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- Master thesis -

**R&D and productivity: A firm level investigation of
the Norwegian manufacturing industry**

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TABLE OF CONTENTS

TABLE OF CONTENTS.....	I
PREFACE.....	II
ABSTRACT.....	III
1. INTRODUCTION.....	1
2. THEORETICAL FRAMEWORK.....	3
2.1 ENDOGENOUS GROWTH THEORY: TECHNICAL PROGRESS AND SPILLOVERS.....	3
2.2 MICROECONOMIC FOUNDATIONS OF THE ENDOGENOUS GROWTH MODEL.....	8
3. EMPIRICAL STUDIES AND RESULTS.....	12
3.1 THE DIRECT EFFECT OF R&D INVESTMENTS.....	12
3.2 THE SPILLOVER EFFECT.....	15
4. METHOD AND APPROACH.....	18
5. EMPIRICAL STRATEGY.....	19
5.1 MODEL ESTIMATION.....	20
5.2 DATA CONSTRUCT.....	21
5.3 CONSTRUCT OF VARIABLES.....	24
5.4 DESCRIPTIVE STATISTICS.....	27
5.5 EMPIRICAL RESULTS.....	31
5.6 ROBUSTNESS TESTS AND GRANGER CAUSALITY.....	38
6. CONCLUSION.....	40
7. POTENTIAL SHORT-COMINGS.....	41
REFERENCES.....	45
APPENDIX 1.....	51
APPENDIX 2.....	52
APPENDIX 3.....	53
APPENDIX 4.....	54
PRELIMINARY THESIS REPORT.....	56

Preface

The overall goal of this thesis is to perform an in-depth study on an economical topic of interest, where we are given an opportunity to apply our accumulated knowledge in a scientific research setting. We chose to investigate the topic of investment in R&D, and whether it leads to growth in firm productivity. The research work for the thesis has been very challenging, and consequently we have learned much, both in terms of underlying economic theories and empirical research on the topic. We want to thank our supervisor Espen R. Moen for good assistance, suggestions and inspiration during the work.

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Abstract

For centuries researchers have grappled with the question: What drives technological progress which in turn powers the all important aggregated growth of the economy? We argue that this question is interesting because it lies at the centre of the endogenous growth theory, which stresses the role of the R&D investments rate as the foremost determinant for productivity growth rates. By utilising the well-known Cobb-Douglas production function we empirically test and quantify the role of R&D investment in a Norwegian manufacturing industry setting. Our firm-level findings lend support to the endogenous growth theory claim, of both a direct and an indirect R&D effect on firms' productivity growth rates.

1. Introduction

In recent years the world economy has experienced a period of high economic prosperity, caused by sustained and increasing productivity growth rates. However, these growth rates have not always been on the rise as was evident under the economical slowdown in the 1970's. In the early 1980's a 'new' growth theory emerged in the wake of empirical research trying to explain these downward movements in the growth rate. This so-called 'endogenous growth' theory builds on the original 'neoclassical growth' model, developed by Solow (1956) and Swan (1956), and stresses the important role of technical change as the engine behind productivity growth. However, the 'new' growth theory deviates from the neoclassical growth theory when it comes to providing an actual explanation for growth. While the neoclassical growth theory defines technical progress as an unexplainable phenomenon, the endogenous growth theory treats the technical progress variable as endogenous, making it in effect dependent on different determinants within the model. Hence, it provides the 'social planner' and agents in the market with an instrument to better understand which economical parameters in the economy that influence growth through the technical progress variable, and how they should manage these economical parameters effectively and optimally.

The endogenous growth model proposes two novel ideas in the growth debate, namely that technical progress is caused by deliberate action taken by different agents in the economy, and that significant technological spillovers occur between different entities in the aggregated economy. Or in other words; technical progress is no longer unexplainable, and there is a difference between the social incentive and private incentive to invest in the technology process due to the presence of externalities in the marketplace. These externalities distort the mechanism of the market, and call for possible governmental intervention in order to ensure a more stable market solution where the social surplus is optimised. Hence, it would be of great interest to measure and quantify this technological spillover effect in an empirical study.

In our empirical paper we will test the following research question: “*Can productivity growth rates in Norway be accounted for by an endogenous growth model, where technical progress is driven by both direct R&D investments and technological spillovers?*” The research question will be tested on an extended Cobb-Douglas production function, augmented with both a direct and an indirect R&D variable, for firms operating in three different sectors of the Norwegian manufacturing industry. The parameters of interest in this analysis will be the output elasticities with respect to the direct and indirect R&D variables, as these variables represent key input factors in a firm’s technical progress¹ (Higón, 2007). These two input variables will be constructed using firms’ individual investments in R&D, since these R&D values are readily available in our data set and comparable with a vast body of empirical studies on the topic.

Besides testing the research question we will also elaborate on the incentives for firms to innovate, and how the social planner can induce the private sector to invest in R&D. These questions are highly relevant in the debate connected to the endogenous growth theory as spillover externalities arguably create a mismatch between the social and private optimal level of R&D investments. Hence, we argue there is scope for the ‘social planner’ to take a more active role in the market and correct for externalities if we are able to detect the presence of spillovers in our model.

The structure of the thesis will be as follows. In section 2 we will cover theories relevant for this paper, starting with a review of the endogenous growth theory, focusing on technical progress and technological spillovers in particular. This section will be two-folded, with an opening part (section 2.1) covering the relevant macroeconomic theory in question, and with a second part (section 2.2) giving a theoretical discussion of the relevant microeconomic theory underpinning the endogenous growth theory. In section 3 we will present results from relevant empirical studies and conduct a literature review.

¹ Although the relationship between R&D and innovation is complex and non-linear, it is clear that substantial advances in technology cannot occur without work undertaken on a systematic basis, and R&D is therefore regarded as a good indicator of this broader phenomenon.

In section 4 we will focus on the methodological approach we intend to take in our empirical analysis. In section 5 we will turn to our actual model of estimation. In this part we will also elaborate on our model and our dataset, and perform different econometrical tests such as; Unit root tests and a Granger causality test. In section 6 we will conclude our paper, before we in section 7 give a short explanation of the potential short-comings of our model and paper.

2. Theoretical framework

In the quest to infer a relationship between R&D spending and productivity growth rates, researchers have in recent years turned to the endogenous growth theory in the search for answers. With its' appealing explanation for the long-run growth rate it provides the researcher with a theoretical framework which stresses the role of R&D investments as the chief determinant for technical progress. In order to fully utilise this framework we will first cover the macroeconomic implication of the endogenous growth theory, before we in the following subsection will turn to the microeconomic foundation of this theory, and its' implied implications for the social planner.

2.1 Endogenous growth theory: technical progress and spillovers

In the macroeconomic literature practitioners are concerned with two overarching aspects of the economy, namely the long-run and short-run phenomena. The former is the study of long-run trend levels in the economy, while the latter focuses on short-run fluctuations in the economy, namely the study of 'Business cycles'. Thus, macroeconomic theories for the long-run intend to explain trend-wise movements of main economic variables, assuming no nominal rigidities in the long-run. That is; wages and prices are fully adjusted in all periods, and the long-run (steady state) equilibrium values can be studied in isolation. Macroeconomic theory for the short-run, on the other hand, is about understanding cyclical fluctuations in chief economic variables (Sørensen and Whitta-Jacobsen, 2005). It is therefore important to utilise the appropriate macroeconomic theory depending on the specific timeframe of our

investigation. Since growth modelling is about depicting the long-run trend levels of the economy, we will in our paper be using long-run macroeconomic theories.

When analysing long-run macroeconomic growth theories one comes across two distinct camps of thought. On one side you have the strand of practitioners who embrace the general Solow model - which states that steady exogenous technological progress is the root of positive long-run growth in GDP per person (Solow, 1956). This so-called ‘exogenous growth’ model² is quite successful in accounting for many important aspect of economical growth. However, it has one major short-coming, namely that it treats the rate of technological change as exogenous; a variable determined outside the model which movements are ‘unexplainable’. This obvious limitation with the traditional growth theory has in recent years been attacked by several macroeconomic practitioners who have developed the endogenous growth theory in response (e.g. Romer, 1986; Lucas, 1988). In this new theoretical setup the rate of technological change is made dependent on basic model parameters such as; investment rates in physical and human capital³. By treating the rate of technical change as endogenous one can investigate the relationship between the determinants of technical change and long-run growth in isolation. This allows the social planner to better understand how he/she can implement economic policies that affect the basic model parameters, which in turn can create the desired long-run growth in income per capita. This is in fact the main advantage of the endogenous growth model as it creates a potential blueprint for policy-makers and business owners on how to maintain and increase current productivity growth rates through adjustments in R&D investment rates.

On the other hand, the main advantage of the endogenous growth model is also its’ main disadvantage, namely its’ fundamental dependency on a tangible

² Also referred to as the neoclassical growth model.

³ With R&D spending acting as the chief proxy for this parameter.

relationship between investment rates and productivity growth rates. If such a relationship is not detected in empirical studies then the foundation of the endogenous growth model will crumble. Empirical research on this matter have produced a variety of results, depending on location, time, and what parts of the economy the researcher studied (e.g. firm level, industry level, or country level). However, the majority of these studies have indeed found an enduring and statistical significant relationship between one of the most important determinants of technical change, namely R&D investment rates, and long-run growth rates in output (e.g. Bernanke and Gurkanyak, 2001; Cameron, 1998).

Conversely, critics of the endogenous growth theory argue that these supporting results might be plagued by the so-called ‘scale effect’, where the growth is in fact generated by increasing population growth rates. Under such circumstances the growth rate of the economy is better explained by the exogenous growth model rather than the endogenous growth model. What it eventually comes down to in the clash between the endogenous growth theory and the exogenous growth theory is a classical trade-off between a complicated model with superior explanatory power, and a simple model with less explanatory power, but which is easier to reconcile with historical data. The same empirical results can also be flawed if they only pick up the transitory relationship of variables converging towards their steady state values. Thus, a time series study with a short time interval will have difficulties in estimating the actual long-run relationship between the measured variables, and will as a consequence only pick up the transitory effect. These are only two examples found in the growth literature of why the relationship between the determinant of technical progress (i.e. R&D investments) and productivity growth rates is so hard to measure (Sørensen and Whitta-Jacobsen, 2005).

The endogenous growth model relies on two important assumptions. Firstly, it assumes that technical changes are created by investments steaming from explicit decisions made by different agents in the economy. Secondly, it assumes that there exist significant externalities (i.e. technology spillovers) within the economy, meaning that the technology producer is not the only one

who benefits from his/hers R&D efforts. The former assumption specifies that technical progress does not come about by chance, but is indeed the result of a conscious business decision. Hence, firms invest in R&D because they expect to obtain some form of returns. However, it is worth noting that this is not a new observation associated only with the endogenous growth model, but has been articulated many times before by economists such as Griliches (1958, and 1964) and Mansfield (1968). The latter assumption is a highly powerful assumption and rather distinct to the endogenous growth theory, as it lays the foundation for the existence of a spillover effect in the aggregated economy. This means that the economy as a whole may face increasing return to scale even if we were to impose the traditional restriction of homogenous outputs and inputs, and constant return to scale on a firm level. We can in other words observe a positive difference between social returns and private returns of R&D (see Appendix 1 for a graphical illustration).

In the time after the original endogenous growth model was first created, new augmented endogenous growth models have emerged with the works by Romer (1990) and Grossman and Helpman, (1991a). These augmented models relax the perfect competition assumption, and leave open the possibility of increasing return to scale on a firm level as well as on the aggregated level. In these models the R&D variable is treated as having two kinds of outputs. On one hand you have general knowledge, which is non-appropriable, and free to spillover from one firm to another. On the other hand you have the rent from the development of blueprints for new products, which is fully appropriable. It is this latter form of output value that acts as a 'direct' incentive instrument for firms to innovate and invest in R&D. This is because it introduces differentiated products into the market setting, which means we are no longer dealing with a perfect competitive market, but rather allow for some degree of monopolistic power within the market structure (i.e. there is profit to be earned). Therefore, we may in these augmented endogenous growth models have increasing return to scale, not only at an aggregated level, but also on a firm level.

In the growth literature and empirical studies the extended Cobb-Douglas production function is used extensively to test the endogenous growth theory, and its' implied spillover effect. As we are interested in both the direct and indirect relationship between R&D and output, we have chosen to utilise this extended Cobb-Douglas production function suggested by Griliches (1990), Romer (1990), and Los and Verspagen (2000):

$$(1) \quad Q_{it} = A F(\sum_j R_{jt}) K_{it}^\alpha L_{it}^\beta R_{it}^\gamma$$

where Q, K, L, and R represent firm i's; output, physical capital input, labour input, and technological capital input in time period t, respectively. $F(\cdot)$ is a function that represents the economy wide technology capital, while A represents a constant. In empirical studies the preferred measure of output is the 'value added' variable as this includes intermediate inputs. However, most studies have been forced to use sales as a measure of output, which is a cruder form of measure. We will in our model use firms' operating income as our dependent variable. This variable is closely related to the sales variable, and includes both income from sales and income from other operating activities. The choice of the direct technological capital input variable will be firms' individual R&D stock⁴. The indirect stock variable will be constructed by aggregating and weighting other firms' R&D stocks.

The reason why we have chosen to adopt this extended Cobb-Douglas production function in our analysis is because of its' direct link to traditional microeconomic and macroeconomic theories which gives it a robust design, high explanatory power, and with the desired degree of comparability to many past studies and models. However, its' simple design makes it vulnerable for missing out on many potentially important explanatory variables such as; international technological spillovers, firm size, and firm liquidity. These variables could potentially explain the actual relationship better. Nevertheless, by including all possible variables we run into the problem of not being able to

⁴ An extensive explanation for the construct of the R&D stock will be given in section 5.3.

interpret our results, and move far away from the macroeconomic theory we are investigating. The extended Cobb-Douglas production function also lacks dynamic interaction functionality, such as those typically found in VAR models, where all variables are treated as endogenous within a recursive system of interaction. This type of approach is more common in *Business cycle* analysis, and is therefore not included in our model as we want to measure the long-run relationship between our variables in question, and not necessarily their short-run interactions.

2.2 Microeconomic foundations of the endogenous growth model

In order to fully understand why profit-motivated firms engage in R&D it is important to investigate the microeconomic foundations underpinning the endogenous growth theory. This is important for two reasons. Firstly, since the model and data we have adopted is based on a firm (micro) level, it would be of great interest to investigate firms' individual reasoning for undertaking R&D. Secondly, if a spillover effect is indeed detected in the data then the endogenous growth theory states that in most cases the social surplus from investing in R&D will be larger than the private sector surplus from investing in R&D (see Appendix 1 for an graphical illustration). It is therefore of great interest to study why firms tend to underinvest in R&D, and how the social planner can induce these agents to invest in R&D at the socially optimal level⁵.

One of the key features of augmented endogenous growth models is its' relaxation of the perfect competition assumption (e.g. Romer, 1990; Grossman and Helpman, 1991a). With such a market structure the different 'profit maximising' agents will compete with each other in order to create or secure a market advantage (Scotchmer, 2004). Their main incentive to invest in R&D is therefore to create a competitive advantage in the market place which fulfils their ultimate goal of increased profit shares (Porter, 1985). In the augmented endogenous growth models intellectual property rights are believed to create

⁵ In this paper the government is considered to be the social planner, which is a social welfare maximising agency who controls all the firms in the economy (Nishimura, 1992).

monopoly power which leaves open the possibility of increasing return to scale on the firm level. Notice that this will create a situation where the market equilibrium will differ from the socially optimal solution associated with the perfect competition equilibrium- where the market price equals aggregated marginal costs. The social planner is locked into a complicated situation where one must give up the efficient market solution (perfect competition and no deadweight loss), and implement intellectual property rights in order to induce firms to engage in R&D. The social planner might just be forced to accept this trade-off as a 'necessary evil', since firms in a perfect competition market setting cannot appropriate the rent from their own innovation, and are therefore quite unwilling to invest in R&D because its 'public good' characteristic⁶. Firms will only invest in R&D when they are able to leverage on future profit streams in order to cover R&D expenses and fixed costs that occur at the research level.

In the endogenous growth literature technological spillovers are usually referred to as knowledge spillover. However, notice that technological spillovers are in fact a combination of two different forms of spillovers, namely; knowledge spillover (also known as the 'standing on shoulders' externality), and rent spillover (also known as the 'surplus appropriability' externality). The first type of spillover captures the cost reduction for competitors due to knowledge leaks, free movement of labour force, and imperfect patenting. Firms are, as a consequence, more reserved regarding investing in R&D since the innovating firm carries the full cost and risk associated with their R&D project, while the profit stream is shared with others. The second type of spillover, namely rent spillover, occurs because competitive pressure prevents the producer of an innovation to capture the whole price increase that results from the quality improvement in the new product relative to the old product. Thus, the innovator cannot appropriate the entire surplus from the innovation. In the endogenous growth theory the role of knowledge spillover is stressed as the most important form of externality and main reason for the resulting underinvestment in R&D. Rent spillover is

⁶ A 'public good' is non-rival and non-excludable good.

usually explained as mispricing in the market and is therefore given less significance within the model. However, it is inherently difficult to separate rent spillovers and knowledge spillovers and most empirical papers tend to generalise the two spillover effects as knowledge spillover as they both represent a general underinvestment in R&D. Notice that we in our paper make no attempt to separate rent and knowledge spillovers, and our empirical results may as a consequence overestimated technological spillovers, due to the presence of rent spillovers in our spillover measure.

The two forms of externalities associated with spillovers lead to underinvestment in R&D compared to the level which is socially optimal. However, there are two other types of externalities arising in the market setting which could also lead to inefficient levels of R&D investments from the social planner's point of view. These are referred to as; 'creative destruction' which can lead to overinvestment, and 'stepping on toes' which either lead to overinvestment if innovations are substitutes, or underinvestment if innovations are complements (Cameron, 1998). Out of these two forms of externalities the Schumpeterian 'creative destruction' has received the most attention. It simply says that future innovation will cause a negative externality on current innovations since the former replaces the latter. A process which according to Aghion and Howitt (1992) will lead to a situation where R&D intensive firms push other firms out of the market. Innovations are in such a context recognised as the source of temporary market power which can explain the dynamics of industrial change throughout the market lifecycle. However, these two externalities are outside the scope of our paper, as our main concern is to measure the spillover effect associated with the endogenous growth theory. They will only be only be used in comparison to our empirical results in section 5.6.

The government, as a social planner, can use several policy instruments to correct for spillover externalities and induce firms to engage in R&D. These can be implemented either ex-ante in terms of grants/awards, or ex-post in terms of patents. The grant/award system is designed such that the first firm

that completes a R&D project is given a fixed amount of money, and the innovation is then treated as a public good. The advantage of the award system is that it does not create a monopoly setting, and the firm gets a monetary compensation for their research effort and accumulated R&D costs. However, this instrument is difficult to implement and may lead to underinvestment in R&D, due to the threat of competition at the research level. Patents, on the other hand, are given to firms in order to prevent ‘copy cats’ or free-riders from taking advantage of the innovation at no or low costs. Consequently, the innovating company is given the opportunity to act as a monopolist and extract a profit share in order to cover the R&D and innovation costs. The government is in effect introducing property rights as a way to eliminate the externalities associated with underinvestment in R&D, by providing firms with the right set of incentives to invest⁷. However, a major short-coming with patents is that they will lead to an inefficient social solution if the monopolist is not able to perfectly price discriminate. This is because of the deadweight loss that arises in the monopolistic situation, which is regarded by the social planner as pure social waste. There is also an issue concerned with how profitable the patent should be. Too high rewards may induce too many firms to invest in R&D, which can create a potential profit-dissipating race. This so-called ‘patent race’ can be both inefficient and disadvantageous for the society if it leads to the pursuit of wrong ideas and duplication of both R&D costs and efforts (Scotchmer, 2004). On the other hand, a patent race may also be beneficial in terms of increasing the probability of success or the time of discovery. Nevertheless, the negative effect tends to dominate the positive effect in most instances (Tirole, 1988).

Another way for the government to correct for externalities is by offering tax relief and subsidies. Both a R&D tax relief and a R&D subsidy will reduce firms’ total costs and act as incentive devices for firms to maximise their profit, since cost minimising is a required necessity of this process. The Norwegian government’s establishment of ‘Skattefunn’ is an example of such a tax

⁷ The Coase Theorem states that if property rights can be assigned, bargaining between firms can achieve an efficient level of output.

scheme where firms that invest in R&D receive tax deductions. Patents, grants, prizes, tax reliefs and subsidies are all instruments available for the social planner to utilise in an effort to improve the incentives for firms to invest in R&D, with patents being the most prominent and most commonly used instrument in both Norway and other industrialised countries.

3. Empirical studies and results

In the empirical literature one finds a vast body of studies which have tried to measure both the spillover effect and direct effect of R&D investments on firms' productivity growth rates. As pointed out earlier, these studies have produced rather mixed results, influenced by different factors such as; the periods of investigation, data sources, number of economic units, measurement methods for R&D and economic performance, aggregation level, and country location of investigation. In section 3 we will first cover the literature concerned with the direct effect of R&D investments, before we the second part will investigate the empirical results linked to the spillover effect.

3.1 The direct effect of R&D investments

In the literature debate, concerning the actual relationship between the direct R&D variable and the productivity variable, there seems to have emerged a consensus in recent decades. The majority of studies have indeed found a

Table 1: Estimates of output elasticity of R&D

Author	Country	Level	Elasticity
Griliches (1986)	USA	Firm	0.09-0.11
Verspagen (1995)	USA	Industry	0.00-0.17
Srinivasan (1996)	USA	Industry	0.24-0.26
Bartelsman (1996)	<i>Netherland</i>	Firm	0.04-0.12
Mansfield (1988)	Japan	Industry	0.42
Nadiri-Prucha (1990)	Japan	Industry	0.27
Mairesse-Cuneo (1985)	France	Firm	0.09-0.26
Mairesse-Hall (1996)	France	Firm	0.00-0.17

Source: Cameron (1998), Griliches (1990), and Nidiri (1993)

positive and statistical significant relationship between these two variables on both a firm level and industry level. The positive output elasticities of R&D, depicted in table 1, show that the output elasticity with respect to the direct R&D variable has been found to be positive for most firms in all levels of the economy. In his literature review paper, Cameron (1998) goes as far as arguing that typically a 1 percent increase in the R&D capital stock leads to a rise in output of between 0.05 and 0.1 percent.

All the studies in table 1 have either utilised an extended Cobb-Douglas production function, Total factor productivity (TFP) function⁸, or a Complex functional forms model in order to estimate the output elasticity with respect to R&D. Alternately, other researchers have opted for a different approach and transformed the extended Cobb-Douglas production function into growth rates, with the R&D intensity (log R/L) included as the chief explanatory variable. With this growth rate approach the parameter belonging to R&D intensity yields the rate of return to knowledge, instead of the output elasticity with respect to the direct R&D stock. Griliches (1992) summarised a large bulk of these empirical studies and found that the estimated rate of return to lie between 0.2 and 0.34, with the most recent estimates falling in the lower part of this range. Notice that these estimates of the marginal productivity of “knowledge” are higher than the marginal productivity of other capital investments, with real stock market returns seldom venturing as high as 10 percent when averaged over several years (Scotchmer, 2004). Thus, one would expect rational agents to always choose R&D investments over other forms of capital investments. However, as it turns out, large degree of risk and uncertainty in the innovation process, as well as information asymmetries between R&D spenders and capital markets, tend to make R&D investments on average equally attractive as other forms of capital investments (Barfield et al, 2003).

⁸Where the stock of R&D capital is regressed on the the *level* of total factor productivity.

In empirical studies, conducted on a firm level, researchers have also found very different R&D output elasticities and rate of return estimates between different sectors of the economy. This is an important discovery as the results typically show that firms in high-tech industries experience higher growth rates as a result of their R&D investments, compared to firms in medium-tech and low-tech industries (e.g. Los and Verspagen, 2000; Barfield et. al, 2003). Such results are typically attributed to the common notion that the high-tech sector is considered to be a growth market where the market is far from saturated. Hence, one would expect to find higher average rate of returns for firms operating in these industries as compared to firms operating in other sectors of the manufacturing industry (Pepall et al, 2005). This claim will be tested extensively and debated in section 5.5.

Notice that these empirical results do face many critical voices in the literature, and not only from followers of the exogenous growth theory. According to a recent strand of researchers the results, depicted in table 1, are in fact highly questionable as the majority of the studies have chosen to utilise sales as the output variable instead of the more appropriate ‘value added’ variable. These authors argue that firms’ growth rates are in reality stochastic of nature and therefore unpredictable (e.g. Gerosky, 1999; Geroski et al, 1997).

Argumentation of this sort is to a large extent based on the well-known Gibrat’s law, which states that sales growth rates can only be explained as a random walk, and no explanatory variables, such as firm size, can be used to explain its’ movements. Thus, there is no purpose of regressing R&D stock on sales growth as one will only infer a spurious relationship. For example, Manganelli (2008) was unable to detect a relationship between the R&D variable and the sales variable when he analysed the determinants of R&D in the Norwegian economy. On the other hand, critics of the Gibrat’s law argue that this kind of argumentation is in fact highly flawed as there is a scope to search for other variables with stochastic trends that could explain the sales growth rates. According to the standard econometric framework for time-series; one can still infer a long-run relationship between the explanatory

variables and the dependent variables if the explanatory variables (K, L, and R) are also non-stationary and co-integrated with the non-stationary sales variable. Recent studies which have adopted this co-integration approach have indeed found long-run elasticities with respect to R&D investments to be even higher than those reported in table 1, thus discarding the Gibrat's law theory and confirming the previous findings (e.g. Del Monte and Papagni, 2002; Los and Verspagen, 2000; Cameron, 2003; Guellec and Van Pottelsberghe de la Potterie, 2004).

3.2 The spillover effect

In empirical literature knowledge spillovers are the source to much of the controversies surrounding the endogenous growth model. This is because knowledge spillovers are inherently difficult to measure as the well-known economist Paul Krugman (1991, p. 53) noted; "knowledge flows...are invisible; they leave little or no paper trail by which they may be measured and tracked, and there is nothing to prevent the theorist from assuming anything about them that she likes". Researchers who analyse the effects of spillovers have to rely on more or less crude proxy variables. As a result, empirical methods of measuring spillovers are necessarily somewhat indirect and open for discussion. In the literature the spillover effect has been measured on all levels of the economy, but with a special focus on the aggregated level and international spillovers in particular. Many of these studies have indeed found the presence of technological spillovers at an industry and country level⁹. For example, in their influential paper Coe and Helpman (1995) were able to detect significant international R&D spillovers in certain countries of the world economy, with output elasticities of the indirect R&D stock averaging between 0.05 and 0.12.

Measuring technological spillovers on a micro level, however, is more of a daunting task as the researcher is faced with different ways of measuring intra-

⁹ See Nadiri (1993) for a survey of estimation results.

industry spillovers. In the simplest form you have the crude measure of indirect R&D as an unweighted sum of the R&D stock of all other firms (e.g. Bernstein and Nadiri, 1989). This method however will introduce a spillover effect which varies little between different firms, and which in practice acts as a common constant parameter for all firms in the model. Many researcher, including Jaffe (1986), Wolff and Nadiri (1993), and Putman and Evenson (1994) have questioned this way of measuring indirect R&D, and rather proposed a weighted system with the indirect R&D flow measured according to the following formula:

$$(2) \quad IR_i(t) = \sum_j \omega_{ij} R_j(t)$$

where the indirect R&D expenditure variable is defined as the aggregated weighted sum of other firms' R&D stock relevant for firm *i*. The weights are determined based on different weighting schemes such as; input-output matrixes, capital flow matrixes, patent matrixes and patent citation matrixes.

The different schemes all have different pros and cons, with the patent matrixes representing the 'purest' form of knowledge spillover. This is because it involves no transactions of commodities and financial goods, thus taking rent spillovers out of the picture (Jaffe, Trjatenberg and Henderson, 1993). On the other hand, critics of this method argue that patent data is inherently difficult to utilise in an empirical investigation due to the deficiency of detailed information (Wolf and Nadiri, 1993). Instead, two alternative methods are proposed, namely the input-output and the capital flow matrix scheme, as they will arguably give a better representation of the true patterns of interaction between different industries. Based on these patterns one can infer the relevant weights for indirect R&D. However, the downside of this last method is that it includes rent spillovers, and will therefore not provide a true measure of 'pure' knowledge spillovers (Coe and Helpman, 1995). By testing these various weighting schemes Los and Verspagen (2000) found elasticities of output with respect to the indirect R&D stock to fall within the range of 0.2 to 0.6,

Table 2: Estimates of the Rate of Return to indirect R&D

Author	Country	Level	User matrix	Indirect rate of return
Scherer (1986, 1984)	USA	Industry	Patents	0.64-1.47
Griliches-Lichtenberg (1983)	USA	Industry	Patents	0.41-0.62
Bernstein-Nidiri (1988)	USA	Industry	Intermediate inputs	0.11-1.11
Wolff-Nadiri (1993)	USA	Industry	Intermediate inputs	0-10-0.90
Bernstein (1989)	Canada	Industry	Intermediate inputs	0.29-0.94
Goto-Suzuki (1989)	Japan	Industry	Intermediate inputs	0.8
Sterlacchini (1989)	UK	Industry	Inovation flow	0.15-0.35

Source: Cameron (1998)

depending on which method used. In table 2 the estimated indirect rates of return to R&D are presented, taken from studies that have attempted to measure R&D spillovers with models specified in growth rates. The results of these studies, whether using patent matrices or input/output tables to weight imported R&D, suggest that spillovers are indeed pervasive and significant in countries such as the USA, Canada, Japan, and the UK (Cameron, 1998). They also depict very clearly that the indirect rate of return to R&D is higher than the direct rate of return to R&D, with the latter as mentioned earlier, ranging somewhere between 0.2 and 0.34. These results highlight an important finding, namely that the social return to R&D (both the direct and indirect rate of return added together) is larger than the private return to R&D. For example, Jones and Williams (1997) found that the optimal amount to invest in R&D is about four times the actual amount invested by the USA. In a European setting the number is found to average somewhat lower than in the USA (Cameron, 1998).

In recent years a new method of constructing the indirect R&D stock has gained popularity in the endogenous growth literature. This so-called ‘Similarity spillover’ method combines the traditional weighting schemes, which focus on similarities in the technological dimension with geographical weighting schemes, which focus on similarities in the geographical dimension (Costa and Izessi, 2005). By combining the two dimensions one gets a richer measure of spillovers than what has been previously available. The new geographical dimension builds on the broadly accepted theoretical assumption that; spatial agglomeration is positively correlated to diffusion of technology

(Marshall, 1920; Arrow, 1962; Jacobs, 1969; Romer, 1986). However, this cluster argument has not been widely tested in an endogenous growth setting (see Aiello and Cardamone, 2006), and to the best of the authors' knowledge totally disregarded by all the existing papers analysing the impact of R&D spillovers in Norway. We will in our paper focus on the geographical dimension of spillovers and adopt a framework of measuring these spillovers, using an exponential decaying weighting function found in a paper by Verspagen (2007). We want to test and quantify the hypothesis that the closer two firms are, the more they will mutually benefit from each others' R&D investments, and thus confirming the existence of a spillover effect. We will in our paper use a spatial weighting scheme based on the great circle distance. The distance we consider is between the administrative cities of the counties where each firm is located. The results obtained can then be compared to other weighting schemes, and also be used to shed some light on the cluster argumentation in an endogenous growth theory context.

4. Method and Approach

In our paper we will be taking an empirical approach to the investigation. The extended Cobb-Douglas model, accounting for both the direct and indirect effect of R&D, will be estimated using two different data sources. The main source of data is the CCGR (Centre for Corporate Governance Research) database. This is an unbalanced panel data set containing accounting data for Norwegian enterprises, spanning from 1994 to 2007. A supplementary data source is the Norwegian Road Authorities' distance table, which contains the physical distance between Norwegian administrative cities. The CCGR panel dataset lays the foundation for our actual calculation of the output elasticity for labour, physical capital, and direct R&D stock. The second sources will enable us to construct the indirect R&D variable in a combination with the CCGR data set. The focus in our investigation will be on firms operating in the manufacturing industry, as this sector of the economy is better represented by a Cobb-Douglas production function, and because product innovations are more important in this sector compared to the service sector. A further assignment of

manufacturing firms into three different sub-groups will be performed (denoted; high-tech sector, medium-tech sector, and low-tech sector) in an effort to identify the differences between these three sectors (see Appendix 2 for the OECD classification of different sectors). This is a useful operation to perform as it allows us to investigate the results from previous empirical studies, which found a stronger relationship between the direct R&D variable and the output variable for firms operating in the high-tech sector than for firms operating in the low-tech sector.

The starting point of our empirical regression analysis will be to run a standard pooled OLS regression on our model. The regression output will then be tested for heteroskedasticity and serial correlation in order to determine the most efficient and optimal regression method. If heteroskedasticity and serial correlation are indeed detected in the regression output, two different instruments will be implemented in order to reduce the problem of underestimated standard errors. Firstly, we will apply a Newey-West estimator to improve the pooled OLS regression statistics, designed to correct for both heteroskedasticity and serial correlation. Secondly, we will implement a set of dummy variables in order to reduce the problem of heteroskedasticity in particular. We will end our empirical strategy section by checking for spurious correlation and testing for causality in the relationship between the productivity variable and the direct R&D variable. All econometrical test and regression calculations will be performed with the Eviews 6 software package.

5. Empirical strategy

The overarching objective of this paper is to test if labour productivity for firms in the Norwegian manufacturing industries is endogenous of nature. That is, we want to investigate whether R&D investments, as a main driver of technological progress, are indeed responsible for productivity growth rates.

5.1 Model of estimation

The empirical analysis will be centred on the extended Cobb-Douglas function outlined in the paper by Los and Verspagen (2000):

$$(3) \quad Q_{it} = A F(IR)_{it}^{\eta} K_{it}^{\alpha} L_{it}^{\beta} R_{it}^{\gamma}$$

We choose to take the logarithm of this function in order to obtain a model where the respective elasticities of output can be calculated:

$$(4) \quad q_{it} = a + \eta(ir)_{it} + \alpha k_{it} + \beta l_{it} + \gamma r_{it} + \varepsilon_{it}$$

Notice that we do not restrict our model to the homogenous assumption of constant return to scale for all direct input factors ($\alpha + \beta + \gamma = 1$), but rather let the regression results indicate their actual values. This is a common approach in empirical studies since researchers are interested in depicting ‘actual’ relations and patterns in the historical data, not being restricted by a theoretical model à priori. The next step is to normalise equation (4) in order to reduce the problem of heteroskedasticity and multicollinearity, and to specify our equation in a labour-intensive form:

$$(5) \quad (q_{it} - l_{it}) = a + \eta(ir)_{it} + \alpha(k_{it} - l_{it}) + \gamma(r_{it} - l_{it}) + (\mu - 1)l_{it} + \varepsilon_{it}$$

where μ , the return to scale parameter with respect to all firm specific inputs, is defined as $\alpha + \gamma + \beta$. Next, we wish to reduce the simultaneous bias between the dependent variable and two of our independent variables by lagging both the direct and indirect R&D stock one year. The practice of lagging these two variables is common in empirical studies, as it has been found that an innovation takes on average 6 to 18 months to reach the finished development stage (e.g. Del Monte and Papagni, 2002)¹⁰. Equation (5) is now in its’ final form. The elasticities of output can be calculated in order to determine the relationship between the two R&D variables and labour productivity. For example, a positive and significant direct R&D output elasticity γ would imply that investments in R&D do in fact materialise into higher productivity. If η is

¹⁰ We also tested our model for different lag lengths and found the one year lag length to give the highest t-statistics and highest output elasticity with respect to the direct and indirect R&D variables.

found to be positive and statistically significant a spillover effect is indeed present in our model, which signifies an underinvestment in R&D. The same result would also imply that the Schumpeterian ‘creative destruction’ externality is inferior to the spillover externality in the Norwegian manufacturing industry (Los and Verspagen, 2000).

5.2 Data construct

The empirical model of this paper is constructed and tested using the accounting data obtained from the CCGR database. This database includes every Norwegian firm with limited liability that are legally obliged to publish full accounting statements. It covers around 130,000 firms per year, with roughly 240 data items per firm (Berzins, Bøhren and Rydland, 2008). The available data set is considerably more extensive than what has been available for research purposes in the past, which makes it ideal for depicting the latest developments in the R&D and labour productivity relationship.

The initial data set contained 2,070,788 yearly firm observations, and we had to undertake an extensive screening and time-consuming filtering process in order to end up with a balanced data set for the manufacturing industry only. The first step of this filtering/screening process was to remove all firms which were not represented in the entire consecutive time period from 1994 up until 2007. This was done because we were after a balanced panel dataset with a timeframe spanning the longest possible length, and with no missing values. This procedure left us with 698,334 yearly observations or 49,881 firms. The second step was to remove all non-manufacturing firms by applying a filter to the *NACE industry classification code*¹¹ data item for each firm. However, since the NACE data item had many missing values and was subject to firm-specific errors in our data set (no auditing requirements), we had to correct

¹¹ NACE industry codes are a common EU industry classification system which places firms into certain sectors of the economy depending on their main production output (see Appendix 2).

these specification errors manually before we could apply a filter. After correcting errors and filtering only the firms in the manufacturing industry (i.e. NACE codes between 17 and 37), we were left with a total of 63,994 yearly observations or 4,571 firms.

The third step was to correct for missing values in the *District number* data item for each firm. This specific data item was also subject to many specification errors which had to be corrected manually. No observations were removed in this process. At this stage of the process we also decided to remove observations for the following years: 1994, 1995, 2005, 2006, and 2007. This was done after we discovered that the dataset was missing data for the *Number of Employees* data item in these respective periods. This action retained the number of firms at the previous level, but reduced our number of total yearly observation to 41,139.

With a total of 4,571 firms in our dataset we next turned to the data cleaning process following the widely adopted ‘*5 step cleaning procedure*’ suggested by Hall and Mairesse (1995). The first step in this procedure was to remove all firms that had zero R&D spending in the entire nine year consecutive period. We were forced to perform this operation since we operate with a log linear specification of our equation, and since an R&D stock is impossible to construct for a firm with zero R&D spending in all nine years. Hence, our research question can only be tested on those firms who have actually reported some degree of spending in R&D in the 1996 to 2004 time period. This consequentially reduces the scope of our paper as we are now only considering firms with direct R&D investments, and the associated spillover effect between these firms. This operation left us with a total of 851 firms. At this first step of the cleaning process we also removed all firms that had annual observations with the value of zero in either: physical capital, operating income, or number of employees. The reasoning behind this operation is similar to that of the

previous operation, since zero or negative values create obvious problems for our logarithmic specification. We were left with a total number of 818 firms.

The second step of the cleaning process was to remove any firm which had annual observation for; operating income per worker, physical capital per worker, or R&D capital per worker outside of three times the inter-quartile range¹² above or below the firm individual median. This cleaning step was designed so as to remove extreme outliers that could potentially distort the regression results. It was evident from our dataset that errors did in fact occur, where for example certain entries had been given some additional zeros at the end. This was especially typical for the physical capital data item. This operation removed 34 firms from the data set.

The third step was to remove any firm for which the growth rates of; operating income, labour, physical capital or R&D capital were less than minus 200 percent or greater than 300 percent. The lower limits were set lower than that of Hall and Mairesse (1995), since we would lose too much data by setting the lower limit to their suggested minimum limit of 90 percent. The purpose of this cleaning step is similar to that of the second step as we want to trim potential outliers. We do not want extreme outliers to dominate the regression statistics. After step three we were left with a balanced data set containing a total of 712 firms, for nine consecutive annual periods. The remaining two steps in Hall and Mairesse's cleaning procedure did not alter our dataset size. Step four proposes ways to deal with the 'double counting' issue of labour and physical capital employed in R&D, which could potentially yield negatively biased estimated elasticities with respect to R&D (Verspagen, 1995). Since we lack the information to correct for this problem we can only refer to the findings of double counting when interpreting our estimation results. The fifth and final step is concerned with removing gaps in the data during certain time periods. Since we had already constructed a balanced panel data set, step 5 in

¹² The 75 percent value minus the 25 percent value.

the cleaning process was completed. Hence, we were left with the final dataset from step 3, containing a total of 712 firms.

5.3 Construct of variables

The variables of interest in our model are: operating income, physical capital, labour, direct R&D stock, and indirect R&D stock, where the first variable is the main output variable in the production process, and the remaining four are the input variables. The operating income variable was taken from the filtered and cleaned panel data set (described in section 5.2) and found under post 33, denoted ‘Operating income’. This variable was then deflated with the OECD producer price index for Norway in order to obtain real values instead of nominal values, since price inflation can potentially distort the measurement of our variables (OECD, 2009)¹³. The physical capital input variable was also extracted from the same data set, and constructed by aggregating post 47 to 50 in the database forming a *net plant, property and equipment* variable. This variable was then deflated using the OECD producer price index for capital stock for Norway (OECD, 2009). The labour variable was found in our data set under post 113; ‘Number of employees’. This variable was not deflated for obvious reasons.

The final variable, taken from our filtered and cleaned CCGR data set, was the direct R&D variable found under post 44. This can be quite a problematic variable as this post is not clearly defined as a pure R&D account in our database. It rather acts as a combined R&D account for patents, licences, goodwill, concessions, and many other R&D related costs. This is a potential short-coming, and has to be kept in mind when interpreting the final regression results. The variable was then deflated with the OECD producer price index for Norway (OECD, 2009). Notice that our data contained annual R&D

¹³ The producer price index serves a similar purpose as that of CPI, and is used to measure the average change in prices for a fixed basket of goods and services of constant quantity traded among companies.

expenditure which can be characterised as a flow variable. Since we operate with an extended Cobb-Douglas production function, where output elasticities are the parameters to be estimated, we must convert this flow variable into a stock variable. To construct the stock of R&D¹⁴ we adopted a perpetual inventory method like that commonly used for physical capital (e.g. Griliches, 1979; Hall and Mairesse, 1995). The equation defines R&D stock as follows:

$$(5) \quad R_t = (1 - \delta)R_{t-1} + RE_t$$

where R_t is beginning period capital stock, and RE_t is R&D expenditures during period t . Two problems arise from this equation, namely that we do not know the appropriate depreciation rate δ , and secondly the fact that we have problems in determining the starting point of the accumulation process for the R&D stock. In our model we implemented a commonly used simplification assumption of a constant depreciation rate of 15 percent (e.g. Griliches, 1990; Los and Verspagen, 2000). This assumption let us overcome our first problem. The second problem was handled by applying the following formula:

$$(6) \quad R_1 = \sum_{s=0}^{\infty} RE_{-s} (1 - \delta)^s = RE_0 \sum_{s=0}^{\infty} \left[\frac{1 - \delta}{1 + g} \right]^s = \frac{RE_1}{g + \delta}$$

This equation, found in Hall and Mairesse seminal paper from 1995, simply says that with an assumed 15 percent depreciation rate δ , and an initial 5 percent R&D stock growth rate g , the first period R&D stock is equal to the first observation in our time series divided by 0.2¹⁵.

After we had constructed the direct R&D stock using equation (5), and dealt with the two problems associated with this equation, we next moved on to construct the more elusive indirect R&D stock. We adopted a weighted system utilising equation (2) described in section 3, where our weights are based on geographical distances. To construct this spatial matrix we started the process

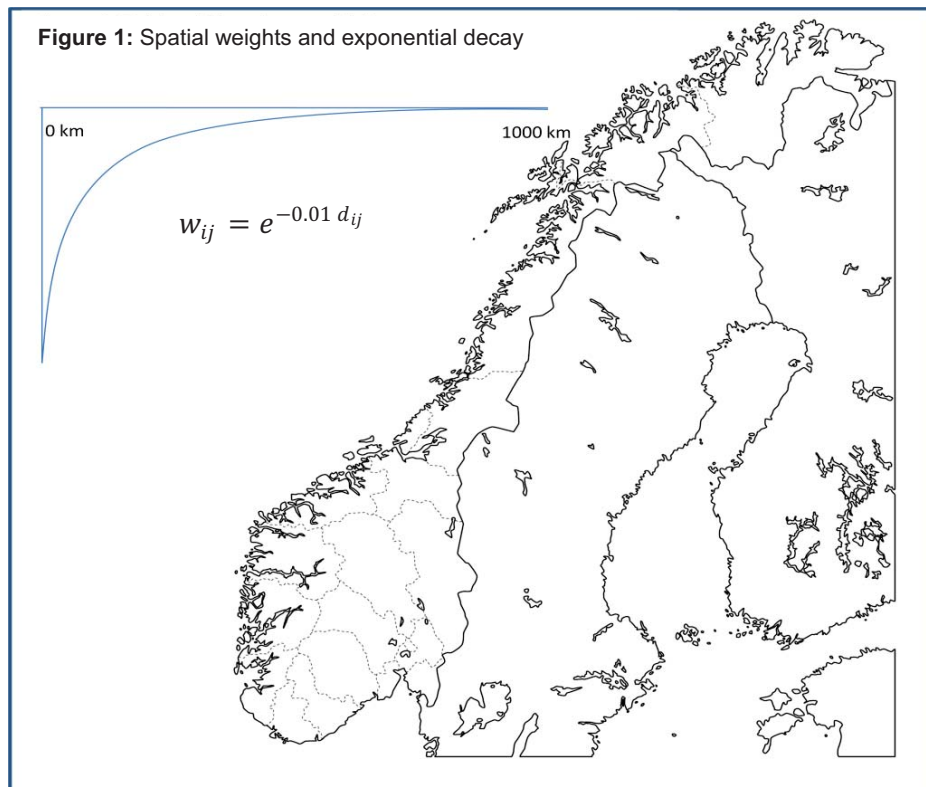
¹⁴ Also typically referred to as the firm's knowledge capital.

¹⁵ This simplified assumption is supported by some of the patent productivity evidence presented in Hall, Griliches and Hausmans' (1986) research paper.

by obtaining a distance table with the physical distance (in kilometres) between Norway's 19 county administrative cities. This information was collected from the Norwegian Road Authority (Statens Vegvesen, 2009). Using this distance table in matrix form we then applied the following formula in order to construct our weighting matrix based on the distance table (see Appendix 3 for the weighted distance matrix output):

$$(7) \quad w_{ij} = e^{-0.01 d_{ij}}$$

This equation simply says that w_{ij} is the spatial weight between firm i and j , and d_{ij} is the distance between the administrative centres of the counties for which the firms belong. The equation will, due to the exponential decay specification, give lower weights to firm which are located far from each other, thus reducing the potential spillover between these two firms. The exponential value of 0.01 is arbitrary chosen, however its' value is based on the value suggested by Verspagen (2007) after he had tested various values. He argued that a value of 0.01 reflects a fairly rapid decline of the weight with distance, which best mimics the actual decaying spillover effect. Notice that the weights



will take on a value between 0 and 1, such that weights are equal to one for firms located in same county. Figure 1 depicts the value of w_{ij} as an exponential decaying function going from 1 to 0 in the 1000 kilometer interval.

Before we used the weights to construct our indirect R&D stock, we chose to standardise the weighting matrix. Each cell in the matrix was divided by the matrix total. With the spatial weighting matrix constructed we next calculated each firm's indirect R&D stock by applying equation (2), where the respective weights w_{ij} were multiplied with other firms' R&D stocks $R_j(t)$ ¹⁶. This was then repeated for every firm in the industry until we had constructed the weighted indirect R&D stock for all 712 firms in our dataset.

5.4 Descriptive Statistics

In order to explain the basic features of the data used in our empirical study we now turn to an investigation of the descriptive statistics. Table 3 displays the mean value, which is a tool for determining the value of the central tendency in

Table 3. Descriptive statistics: Mean values

	Total sample	High-tech sectors	Medium-tech sectors	Low-tech sectors
log Q/L	14.080 (0.728)	14.154 (0.712)	13.915 (0.638)	14.128 (0.777)
log K/L	11.218 (1.770)	11.256 (1.772)	11.103 (1.586)	11.262 (1.879)
log R/L	11.915 (1.354)	11.739 (1.402)	11.973 (1.247)	12.023 (1.368)
N	712	236	189	287

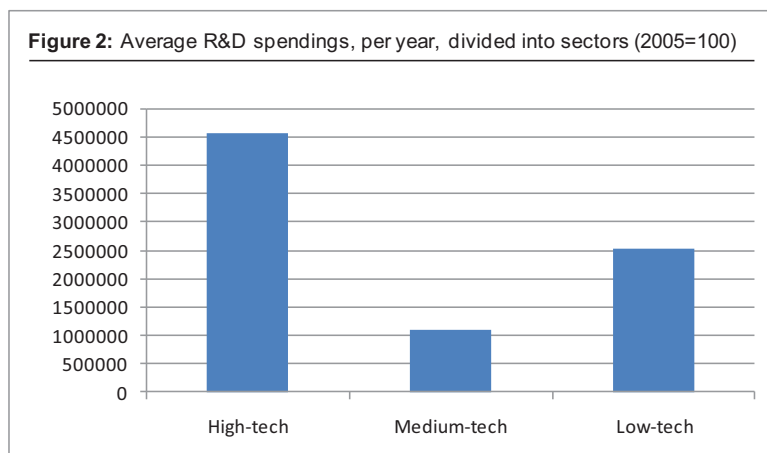
Standard deviations in parenthesis. N: number of firms. Q, K and R of 2005 NOK.

the dataset, with the standard deviation reported in the parenthesis. At first glance one notice the mean values do not change much between the different sectors. The mean value of log Q/L is found to average around 14, with the high-tech supporting the highest ratio and the medium-tech sector supporting the lowest ratio. The mean values of log K/L lie slightly above 11 for both the

¹⁶ Notice that the spatial weight is set equal to zero when firm i line up with itself in the matrix. Hence, the diagonal in the final matrix will contain a value of zero.

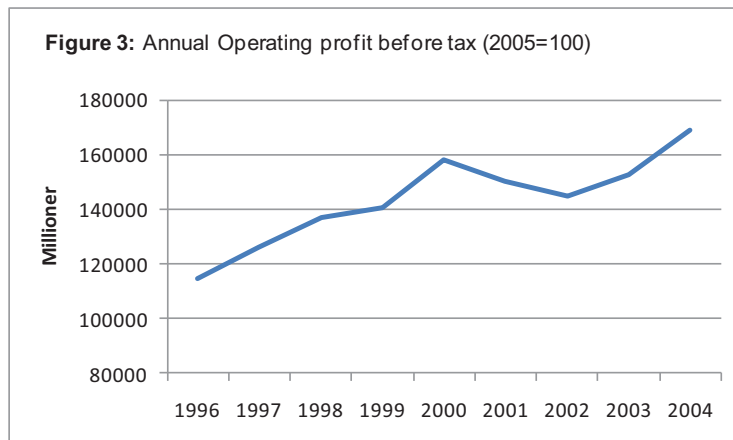
total sample and the different sectors samples; with the low-tech sector mean value just above the high-tech sector mean value. For the third and last variable log R/L, we find values centring around 12 for all samples. Our expectation for this research intensity variable, based on prior research, is that the mean value should be highest in the high-tech sector and lowest in the low-tech sector (e.g. Del Monte and Papani, 2002). Notice, however, that our log R/L gives the opposite result. The mean value is highest in the low-tech sector with a value of 12.023, and smallest in the high-tech sector with a value of 11.739. A possible reason for this rather unexpected result could be linked to the labour share in different sectors. The average rate of employees per year in the high-tech sector is approximately 148, and 93 in the low-tech sector. This implies that the high-tech sector must undertake more R&D than the low-tech sector in order to obtain the same log R/L ratio.

Figure 2 displays the yearly R&D expenditure for the average firm in three different sectors. When comparing these numbers with the research intensity (log R/L) in table 3 one can observe that when R&D spendings are divided by number of firms instead of number of workers, firms in the high-tech sector have higher average R&D investments than firms in both the low-tech and the medium-tech sectors. This gives us values which fit better with empirical results, obtained in previous studies, yielding higher average research intensity values for firms in the high-tech sector than for firms in the two other sectors

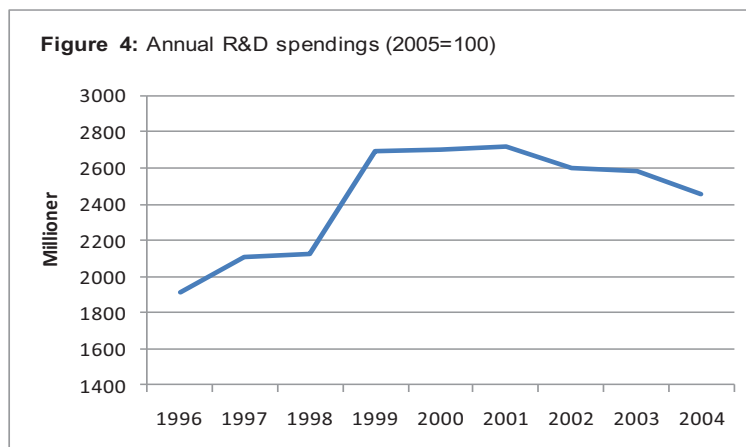


(see; Los and Verspagen, 2000; and Ortega-Argiles, Piva, Potter and Vivarelli, 2009).

The graphical plot of total annual operating income is illustrated in figure 3. As the graph displays, annual operating income increased stepwise upwards from 1996 until it peaked in the middle of year 2000, thereafter decreasing until it

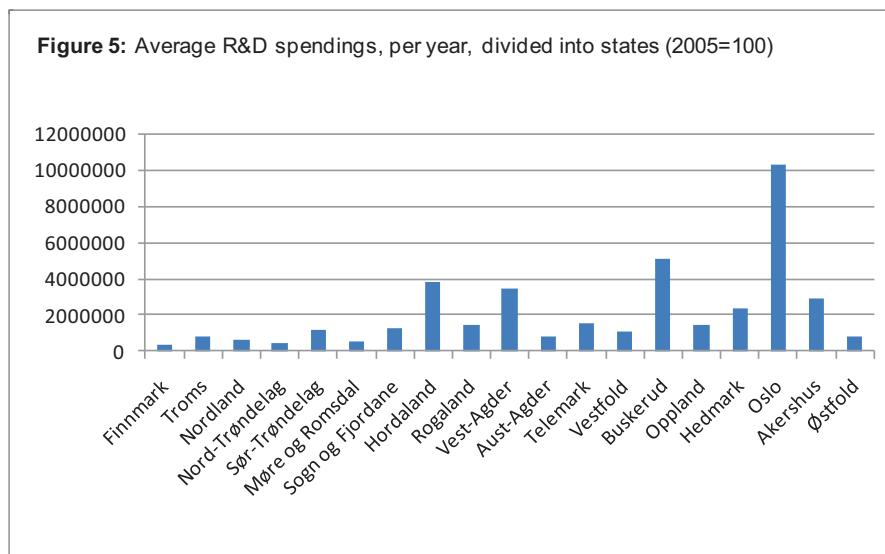


reached yet another turning point in year 2002. As expected, this graph mimics the movements of the actual business cycle in Norway during the same time period (Statistics Norway, 2009). Figure 4 illustrates the total annual R&D spendings for the manufacturing industry. By comparing this figure with figure 3, one observes that annual R&D spendings do not go hand in hand with the annual operating income. However, it appears from a purely visual point of



view that R&D spending acts as a leading indicator for operating income from year 1996 up to year 2002. This movement lends support to the endogenous growth theory's assumption of a casual relationship running from R&D to operating income. On the other hand, if R&D actually where a leading indicator, one would have expected that annual R&D spending reached a turning point in 2001, which it does not. Since the dataset is relative short and ends in year 2004 it is not possible to draw any concrete conclusions on this subject based on a simple graphical inspection.

Figure 5 reports the average R&D spendings per year divided into nineteen Norwegian counties. This gives a good graphical illustration over the allocation of R&D spendings throughout Norway for our particular dataset. As expected the R&D spendings are highest in Oslo and the surrounding areas; Akershus and Buskerud. In Hordaland and Vest-Agder, where we also know clusters of technology firms are located, we can observe relative high average R&D spendings. Further, the anticipation of low R&D spendings in the northern counties where confirmed, where firms in Finnmark, Nordland and Nord-Trøndelag report the lowest average R&D spendings.



5.5 Empirical Results

As mentioned in section 5.1 we will in this section be estimating the relationship between productivity and R&D by utilising equation 5; the labour intensive Cobb- Douglas production function augmented with both a direct R&D stock and an indirect R&D stock. In table 4 the initial regression results,

Table 4. Estimation results (Pooled OLS model).

	Total sample	High-tech sectors	Medium-tech sectors	Low-tech sectors
a	9.720 (71.486)***	10.330 (45.478)***	10.173 (37.049)***	8.796 (41.024)***
α	0.145 (22.299)***	0.093 (8.508)***	0.122 (9.755)***	0.219 (21.132)***
($\mu-1$)	0.0807 (13.747)***	0.073 (7.465)***	0.062 (5.470)***	0.077 (8.090)***
γ	0.131 (26.464)***	0.120 (13.708)***	0.106 (10.747)***	0.135 (18.083)***
η	0.054 (8.988)***	0.066 (6.381)***	0.053 (4.598)***	0.055 (5.831)***
NOB	5696	1888	1512	2296
Adj. R²	0.243	0.192	0.156	0.338976

*** Significance at the 1% level. **Significance at the 5% level. *Significance at the 10% level.

T-values in parenthesis.

using pooled regression estimators on the total sample and the three subsamples, are presented. From these initial regression results it is clear that all the coefficients have very large t- values, all statistical significant at a 1 percent level. Since, high t-statistics can be a common sign of either autocorrelation or heteroskedasticity (i.e. caused by underestimated standard errors) we decided to run two independent residual tests aimed specifically of detecting their presence. Notice that serial correlation and heteroskedasticity do not cause the Ordinary Least Square (OLS) regression to be biased, thus violating the BLUE (Best Linear Unbiased Estimator) principal per say. However, it violates the OLS assumption of uncorrelated errors, which cause the OLS standard errors to be incorrect, and they should as a consequence not be used for inference. Hence, we will postpone our discussion of the coefficient results until the model is properly tested and if necessary corrected.

The first test we ran was a Breusch-Pagan-Godfrey (BPG) heteroskedasticity test¹⁷ presented in table 5. The BPG test's null hypothesis is no heteroskedasticity. It is a Chi-square test based on an auxiliary regression,

Table 5. Heteroskedasticity Test: Breusch-Pagan-Godfrey

	Total sample	High-tech sectors	Medium-tech sectors	Low-tech sectors
Scaled explained SS	501.434 (0.000)	207.131 (0.000)	18.452 (0.001)	305.286 (0.000)
Obs*R-squared	224.301 (0.000)	81.570 (0.000)	14.496 (0.006)	141.167 (0.000)

P-values in parenthesis. Ho=Homoskedasticity, Ha=Heteroskedasticity.

which means that it will reject the null hypothesis with p-values bellow the significance level. In table 5 we have also included the Observed R-square test statistic introduced by Koenker (1981) which is in essence a simplified BPG test, and similar in interpretation. It is evident that both test statistics reject the null hypothesis. We conclude that we do in fact have a problem of heteroskedasticity in our model.

Next we turned to the second residual test, namely the Breusch-Godfrey Lagrange Multiplier (BG-LM) test presented in table 6. The BG-LM test's null

Table 6. Serial Correlation LM Test: Breusch-Godfrey

	Total sample	High-tech sectors	Medium-tech sectors	Low-tech sectors
F-statistic	1033.607 (0.000)	305.507 (0.000)	232.901 (0.000)	519.248 (0.000)
Obs*R-squared	3536.118 (0.000)	1122.766 (0.000)	881.808 (0.000)	1409.989 (0.000)

P-values in parenthesis. Ho=No serial correlation, Ha=Serial correlation.

hypothesis is no autocorrelation in the residuals up to a specific order (i.e. number of lags). It is also a Chi-square test based on an auxiliary regression, rejecting the null hypothesis with p-values bellow the significance level. This test provides a more general testing framework than that of the common Durbin Watson autocorrelation test. The BG-LM test also reports a F-statistic, which is commonly used as an informal test of the null hypothesis. Both test statistics reject the null hypothesis of no autocorrelation with a maximum order

¹⁷ The BPG test is sensitive to the normality assumption. Hence, with our residual following a normal distribution for all samples this method is preferred to for example the White heteroskedasticity test.

of nine. Hence, we conclude that we do in fact have a problem with autocorrelation in our model.

With both autocorrelation and heteroskedasticity in our data sample we decided to implement econometrical instruments to correct for these violations of the OLS assumption. A common way to overcome these problems in the statistical econometrics literature is to implement a Heteroskedasticity and Autocorrelation (HAC) Consistent Covariance estimator. Newey and West (1987b) provide such a HAC consistent covariance estimator which does not change the point estimates, only the standard errors. Hence, we chose to implement the Newey-West HAC estimator in our model to correct for the OLS violations. In addition we chose to include dummy variables for both the cross-sectional dimension, constructed from the NACE industry codes, and the time dimension, with dummies for year 1996 up to 2004. The choice to include dummy variables and adopting a fixed effect (within) model was to correct for heteroskedasticity and fixed individual differences (see Appendix 4 for regression results for dummy variables).

Our fixed effect model is now in its' final form with HAC consistent covariance estimates for an 8 years lag truncation. In table 7 the estimation

Table 7. Estimation results (Fixed effect model).

	Total sample	High-tech sectors	Medium-tech sectors	Low-tech sectors
α	0.134 (6.549)***	0.061 (2.049)**	0.101 (3.459)***	0.215 (6.078)***
$(\mu-1)$	0.059 (3.768)***	0.058 (2.452)**	0.046 (1.732)*	0.064 (2.318)**
γ	0.126 (9.647)***	0.123 (5.172)***	0.095 (4.923)***	0.133 (6.900)***
η	0.058 (4.060)***	0.054 (2.538)**	0.059 (2.226)**	0.065 (2.667)***
NOB	5696	1888	1512	2296
Adj. R²	0.292	0.224	0.229	0.361

*** Significance at the 1% level. **Significance at the 5% level. *Significance at the 10% level.

T-values in parenthesis.

results for our model are presented¹⁸. One of the most prominent features of the estimation results in table 7, compared to the pooled OLS estimation results in table 3, is that the t-statistics have indeed dropped significantly for all coefficients, and the adjusted R-square values have increased in all samples. Nevertheless, all coefficients in the total sample are still statistical significant at a 1 percent level. The subsample coefficients are also statistical significant, but at different significance levels.

The estimated value of one of the key parameters of interest, namely the output elasticity with respect to the direct R&D stock γ , is found to be both positive and significant at a 1 percent level, with a value of 0.126 in the total sample. This value fits nicely with the output elasticities of R&D found in the previous studies, and the predictions of the endogenous growth theory. When we compare the estimated R&D elasticities in different sectors of the economy, an interesting observation can be observed for the high-tech sector and the low-tech sector in particular. The low-tech sector actually supports a higher R&D elasticity, which contrasts previous empirical results, where the opposite result holds (e.g. Los and Verspagen, 2000; Ortega-Argiles, Piva, Potter and Vivarelli, 2009).

One possible theoretical explanation for this unexpected result can be the fact that Norwegian firms in the high-tech sector invest on average substantial large amounts in R&D (see section 5.4, figure 2). The decision to invest in R&D for these firms might be based on a continuous patent race setting, where one either invests or exits the race (Tirole, 1988). This is a setting where the efficiency effect dominates the agents' incentives to invest in R&D. Firms invest in R&D in order to protect current profit and maintaining barriers to entry. Thus, the direct 'pay-off' from the specific R&D innovation is considered less important for firms operating in this sector. The patent race might therefore lead to duplication of R&D costs, and decreasing profit

¹⁸ We do not report the constant in the empirical results since the dummy variables makes this term redundant.

opportunities in the high-tech sector. In the low-tech sector where few actors invest in R&D, on the other hand, a sudden innovation made by firms can yield high direct ‘pay-off’ in the short-run, as long as no other firms are able to copy the firm’s innovation within that short timeframe.

Another possible explanation for these rather unexpected results can be the fact that export-based traditional industries are placed in the low-tech sector in our sample, set according to the OECD classification. These export-based firms operate in international markets, and enjoy patents which are multinational in scope. Hence, these patents are most likely more profitable than a patent belonging to a high-tech firm operating in a single country setting. This means that traditional Norwegian firms doing research can create patents allowing them to enjoy a competitive advantage not only in the Norwegian market, but also in foreign markets. The result can lead to a higher direct R&D output elasticity in the low-tech sector. Hence, our finding which contrasts previous results might just be a peculiarity of the Norwegian industrial system, where an OECD classification will produce misleading results for a sector comparison analysis¹⁹. In their paper Aiello and Cardamone (2006) find similar results for the Italian manufacturing industry, where low-tech firms experience higher output elasticities with respect to direct R&D than that of firms in the high-tech sector.

The second key parameter of interest is the output elasticity with respect to indirect R&D η . This indirect R&D elasticity is found to be both positive and significant at a 1 percent level, with a value of 0.058 in the total sample. This result lends support to the endogenous growth theory, and its’ claim of a spillover effect in the manufacturing industry. When comparing the actual magnitude of the elasticity in question we notice that it falls below the estimates found by Los and Verspagen (2000) when they tested four traditional

¹⁹ Notice that we also found high research intensity in the low-tech sector in Norway (see table 3) which directly contradicts the construct of the OECD classification system, where industry are classified according to the sectoral average research intensity.

spillover measures, and similar in magnitude of those estimates found by Coe and Helpman (1995) in their paper measuring international spillovers. According to our estimates the productivity enhancing effect of spillovers clearly dominates over the negative effect of spillovers, the so-called ‘creative destruction’ externality. However, while a positive spillover effect leads to increasing return to scale in the economy at an aggregated level, it might reduce the incentives for firms to invest in R&D for future periods. Hence, our findings indicate that there is scope for the social planner to correct and improve policy instruments such as; patents, grants, prices, and tax deductions in order to strengthen future incentives for firms to invest in R&D.

When comparing the magnitude of the indirect R&D elasticity in our three different sector samples, we once again obtain a higher elasticity in the low-tech sector than in the two other sectors. A possible explanation for this result is that firms in the low-tech sector have lower barriers to entry. Hence, only a short time after a new innovation has been launched by one firm the competing firms in the industry are able to copy the innovation. As a consequence the spillover effect is higher in the low-tech sector than in the high-tech sector, although the differences are only minor. If these results reflect the actual spillovers in the Norwegian economy they may call for a greater social planner intervention in the markets with the highest output elasticity with respect to the indirect R&D variable, which in our case would be the low-tech sector. However, we will be careful to draw a strong conclusion on the matter as our sector classification might be biased for reasons previously mentioned.

Another parameter of interest is the return to scale parameter ($\mu - 1$) in our estimation results. A positive value would indicate increasing return to scale. In table 7 all ($\mu - 1$) coefficients are positive and significant for all sectors. With μ defined as; $\alpha + \gamma + \beta$, we can see that the direct R&D effect cause increasing return to scale in all sectors. Notice, that without the direct R&D coefficient entering the return to scale parameter it would actually be decreasing, thus

violating the constant return to scale assumption in the standard Cobb-Douglas production function. The final parameter in table 7 is the output elasticity with respect to physical capital α . This is positive and significant at a 1 percent level in the total sample. Its' value is also highest in the low-tech sector, as was expected from previous empirical studies (e.g. Los and Verspagen, 2000).

In all our samples the adjusted R-square values are relative low, but fall within the acceptable range as indicated by previous studies, which found the usual adjusted R-square value for a Cobb-Douglas production function to lie somewhere in the range from 0.2 to 0.5 (e.g. Cameron, 2003). As previously mentioned, other explanatory variable could undoubtedly have been included in our model leading to a boost the adjusted R-square value. However, such a model could easily lose its' simplicity and high explanatory value.

As a detour to the main empirical results, we have in table 8 also presented the estimation results for firms located in two selected counties. The counties have been chosen on the basis of their locations and differences in the mean R&D intensity. The estimation results show that firms in the county of Oslo have higher output elasticities with respect to both the direct R&D stock and the indirect R&D stock. These results seem to indicate that there exists a cluster effect in areas with a high concentration of R&D intensive firms. According to

Table 8. Estimation results for specific counties (fixed effect model).

	Oslo	Nordland
α	0.223 (5.976)***	0.269 (6.315)***
$(\mu-1)$	0.053 (1.711)*	0.009 (0.919)
γ	0.169 (4.343)***	0.052 (2.315)**
η	0.071 (2.171)**	0.018 (1.699)*
NOB	696	240
Adj. R²	0.345	0.429

*** Significance at the 1% level. **Significance at the 5% level. *Significance at the 10% level.
T-values in parenthesis.

these estimates, firms in the Oslo area get ‘more bang for their buck’ on their R&D investments, but they also experience more spillovers than firms located in Nordland. However, we will be careful to infer too much from these results in relation to well-funded cluster theories, as these are outside the scope of this paper.

Both our main estimation and detour results do indeed lend support to the endogenous growth theory, and the claim that technical progress is driven by both direct R&D investments and technological spillovers. However, in order to test the robustness of these results we will in the next section perform panel unit root tests for all our individual variables in an attempt to rule out spurious correlations. We will also run a Granger causality test to investigate the directional relationship between two of our key variables.

5.6 Robustness tests and Granger causality

In this section we will first perform robustness tests on our variables by testing for a unit-root. This is important because a variable with a time series following a non-stationary process (i.e. unit root) will create spurious relations in our estimation result, consequentially leading to an upward bias in the estimated t-values and R-square values. It has the potential to infer a relationship between two variables when in reality there is none (Hamilton, 1994). The unit root test of our dependent variable is also important in order to test the validity of Gibrat’s law discussed in section 3, since operating income is strongly linked to the sales variable. Notice that we operate with a level specification of our dependent variable y_t , and not with the growth rate specification Δy (i.e. first-difference form), as that postulated in the Gibrat’s law. However, a variable with a trend-stationary time series in the level specification will also be stationary in the first-difference series, so the results of our unit-root tests can indeed be used to infer something about the validity of Gibrat’s law. Table 9 reports the unit root tests for all variables in

Table 9. Individual Unit root test of the variables in the regression: Im, Pesaran, and Shin W stat

Variable	q - I	k - I	r - I	I	ir
Statistic	-7.24369	-5.07811	-4.87920	-6.5445	-9.6555
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

P-values in parenthesis. Ho=Unit root, Ha=No unit root.

our model. In the individual unit-root test proposed by Im, Pesaran and Shin (1996) the null hypothesis is unit root. A p-value below the significance level will lead us to reject the null hypothesis. It is evident from our unit root test that we can reject the null hypothesis at all usual levels of significance, and conclude that we do in fact have variables which follow a (trend) stationary process. These results also disconfirm the main assumption of Gibrat's law saying that the dependent variable follows a random walk process. Our results from section 5.5 are robust when it comes to spurious correlations.

The final issue we will touch upon in section 5 is to test the causal direction of the relationship between operating income (dependent variable) and direct R&D stock (explanatory variable). Since causality is of great importance in the relationship between R&D and productivity, we will use the Granger causality test to infer something about the direction. Notice, however, that the Granger causality test is a very crude and simplified measure, and Granger causality does not imply 'true' causality. It rather acts as an indicator for the broader phenomenon. In table 10 we have presented the Granger causality test for different lag lengths. The test tells us that with a lag length of one R&D

Table 10. Granger causality test: R&D (R) and Operating profit before tax (Y)

	Lag length 1	Lag length 8
Y does not Granger Cause R	1.486 (0.223)	5.637 (0.000)
R does not Granger Cause Y	17.717 (0.000)	1.247 (0.269)

P-values in parenthesis.

granger causes operating income. However, with a lag length of 8 the story is reversed and operating income now granger cause R&D. The former result supports previous studies which have found a casual relationship running from R&D to productivity (e.g. Cameron, 1998; Del Monte and Papagni, 2002; Los

and Verspagen, 2007), thus supporting our method of lagging direct and indirect R&D stock with a one year period. The latter result might pick up the effect where increases in the cumulative income level give rise to an increase in R&D funding possibilities. Hence, higher profit levels might ease and increase funding of R&D in the long-run. Nevertheless, there is still much debate on what drives what in the economical literature, and a simple Granger causality test can by no means depict the true causality with total confidence.

6. Conclusion

In this paper we have investigated how well the predictions of the endogenous growth theory fit the Norwegian manufacturing industry. An extended Cobb-Douglas production function has been utilised in order to test these predictions on a relative new and unused data set for the Norwegian manufacturing industry. The key feature of this extended production function is the inclusion of both a direct R&D stock and an indirect R&D stock, which act as proxies for technological progress. To construct the elusive indirect R&D stock we used the relative novel spatial weighting method with geographical distance weights. The regression results of our analysis confirm the existence of both a direct and an indirect relationship between investments in R&D and labour productivity. These findings lend support to the endogenous growth theory's claim that productivity growth rates are endogenous of nature, driven by technical progress which is determined in turn by both 'own' R&D investments and technological spillovers. However, while the spillover effect creates growth in the aggregated economy it also leads to underinvestment in R&D for future periods, since agents are not able to appropriate the entire profit stream steaming from their innovation. Hence, our findings suggest that there is scope for the social planner to improve and modify current R&D incentive instruments in the Norwegian manufacturing industry.

A result of particular interest is the unexpected result of higher direct R&D output elasticities in the low-tech sector than in the high-tech sector. This

finding contradicts previous findings, and is rather surprising as we would not expect research in the low-tech sector to make a substantial difference to firms' competitiveness. However, this may well be just a peculiarity of the Norwegian industrial system, since the OECD classification can produce misleading sector classifications. The estimation results also show that the spillover effect is marginally larger in the low-tech sector than in the high-tech sector, with all sectors experiencing increasing return to scale. These findings imply possible policy implication for the 'social planner', such as to which sectors of the industry they should direct their attention. However, as the sectorial results might be plagued by misspecification of sectors (set according to the OECD classification) we will caution the reader to infer too much from these sectorial results.

7. Potential Short-comings

Our research model is based on a well-known model, namely the extended Cobb-Douglas production function. It is extensively utilised in the growth theory literature, and form the basis for the theoretical endogenous growth model. It is a convenient model to adopt in our empirical study as it includes key input variables in a production process such as; physical capital, labour, and technological investments. However, this production function is designed to fit the theoretical framework well, and is therefore somewhat vague in its' description of the 'true' profit maximising firm in a 'real' market setting. By focusing only on very basic input factors it leaves out other important determinants of output (e.g. natural resources etc). Critics argue that the extended Cobb-Douglas production function is in fact too simple to represent the 'real' production function for a firm, and there is scope to search for other explanatory variables.

Our model might also be plagued by an endogeneity problem, where the positive output elasticities we found are be caused by a common unknown variable, which is not explicitly included as an explanatory variable. Hence, we

might potentially infer a relationship between two variables that is in reality non-existing, and only caused by an unknown phenomenon. For example, the spillover effect might not be caused by investments in R&D, but other factors such as; infrastructure and access to skilled labour in a particular geographical location, while the direct effect of R&D might be caused by other factors such as; firm size and the shut-down effect. For example, according to Olley and Pakes (1996), productivity gains are a result of reallocation of output and capital to the more productive firms. This implies that productivity growth might be caused by the shut-downs of unproductive firms, leaving resources to the more productive firms and new productive establishments. In other terms, Olley and Pakes (1996) argues that it is the most productive firms that receive the highest rates of return of investing in R&D, and therefore chose to invest the most in R&D. In our model we operate with a balanced panel data set, and we are therefore left with no possibilities for studying this shut-down effect or the effect of new establishments.

The restriction of homogenous goods and constant return to scale in the market setting is also a highly theoretical proposition. Researchers have avoided this problem by unrestricting this assumption and rather let the estimation results indicate whether or not there is constant or increasing return to scale on a firm level. Hence, the estimation results from our model cannot by no means confirm or disconfirm the theoretical endogenous growth model per say. Instead they can be used to investigate and shed some light on the main assumptions of the theory.

In our model we performed an extensive screening and filtering process which ultimately lead to a database which cannot be seen as a random sample. For example, the spillover effect is measured only between firms in the manufacturing industry. This means we miss out on the overall spillover effect in the total economy. Notice however that the descriptive statistics show that our sample is quite evenly balanced looking at the cross-sectional dimension of

our data (e.g. similar number of firms in each sub sample). Hence, we argue that it represents the population fairly well.

The model also suffers with respect to how we constructed both the direct R&D stock and the indirect R&D stock. For example, our use of the perpetual inventory formula to construct the direct R&D stock is a highly questionable practice, solely due to the formulas' simplistic design. The model is also attempting to measure knowledge spillovers which are inherently difficult to measure, since they leave very little paper trails. The method we have opted for in our paper with exponential decreasing weights based on geographical distance, is a relative new way of measuring the spillover effect. Hence, there are no guaranties that we have in fact adopted the correct way to measure the spillover effect occurring in the manufacturing industry. Our method, for example, makes no attempt to separate rent and knowledge spillovers, which may lead to overestimated technology spillover values in our empirical results.

Our model also suffers the short-coming of being potentially limited in scope. Firstly, we only considered geographical similarities when we constructed the spillover weights, ignoring the issue of technological similarity, mentioned in section 3. Hence, our findings might not capture the true spillover effect occurring in the economy. Secondly, international spillovers are not included in the model, which leaves out the impact of indirect foreign R&D investment. Hence, we do not measure one of the main sources of technological spillovers in the Norwegian economy.

In our model we have assumed that the direction of the relationship runs from R&D to the productivity. However, as we pointed out before, there is no clear-cut conclusion drawn on this topic. Researchers are still debating the classical problem of what came first; the egg or the chicken? Does high productivity lead to increases in R&D investments, or do investments in R&D lead to higher

productivity? As mentioned in section 5.6 the Granger causality test does by no means produce the final answer, nor does a simple glance at the graphs in section 5.4. Last but not least, the problem of a rather short dataset with a time span of nine years is a great problem since it makes it difficult to infer long-run relationship between our respective variables. We might only be able to depict a transitory short-run effect in the industry, which does not represent the actual long-run relationship between our dependent variable and explanatory variables.

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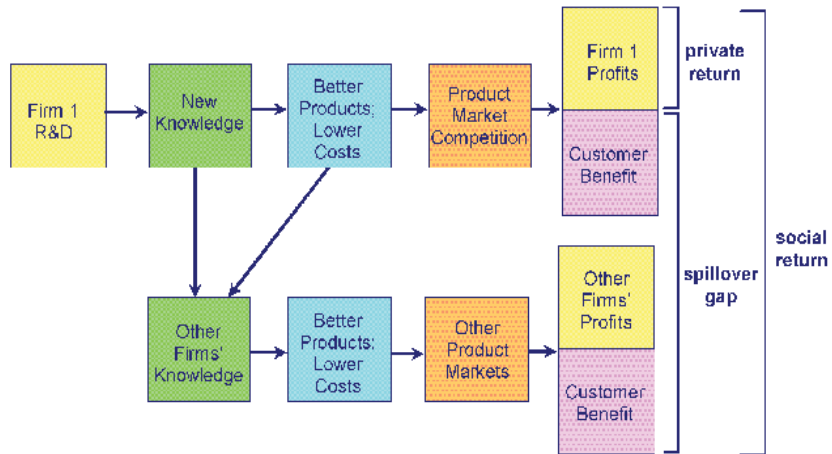
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Appendix 1:

A graphical representation of the differences between the private and social returns to R&D investments.

Private and Social Returns to R&D

Source: Cameron (1998)

Appendix 2:

OCED classification- *Manufacturing industries classified according to their global technological intensity- NACE Revision 1.1* (Note: In our study the two sub groups; medium-high-tech sector and medium low-tech sector, where combined to form an aggregated medium-tech sector):

High-technology	NACE Revision 1.1
1. Aerospace	35.3
2. Computers, office machinery	30
3. Electronics-communications	32
4. Pharmaceuticals	24.4
5. Scientific instruments	33
Medium-high-technology	
6. Motor vehicles	34
7. Electrical machinery	31
8. Chemicals	24-24.4
9. Other transport equipment	35.2+35.4+35.5
10. Non-electrical machinery	29
Medium-low-technology	
11. Rubber and plastic products	25
12. Shipbuilding	35.1
13. Other manufacturing	36.2 through 36.6
14. Non-ferrous metals	27.4+27.53/54
15. Non-metallic mineral products	26
16. Fabricated metal products	28
17. Petroleum refining	23
18. Ferrous metals	27.1 through 27.3+27.51/52
Low-technology	
19. Paper printing	21+22
20. Textile and clothing	17 through 19
21. Food, beverages, and tobacco	15+16
22. Wood and furniture	20+36.1

Source: http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/Annexes/reg_hrst_base_an3.pdf

Appendix 3:

Distance matrix:

	Sarps	Sandv	Oslo	Hamar	Lille	Dramm	Tønsb	Skien	Arend	Kristian	Stavan	Berge	Sognd	Molde	Trondh	Steink	Bode	Troms	Vadse
Sarpsborg	0	103	89	203	252	96	83	127	223	290	474	493	398	567	563	678	1274	1702	2396
Sandvika	103	0	15	141	198	29	89	118	248	314	525	471	325	517	510	627	1224	1662	2365
Oslo	89	15	0	124	166	42	89	131	247	314	446	461	335	482	484	599	1195	1623	2287
Hamar	203	141	124	0	58	165	208	254	368	435	566	451	303	375	371	486	1083	1509	2173
Lillehammer	252	198	166	58	0	165	243	274	390	457	540	425	270	318	336	451	1048	1474	2139
Drammen	96	29	42	165	185	0	59	91	207	274	404	419	303	497	519	634	1231	1657	2321
Tønsberg	63	89	89	208	243	59	0	72	166	233	417	450	358	555	568	684	1280	1707	2371
Skien	127	118	131	254	274	91	72	0	117	184	351	393	371	583	608	723	1320	1746	2410
Arendal	223	248	247	368	390	207	166	117	0	68	293	446	488	700	724	839	1435	1863	2527
Kristiansand	290	314	314	435	457	274	233	184	68	0	230	437	535	767	791	906	1504	1930	2594
Stavanger	474	525	446	566	540	404	417	351	293	230	0	208	396	647	799	915	1511	1938	2602
Berge	493	471	461	451	425	419	450	393	448	437	208	0	217	438	620	735	1331	1758	2422
Sogndal	398	325	335	303	270	303	358	371	488	535	398	217	0	285	407	522	1119	1545	2209
Molde	567	517	462	375	318	497	555	583	700	767	647	438	285	0	221	337	934	1360	2024
Trondheim	563	510	484	371	336	519	568	608	724	791	799	620	407	221	0	119	715	1142	1806
Steinkjer	678	627	599	486	451	634	684	723	839	906	915	735	522	337	119	0	597	1024	1688
Bodo	1274	1224	1195	1063	1048	1231	1280	1320	1435	1504	1511	1331	1119	934	715	597	0	551	1215
Tromsø	1702	1662	1623	1509	1474	1657	1707	1746	1863	1930	1938	1758	1545	1360	1142	1024	551	0	750
Vadse	2396	2365	2287	2173	2139	2321	2371	2410	2527	2594	2602	2422	2209	2024	1806	1688	1215	750	0

Weighted distance matrix (with the exponential decaying formula):

	1	2	3	4	5	6	7	8	9	10	11	12	14	15	16	17	18	19	20
1	1	0.35701	0.41066	0.13134	0.08046	0.38289	0.53259	0.28083	0.10753	0.05502	0.00874	0.00723	0.01869	0.00345	0.00359	0.00114	2.9E-06	4.1E-08	5.3E-11
2	0.35701	1	0.86071	0.24414	0.13807	0.74826	0.41066	0.30728	0.08374	0.04328	0.00525	0.009	0.03877	0.00568	0.00061	0.00189	4.8E-06	6.1E-08	5.4E-11
3	0.41066	0.86071	1	0.28938	0.19014	0.65705	0.41066	0.26982	0.08458	0.04328	0.01156	0.00995	0.03508	0.00807	0.00791	0.0025	6.5E-06	8.9E-08	1.2E-10
4	0.13134	0.24414	0.28938	1	0.5599	0.19205	0.12493	0.07887	0.02522	0.01291	0.00348	0.011	0.04832	0.02352	0.02448	0.00775	2E-05	2.8E-07	3.7E-10
5	0.08046	0.13807	0.19014	0.5599	1	0.15724	0.08804	0.06457	0.02024	0.01036	0.00452	0.01426	0.06721	0.04159	0.03474	0.011	2.8E-05	4E-07	5.1E-10
6	0.38289	0.74826	0.65705	0.19205	0.15724	1	0.55433	0.40252	0.12619	0.06457	0.0176	0.01515	0.04832	0.00694	0.00567	0.00176	4.5E-06	6.4E-08	8.3E-11
7	0.53259	0.41066	0.41066	0.12493	0.08804	0.55433	1	0.48675	0.19014	0.0973	0.01545	0.01111	0.02788	0.00389	0.00341	0.00107	2.8E-06	3.9E-08	5E-11
8	0.28083	0.30728	0.26982	0.07887	0.06457	0.40252	0.48675	1	0.31037	0.15882	0.0299	0.01964	0.02448	0.00294	0.00229	0.00072	1.9E-06	2.6E-08	3.4E-11
9	0.10753	0.08374	0.08458	0.02522	0.02024	0.12619	0.19014	0.31037	1	0.50862	0.0534	0.01156	0.0076	0.00091	0.00072	0.00023	5.9E-07	8.1E-09	1.1E-11
10	0.05502	0.04328	0.04328	0.01291	0.01036	0.06457	0.0973	0.15882	0.50862	1	0.10026	0.01265	0.00475	0.00047	0.00037	0.00012	2.9E-07	4.2E-09	5.4E-12
11	0.00874	0.00525	0.01156	0.00348	0.00452	0.0176	0.01545	0.0299	0.0534	0.10026	1	0.12493	0.01906	0.00155	0.00034	0.00011	2.7E-07	3.8E-09	5E-12
12	0.00723	0.009	0.00995	0.011	0.01426	0.01515	0.01111	0.01964	0.01156	0.01265	0.12493	1	0.11418	0.01253	0.00203	0.00064	1.7E-06	2.3E-08	3E-11
14	0.01869	0.03877	0.03508	0.04832	0.06721	0.04832	0.02788	0.02448	0.0076	0.00475	0.01906	0.11418	1	0.05784	0.01708	0.00541	1.4E-05	2E-07	2.5E-10
15	0.00345	0.00568	0.00807	0.02352	0.04159	0.00694	0.00389	0.00294	0.00091	0.00047	0.00155	0.01253	0.05784	1	0.1097	0.03439	8.8E-05	1.2E-06	1.6E-09
16	0.00359	0.0061	0.00791	0.02448	0.03474	0.00557	0.00341	0.00229	0.00072	0.00037	0.00034	0.00203	0.01708	0.1097	1	0.30422	0.00078	1.1E-05	1.4E-08
17	0.00114	0.00189	0.0025	0.00775	0.011	0.00176	0.00107	0.00072	0.00023	0.00012	0.00011	0.00064	0.00541	0.03439	0.30422	1	0.00255	3.6E-05	4.7E-08
18	2.9E-06	4.8E-06	6.5E-06	2E-05	2.8E-05	4.5E-06	2.8E-06	1.9E-06	5.9E-07	2.9E-07	2.7E-07	1.7E-06	1.4E-05	8.8E-05	0.00078	0.00255	1	0.00405	5.3E-06
19	4.1E-08	6.1E-08	8.9E-08	2.8E-07	4E-07	6.4E-08	3.9E-08	2.6E-08	8.1E-09	4.2E-09	3.8E-09	2.3E-08	2E-07	6.4E-06	1.1E-05	3.6E-05	0.00405	1	0.00055
20	5.3E-11	5.4E-11	1.2E-10	3.7E-10	5.1E-10	8.3E-11	5E-11	3.4E-11	1.1E-11	5.4E-12	5E-12	3E-11	2.5E-10	1.6E-09	1.4E-08	4.7E-08	5.3E-06	0.00055	1

Standardized distance matrix (with cell entries divided by matrix total):

	1	2	3	4	5	6	7	8	9	10	11	12	14	15	16	17	18	19	20
1	0.01107613	0.00395426	0.00454848	0.00145469	0.00089118	0.00424097	0.00589906	0.00311053	0.001191	0.00060944	9.679E-05	8.0042E-05	0.00020696	3.8189E-05	3.9748E-05	1.2586E-05	3.247E-08	4.4947E-10	5.8746E-13
2	0.00395426	0.01107613	0.00953332	0.00270416	0.00152927	0.00828787	0.00454848	0.00340346	0.00092755	0.00047941	5.8122E-05	9.9738E-05	0.00042947	6.2963E-05	6.7528E-05	2.0959E-05	5.3533E-08	6.7052E-10	5.9337E-13
3	0.00454848	0.00953332	0.01107613	0.00320526	0.002106	0.00727754	0.00454848	0.00298856	0.00093687	0.00047941	0.00012807	0.00011023	0.0003886	8.9349E-05	8.758E-05	2.7731E-05	7.1543E-08	9.9035E-10	1.2944E-12
4	0.00145469	0.00270416	0.00320526	0.01107613	0.00620151	0.00212717	0.00138374	0.00067353	0.00027937	0.00014296	3.8573E-05	0.00012182	0.00053515	0.00026049	0.00027112	8.5845E-05	2.1927E-07	3.0966E-09	4.0473E-12
5	0.00089118	0.00152927	0.002106	0.00620151	0.01107613	0.00174158	0.00097511	0.00071519	0.0002242	0.00011473	5.026E-05	0.00015799	0.00074438	0.00046061	0.00038473	0.00012182	3.1116E-07	4.3943E-09	5.6863E-12
6	0.00424097	0.00828787	0.00727754	0.00212717	0.00174158	0.0061398	0.00454848	0.00139765	0.00071519	0.00019491	0.00016776	0.00017519	0.00053515	7.6903E-05	6.1716E-05	1.9542E-05	4.9914E-08	7.049E-10	9.2133E-13
7	0.00589906	0.00454848	0.00454848	0.00138374	0.00097511	0.0061398	0.01107613	0.00539133	0.002106	0.00107766	0.00017115	0.00012304	0.00030875	4.3058E-05	3.7809E-05	1.1853E-05	3.0579E-08	4.2754E-10	5.5881E-13
8	0.00311053	0.00060944	0.00029856	0.00097511	0.00045841	0.00539133	0.01107613	0.00343767	0.00175908	0.00033114	0.00021758	0.00027112	0.00021758	2.5344E-05	2.5344E-05	8.0259E-06	2.0498E-08	2.8947E-10	3.7835E-13
9	0.001191	0.00092755	0.00093687	0.00027937	0.0002242	0.00139765	0.002106	0.00343767	0.01107613	0.00561136	0.00059143	0.00012807	8.4146E-05	1.01E-05	7.945E-06	2.5157E-06	6.4903E-09	8.9403E-11	1.1743E-13
10	0.00060944	0.00047941	0.00047941	0.00014296	0.00011473	0.00071519	0.00107766	0.00175908	0.00561136	0.01107613	0.0011048	0.00014013	5.2591E-05	5.1683E-06	4.0655E-06	1.2873E-06	3.2554E-09	4.5973E-11	6.0088E-14
11	9.679E-05	5.8122E-05	0.00012807	3.8573E-05	5.0026E-05	0.00019491	0.00017115	0.00003314	0.000059143	0.0011048	0.01107613	0.00138374	0.00021115	1.719E-05	3.753E-06	1.1765E-06	3.0333E-09	4.2493E-11	5.5468E-14
12	8.0042E-05	9.9738E-05	0.00011023	0.0002182	0.00015799	0.00016776	0.00012304	0.00021758	0.00012807	0.00014013	0.00138374	0.01107613	0.00126465	0.00013873	2.4787E-05	7.1174E-06	1.8362E-08	2.5674E-10	3.3556E-13
14	0.00020696	0.00042947	0.0003886	0.00053515	0.00074438	0.00053515	0.00030875	0.00027112	8.4146E-05	5.2591E-05	0.00021115	0.00126465	0.01107613	0.00064069	0.00018915	5.9892E-05	1.5298E-05	2.1604E-09	2.8237E-12
15	3.8189E-05	6.2963E-05	8.9349E-05	0.00026049	0.00046061	7.6903E-05	4.3058E-05	3.2543E-05	1.01E-05	5.1683E-06									

Appendix 4:

Total sample regression results:

Dependent Variable: Y
Method: Least Squares
Newey-West HAC Standard Errors & Covariance (lag truncation=9)

	Coefficient	Std. Error	t-Statistic	Prob.
C	9.944652	0.471259	21.10231	0.0000
G	0.134968	0.020607	6.549673	0.0000
LOG_ANNSATTE	0.059947	0.015908	3.768315	0.0002
LAG1_R	0.126498	0.013111	9.647950	0.0000
LAG1_LOG_IR_FOU	0.058937	0.014515	4.060509	0.0000
INDUSTRIKODER=15	0.247620	0.128401	1.928490	0.0538
INDUSTRIKODER=17	-0.066046	0.149165	-0.442771	0.6579
INDUSTRIKODER=18	0.047972	0.224414	0.213765	0.8307
INDUSTRIKODER=19	-0.004503	0.172017	-0.026177	0.9791
INDUSTRIKODER=20	-0.050486	0.144632	-0.349067	0.7271
INDUSTRIKODER=21	0.072824	0.172974	0.421014	0.6738
INDUSTRIKODER=22	-0.038135	0.114941	-0.331780	0.7401
INDUSTRIKODER=24	0.279725	0.148657	1.881683	0.0599
INDUSTRIKODER=25	-0.004443	0.126960	-0.034993	0.9721
INDUSTRIKODER=26	0.014578	0.130059	0.112086	0.9108
INDUSTRIKODER=27	0.391978	0.215354	1.820155	0.0688
INDUSTRIKODER=28	-0.226082	0.122831	-1.840596	0.0657
INDUSTRIKODER=29	0.108930	0.120339	0.905198	0.3654
INDUSTRIKODER=30	0.325291	0.142151	2.288349	0.0222
INDUSTRIKODER=31	0.069600	0.149904	0.464296	0.6425
INDUSTRIKODER=32	-0.032647	0.227517	-0.143493	0.8859
INDUSTRIKODER=33	-0.087673	0.160769	-0.545335	0.5855
INDUSTRIKODER=34	0.361220	0.160000	2.257626	0.0240
INDUSTRIKODER=35	0.070121	0.129688	0.540692	0.5887
INDUSTRIKODER=36	-0.245592	0.123939	-1.981561	0.0476
YEAR=1997	-0.151043	0.030092	-5.019426	0.0000
YEAR=1998	-0.087273	0.028694	-3.041461	0.0024
YEAR=1999	-0.130114	0.026360	-4.935966	0.0000
YEAR=2000	-0.173626	0.024084	-7.209079	0.0000
YEAR=2001	-0.109737	0.021606	-5.078933	0.0000
YEAR=2002	-0.036658	0.018239	-2.009905	0.0445
YEAR=2003	-0.024493	0.013652	-1.794087	0.0729
R-squared	0.296196	Adjusted R-squared		0.292344

High-tech sample regression results:

Dependent Variable: Y
Method: Least Squares
Newey-West HAC Standard Errors & Covariance (lag truncation=9)

	Coefficient	Std. Error	t-Statistic	Prob.
C	10.94326	0.657235	16.65044	0.0000
G	0.061386	0.029946	2.049873	0.0405
LOG_ANNSATTE	0.058576	0.023880	2.452961	0.0143
LAG1_R	0.123392	0.023855	5.172619	0.0000
LAG1_LOG_IR_FOU	0.054153	0.021330	2.538793	0.0112
INDUSTRIKODER=24	0.382949	0.152668	2.508372	0.0122
INDUSTRIKODER=29	0.058035	0.078486	0.739431	0.4597
INDUSTRIKODER=30	0.052293	0.112380	0.465323	0.6418
INDUSTRIKODER=31	-0.000413	0.111659	-0.003695	0.9971
INDUSTRIKODER=32	-0.030233	0.188946	-0.160011	0.8729
INDUSTRIKODER=33	-0.140980	0.122288	-1.152857	0.2491
INDUSTRIKODER=34	0.282674	0.113436	2.491931	0.0128
YEAR=1997	-0.119269	0.058635	-2.034084	0.0421
YEAR=1998	-0.045426	0.054611	-0.831803	0.4056
YEAR=1999	-0.101433	0.050192	-2.020902	0.0434
YEAR=2000	-0.153924	0.045619	-3.374124	0.0008
YEAR=2001	-0.081799	0.041381	-1.976747	0.0482
YEAR=2002	-0.024511	0.035328	-0.693793	0.4879
YEAR=2003	-0.000105	0.027126	-0.003875	0.9969
R-squared	0.231440	Adjusted R-squared		0.224038

Medium-tech sample regression results:

Dependent Variable: Y
 Method: Least Squares
 Newey-West HAC Standard Errors & Covariance (lag truncation=9)

	Coefficient	Std. Error	t-Statistic	Prob.
C	10.48698	0.669046	15.67452	0.0000
G	0.101668	0.029386	3.459714	0.0006
LOG_ANNSATTE	0.046298	0.026715	1.732991	0.0833
LAG1_R	0.095139	0.019322	4.923975	0.0000
LAG1_LOG_IR_FOU	0.059561	0.026748	2.226806	0.0261
INDUSTRIKODER=25	0.264625	0.090597	2.920890	0.0035
INDUSTRIKODER=26	0.297246	0.095241	3.120981	0.0018
INDUSTRIKODER=27	0.699002	0.200213	3.491297	0.0005
INDUSTRIKODER=28	0.011850	0.078150	0.151631	0.8795
YEAR=1997	-0.183129	0.059530	-3.076233	0.0021
YEAR=1998	-0.109992	0.057304	-1.919455	0.0551
YEAR=1999	-0.184469	0.052015	-3.546432	0.0004
YEAR=2000	-0.213450	0.047424	-4.500888	0.0000
YEAR=2001	-0.127910	0.044068	-2.902538	0.0038
YEAR=2002	-0.058832	0.036070	-1.631062	0.1031
YEAR=2003	-0.057268	0.026667	-2.147522	0.0319
R-squared	0.236712	Adjusted R-squared	0.229059	

Low-tech sample regression results:

Dependent Variable: Y
 Method: Least Squares
 Newey-West HAC Standard Errors & Covariance (lag truncation=9)

	Coefficient	Std. Error	t-Statistic	Prob.
C	8.980679	0.715055	12.55942	0.0000
G	0.215431	0.035442	6.078436	0.0000
LOG_ANNSATTE	0.064946	0.028016	2.318197	0.0205
LAG1_R	0.133708	0.019378	6.900134	0.0000
LAG1_LOG_IR_FOU	0.065405	0.024520	2.667365	0.0077
INDUSTRIKODER=17	-0.277267	0.113169	-2.450030	0.0144
INDUSTRIKODER=18	-0.052693	0.214032	-0.246192	0.8056
INDUSTRIKODER=19	-0.226881	0.158915	-1.427686	0.1535
INDUSTRIKODER=20	-0.260600	0.110745	-2.353152	0.0187
INDUSTRIKODER=21	-0.198542	0.158622	-1.251673	0.2108
INDUSTRIKODER=22	-0.210513	0.079010	-2.664399	0.0078
INDUSTRIKODER=37	-0.318201	0.129994	-2.447821	0.0144
YEAR=1997	-0.178254	0.050451	-3.533216	0.0004
YEAR=1998	-0.131511	0.047593	-2.763248	0.0058
YEAR=1999	-0.144219	0.043939	-3.282285	0.0010
YEAR=2000	-0.181676	0.039971	-4.545204	0.0000
YEAR=2001	-0.135552	0.035818	-3.784516	0.0002
YEAR=2002	-0.038148	0.030088	-1.267904	0.2050
YEAR=2003	-0.019197	0.022385	-0.857590	0.3912
R-squared	0.366430	Adjusted R-squared	0.361422	