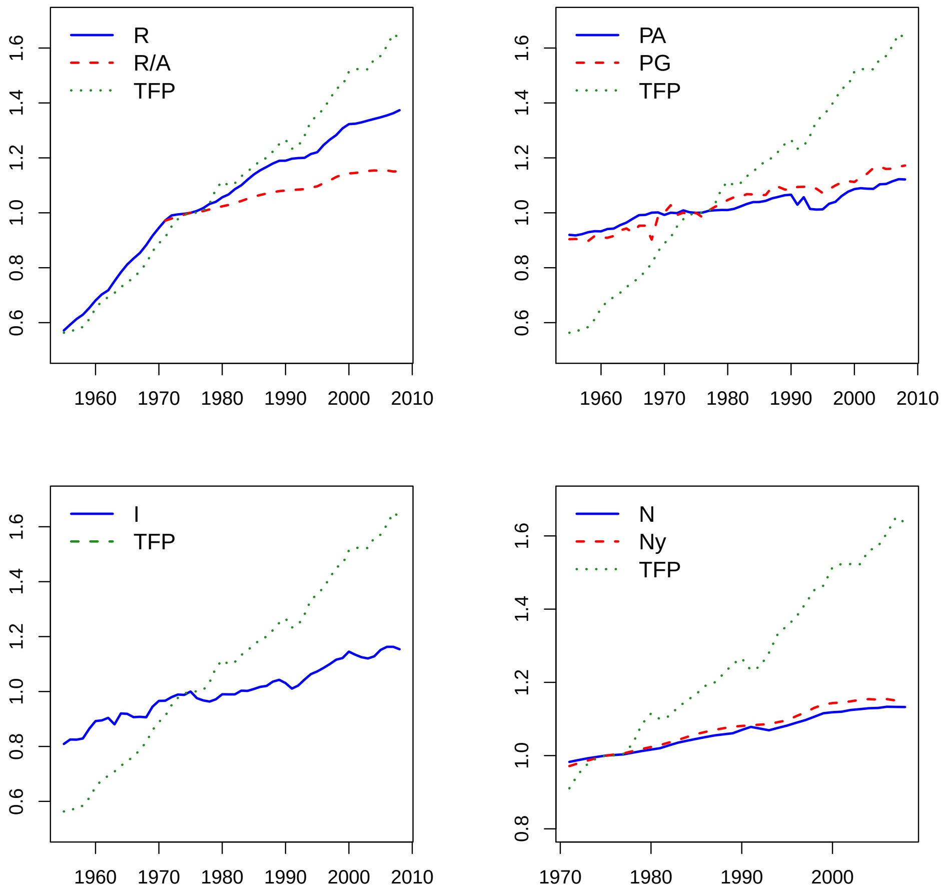

Figure 3.4: Variables indicating R&D input plotted with TFP (all variables are indexed for the graph).

they use R&D workers in G5 countries, R&D workers in the U.S. and productivity adjusted R&D expenditures of the U.S. as a measure. Our findings are similar only when R&D expenditures is used as a measure, the other R&D input variables do not show a clear downward trend. Therefore all our variables excluding R&D expenditures are in line with the semi-endogenous theory.

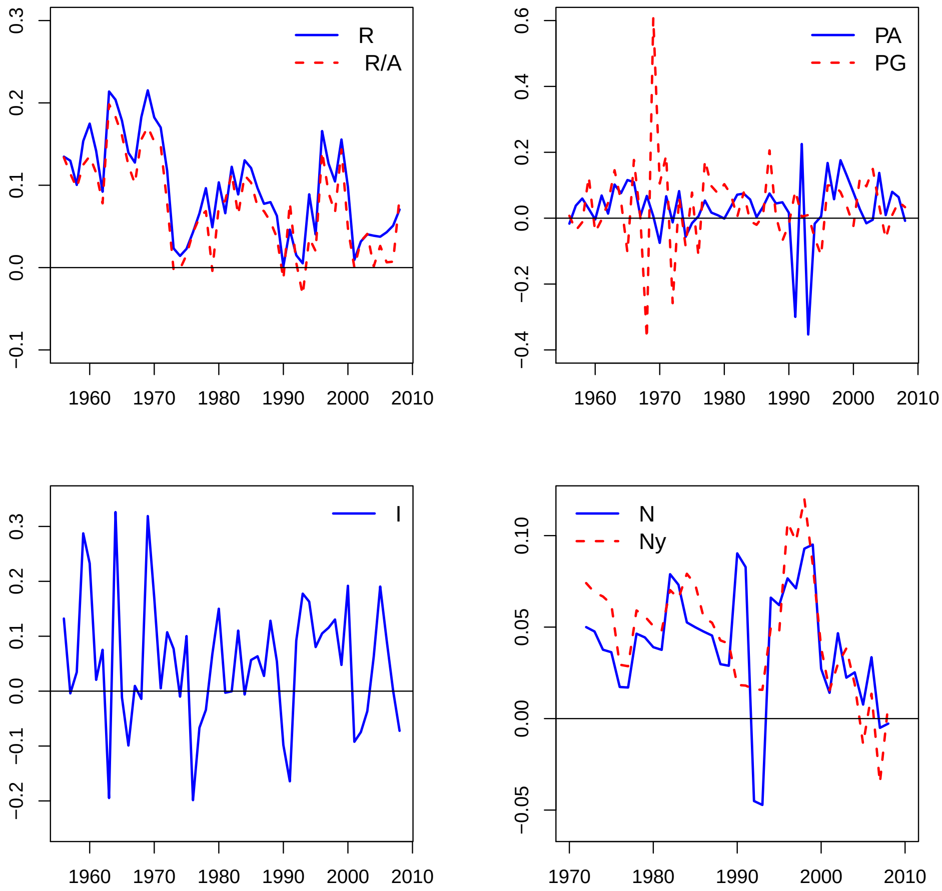

Figure 3.5: Variables indicating growth of R&D input.

3.4 Variables Indicating Schumpeterian R&D Intensity

If the data was generated by a Schumpeterian growth model, the constancy in productivity growth implies that there should be no trend in R&D *intensity*, which is defined as R&D input X adjusted with the product proliferation variable Q. Ha & Howitt (2007) use three different measures for Q: Y, L and hL, where h is human capital. We here use the first two measures (due to us not having data on human capital). Thus we have a total of fourteen variables indicating R&D intensity.

The assumption of having no trend in R&D intensity is backed up by the U.S. and G5 evidence presented in Ha & Howitt (2007). The theory also suggests that there is a firm cointegration relation between R&D input and product variety, so that they go "hand-in-hand" and their log-difference ($\ln X_t - \ln Q_t$) is a stationary process.

R&D intensity -variables (or to be precise the log-differences) are presented in figure 3.6. The Finnish evidence seems to be quite different from the U.S. When adjusted with labour L the increasing trend is visible in all of the variables, since as we already saw, labour as measured by hours worked, has not been growing in Finland. The increasing linear trends in all the intensity -variables using L, are statistically significant at a 99% level.

However, adjusting R&D input with GDP partially offsets the trend in the R&D input. The slope of the trend has indeed decreased in most of the cases but none of the variables still seem to be fluctuating around a constant, except maybe the patent variables. The trend tests suggests that the only variable with no statistically significant trend is patent applications adjusted with GDP.[28]

The semi-endogenous theory also suggests that R&D intensity variables should be stationary. Just by looking at the figures it also seems like none of the variables adjusted with labour are stationary and from those adjusted with GDP it looks like at least R&D expenditure and workforce intensity -variables are not stationary. This inspection is in line with our empirical findings presented in chapter 5, the only model where the data fits the model that incorporates this assumption is patent applications adjusted with GDP.

Labour (as measured by hours worked) thus seems to be a very poor measure of the "scale" or the "product variety" of the in the Finnish case, since even though there has been significant economic growth, it is not due to the increase in labour input. Nonetheless, our other measure of product proliferation, GDP, has had a clearly increasing trend and probably is as good a proxy for the scale of the economy for

[28]Note that the y-axis of each graphs plotted next to each other are of the same length.

Finland as it is for the U.S. As we show in the estimation results in chapter 5, the Schumpeterian model fits the data just slightly better when GDP is used as product variety instead of labour (even though in that case also, very poorly). Theoretically however, there is no reason to oppose the use of labour as product variety measure.

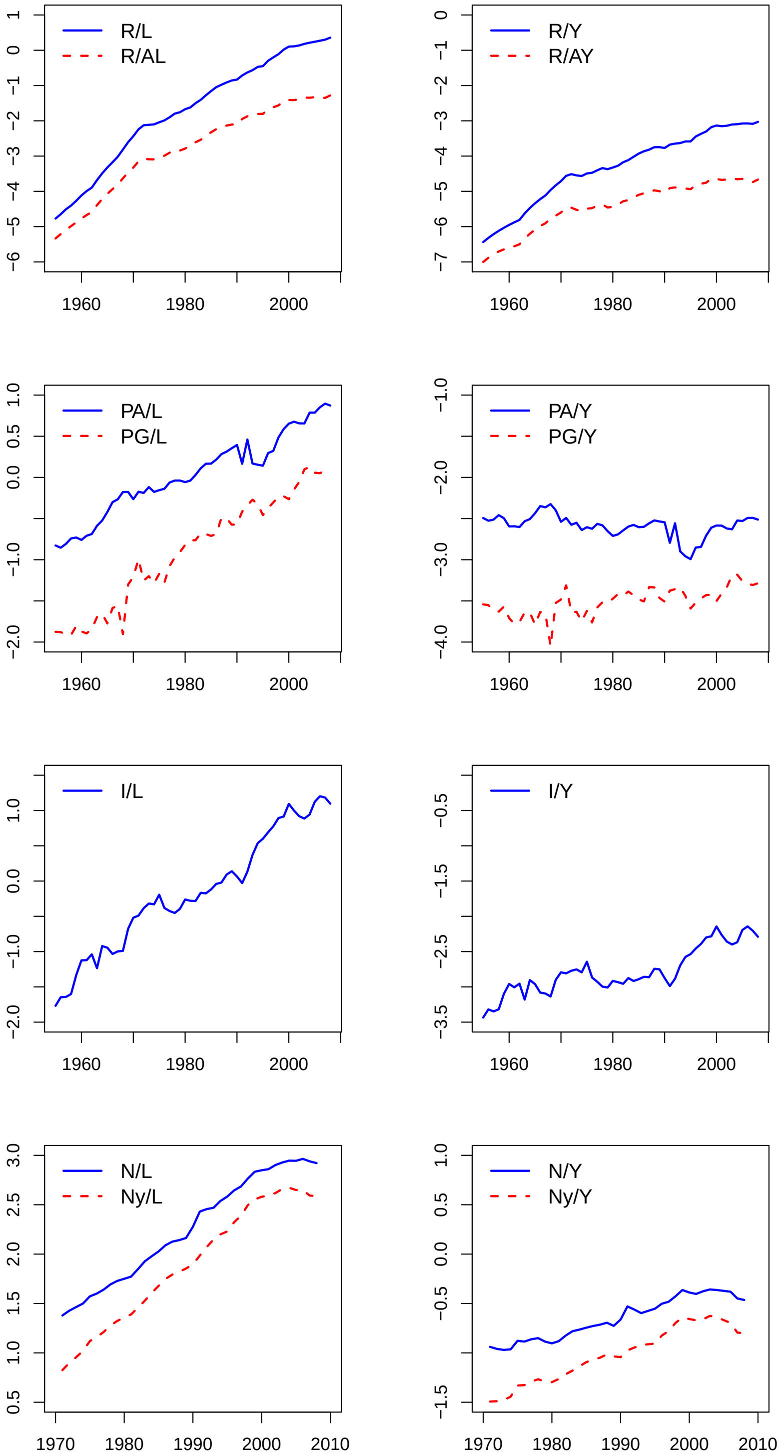

Figure 3.6: Variables indicating R&D intensity X/Q.

Chapter 4

Econometric Methods: Vector Autoregressive and Vector Error Correction Models

In this chapter we present the econometric methods used in studying the relation between R&D input and total factor productivity by using a cointegrated vector autoregressive model.

The model in interest is a VAR-model for variables that are (asymptotically) nonstationary and have a unit root e.g. are integrated of order one (denoted hereafter as I(1)). A VAR-model for I(1)-variables is presented in a so-called vector error correction (VECM) -form. Integration of order one means that when we differentiate the time series it will be a stationary process (denoted by I(0)). Graphical inspection of our variables allows us to assume that these variables are generated by a nonstationary process and the formal proof will be presented in chapter 5.

We estimate the general form of the productivity-growth function of R&D-based endogenous growth models by Ha & Howitt (2007), which we call the unrestricted model, with the Johansen maximum likelihood approach (see for example Johansen 1995, 1988; Johansen & Juselius 1990 and Johansen 1991) and the semi-endogenous and the Schumpeterian models (the restricted models) with a simple two step method (S2S) (see for example Ahn & Reinsel 1990, or Lütkepohl & Krätsig 2004, ch. 3).

The VAR-model which is a multivariate time series model with p variables is of the form (Johansen 1995)

$$X_t = \Pi_1 X_{t-1} + ... + \Pi_k X_{t-k} + \Phi D_t + \epsilon_t, \qquad t = 1, ..., T \tag{4.1}$$

where X_t is a p-dimensional autoregressive process (with now all its variables being I(1)) and D_t consists of deterministic variables such as a constant and trend (and can also have any non-stochastic variable such as seasonal dummies). $\Pi_1, \ldots, \Pi_k$ and Φ are coefficient matrices and $\epsilon_t \sim \text{iid}(0, \Omega)$ is an error term.

A VAR-model is used in this form when one wants to study the relations between stationary time series. However, even though the representation can be used for nonstationary series, we will have to modify the VAR-model in order to study the relations between nonstationary time series. For these nonstationary series the general VAR-model can be represented in a Vector Error Correction Model (VECM) form[29]

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Phi D_t + \epsilon_t, \tag{4.3}$$

[29]Starting from the VAR form in equation 4.1 we get the VECM-form by defining a polynomial matrix $\Pi(B) = I_n - \Pi_1 B - \ldots - \Pi_k B^k$ (using a property of a lag-operator $\Pi(B) = \Pi(1) + (1 - B)G(B)$, where $R(B) = \sum_{j=0}^{\infty} C_j B^j$, and $\sum_{j=1}^{\infty} \parallel C_j \parallel < \infty$, without going further to its details) we can write the polynomial as

$$\Pi(B) = \Pi(1)B + \left(I_n - \sum_{i=1}^{k-1} \Gamma_i B^i \right) \Delta, \tag{4.2}$$

so using this in equation 4.1 gives us

where thus $\Pi = \sum_{i=1}^{k} \Pi_i - I_n$. The deterministic terms ΦD_t enable the relationship between the variables to change over time. As we see, the LHS is now a difference of X_t and therefore stationary. Also the lags are differences apart from the term ΠX_{t-1}, which is called the error correction term. However, since all other terms in the equation clearly are stationary, this term also needs to be stationary. By estimating matrix Π we can find out whether there are linear combinations of the variables in X_{t-1} that are stationary. If linear combinations of the nonstationary variables exist, the linear combinations are then stationary, I(0), and the variables included in the linear combination are said to be cointegrated.

Therefore the test for cointegration between variables in X_{t-1} is done by estimating the coefficient matrix Π. If there is no cointegration between the variables, then Π has full rank, p. If cointegration exists the rank is r $(r < p)$. The hypothesis that Π has rank r can be expressed as

$$H(r) : \Pi = \alpha\beta' \tag{4.4}$$

where α and β are $p \times r$ matrices. Matrix β defines the cointegrating vectors and elements in α are known as adjustment parameters. By replacing Π in equation 4.3 with $\alpha\beta'$, we have the reduced form error correction model. (Johansen 1995, ch. 5) presented here again for clarity

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$$\begin{aligned}\Pi(B)X_t &= \left(\Pi(1)B + \left(I_n - \sum_{i=1}^{k-1} \Gamma_i B^i\right)\Delta\right)X_t \\ &= \Pi(1)X_{t-1} + \Delta X_t - \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} \\ &= \Phi D_t + \epsilon_t\end{aligned}$$

where $\Gamma_i = -\sum_{j=i+1}^{k} \Pi_j$. By replacing $\Pi(1) = \Pi$ we get equation 4.3.

$$\Delta X_t = \alpha\beta' X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Phi D_t + \epsilon_t. \tag{4.5}$$

When the hypothesis of r cointegrating vectors holds, $\beta' X_t$ is stationary.

In determining the cointegration rank we use a likelihood ratio tests, the trace test. The model that we estimate for the trace test is a VAR with a constant (and no trend). In this case the deterministic term in equation 4.3 is defined as $D_t = \mu_0$. The constant term can be thought to be inside the cointegration relation so that model 4.3 can be written as

$$\Delta X_t = \Pi^* \begin{bmatrix} X_{t-1} \\ 1 \end{bmatrix} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \epsilon_t, \tag{4.6}$$

where $\Pi^* = [\Pi : \nu_0]$ is $K \times (K+1)$ with $\nu_0 = -\Pi\mu_0$. This model is used for testing the statistical significance of Π with the reduced rank -hypothesis (Johansen 1995, ch. 6). The test is defined as

$$-2 \ln Q(H(r)|H(p)) = -T \sum_{i=r+1}^{p} \ln(1 - \hat{\lambda}_i), \tag{4.7}$$

where eigenvalues $\hat{\lambda}_i$ are the squared canonical correlations. The trace statistic thus tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of p cointegrating vectors (Johansen 1995, ch. 6). The test statistic does not follow a commonly known distribution; the asymptotic distribution is defined as

$$(4.8) \qquad 2\ln Q(H(r)|H(p)) \to tr\left\{\int_0^1 (dB)F'\left[\int_0^1 FF'du\right]^{-1}\int_0^1 F(dB)'\right\}$$

where $F = B$ is a $p-r$ dimensional Brownian motion. The critical values are obtained by simulation (Johansen 1995, ch. 15).

After the cointegrating rank has been determined, the matrix $\Pi = \alpha\beta'$ and also the Γ_i matrices can be estimated. It is noteworthy that since we estimate first the rank of the matrix, we have as a result a certain number of vectors that span the cointegrating space. There is thus no unique solution to Π, but there are many possible α and β that contain the cointegrating relations or linear transformations of them.[30] Thus no economic interpretation can be given to α and β.

A unique (identifying) and consistent solution can be obtained by imposing indentifying restrictions. A common restriction is to set $\beta' = [\mathtt{I}_r : \beta'_{K-r}]$, where β'_{K-r} is a $(K-r)\times r$ matrix. For $r = 1$ (which is the case we are considering later in chapter 5), the normalization reduces to a case where one element of the β-vector is set to one.

This kind of normalization is not however a trivial task, economically interpretable cointegrating results should emerge from the estimation and an unsuitable normalization may cause problems (for example if we normalize by a variable that does not belong to the cointegrating relation). We will not however go deeper into this question, since in our model, the normalization vector is given by theory.

An important outcome of normalized vectors is that we are able to find if there are variables that are in fact stationary processes. For the normalization case described, if any of the r variables with respect to which we normalize were a stationary process (thus the ones corresponding to $\mathtt{I}_r$), the estimates of the vector, β'_{K-r} would be zero (Lütkepohl 2005, ch. 6).

After having determined the cointegration rank, the Johansen maximum likeli-

[30]Since $\Pi = \alpha\beta' = (\alpha\xi^{-1})(\beta\xi')'$ with a non-singular $r \times r$ matrix ξ.

hood procedure is used to estimate α, β and Γ_i. The ML-estimator of β defines the combination of X_{t-1} that yields the r largest so-called canonical correlations of ΔX_t with X_{t-1} (after correcting for lagged differences and deterministic variables). Intuitively, β -matrix describes the long run relations of the variables in question, which is what we are interested in.

Matrix α is often called "loading matrix" or "adjustment matrix" meaning that for each equation of the model, it gives the weights attached to the cointegrating relations. These estimates represent how the deviations from the long-run relations affect the changes in the variables observed. Matrix α can be used to study if any of the variables in the study is weakly exogenous. In the case where the cointegrating rank is one, thus both β and α are vectors, having the ith element of α equal to zero, would mean that the ith variable is weakly exogenous. Thus an intuitive explanation for the weak exogeneity is that the variable can be regarded as representing a sort of "explanatory variable", even though this term is not used in the literature. The Γ_i matrices are connected to the short run dynamics of the model, but their analysis is left out from this study.

The distributions of β, α and Γ_i are Gaussian when we condition on the observations of explanatory variables. The unconditioned distribution is however not normal, but it is a so-called mixture of Gaussian distributions. In statistical inference only the conditional distribution is needed so we do not explain the properties of the mixture of Gaussian distributions here. We can thus conclude that we use an asymptotic normal distribution to determine the critical values of the parameters of β (as well as α and Γ_i) and an asymptotic χ^2 -distribution in the Wald test (see for example Johansen 1988, 1991).

The unrestricted model is estimated with the Johansen approach but the semi-endogenous and Schumpeterian models are estimated with the so called simple two step (S2S) method (see Ahn & Reinsel 1990; Lütkepohl & Krätsig 2004).

Estimation of the semi-endogenous and Schumpeterian model is done so that the cointegration rank is set to one in all of the cases and then restrictions to the parameter vector β are imposed.

After we have used the Johansen procedure in estimating the unrestricted model, we can in that framework test restrictions of the form

$$H_0 = R\text{vec}(\beta^{*'}_{K-r}) = r \qquad \text{vs.} \qquad H_1 = R\text{vec}(\beta^{*'}_{K-r}) \neq r, \tag{4.9}$$

When J is the number of linearly independent restrictions for the coefficients of $\beta^{*'}_{K-r}$, then R is a $J \times (K-r)r$ coefficient matrix and r is a J -dimensional vector. A Wald test is used with a $\chi^2(J)$ distribution (Lütkepohl & Krätsig 2004, ch. 3).

After running the Wald test we can estimate the restricted models with the simple two step (S2S) method. For complex restrictions the Johansen approach is computationally more demanding, and the S2S gives a solution in closed form. The Johansen approach is thus feasible for the models we are estimating but the software that we use, JMulti, has restricted the estimation of models where restrictions on β are imposed to S2S only.

The simple two step estimation represents equation 4.3 as

$$\Delta X_t - \Pi_1 X^{(1)}_{t-1} - \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} = \Pi_2 X^{(2)}_{t-1} + u_t, \tag{4.10}$$

where $X^{(1)}_{t-1}$ is $r \times 1$ and $X^{(2)}_{t-1}$ is $K - r \times 1$. The matrices Π_1 and Π_2 are $K \times r$ and $K \times K - r$, respectively such that $[\Pi_1 : \Pi_2] = \Pi_1 = \alpha\beta'$. With the normalization $\Pi_1 = \alpha$ and $\Pi_2 = \alpha\beta'_{K-r}$.

Only the general idea of the S2S estimation is presented here. In the two-step procedure the first step eliminates the short-term parameters by replacing them with their OLS estimators. Then it is possible to estimate $\Pi = [\Pi_1 : \Pi_2]$ with OLS and obtain the estimator for α. With these results, it is possible to estimate the resulting free parameters β'_{K-r} with OLS.

In the S2S estimation a formulation for the restrictions in β is defined as $\beta = H\varphi$.[31] In the restricted case we first get an estimator for φ from where we get the final restricted estimator $\hat{\beta} = H\hat{\varphi}$ (Lütkepohl & Krätsig 2004, ch. 3). The S2S estimator has same asymptotic properties as the ML estimator obtained in Johansen approach (Ahn & Reinsel 1990). Thus for inference we can therefore use normal distribution. Also other parameters of the model, Γ_i and deterministic terms, can be estimated with S2S.

[31] Details of this restriction are intentionally left out.

Chapter 5

Results

In this chapter we report and discuss our results from estimating the productivity-growth function introduced by Ha & Howitt (2007) with the Finnish data.

The general result from the estimation is that there is clear evidence to support the semi-endogenous model but the Schumpeterian model does not fit the Finnish data, however we cannot fully reject the Schumpeterian idea of product proliferation. Our estimation technique can be argued to be relatively robust compared to those used by Ha & Howitt (2007) and Madsen et al. (2010). They use two separate statistical frameworks in estimating the model whereas our submodels are statistically defined as "nested models"; they use a common framework in which parameter restrictions are imposed.

5.1 Estimation Equation

The estimated equation is the general form of the growth models, equation 2.1:

$$g_A = \lambda \left(\frac{X}{Q} \right)^{\sigma} A^{\phi - 1},$$

where in steady state

$$Q \propto L^{\beta}.$$

By taking logs and making a discrete time approximation of the equation in steady state we obtain[32]

$$\Delta \ln A_t = \gamma_0 + \gamma_1 \left(\ln X_t - \beta \ln Q_t + \frac{\phi - 1}{\sigma} \ln A_t \right) + \epsilon_t, \tag{5.1}$$

where ϵ_t is an error term, which is identically and independently distributed with mean zero. A cointegration relation would mean that when $\Delta \ln A_t$ is stationary, then the term inside the brackets

$$E_t = \ln X_t - \beta \ln Q_t + \frac{\phi - 1}{\sigma} \ln A_t, \tag{5.2}$$

denoted now by E_t, would also be stationary. Then for the semi-endogenous theory where β is zero and thus $\ln Q_t$ vanishes, equation 5.2 reduces to the form

$$E_t^{se} = \ln X_t + \left(\frac{\phi - 1}{\sigma} \right) \ln A_t, \tag{5.3}$$

where the superscript in E_t^{se} stands for semi-endogenous. Note that coefficient $\frac{\phi-1}{\sigma} < 0$, since the theory states that $\phi < 1$ and $\sigma > 0$.

According to the semi-endogenous theory, having E_t^{se} as a stationary process would mean two things: that the linear combination of $\ln X$ and $\ln A$ must be stationary, hence if the two variables are nonstationary, then they must be cointegrated.

In the Schumpeterian model equation 5.2 reduces to the form

[32]since $\Delta \ln A_t = \ln \lambda + \sigma \left(\ln X_t - \beta \ln L - \frac{\phi-1}{\sigma} \ln A_t \right)$, now γ_0 denotes $ln\lambda$ and γ_1 denotes the σ outside the brackets.

$$E_t^{sc} = \ln X_t - \ln Q_t, \tag{5.4}$$

where the superscript in E_t^{sc} stands for Schumpeterian. Since the theory claims that $\phi = 1$, the term $\left(\frac{\phi-1}{\sigma}\right) \ln A_t$ vanishes from the equation.

Unlike Ha & Howitt (2007) and Madsen et al. (2010) we will estimate the general form presented in equation 5.2 first, so that no parameter restrictions of the submodels are taken into consideration. This model is not backed up any economic theory as such. On the contrary, it is more like a compromise between the models and therefore intriguing to estimate.[33] If the freely estimated parameters did not fit the model, roughly it would indicate a rejection of the R&D-based models in a larger sense implying that R&D-based endogenous growth theories do not describe well the Finnish productivity growth. However, as described in more detail later, the unrestricted models are generally well specified and do support the idea that Finnish productivity growth is driven by some kind of R&D-based growth model in general.

If, hypothetically, this general form of the model gave a good description of the data the three variables should be cointegrated as presented in equation 5.1, so that $\beta = 0$ or $\beta = -1$ and $\frac{\phi-1}{\sigma} \leq 0$. In estimating the general model it makes sense to estimate β freely so we expect it to be *between* 0 and -1. If we allowed for the parametrization considered by Jones (1999), β could also be smaller than -1.

The hypothesis that the data was generated by a semi-endogenous growth model would imply one restriction to the unrestricted model, namely H0: $\beta = 0$, so that there exists a cointegrating relation between R&D input and TFP. The restriction $\frac{\phi-1}{\sigma} \leq 0$ is also assumed as previously, but not formally imposed.

The hypothesis that the data was generated by a Schumpeterian growth model instead would indicate a joint hypothesis of two restrictions, H0: $\beta = -1$ and

[33] Compromising between the models is also attempted by Jones (1999) who studies a model with unrestricted β and $\phi < 1$, thus not far from the restrictions in our general model.

$\frac{\phi-1}{\sigma} = 0$ (since $\phi = 1$).[34]

This estimation can be argued to be very robust compared to the estimations of both Ha & Howitt (2007) and Madsen et al. (2010). Ha & Howitt (2007) estimate the semi-endogenous model with cointegration but leaving the product proliferation variable outside the estimation, therefore there is no restriction to study the validity of the hypothesis $\beta = 0$ as in our study. The estimation of the Schumpeterian model reduces to a unit root test and as a matter of fact Ha & Howitt (2007) have studied the model only by running an ADF-test to the difference of X_t and Q_t. Hence, they do not get any support for their claim that $\frac{\phi-1}{\sigma} = 0$. Madsen et al. (2010) have used cointegration in estimating the Schumpeterian model, but unlike us, they have estimated freely the coefficient of Q so that the equation is as a matter of fact $E_t^{sc} = \ln X_t - \beta \ln Q_t$.

However, by estimating the nested model, we are able to make inference on all of the parameter restrictions suggested by both of the models and compare them in a robust way. Finding firm support for the semi-endogenous model and almost no support for the semi-endogenous model in this statistically comparable framework can be regarded as very firm evidence for the Finnish case compared to the contradictory evidence presented by Ha & Howitt (2007) of the U.S. and Madsen et al. (2010) of India.

5.2 Cointegration Test of the Unrestricted Model

The results of the unrestricted model are presented in table 5.1. The first columns tell the result of the trace test and for clarity the number of cointegration vectors given by the test is presented in column r(95%, 99%). However, since our theory states that there exists only one cointegration vector, we have restricted the rank of β to one in all the cases in the table. The estimated cointegrating vector is presented

[34] Thus in all of these cases we have normalized the cointegration vector to the term $\ln X_t$.

in the last column, standard errors are in brackets. All of the cointegrating residuals are presented in figures 5.1, 5.2 and 5.3.

The lag length of the model was chosen so that in the VAR-form of the models there is no autocorrelation of residuals. In all of the models include an intercept and a trend. The residual diagnostics of the VAR are reported in the Appendix, table C.1. The trace test for determining the cointegration rank was then conducted to this VAR-model and the resulting VECM-model is unrestricted in the theoretical sense but restricted in as having one cointegrating vector. All of the VECM-models included an intercept outside the cointegration relation but no trend. Residuals diagnostics of the unrestricted model are reported in table C.2.

Estimation of the general form model reveals that R&D-based growth theories are generally speaking capable of explaining Finnish productivity growth. The substantial differences in the product proliferation and R&D input measures used is however visible in the results. Despite the differences, almost all the models are well specified (autocorrelation is present in only three cases) and there can be said to be some sort of cointegration (rank being either one or two) in 11/14 cases and precisely one cointegrating vector in 8/14 cases (when both reported confidence intervals are considered). Almost all of the parameter estimates are statistically significant (at the 95% level as much as 22/28 and at the 99% level 18/28 of all the parameter estimates).

Since the estimates are different from zero we can also draw the conclusion that the assumption of a unit root process holds as explained in chapter 4. However, since the cointegration vector is normalized to the R&D input variables, the unit root of three variables, A, Y and L, is not being studied. Therefore we ran an ADF tests to these three variables and in all the cases we could not reject the null of the unit root even at the 90% confidence level, the results are reported in Appendix B. Thus the assumption of all the variables being created by a nonstationary process holds.

The results favouring the semi-endogenous model and refuting the Schumpete-

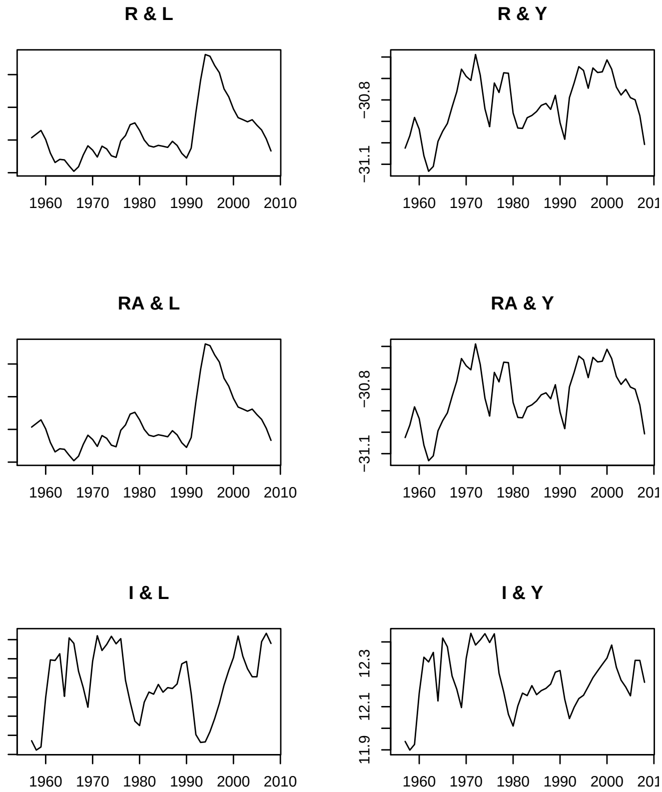

Figure 5.1: The cointegrating residuals of the unrestricted models with R&D expenditures, productivity adjusted R&D expenditures and high technology imports.

rian are not as clearly visible in the general model as it is in the nested models. However, we can clearly see that even though the product proliferation variables are statistically significant, only 6 of the 14 estimates have a confidence interval that includes the value -1 and also 6 of the parameter estimates of $\frac{\phi-1}{\sigma}$ have zero inside the confidence interval, results that would favour the Schumpeterian model. The models with GDP indicating product variety look just slightly more promising for the Schumpeterian model.

On the contrary for the semi-endogenous case, 11 of the 14 estimates for $\frac{\phi-1}{\sigma}$ are negative, thus of the right sign. However, none of the product proliferation variables has the value zero inside the confidence interval, thus we cannot reject the hypothesis that product variety plays a role in the kind of R&D based endogenous growth that

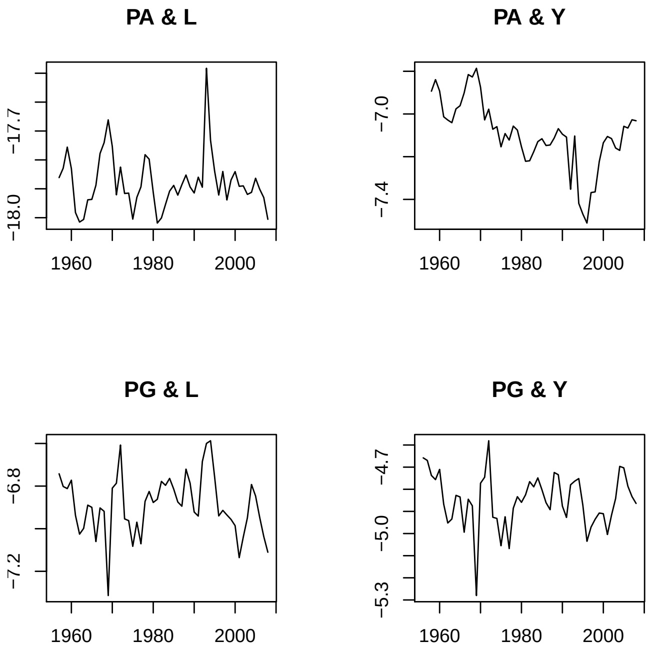

Figure 5.2: The cointegrating residuals of the unrestricted models with patent applications and patent grants.

Finland has experienced. But as the estimation of the Schumpeterian model reveals, product variety cannot be said being strictly proportional to the R&D input in a way suggested by the Schumpeterian model.

We will not study more closely the 14 different models estimated because it is more interesting to study them inside the nested models. However, we will present briefly some interesting remarks. Two of the three models with high autocorrelations were models with an R&D workforce variable and the models with these variables were also the ones that had no cointegration. It is a peculiar result since R&D workers are regarded as being a rather good proxy for R&D activity. However, we must keep in mind the shorter time span of these variables. Therefore it is plausible that the results differ from others so much because the sample size is not large enough for asymptotically as valid estimation results as the other models have.

It is also noteworthy that three of the models have estimates that are very large

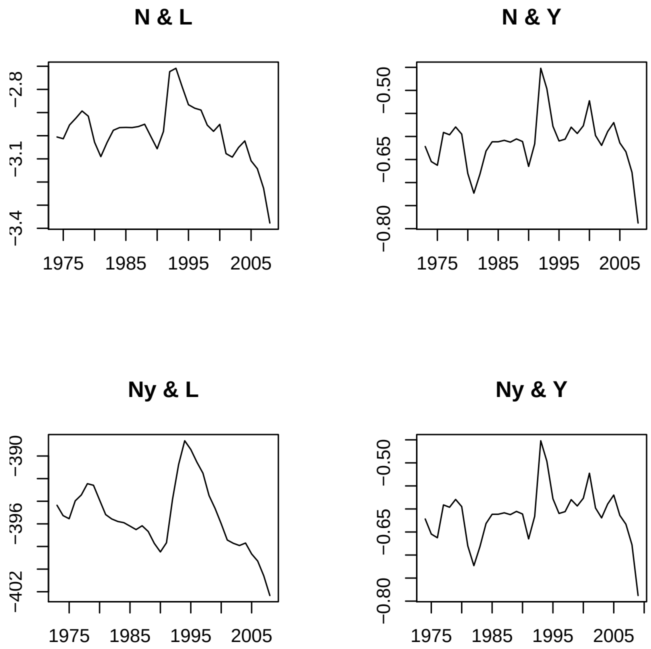

Figure 5.3: The cointegrating residuals of the unrestricted models with R&D workforce and R&D person-years.

in absolute value. This result is no more present in the estimations of the nested models, so it could be a difference arising from the two different estimation methods used, the Johansen approach and the S2S approach but we cannot be sure about this.

5.3 Cointegration Test of the Semi-Endogenous Model

The semi-endogenous model is formed by restricting the general model so that $\beta = 0$. This restriction is tested with the Wald test (with the alternative hypothesis being $\beta \neq 0$). The results of the Wald test and the estimation of the models are given in table 5.3.

The results of the Wald test indicate that the null hypothesis that the second element is zero is rejected in all but three of the cases. However, the parameter estimates of the semi-endogenous model are *all* statistically significant at the 99% significance level and of the right sign. Most of the models also have well-behaving residuals, but there are some exceptions where problems arise. In import and patent models the cointegrating residuals are clearly stationary, in R&D expenditure and workforce models stationarity is not so evident. For each R&D input variable the cointegrating residual looks very much the same regardless of which of the two product proliferation variables is used in the model (which is probably due to having the zero-restriction). This general inspection gives support for the semi-endogenous model.

Interesting additional results arising from the estimation of the semi-endogenous model specifically are the α-vectors. A desirable result would be that R&D input is a weakly exogenous variable (thus the corresponding element of the α-vector not being statistically significantly different from zero) and TFP is an endogenous variable (the corresponding element of α being different from zero). This would suggest that the adjustment from the long-run relations happens through TFP and so R&D input could be regarded as an "explanatory variable"[35]. Probably due to the great differences in the variables studied, the evidence is rather mixed. In four cases, all with R&D expenditure or workforce variables, the α connected to TFP can be regarded as endogenous and R&D input variable as exogenous at the 95% level. In five cases, patent and import models, the relation goes the other way around, TFP is weakly exogenous and R&D input endogenous. In the rest of the cases the evidence was not clear in one way or another. Note however, that the estimated model does not technically impose any assumptions on the α-vector.

Let's study the results more closely. The model with high technology imports and output has the best result in the Wald test being the only one where the null hypothesis cannot be rejected at the 95% level. However, the model has very high autocorrelations and the normality assumption is not met either, thus it is clearly

[35]Note that this is not a formal description but rather just clarifying the idea behind.

not a valid model. In the model with high technology imports and labour the Wald test cannot be rejected at the 99% level. The estimates of the β-vectors in these models are significant and the cointegrating residuals look stationary. The model with labour has well-behaving residuals and thus seems to give good support for the semi-endogenous theory. In both of these models TFP can be considered as weakly exogenous and high technology imports as endogenous. So the relation would most probably be from TFP to high technology imports and not the other way around.

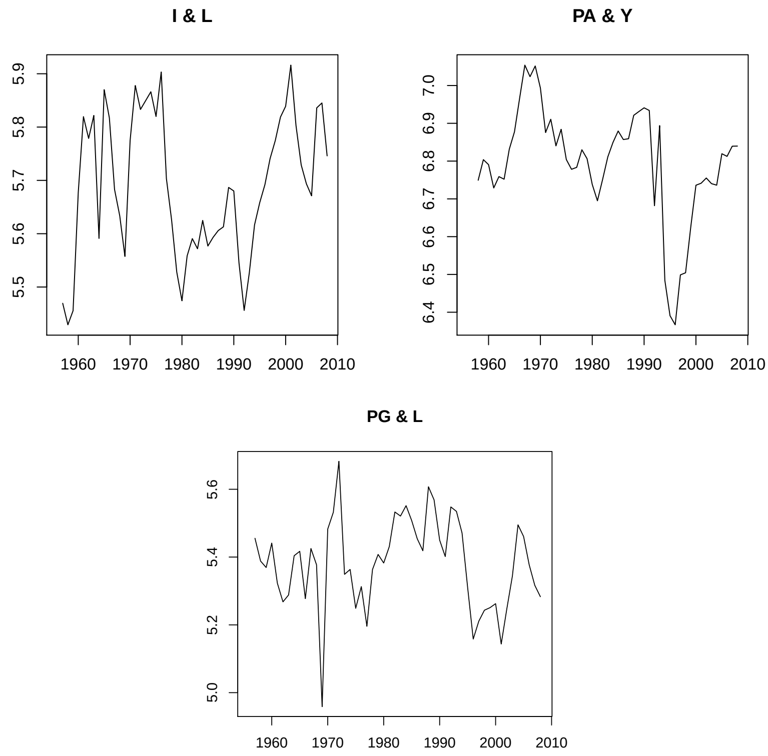

Figure 5.4: Cointegration residuals of the semi-endogenous model, up left: High technology imports & labour, up right: Patent applications & output, down: Patent grants & labour.

Also in the model with patent applications and output, the Wald test is not rejected at the 99% level and the cointegrating residual looks rather stationary, but the residuals of the model do not meet the normality assumption. Heteroscedastity is a problem in the model with patent applications and labour.

Both of the models with patent grants have some minor problems. In the model with PG and L the residuals do not satisfy the normality assumption and there is also minor heteroscedasticity in one of the residual vectors. In the model with PG and Y this problem remains, with a bit more heteroscedasticity. However, there is no autocorrelation so we can draw the conclusion that all the patent models are acceptable with precautions. In all of the four patent models TFP can be considered weakly exogenous and patent variables endogenous, thus contradicting our assumption.

In the R&D workforce models, we see that the model with R&D person-years N_y and L, there is quite high autocorrelations and also some high cross-correlations so the estimation result is clearly not valid. In all of these models, the normality assumption is not met or is on the limit, which is probably due, at least to some extent, to the small sample size. However, in these models TFP is endogenous and the workforce variables are weakly exogenous (except the model with N and L where both can be regarded as endogenous), hence supporting the model.

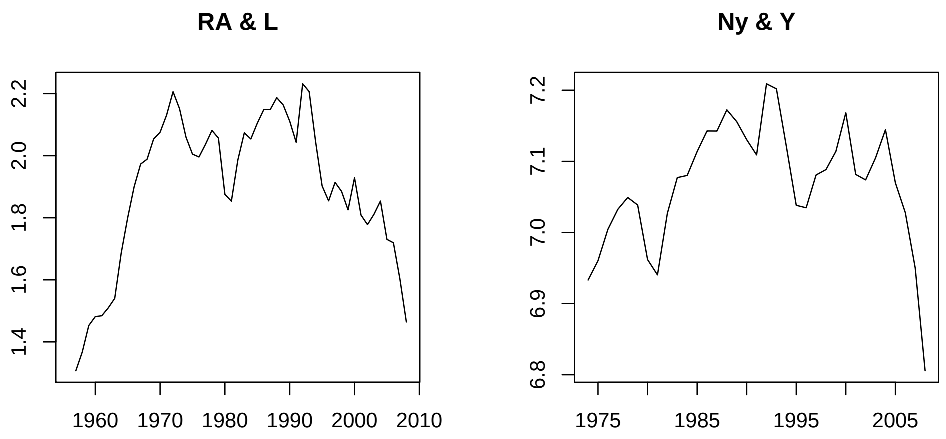

Figure 5.5: Cointegration residuals of the semi-endogenous model, left: Productivity adjusted R&D-expenditures & labour, right: R&D person-years & output.

Finally, the models with R&D -expenditures (both with and without productivity adjustment) support somewhat the semi-endogenous theory: The Wald test is not favourable but the residual analysis suggests that the models are well defined and the parameter estimates are statistically significant. The cointegration residuals are not clearly stationary though, there seems to be first an upward and then a downward trend, however, there is no clear trend across the whole series. In the model with R&D -expenditures and GDP, R&D -expenditures is weakly exogenous and GDP endogenous thus supporting the model. In the three remaining cases there was no clear evidence for or against the model in this sense.

We can thus draw the conclusion that the semi-endogenous models describes well the Finnish economy. Most of the models are well defined and we can also say that the models which do not have autocorrelation but do have some heteroscedasticity or normality -problems still, as a whole, give support for the semi-endogenous model. It also seems clear from these estimations that R&D expenditures and workforce variables are good measures for R&D input in the sense that they were the ones that could be regarded as weakly exogenous variables in the model.

5.4 Cointegration Test of the Schumpeterian Model

In the Schumpeterian model there are two parameter restrictions, $\beta = -1$ and $\frac{\phi-1}{\sigma} = 0$. We ran a joint Wald test with the null hypothesis that both of the restrictions hold, against the hypothesis that neither of them holds. The results of the Schumpeterian estimation are reported in table 5.4. Note that unlike in the semi-endogenous model reported in table 5.3, now we have not reported the cointegration vectors since they are the same in all of the cases. Since the model is fully restricted and reduced to a unit root test, the estimators do not have standard errors or t-values either, analysing the model is done simply by the Wald test, the cointegrating residuals and by residuals diagnostics. We have not analysed the α-vector in the Schumpeterian model since the model simply claims that the vertical R&D input and horizontal product variety move "hand-in-hand", thus the weak exogeneity is not something that would be interesting for the model. Moreover, since most of the models are not well defined, the estimates for α are not even reliable.

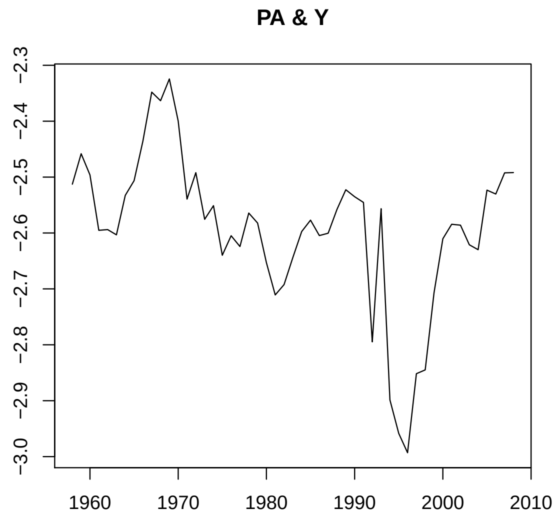

Figure 5.6: The cointegrating residual of the model with patent applications and output.

There is very little evidence in favour of the Schumpeterian model. Firstly, we can see that the results for the Wald tests are all poor for the Schumpeterian model. In all cases except one, the joint test that $\beta = -1$ and $\frac{\phi-1}{\sigma} = 0$, is rejected both at the 95% and the 99% level. The model with patent applications and output is the only one that supports the restriction. The cointegrating residual of this model does not have a clear trend and looks rather stationary but does have two peaks that look striking. The latter one is probably a result of the decrease in the patent application series in mid-90's (due to moving to the EU) but the previous peak, the upward peak in mid-60's, is not so straightforward to interpret, it is probably also due to the patent series having a small peak around that time.

The rest of the models are all rejected in the Wald test but we can also see from the residual analysis that all of them have highly autocorrelated residuals. In all of the models we can reject the null that there is no autocorrelation at one lag at the 99% level. Normality and heteroscedasticity -assumptions do hold for some of the models but the autocorrelations being a stronger prerequisite for a well-defined model leaves us with all except one of the models being not valid. We can also see this from the cointegrating residuals which all look more or less nonstationary, except the model with PG and output and the model with PA and labour in which the cointegrating residuals look somewhat stationary, but since the models are not well-specified, these findings are worthless.

5.5 Discussion

In this chapter, we discuss the results and compare then with first international and then Finnish literature. Lastly we discuss the steady state properties on the model and sum up our analysis.

5.5.1 Comparison with International Literature

In the Finnish case, the semi-endogenous model fits the data rather well whereas the Schumpeterian model can be clearly rejected in all cases except one. However, it seems that the idea of product proliferation cannot be rejected as such.

Ha & Howitt (2007) and Madsen et al. (2010) have also compared these models and both of them claim that their results are clearly in favour of the Schumpeterian model. Like noted before however, their models are not based on the nested model approach like ours. Instead, in both articles the semi-endogenous theory is tested with the Johansen cointegration test using equation 5.3, thus excluding product proliferation totally from the estimation. In Ha & Howitt (2007) the Schumpeterian model is estimated by testing the unit root in equation 5.4. Madsen et al. (2010) claim that in testing the Schumpeterian model they are estimating equation 5.4, but in fact, as table 1 in the article shows, they have estimated freely the coefficient of Q, so that the equation is in fact $E_t^{sc} = \ln X_t - \beta \ln Q_t$, which is strictly speaking, not a possibility inside the Schumpeterian model (Ha & Howitt 2007).

In estimating the semi-endogenous model, Ha & Howitt (2007) find no cointegration between the variables. Madsen et al. (2010) also claim that they do not find support for the semi-endogenous model in the Indian case, but in fact table 1 reveals that there is cointegration in 6 out of 8 cases, of which only 2 estimates though, are of the right sign. Hence, to our view the evidence against the semi-endogenous model is not that unambiguous.

In support of the Schumpeterian model Ha & Howitt (2007) find clear evidence since the null of unit root (described in equation 5.4) is rejected in all cases. The result of Madsen et al. (2010) of the Schumpeterian case is that in 10 out of 12 cases there is cointegration, but in fact, inspection of table 2 reveals that in only 2 cases the value $\beta = -1$ is inside the 95% confidence interval. Therefore Madsen's evidence in support of the Schumpeterian model is rather weak.

Ha & Howitt (2007) also forecast TFP out of sample using both of these theories. Their results suggest that the semi-endogenous theory gives a too pessimistic forecast, and that the Schumpeterian forecast fits the data better. However, in obtaining this result, Ha & Howitt (2007) have made an additional restriction to the semi-endogenous model and fixed the value of the parameter estimate of $\frac{\sigma}{1-\phi}$ to be equal to a value estimated in Jones (2002), so that there is a similar amount of parameters to estimate in both of the models. We regard this somewhat manipulative since the assumptions of the parameter restrictions are important theoretical properties of the models, if the assumptions of the Schumpeterian model are too strict to fit the data, then the flaw is in the theory, not in the estimation process. Therefore we do not see any good reason for imposing artificial parameter restrictions to the semi-endogenous model. The semi-endogenous model gives a slightly better result when this restriction is not imposed. To our view, the results are again somewhat mixed, but still favour more the semi-endogenous than the Schumpeterian model.

All in all, Ha & Howitt (2007) seem to have more support for the Schumpeterian model than the semi-endogenous model, but in our view the evidence *against* the semi-endogenous model is much weaker than they claim. Also Madsen et al. (2010) argue that their evidence supports clearly the Schumpeterian theory against the semi-endogenous theory. In our view, this argument seems a bit exaggerated since their evidence for both of the theories is rather mixed. Finally, considering all evidence discussed, our findings are quite not as contradictory with the results of Ha & Howitt (2007) and Madsen et al. (2010) as it seemed at first glance.

An important factor to notice at this point is that both Madsen et al. (2010) and Ha & Howitt (2007) use growth accounting to calculate TFP, but what is different from our approach is that they also include a measure of human capital in the production function. A further difference with Ha & Howitt (2007) is that they include only labour-augmented technology in their TFP measure. Thus our measure of TFP can be said to be rather all-encompassing compared to theirs, since it does not exclude human capital or capital-augmenting technical change.

For measuring technology transfers, Madsen et al. (2010) and Madsen (2008) (who studies a group of 21 OECD countries), use the import-ratio weighting scheme described in chapter 2.3. The measure consists of data on high technology imports weighted with a measure of the domestic R&D of each trading partner. In this sense, their measure for technology transfers is more sophisticated than ours. However, the measure of high technology imports is much rougher than ours:[36] Madsen et al. (2010) and Madsen (2008) include chemicals and related products (SITC Section 5), machinery and transport equipment (SITC Section 7), and professional and scientific instruments (SITC Section 8.7). Note for instance that SITC Section 5 contains all sorts of chemicals which certainly do not represent high technology, such as fertilizers (section 5.6), essential oils and resinoids and perfume materials; toilet, polishing and cleansing preparations (section 5.5) and plastics in primary forms (section 5.7) (United Nations Statistic Division 2012). Thus in this aspect, our measure of high technology imports is more precise.

Contradicting our results supporting the semi-endogenous model, some recent studies find support for the Schumpeterian model using different methods from ours. For example Madsen (2008) and Madsen et al. (2010) use OLS with several explanatory variables for R&D input and intensity. In the Indian case R&D intensity,

[36]see Appendix D for our measure.

foreign even more than domestic, explains TFP growth better than R&D input, hence supporting the Schumpeterian theory more than the semi-endogenous. In a study of OECD countries Madsen (2008) uses dynamic least squares to compare between the two growth models finding more evidence for the Schumpeterian model.

Madsen (2008) also finds that R&D intensity Granger-causes TFP (and not the other way around). In this Granger-causality context, we can regard R&D input and intensity being relatively comparable measures. Therefore we can claim that our findings of the weak exogeneity in the semi-endogenous framework are partly in accordance of this evidence and partly oppose it. Just 5 out of 14 of our models had weakly exogenous R&D input variables, namely models with R&D expenditures and workforce.

Apart from Madsen (2008), none of the articles mentioned provide any tests on the "direction" of the relation between R&D and TFP, whether it be a test of Granger causality or just an inspection of the short-run dynamics through α or Γ -matrices. It could have been an interesting additional insight for Madsen et al. (2010) and Ha & Howitt (2007) to include an analysis of the weak exogeneity of the R&D input variables.

In two recent articles, Zachariadis (2003, 2004) tests the Schumpeterian model. Zachariadis (2004) performs an iterated Seemingly Unrelated Regressions (SUR) estimation testing the impact of R&D intensity to productivity and output growth for 10 OECD countries ending up rejecting the null hypothesis that growth is not induced by R&D intensity in the steady state.

Zachariadis (2003) studies a panel of industries in the manufacturing sector of the U.S., which accounted for more than 90% of R&D expenditures during 1963–88. The estimated equations are based on the three-sector approach introduced in 2.1.3. Zachariadis shows that R&D intensity had a positive impact on the rate of patenting, which in turn is shown to drive technological progress which then drives the growth rate of output per worker. Zachariadis suggests that R&D from the manufacturing sector has positive externalities, both across manufacturing industries and to the rest of the economy. These results favour the Schumpeterian model, but it is impossible to say what kind of results would have been obtained if the semi-endogenous R&D input had been studied in the same framework.

There exists no unambiguous way to see what is the correct size of the economy the R&D based endogenous growth theories refer to. This is why many studies have concentrated on large entities, namely either the U.S. or a entity consisting of several countries at the high technology frontier. However, these cross-country studies have the common feature that they often cover a shorter time span than studies concentrating on one country, since from a practical point of view a dataset with a longer time span is easier to construct for one single country. Our data ranges from as early as 1955 to 2008 and also Madsen et al. (2010) and Ha & Howitt (2007) have datasets starting from the 50's. Studies concentrating on OECD (Coe & Helpman 1995; Coe et al. 2009; Zachariadis 2004) have much shorter datasets, all starting from 1971.

Apart from purely practical benefits, a country-level setting gets support from Pessoa (2010), who claims that the exact form of the relationship between R&D and economic growth differs from country to country. Finland seems to be in a good position in his study, it is among three of the countries where both R&D intensity and GDP growth rate is higher than the OECD average (together with the U.S. and South Korea).

Unlike this study, some empirical studies on the effects of R&D to growth do not use any theoretical framework. For instance Coe & Helpman (1995) and Coe et al. (2009) have a purely practical approach not explicitly linking their study to any specific growth theory. Both of the articles find that there is a relation between both domestic and foreign R&D capital stock (which is defined as cumulated R&D expenditures) with TFP in a cross-country setting consisting mostly of OECD countries. To our view, using cumulated R&D expenditures as a measure of R&D activity instead of R&D intensity, gives support for the semi-endogenous model rather than the Schumpeterian model. Therefore the results seem to be more or less in line with our findings.

Coe & Helpman (1995) find out that for small countries in particular, foreign R&D capital stock may be at least as important as domestic R&D capital stock while for large countries (the study refers to G7 countries), domestic R&D capital stock may be more important. This result is in accordance with our finding that high technology imports matter for Finnish TFP growth.

Methodologically the study of Coe et al. (2009) is comparable to ours, since they use panel cointegration technique for 24 countries (one being Finland) for the years 1971–2004 finding robust evidence of cointegration between TFP and both domestic and foreign R&D capital stock.

Another result suggested by Coe et al. (2009) is that institutions matter for R&D-based growth. Countries where the ease of doing business and the quality of tertiary education systems are relatively high, benefit more from both domestic and foreign R&D and from human capital formation. Countries with Scandinavian and French -based legal systems benefit less from domestic R&D capital than other countries. Finland was close to the average in ease of doing business and patent protection but ranked high in the quality of tertiary education.

5.5.2 Studies on Finnish Productivity

Even though the cross-country evidence is generally speaking consistent with out estimates; it is not enough to shed light on Finnish productivity growth in particular. Macro-level studies on Finnish productivity growth covering a long time span like ours are very few.

Most of the studies on Finnish productivity have industry level data and a shorter time span than our study. They also share the common feature that emphasis is given to the ICT sector, which has been the driver of Finnish productivity since the 90's. Thus this kind of academic discussion sheds light in understanding why Finland has been in the front line of several international productivity studies in recent years (see for example OECD 2006).

The impacts of R&D to productivity are often considered only implicitly as it is evident that the rise of the ICT sector is a result innovating activity. However, there are studies that concentrate explicitly on the impacts of R&D to productivity growth. One example is a firm-level study of Piekkola (2007), which found significant impacts of R&D subsidies on productivity growth for small and medium sized firms.

Several studies on Finland concentrate on the acceleration of labour productivity, which has taken place since the 80's, a development that coincides with economy-wide deregulation, liberalization, and the opening up of Finland (Maliranta et al. 2010).

The studies of Daveri & Silva (2004) and Jalava & Pohjola (2007) emphasize the significance of the ICT sector. Daveri & Silva (2004) find that Nokia has contributed directly and substantially to productivity growth in Finland and Jalava & Pohjola (2007) present that almost 70 percent of the aggregate TFP growth can be attributed to ICT during 1995–2004. Daveri & Silva (2004) find that TFP at the "Nokia-sector" accelerated during the 90's which coincided with a significant, albeit smaller, rise in the TFP of ICT-related service sectors. However, the authors show that these two sectors had little connection to each other and rather, the productivity growth in the service sector is probably linked to global technology trends. Also labour productivity growth gains outside ICT industries have been rather small.

As Daveri & Silva (2004) point out, labour productivity does not correct for capital deepening (changes in the amount of capital per worker). While the two measures move in parallel in most nations, this is not the case in Finland. Finnish labour productivity has risen significantly since the 50's, while capital productivity has stayed at the same level, and only started modestly increasing after the recession (Jalava et al. 2006). Therefore Daveri & Silva (2004) share our view of TFP being a better measure in understanding Finnish productivity growth than labour productivity, which is mostly used in Finnish productivity studies.

Despite this benefit, Daveri & Silva (2004) criticize TFP for being a procyclical measure, because it is calculated as a Solow-residual of GDP, so that any procyclicality present in the GDP growth rate gets transmitted into TFP growth. However, our measure of GDP is quite well adjusted for business cycles since we have excluded housing services form our measure of GDP. Also graphically it seems that there is not much procyclicality in our TFP measure, as we can see from figure 3.2, the long-run trend dominates the series.

Since TFP has grown steadily already for decades, it makes sense to us to study TFP growth on a long time span. Finnish productivity growth has been studied from a historical point of view by for instance Jalava et al. (2002) and Jalava & Pohjola (2008). Jalava et al. (2002) study TFP growth in the manufacturing sector of Finland during 1925–2000. A central result of the article is that until the 90's TFP growth in manufacturing is a story of "catching-up", and in the 90's it is mostly due to ICT production (and ICT-use), a story of technical change.

The study by Jalava & Pohjola (2008) compares ICT with electricity, which have both been new general-purpose technologies of their time, showing that ICT's contribution to GDP growth in 1990–2004 was three times as large as electricity's contribution in 1920–1938. In this historical context, our study aims at answering the question posed by Jalava et al. (2002), namely why has the TFP growth been so fast in Finland. The contribution of our study would be that not only R&D played an important role during the ICT -era, but that the link was already present much earlier, during times when Finland was lagging behind the high technology frontier.

Among the productivity studies of Finland, our study is not the only one presenting some kind of a Schumpeterian approach. Maliranta et al. (2010) study Finnish labour productivity on an industry level from the point of view of creative destruction, which they view as "productivity-enhancing restructuring at the plant or firm level through entry and exit as well as resource reallocation among continuing plants or firms". Unlike in our study, the notion of creative destruction is explicitly studied among Finnish industries. Maliranta et al. (2010) found that productivity-enhancing restructuring was already intense before the Finnish great recession of the early 90's and during the recovery after the recession. Maliranta et al. (2010) claim that entry, exit, and resource reallocation among continuing plants explain about one third of the labour productivity growth in Finnish manufacturing since 1975, and virtually all of the labour productivity acceleration since 1985.

5.5.3 Discussing the Steady State and Final Remarks

Finally moving back to discussing on our estimation results, we pose a central question that still remains unanswered: has the Finnish economy been in steady state during the period analysed? Whether or not the economy has been in steady state affects the conclusions drawn from the estimations.

Regarding the evidence presented by Jones (2002) for the U.S., we should reflect the idea that Finnish TFP growth could have been transitory. Also due to the severe depression in the 90's, we cannot reject the idea that there was a structural break, and therefore Finnish growth undoubtedly has not been on a balanced growth path during the *entire* time of the study. It is however unclear how long the periods of transitory growth around this structural break have lasted. Nevertheless, our data being formed so that the long run trend dominates the series, the impact of this structural break has been smoothed.

Even though we have been able to smooth the TFP and GDP series, the data on labour (hours worked) shows quite the opposite, in fact the depression in the 90's strikes out clearly showing how unemployment was a major outcome of the depression. Thus the poor results of the Schumpeterian model are hardly surprising in the models with labour as product variety. The assumption that R&D input and product variety move in lockstep ($\beta = -1$), which is supposed to hold in the steady state, is not in accordance with our data. It is therefore surprising that even though the GDP series used increases steadily, which could be interpreted as balanced growth; in the unrestricted estimation the models with GDP were only slightly more promising for the Schumpeterian model.

The estimation of the Schumpeterian model shows that the hypothesis $\beta = -1$, reflecting the idea that R&D input and product variety grow proportionately in steady state, is rejected in the Finnish case. When labour is used as a measure, the most plausible explanation for the rejection is simply that labour is a poor proxy for product variety for the Finnish case. However, when GDP is used as a measure, the rejection of the hypothesis $\beta = -1$ has several plausible explanations. Firstly, the assumption made by Ha & Howitt (2007) that GDP can be used as a measure of product variety could just not be accurate for the Finnish case, but it is hard to see why it would be a worse measure for Finland than for the U.S.

Secondly, we could speculate that Finnish growth has been transitory in a manner suggested by the Schumpeterian model, so that β is different from -1: In estimating the unrestricted model, the product variety variables were mostly statistically significantly different from zero and also in the Wald test in the semi-endogenous model, the null of $\beta = 0$ was rejected in most cases. Thus we cannot reject the hypothesis that product variety is somehow present in productivity growth of Finland. However, this is unlikely since we did not find support for the other parameter restriction imposed by the model either, namely that $\frac{\phi-1}{\sigma} = 0$ and the model just did not fit the data in any way.

All in all, the semi-endogenous model fits the data much better than the Schumpeterian model. The finding of TFP growth being much faster than the growth of any of the R&D input variables studied, does not contradict the steady state assumption of the model, namely that TFP growth rate approaches a fraction of R&D input growth (presented as $g_A = \frac{\sigma}{1-\phi} g_X$). This in fact allows the TFP growth rate to be higher in steady state than the growth rate of R&D input since it is possible that $\frac{\sigma}{1-\phi} > 1$, because $0 < \sigma < 1$ and $\phi < 1$.

It is also possible that transitional or "constant growth" dominates the whole time span, as suggested by Jones (2002). Whichever is the case, it seems that an increasing level of R&D input is required also in a small economy such as Finland, to maintain this constant growth rate of TFP.

As we have already shown, several R&D input measures from 1955 are cointegrated with TFP growth as suggested by the semi-endogenous theory. However, cointegration was not found in R&D workforce variables in which the data started in 1971, which might be due to the small sample size. Whatever the reason is, at least we cannot say that we have evidence that R&D has had a more significant role since the 70's than since the 50's, which is a peculiar considering other productivity literature.

It is also remarkable that TFP growth has been much faster than the growth of any of the R&D input variables studied during the whole time span of the study. Therefore intuitively it seems that albeit the R&D variables being cointegrated with TFP, there must be a myriad of factors that have effected on productivity growth throughout the decades.

Throughout the period of this study the structure of the Finnish economy has altered significantly. There have been different drivers in economic growth, wood, metal and ICT to name the most central ones. There are however some central developments that have been persistent throughout the time span of the study.

Firstly, the level of education has increased significantly, which of course interacts with especially public sector research expenditures. Thus a strong common trend has been the emphasis given to education on a broad sense. Secondly, globalization is another development characterizing the recent decades. In Finland, where the export sector is given much emphasis in public discussion, it is also noteworthy that high technology imports have a strong relation with growth. Through high technology imports, the nonrival nature of ideas can create a positive externality in the economy and therefore possibilities to benefit from learning by doing should be encouraged.

Finally, we can conclude that this study suggests that aggregate R&D, consisting of both public and private R&D and also foreign technology, have a relation with productivity growth. Thus letting the aggregate level of R&D input fall could have negative consequences.

Table 5.1: The unrestricted model (Johansen approach)

Model:	H(r)	Trace	r (95% , 99%)	Lags	Cointegrating vector		
Q as L							
R	0	42.73	2, 1	2	(1	-71.6	-10.6)
	1	20.42				(21.4)	(6.0)
	2	8.49					
R/A	0	42.73	2, 1	2	(1	-71.64	-9.62)
	1	20.42				(21.44)	(6.01)
	2	8.49					
I	0	51.23	2, 1	2	(1	1.63	-1.98)
	1	20.44				(0.78)	(0.19)
	2	5.57					
PA	0	77.28	2, 2	2	(1	-2.90	-1.89)
	1	34.33				(0.21)	(0.05)
	2	6.87					
PG	0	58.73	2, 2	2	(1	-1.43	-2.17)
	1	27.49				(0.50)	(0.12)
	2	9.49					
N	0	54.08	1, 1	3	(1	-1.21	-2.76)
	1	12.01				(0.19)	(0.07)
	2	4.64					
N_y	0	18.40	0, 0	2	(1	-45.95	-18.08)
	1	7.24				(8.28)	(3.26)
	2	2.7					
Q as Y							
R	0	36.37	1, 0	2	(1	-3.50	0.84)
	1	19.45				(0.54)	(0.80)
	2	6.80					
R/A	0	36.37	1, 0	2	(1	-3.50	1.84)
	1	19.45				(0.54)	(0.80)
	2	6.8					
I	0	46.09	1, 1	2	(1	1.156	-3.95)
	1	19.62				(0.60)	(0.90)
	2	5.07					
PA	0	48.26	2, 1	3	(1	-1.47	-0.56)
	1	21.03				(0.72)	(1.08)
	2	8.96					
PG	0	83.56	2, 2	1	(1	-1.10	-0.26)
	1	27.99				(0.40)	(0.60)
	2	6.20					
N	0	33.42	0, 0	2	(1	-0.87	-1.14)
	1	7.58				(0.25)	(0.33)
	2	2.95					
N_y	0	20.87	0, 0	3	(1	-2.23	0.47)
	1	6.48				(0.77)	(1.00)
	2	2.91					

Table 5.2: Critical values of the trace-test

Critical values	90 %	95 %	99 %
r=0	32.25	35.07	40.78
r=1	17.98	20.16	24.69
r=2	7.6	9.14	12.53

Table 5.3: The semi-endogenous model (S2S approach)

Model	Wald test	p-value	Lags (levels)	Cointegrating vector
Q as L				
R	11.2	0.001	2	(1 0 -4.35)
				(0.33)
R/A	11.2	0.001	2	(1 0 -3.35)
				(0.33)
I	4.3	0.037	2	(1 0 -2.29)
				(0.11)
PA	193.9	0.000	2	(1 0 -1.32)
				(0.07)
PG	8.4	0.004	2	(1 0 -1.90)
				(0.08)
N	38.7	0.000	3	(1 0 -2.45)
				(0.05)
N_y	30.8	0.000	2	(1 0 -2.70)
				(0.15)
Q as Y				
R	57.7	0.000	2	(1 0 -4.39)
				(0.16)
R/A	42.7	0.000	2	(1 0 -3.39)
				(0.16)
I	3.7	0.055	2	(1 0 -2.32)
				(0.11)
PA	4.2	0.042	3	(1 0 -1.45)
				(0.12)
PG	7.7	0.006	1	(1 0 -1.88)
				(0.08)
N	12.0	0.001	2	(1 0 -2.27)
				(0.05)
N_y	8.4	0.004	3	(1 0 -2.50)
				(0.15)

Table 5.4: The Schumpeterian model (S2S approach)

Model	Wald test	p-value	Lags
Q as L			
R	11.26	0.0036	2
R/A	11.60	0.0030	2
I	422.44	0.0000	2
PA	2174.99	0.0000	2
PG	704.80	0.0000	2
N	3808.87	0.0000	3
N_y	34.72	0.0000	2
Q as Y			
R	579.82	0.0000	2
R/A	263.43	0.0000	2
I	59.40	0.0000	2
PA	1.40	0.4961	3
PG	30.04	0.0000	1
N	491.85	0.0000	2
N_y	63.15	0.0000	3

Chapter 6

Conclusions

This study aims at answering the question: Has R&D had an effect on Finnish productivity growth already since the 1950's? The question is relevant since Finland has experienced high TFP growth for decades, but only the growth during the ICT -era has been studied from the point of view of R&D.

Our results show that Finnish TFP growth has followed a framework suggested by R&D-based growth theories. Contradictory to many recent studies, the semi-endogenous growth model fits better the Finnish data than the Schumpeterian model. Thus is seems that for the Finnish case, increasing R&D input is needed to sustain a constant growth rate of TFP.

The Schumpeterian model implies that a constant level of R&D *intensity*, the idea that as the economy grows, R&D input is diluted to a larger number of sectors, generates constant growth in steady state. In steady state the constant level of R&D intensity is obtained by having R&D input and product variety growing in lockstep. This assumption is clearly rejected in this study, but are unable to reject the hypothesis that product variety has some kind of role.

One might therefore think that a simple and evident extension of this work would be to estimate the Schumpeterian model outside its steady state, so that R&D input and product proliferation are not assumed to grow strictly proportionately.

However, the underlying theoretical articles do not support this idea, instead the usual assumption of a steady long-run growth rate implying a balanced growth path, is taken as given. Also having strong evidence for the semi-endogenous model undermines the relevance of this task.

A benefit of the semi-endogenous model is that it provides an explanation to the possibility that Finnish growth has not been on a balanced growth path throughout the whole time span of the study. We have a reason to assume so, due to extreme depression in early 90's. Therefore, the result obtained could also mean that the semi-endogenous model does hold but that the economy has been on a "constant growth path" as suggested by Jones (2002).

We will thus conclude that whether or not the economy was on a balanced growth path during the timespan of the study, the semi-endogenous model fits the Finnish data better than the Schumpeterian model.

Our results of the models are formally comparable since they are estimated as nested models. Therefore an important and useful extension to the empirical literature of R&D-based endogenous growth would be to update the previous research conducted on the U.S., OECD, etc, with this statistically sophisticated framework.

Our dataset is collected and combined from various resources and has a longer time span than many other studies of Finnish productivity. Useful results could be obtained if a measure of human capital was added to the dataset. Also, if one day the historical trade statistics will be available on a digital form, it could be interesting to construct a more complex measure of high technology imports. A sectoral study with this time span would shed more light on how R&D exactly affects growth, and it would be interesting to find out which sectors in the economy have benefited most from R&D in productivity terms throughout the decades.

Finally, since Finland has benefited from R&D before being in the world technology frontier, it could be interesting to study whether or not these type of growth models, with R&D input being both domestic and foreign, are relevant in countries that are currently lagging behind.

Appendix A

Empirical Variables

List of empirical variables. All estimations are done with logaritmized variables.

Variable	Description
L	Labour (hours worked in the economy excluding housing sector)
Y	GDP (excluding housing sector) (real)
A	Total factor productivity, index (TFP)
R&D input variables	
R	R&D expenditures (real)
R/A	Productivity adjusted R&D expenditures (real)
I	High technology imports (real)
PA	Number of patent applications
PG	Number of patent grants
N	Number of R&D workers
N_y	Number of R&D person-years
Variables indicating R&D intensity	
$R/L, R/AL, I/L, PA/L, PG/L, N/L$ and N_y/L	
$R/Y, R/AY, I/Y, PA/Y, PG/Y, N/Y$ and N_y/Y	

Appendix B

Unit Root Tests

Table B.1: Unit root tests

Variable	A	L	Y
model	drift & trend	drift	drift & trend
Lags (differences)	1	2	1
ADF test statistic	-2.38	-1.65	-2.48
Residual diagnostics:			
Portmonteau test (2 lags)	0.33	0.31	1.51
p-value	0.85	0.86	0.47
ARCH-LM test (2 lags)	5.69	3.01	3.22
p-value	0.06	0.22	0.20
Jarque-Bera test	3.60	4.98	2.66
p-value	0.16	0.08	0.26
Critical values	1 %	5 %	10 %
Model with drift	-3.43	-2.86	-2.57
Model with drift & trend	-3.96	-3.41	-3.13

Critical values are from Davidson & MacKinnon (1993, p. 708).

Appendix C

Residual Diagnostics

The test for autocorrelation is Breusch-Godfrey LM test by Breusch (1978), Godfrey (1978) and reviewed by Godfrey (1988). Test for non-normality is from Lütkepohl (1993, p.153). Heteroscedasticity tests is a multivariate ARCH-LM test by Doornik & Hendry (1997, Sec. 10.9.2.4).

Table C.1: Residuals of the VAR model

	Autocorrelation		Normality		Heteroscedasticity	
Model	test statistic	p-value	test statistic	p-value	test statistic	p-value
Q as L						
R	14.08	0.12	10.21	0.12	19.03	0.99
R/A	14.08	0.12	8.01	0.24	19.03	0.99
I	11.59	0.24	11.25	0.08	40.23	0.29
PA	5.41	0.80	45.36	0.00	53.80	0.03
PG	7.12	0.62	49.60	0.00	46.30	0.12
N	25.38	0.00	3.44	0.75	31.84	0.67
N_y	16.32	0.06	9.19	0.16	18.81	0.99
Q as Y						
R	11.51	0.24	7.39	0.29	26.31	0.88
R/A	11.51	0.24	5.84	0.44	26.31	0.88
I	6.30	0.71	37.83	0.00	33.31	0.60
PA	12.81	0.17	36.42	0.00	39.12	0.33
PG	14.54	0.10	49.02	0.00	51.36	0.05
N	8.67	0.47	26.46	0.00	41.07	0.26
N_y	7.75	0.56	26.42	0.00	20.03	0.99

Table C.2: Residuals of the unrestricted model (Johansen approach)

	Autocorrelation		Normality		Heteroscedasticity	
Model	test statistic	p-value	test statistic	p-value	test statistic	p-value
Q as L						
R	12.96	0.16	16.48	0.01	23.64	0.94
R/A	12.96	0.16	14.12	0.03	23.64	0.94
I	14.15	0.12	7.36	0.29	42.42	0.21
PA	5.31	0.81	41.28	0.00	53.10	0.03
PG	12.59	0.18	55.87	0.00	54.00	0.03
N	15.10	0.09	8.42	0.21	42.74	0.20
N_y	12.34	0.20	9.49	0.15	26.15	0.89
Q as Y						
R	13.55	0.14	6.07	0.42	32.91	0.62
R/A	13.55	0.14	3.07	0.80	32.91	0.62
I	13.88	0.13	17.76	0.01	40.67	0.27
PA	7.48	0.59	99.50	0.00	32.80	0.62
PG	17.37	0.04	44.66	0.00	64.76	0.00
N	9.03	0.43	19.99	0.00	43.54	0.18
N_y	18.06	0.03	5.93	0.43	32.52	0.63

Table C.3: Residuals of the semi-endogenous model

	Autocorrelation		Normality		Heteroscedasticity	
Model	test statistic	p-value	test statistic	p-value	test statistic	p-value
Q as L						
R	9.23	0.42	9.85	0.13	26.78	0.87
R/A	9.23	0.42	7.32	0.29	26.78	0.87
I	4.08	0.91	7.36	0.29	42.51	0.21
PA	1.22	0.99	11.18	0.08	75.39	0.00
PG	5.19	0.82	36.99	0.00	50.14	0.06
N	6.75	0.66	13.17	0.04	28.62	0.80
N_y	25.79	0.00	16.01	0.01	16.14	0.99
Q as Y						
R	6.46	0.69	4.56	0.60	38.27	0.37
R/A	6.46	0.69	3.70	0.72	38.27	0.37
I	33.69	0.00	35.16	0.00	34.08	0.56
PA	4.75	0.86	69.81	0.00	33.69	0.58
PG	6.74	0.66	26.85	0.00	61.33	0.01
N	3.20	0.96	24.01	0.00	38.28	0.37
N_y	11.69	0.23	12.22	0.06	34.05	0.56

Table C.4: Residuals of the Schumpeterian model

	Autocorrelation		Normality		Heteroscedasticity	
Model	test statistic	p-value	test statistic	p-value	test statistic	p-value
Q as L						
R	987.2	0.00	5.11	0.53	29.11	0.79
R/A	987.2	0.00	5.11	0.53	29.11	0.79
I	11430.9	0.00	13.85	0.03	44.83	0.15
PA	542.7	0.00	14.28	0.03	72.20	0.00
PG	23431.9	0.00	13.99	0.03	52.80	0.04
N	12023.6	0.00	6.82	0.34	51.72	0.04
N_y	6480.2	0.00	8.26	0.22	39.58	0.31
Q as Y						
R	334.5	0.00	8.14	0.23	60.59	0.01
R/A	83.9	0.00	2.38	0.88	53.17	0.03
I	403.0	0.00	10.79	0.10	38.41	0.36
PA	2.7	0.98	95.28	0.00	31.36	0.69
PG	50.2	0.00	26.83	0.00	63.63	0.00
N	1358.8	0.00	3.85	0.70	49.48	0.07
N_y	56.3	0.00	25.95	0.00	38.20	0.37

Appendix D

SITC-classifications

The SITC-classifications used for high technology imports, I.

- **2002–2008 SITC Revision 4**

  54 Medicinal and pharmaceutical products

  71 Power-generating machinery and equipment

  73 Metalworking machinery

  75 Office machines and automatic data-processing machines

  76 Telecommunications and sound-recording and reproducing apparatus and equipment

  77 Electrical machinery, apparatus and appliances, n.e.s., and electrical parts thereof (including non-electrical counterparts, n.e.s., of electrical household-type equipment)

  79 Other transport equipment

  87 Professional, scientific and controlling instruments and apparatus, n.e.s.

  88 Photographic apparatus, equipment and supplies and optical goods, n.e.s.; watches and clocks

- **1986–2001 SITC Revision 3**

  54 Medicinal and pharmaceutical products

71 Power generating machinery and equipment

73 Metal working machinery

75 Office machines and automatic data processing machines

76 Telecommunications and sound recording and reproducing apparatus and equipment

77 Electrical machinery, apparatus and appliances, n.e.s., and electrical parts thereof (including non-electrical counterparts, n.e.s., of electrical household type equipment)

79 Other transport equipment

87 Professional, scientific and controlling instruments and apparatus, n.e.s.

88 Photographic apparatus, equipment and supplies and optical goods, n.e.s.; watches and clocks

- **1976–1985 SITC Revision 2**

54 Medicinal and pharmaceutical products

71 Power generating machinery and equipment

73 Metalworking machinery

75 Office machines and automatic data processing equipment

76 Telecommunications and sound recording and reproducing apparatus and equipment

77 Electrical machinery, apparatus and appliances, n.e.s., and electrical parts thereof (including non-electrical counterparts, n.e.s., of electrical household type equipment)

79 Other transport equipment

87 Professional, scientific and controlling instruments and apparatus, n.e.s.

88 Photographic apparatus, equipment and supplies and optical goods, n.e.s.; watches and clocks

- **1962–1975 SITC Revised**

54 Medicinal and pharmaceutical products

72 Electrical machinery, apparatus and appliances

73 Transport equipment

86 Professional, scientific and controlling instruments, photographic and optical goods, watches and clocks

- **1955–1961 SITC (Original)**

511 Inorganic chemicals

713 Tractors other than steam

721 Electric machinery, apparatus and appliances

732 Road motor vehicles

734 Aircraft

735 Ships and boats

861 Scientific, medical, optical, measuring and controlling instruments and apparatus

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