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MODELS OF R&D-INDUCED GROWTH: AN EMPIRICAL INVESTIGATION

DISСЕRТАTІОN

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of The Ohio State University.

By
Marios Zachariadis, M.A.

The Ohio State University
2000

Dissertation Committee:Approved by
Professor Paul Evans, Adviser
Professor Peter Howitt
Professor Mario Crucini

Adviser
Economics Graduate Program
ABSTRACT

In the first chapter, I derive and estimate a system implied by a model of R&D-induced growth that relates R&D, patenting, technological change, and output growth. Regressing the rate of patenting on R&D intensity lags, technological change on rate of patenting and R&D intensity lags, and output growth on technological change lags, should give nonzero sums of the slope coefficients for this endogenous growth framework. A zero sum of slope coefficients for any of the three equations in the system would imply non-rejection of the null hypothesis that growth is not induced by R&D. Using US manufacturing industry data, I find evidence of positive long-run impact of the explanatory variables for all equations. The null hypothesis that growth is not induced by R&D is therefore rejected. Moreover, I find evidence of technological spillovers from aggregate research intensity to industry-level economic performance, as well as evidence for long lags between innovative activity and economic growth. Finally, the theoretically implied system estimation is more efficient and often provides quite different estimates than the estimation of single equations.

In the second chapter, I use data for a group of OECD countries to estimate a somewhat modified version of the system of equations estimated in the first essay. This system interrelates R&D intensity, productivity growth, and output
growth. I obtain results similar to those for the United States. The estimates are bigger for aggregate data compared to industry-level data.

In the final chapter, I present a model with a sector whose R&D expenditures induce technological progress for the domestic economy. Productivity differences across countries are predicted to have a negative relation with cross-country price differences of manufacturing goods. An extension which considers a non-tradeables sector, implies instead a positive relation between cross-country productivity and price differences. Using absolute price data for six European countries, I find that countries with higher R&D stocks have a higher relative price of non-tradeables to tradeables. I also find that the high productivity countries have lower prices for traded goods. Thus, in contrast to the Balassa-Samuelson hypothesis, the overall price level might be lower in the more productive country since tradeables prices are not equalized.
Dedicated to my brother Haris
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VITA

September 11, 1969

Born Larnaka, Cyprus

June 1993

B.S., Economics: Mathematical Emphasis, University of Wisconsin at Madison

September 1994

M.A., Economics, The Ohio State University

September 1994-January 1995

Research Associate, Center of Wisconsin Strategy

February 1995-August 1996

Research Associate, University of Cyprus

September 1996-August 1998

Graduate Teaching Associate, Department of Economics, The Ohio State University

September 1998-June 1999

Graduate Research Associate, Journal of Money Credit and Banking

Summer 1999

PEGS Dissertation Grant, Department of Economics, The Ohio State University

Fall 1999

Dice Fellowship Award, Department of Economics, The Ohio State University

January 2000-June 2000

Graduate Teaching Associate, Department of Economics, The Ohio State University

vi
FIELDS OF STUDY

Major Field: Economics
# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abstract</td>
<td>ii</td>
</tr>
<tr>
<td>Dedication</td>
<td>iv</td>
</tr>
<tr>
<td>Acknowledgments</td>
<td>v</td>
</tr>
<tr>
<td>Vita</td>
<td>vi</td>
</tr>
<tr>
<td>List of Tables</td>
<td>x</td>
</tr>
<tr>
<td>List of Figures</td>
<td>xi</td>
</tr>
<tr>
<td>Introduction</td>
<td>1</td>
</tr>
<tr>
<td>Chapters:</td>
<td></td>
</tr>
<tr>
<td>1. R&amp;D-Induced Growth? Evidence from US Manufacturing</td>
<td>7</td>
</tr>
<tr>
<td>1.1 Introduction</td>
<td>7</td>
</tr>
<tr>
<td>1.2 The Schumpeterian model and its implications</td>
<td>16</td>
</tr>
<tr>
<td>1.3 A preliminary look at the data</td>
<td>21</td>
</tr>
<tr>
<td>1.4 Empirical analysis and results</td>
<td>32</td>
</tr>
<tr>
<td>1.5 Conclusion</td>
<td>44</td>
</tr>
<tr>
<td>2. R&amp;D-Induced Growth in the OECD?</td>
<td>51</td>
</tr>
</tbody>
</table>

viii
2.1 Introduction .............................................................................................51
2.2 Data ...........................................................................................................54
2.3 Empirical analysis and results ..............................................................57
2.4 Conclusion ................................................................................................74

3. R&D-Induced Productivity and international prices .........................78
   3.1 Introduction ............................................................................................78
   3.2 Data ..........................................................................................................82
   3.3 The model ...............................................................................................92
   3.4 The empirical analysis ..........................................................................96
   3.5 Extensions of the model ........................................................................98
   3.6 Conclusion .............................................................................................107

Appendix ...............................................................................................................111

Data sources and construction for Chapter 1 .................................................111

Bibliography......................................................................................................113
LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Summary statistics over 1969-88 for R&amp;D intensity, the rate of patenting, technological progress and output growth</td>
<td>22</td>
</tr>
<tr>
<td>1.2</td>
<td>P-values for the stationarity null (G test, Park 1990)</td>
<td>26</td>
</tr>
<tr>
<td>1.3</td>
<td>Coefficients' sum of parameters</td>
<td>37</td>
</tr>
<tr>
<td>1.4</td>
<td>Coefficients' sum of parameters using instruments</td>
<td>45</td>
</tr>
<tr>
<td>1.5</td>
<td>Coefficients' sum of parameters with TFP growth</td>
<td>46</td>
</tr>
<tr>
<td>1.6</td>
<td>Coefficients' sum of parameters with TFP growth using instruments</td>
<td>47</td>
</tr>
<tr>
<td>2.1</td>
<td>P-values for the Null of stationarity using Park's (1990) G test</td>
<td>60</td>
</tr>
<tr>
<td>2.2</td>
<td>P-values for the Null of stationarity using Park's (1990) G test</td>
<td>61</td>
</tr>
<tr>
<td>2.3</td>
<td>Estimation of (3) and (4) using aggregate data</td>
<td>68</td>
</tr>
<tr>
<td>2.4</td>
<td>System estimation using aggregate data</td>
<td>70</td>
</tr>
<tr>
<td>2.5</td>
<td>Estimation of (3) and (4) using manufacturing industry data</td>
<td>75</td>
</tr>
<tr>
<td>2.6</td>
<td>Estimation using manufacturing industry data</td>
<td>76</td>
</tr>
<tr>
<td>3.1</td>
<td>Explaining cross-country price differences of manufactures</td>
<td>99</td>
</tr>
<tr>
<td>3.2</td>
<td>Explaining cross-country price differences</td>
<td>108</td>
</tr>
<tr>
<td>3.3</td>
<td>Absolute R&amp;D stock differences of 5 EC countries from Germany</td>
<td>109</td>
</tr>
</tbody>
</table>
# LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1 R&amp;D expenditures, Scientists and Engineers (S&amp;E), TFP Growth</td>
<td>9</td>
</tr>
<tr>
<td>1.2 R&amp;D intensity, S&amp;E over employment, and technological progress</td>
<td>10</td>
</tr>
<tr>
<td>1.3 The rate of patenting in US manufacturing</td>
<td>25</td>
</tr>
<tr>
<td>1.4 The rate of patenting in US manufacturing</td>
<td>27</td>
</tr>
<tr>
<td>1.5 The rate of patenting in US manufacturing</td>
<td>28</td>
</tr>
<tr>
<td>1.6 R&amp;D intensity in US manufacturing</td>
<td>29</td>
</tr>
<tr>
<td>1.7 R&amp;D intensity in US manufacturing</td>
<td>30</td>
</tr>
<tr>
<td>1.8 R&amp;D intensity in US manufacturing</td>
<td>31</td>
</tr>
<tr>
<td>2.1 R&amp;D intensities for the G7 countries</td>
<td>59</td>
</tr>
<tr>
<td>2.2 GDP growth for US, Japan, Canada, Germany, and France</td>
<td>62</td>
</tr>
<tr>
<td>2.3 TFP growth for US, Japan, Canada, Germany, and France</td>
<td>63</td>
</tr>
<tr>
<td>3.1 1980 German Real Exchange Rates for Traded Goods</td>
<td>84</td>
</tr>
<tr>
<td>3.2 1980 German Real Exchange Rates for Non-Traded Goods</td>
<td>85</td>
</tr>
<tr>
<td>3.3 1985 German Real Exchange Rates for Traded Goods</td>
<td>86</td>
</tr>
<tr>
<td>3.4 1985 German Real Exchange Rates for Non-Traded Goods</td>
<td>87</td>
</tr>
<tr>
<td>3.5 1980 R&amp;D stocks in millions of constant $US</td>
<td>89</td>
</tr>
</tbody>
</table>
3.6 1985 R&D stocks in millions of constant SUS.................................90
3.7 1980 and 1985 GDP per capita in millions of constant SUS...............91
INTRODUCTION

Output growth is probably the single most important economic indicator. After all, a four percent annual rate of growth is sufficient to double a society's living standards in about the same time it takes a four year old to complete her education, assuming she does not choose to attend graduate school. The extent to which growth is in general endogenous (caused by economic decisions within the system that are potentially influenced by policy), or exogenous (caused by factors not determined within the economic system) indicates the determinants of growth and what, if anything, a government or other institution can do to influence these and thus, indirectly, promote growth.

During the second half of the last decade several papers have addressed the question of testing endogenous growth theory based on its implications about convergence (Evans 1996a,b, 1997b), and the relation of output growth with government-related variables (Evans 1997a, Kocherlakota and Yi 1997), money (Evans 1996c), investment and R&D expenditures (Jones 1995a,b). With the exception of the Kocherlakota and Yi (1997) paper the evidence appears to be against the empirical relevance of endogenous growth theory.
Here, I implement tests of endogenous growth theory based on a Schumpeterian model as augmented by Aghion and Howitt (1998). This framework deals with most of the empirical critiques that have been raised to this date as explained in Howitt (1998), but implies several testable relations between innovative activity, technological change, and output growth. I look for evidence of R&D-induced growth in US manufacturing, and for a group of OECD countries. The US alone accounts for over 35 percent of world R&D expenditures and the OECD for 90 percent.\(^1\) The rest of the world can thus be best thought of as an importer of technologies developed in the US and the rest of the OECD. In this sense, R&D-induced growth in the OECD would lead to productivity and output growth in the rest of the world so that R&D can easily be the engine of growth even for countries which do not perform extensive R&D.

For US manufacturing, I estimate a system implied by a model of R&D-induced growth which relates R&D, patenting, technological change, and economic growth. In the case of the OECD countries, I estimate a system which relates R&D, productivity growth, and economic growth.\(^2\) I test each of the theoretical implications separately as well as by estimating a system of equations which takes simultaneously into account the interaction between innovative activity, technological change, and output growth.

\(^1\)Reported by Acemoglu and Zilibotti (1999.)

\(^2\)I do not use patents across the OECD because these are not always available at a sufficient detail and when they are, it is hard to argue that these are comparable across counties.
Performing the same tests of endogenous growth across countries shows how robust the results obtained for the US actually are, and can help us distinguish between the view that theories of endogenous growth are useful for understanding long-run growth primarily for countries at the technological frontier versus the view that these theories apply to a broader group of countries.

A simple version of the Aghion and Howitt growth model implies contemporaneous relationships for the variables of interest whereas the empirical specification I consider here allows for lagged relationships, taking into account that the essence of these growth models relates to medium to long-run rather than contemporaneous or short-run relationships. I attempt to use proxies which correspond closely to the theoretical concepts. The decision of what empirical proxies to use for the theoretical variables of the model is an important part of this project. Both the relevance and the quality of the data are likely to have an important effect on the results of the various tests. I use the Basu, Fernald, and Kimball (1998) estimates of technological progress, and construct measures of the rate of patenting and R&D intensity for US manufacturing industries, and of R&D intensity for a group of OECD countries.

An indirect test of the relation between endogenously determined innovative activity and technology or productivity levels is the degree to which
the former can explain cross-country price differences. I consider this in the third chapter. To the extent that technological change is endogenously induced by innovation-related activity, the intensity of this activity over time as measured by the stock of Research and Development should affect the productivity level. Thus, models of R&D-induced growth predict that the intensity of innovation-related activity over time as measured by the stock of Research and Development should largely determine the productivity level.

I construct and estimate a model that explores the relationship between R&D-induced productivity and prices. Productivity is determined by the accumulation of R&D stock in the manufacturing sector. In this framework, the stock of R&D can be interpreted as the accumulated stock of knowledge in the domestic economy. The latter implies the productivity level for the domestic economy as in models of “R&D-induced” or “idea-based” growth. Productivity differences across countries are predicted to have a negative relation with cross-country price differences of manufacturing goods.

An extension of the model which considers a non-tradeables sector which does not perform R&D, implies instead a positive relation between productivity differences and price differences across countries.

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3 This is an issue of separate interest in studying purchasing power parity and the law of one price.

4 Kortum (1997) considers a model where productivity is determined by the stock of past research. In proposition 2.1 he states that “At time t, given the path of research up to that date, the distribution function of the state of the art for producing good j depends only on the stock of research.”

Keller 1997,1998 considers the relation between the level of productivity and the accumulated stock of R&D, in an international trade model context.
This chapter makes two main contributions to the existing literature. First, it highlights the relevance of models of R&D-induced growth to international macroeconomic issues. There is no previous attempt to my knowledge to relate a model of R&D induced growth to international price differences. In doing so, this chapter provides a justification for the use of R&D stocks as an indirect proxy to productivity that is free of the usual problems associated with direct measures of labor productivity or total factor productivity. Second, in contrast to previous work on international productivity and price differences, the empirical part of this chapter uses a disaggregated dataset of individual prices rather than using aggregate price indices. This allows for a more careful study of the role of tradeability in determining price differences across locations.

I use a broad cross-section of disaggregated prices in six European countries, to look at the relation between commodity-specific real exchange rates and cross-country productivity differences proxied by differences in R&D stocks. I distinguish between the effect of cross-country productivity differences on price differences of nontraded and of traded goods. I find that individual real exchange rates of traded goods are negatively related to cross-country productivity differences. I also find that, consistent with a basic premise of the Balassa-Samuelson hypothesis, the relative price of non-traded to traded goods appears positively related with productivity differences. Nevertheless, the overall effect of productivity differences on price level differences
may not be positive. In the absence of price equalization for traded goods, high productivity countries can have lower price levels in contrast to the Balassa-Samuelson hypothesis. Finally, the above findings point to a strong relation between a concept of the knowledge stock and the level of productivity in a country.

It should be noted here that the endogenous growth framework considered in this study is best seen as a model applicable to developed countries that perform R&D. For this reason, and due to the greater availability of data for such countries, I test this model using data from developed countries alone. Ignoring less developed countries in a study of growth might appear as evading the real question: “How can poorer countries grow?” Nevertheless, the findings of the current study concerning the empirical validity of an important class of endogenous growth models should be useful in suggesting the kind of policies governments or other institutions should be adopting or avoiding. To the extent that the data do not reject the implications outlined in the previous paragraphs, R&D-Induced growth appears plausible.
CHAPTER 1

R&D-INDUCED GROWTH? EVIDENCE FROM US MANUFACTURING

1.1 INTRODUCTION

During the second half of the last decade several papers have addressed the question of testing endogenous growth theory based on its implications about convergence (Evans 1996a,b, 1997b), and the relation of output growth with government-related variables (Evans 1997a, Kocherlakota and Yi 1997), money (Evans 1996c), investment, and R&D expenditures (Jones 1995a,b). With the exception of Kocherlakota and Yi (1997) the evidence from these papers appears to be against the empirical relevance of endogenous growth theory.

In this chapter, I implement tests of endogenous growth theory based on a Schumpeterian model as augmented by Aghion and Howitt (1998). This framework deals with most of the empirical critiques that have been raised to date as explained in Howitt (1998, 1999), but implies several testable relations between innovative activity, technological change, and output growth.
This endogenous growth framework predicts that the fraction of GDP allocated to R&D remains constant during periods of steady growth whereas Jones (1995a) considers a model which predicts instead that the number of scientists and engineers remains constant during periods of steady growth. Jones argument essentially rejects models of R&D-induced growth by pointing to the rising R&D expenditures or the rising number of scientists and engineers in relation to the constancy of TFP growth. This argument is portrayed in figure 1.1 for US manufacturing. Instead, the Schumpeterian framework of R&D-induced growth points to an indirect relation between R&D intensity and technological progress. Both variables are shown in figure 1.2 for US manufacturing. I attempt to capture this indirect relationship by looking at the relation of R&D intensity with patenting, and patenting with technological progress.

I look for evidence of R&D-induced growth in US manufacturing. I derive and estimate the implications of the Schumpeterian framework of endogenous growth as a system of inter-related equations which relates R&D, patenting, technological change, and output growth. I view the link as being inherently dynamic and sequential: from R&D intensity to patenting, from patenting to productivity enhancement, and from productivity growth to output growth. A simple version of the Aghion and Howitt growth model implies

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5The data shown here are for aggregate US manufacturing whereas in my application I look at two-digit SIC subdivisions of US manufacturing.
Figure 1.1: Research and Development in Billions of 1987 $US (R&D), Scientists and Engineers in Hundreds of Thousands (S&E), and Total Factor Productivity Growth in Percent (TFP).
Figure 1.2: R&D Intensity, Scientists and Engineers over Employment, and Technological Progress in US Manufacturing.
contemporaneous relationships for the variables of interest whereas the empirical specification I consider here allows for lagged relationships, taking into account that the essence of these growth models relates to medium to long-run rather than contemporaneous or short-run relationships. Finally, consistent with the idea that individual industries can draw from an aggregate pool of knowledge, I consider the effect of total manufacturing innovative activity variables on the average industry's technological progress.

In related work, Caballero and Jaffe (1993) use a rich dataset of patent citations for a large number of US firms over time to estimate rates of creative destruction, technological obsolescence, and diffusion, in an endogenous growth framework. They do not attempt to estimate the overall system of equations implied by the model as a whole. Pakes and Griliches (1984) study the relationship between R&D and Patenting using a short time period between 1968 and 1975 for a large number of firms. They consider the contemporaneous effect as well as five lags of R&D and find that the sum of the contemporaneous and lagged effects is positive and significant. This conclusion is driven primarily by a large contemporaneous effect which, as Griliches (1990) points out, might be due to reverse causality. Moreover, they find a strong negative time trend coefficient which they view as capturing a falling propensity to patent. In the same paper, they report a gestation lag between R&D and invention of 1.6 years. Pakes and Schankerman (1984) find gestation lags ranging from 0.82 years for electronics to 2.09 for machinery with
an average gestation lag of 1.34 years. In a review of this literature, Griliches (1990) concludes that there is a strong and positive relationship between R&D and patents at the cross-sectional level across firms and industries, but only a weak relationship in the within-firms time series dimension. Finally, Kortum (1993) looks at the patents-productivity relation using a panel of industries. He finds a positive and significant coefficient for the growth rate of the patent stock (0.91 with a standard error of 0.44) but low $R^2$ (0.02). He also finds that the rate of patenting, which is more relevant for quality-ladder models, performs worse than the growth rate of the patent stock.

Studies of the R&D-productivity relation include Griliches (1980a,b), Mansfield (1988), and Griliches and Mairesse (1990).\(^6\) Griliches (1980a) uses a panel of 3-digit manufacturing industry data and finds that the estimate of the R&D coefficient is sensitive to the time period under study; for the period 1959 to 1968 he estimates a positive and significant coefficient, 0.07, whereas for the period 1969 to 1977 the estimated R&D coefficient is close to zero. Griliches (1980b) uses a short time series between 1957 and 1963 for a large cross-section of firms and finds a positive relationship between company productivity and R&D intensity with the estimated R&D coefficient between 0.05 and 0.1, with an average about 0.07. Mansfield (1988) uses a cross-section of industries averaging the data for the period 1960 to 1979 for Japan and for the period 1948 to 1966 for the United States. He finds\(^6\) These authors use a Cobb-Douglas production function that includes R&D stock as one of three inputs, to derive a relation between productivity and R&D.
a high positive coefficient for applied R&D in Japan, 0.42, but a negative and statistically insignificant coefficient for basic research. In the US, the coefficient for applied research is 0.07 and for basic research it equals 1.49. Finally, Griliches and Mairesse (1990) use a cross-section of firms for the US and Japan for the short time period 1973 to 1980 and find mixed results; for a number of firms R&D-intensity coefficients are negative, for some firms this same coefficient is between zero and 0.05, and for other firms this is greater than 0.05. A review of this literature is found in Nadiri (1993). More recently, Keller (1998) uses a panel of industries and countries to study the role of international spillovers on the relation between R&D and productivity growth.

Part of the value added of my approach to the existing literature is that using a relatively larger time series dimension, I consider the lags between R&D and patenting and patenting and productivity in the chain of events giving rise to economic growth.

The framework I consider here is consistent with Kirchhoff's (1994) and Geroski's (1994) discussions on innovative activity. R&D expenditures are considered as an input into the production of patents or inventions, and patents are intermediate inputs into the production of innovations. The usual practice of relating R&D directly to productivity growth might be insufficient since it ignores the indirect nature of the relationship. I consider, instead, the relation of R&D intensity with the rate of patenting, as implied by the
"production function" of inventions which uses R&D as an input.

I attempt to use proxies which correspond closely to the theoretical concepts. The decision of what empirical proxies to use for the theoretical variables of the model is an important part of this project. Both the relevance and the quality of the data are likely to have an important effect on the results of the various tests. I use the Basu, Fernald, and Kimball (1998) estimates of technological progress, and construct measures of the rate of patenting and R&D intensity for US manufacturing industries.

In order to improve the power of the tests, I look at average manufacturing relations using a panel of industries from US manufacturing rather than looking at aggregate data. The justification for considering the manufacturing sector to look for evidence of R&D-induced growth comes from the observation that this sector has accounted for an average of above ninety percent of R&D expenditures in the US until the late eighties.

Regressing the rate of patenting on R&D intensity lags, technological change on rate of patenting and R&D intensity lags, and output growth on technological change lags, should give nonzero sums of the slope coefficients for the endogenous growth framework I consider here. A zero sum of slope coefficients for any of the three equations in the system would imply non-rejection of the null hypothesis that growth is not induced by R&D. I find evidence for a positive impact of R&D intensity on the rate of patenting, of the rate of patenting and R&D intensity on technological change, and of
technological change on output growth.

The estimates from the first equation of the system relating R&D intensity to the rate of patenting show that the former has a strong long-run impact on the latter. Furthermore, aggregate manufacturing R&D has a strong positive impact on the rate of patenting implying technology spillovers across manufacturing industries. The estimates from the second equation suggest a strong long-run impact of R&D intensity on technological progress, and a strong long-run impact of the rate of patenting on technological progress when one ignores the short-run effect of the first three years. The final equation implies a strong long-run impact of technological progress on output growth. The estimates from this system of equations imply rejection of the null hypothesis that growth is not induced by R&D. This suggests the plausibility of R&D-induced growth in US manufacturing even when productivity growth appears stable while R&D expenditures have been increasing over time. In the next section I provide briefly some theoretical background. I turn to the data in the third section, and in the fourth section I describe the empirical analysis and results. Section five concludes.
1.2 THE SCHUMPETERIAN MODEL AND ITS IMPLICATIONS

The endogenous growth framework I consider here is based on the augmented Schumpeterian model presented in Aghion and Howitt (1998, ch. 12). All growth in this model is driven by vertical drastic innovations which improve the quality of goods and displace previous incumbents. Furthermore, this framework should be seen as a model applicable to developed countries which perform R&D. Below is a brief and non-rigorous description of the main components of this model.

Output of the single final good, \( Y_t \), at time \( t \) is produced as

\[
Y_t = \left( \frac{L_t}{Q_t} \right)^{1-\alpha} \int_0^{Q_t} A_{it} x_{it}^\alpha di
\]

with \( A_{it} \) a productivity parameter attached to the latest version of intermediate product \( i \), \( x_{it} \) the output flow of intermediate product \( i \), \( Q_t \) the number of existing intermediate products, and \( L_t \) the labor input in the final goods sector growing at the exogenous population rate, \( g_L \). Division of \( L_t \) by \( Q_t \) eliminates any productivity gain resulting from product proliferation. The assumption here is that population and product variety grow at the same rate.\(^7\) This assumption allows the current model to deal with the demand-driven scale effects implied by earlier endogenous growth models.

Each intermediate sector is monopolized and sells its product to the com-

---

\(^7\)I intend to test this relationship using a survey of brands across European countries.
petitive final sector at a price equal to the marginal product of that intermediate input in producing the final good. Capital is used as an input in the production of intermediate goods so that the output flow of intermediate input in sector \( i \) in period \( t \) is given by \( x_{it} = \frac{K_{it}}{A_{it}} \) where \( K_{it} \) is the capital input for sector \( i \), and \( A_{it} \) is the sector-specific productivity parameter attached to the latest version of intermediate product \( i \). Division of the capital input by this productivity parameter indicates that successive vintages of the intermediate product \( i \) are produced by increasingly capital-intensive techniques.

The flow of innovation output in the research sector looking to develop the next generation of an intermediate input \( i \) is given by \( \phi_{it} \) in equation (1)

\[
\phi_{it} = \lambda \phi(n_{it}) = \lambda \phi\left(\frac{R_{it}}{A_{t}^{\text{max}}}\right), \phi' > 0, \phi'' < 0
\]

where \( \lambda > 0 \) is the flow probability of an innovation and indicates R&D productivity; the function \( \phi \) exhibits decreasing returns to R&D as a result of a research congestion externality within anyone product associated with duplication and overlap, and \( n_{it} = \frac{R_{it}}{A_{t}^{\text{max}}} \) is the research intensity with \( R_{it} \) the total amount of final output invested in R&D at date \( t \). The same equilibrium flow of research input \( R_{it} \) is used for any intermediate input \( i \) so that \( R_{it} = R_t \). \( A_{t}^{\text{max}} \) is the leading-edge productivity parameter at date \( t \) and division by this indicates that the cost of further advances increases proportionately to technological advances as a result of increasing complexity. Equation (1) implies a positive relationship between the rate of arrival of
innovations proxied by the rate of patenting or new product arrival, and
the productivity-adjusted level of R&D at time \( t \) given by \( n_t \). The main
difference from Jones (1995a) is that here the input \( R_t \) includes capital.\(^8\)
Thus the current framework predicts that the fraction of output allocated
to R&D remains constant during periods of steady growth where Jones's
model predicts instead that the number of scientists and engineers remains
constant during periods of steady growth. In figures 1.1 and 1.2, I present
respectively the unweighted variable of Scientists and Engineers (S&E) (or
Research and Development expenditures (R&D) ) which Jones's framework
considers and the weighted variable of R&D intensity (R&D/Y) (or Scientists
and Engineers over labor (S&E/L) ) which the Schumpeterian framework
considers. Clearly, the rising number of scientists and engineers (or the rising
R&D expenditures) is not reflected in a proportional increase of the weighted
variables.

The arrival rates of innovations in different sectors draw from the same
pool of knowledge whose state is represented by the leading-edge technology
parameter \( A_t^{\text{max}} \). The ratio of the leading edge to average technology is
\( A_t^{\text{max}} = (1+\sigma)A_t^{\text{avr}} \) implying \( \frac{A_t^{\text{avr}}}{A_t^{\text{max}}} = \frac{A_t^{\text{max}}}{A_t^{\text{max}}} \) with \( \sigma \), the size of innovations, con-
stant. An important characteristic of the current framework is that growth

\(^8\)In the special case where function \( \phi(n_t) = n_t^\gamma \) then \( \frac{A_t^{\text{avr}}}{A_t^{\text{max}}} = \nu(R_t)^\gamma(A_t^{\text{avr}})^{-\gamma} \) with
\( \nu = \sigma \lambda (1 + \sigma)^{-\gamma} \). The last equation for the growth rate of average productivity resembles
the research technology in Jones (1995) with \( 0 < \gamma \leq 1 \), the main difference being that
here the input \( R_t \) includes capital.
in the leading edge technology, \( A_t^{\text{max}} \), occurs as a result of the knowledge spillovers produced by innovations. Each innovation is implementable only in the intermediate sector it is used in but it increases the knowledge stock so that the next innovator in any intermediate sector can draw from an expanded pool of knowledge. Knowledge grows at a rate proportional to the average rate of innovations, \( A_t^{\text{aur}} \), and is publicly available and costly.

The steady-state rate of technological progress is given by \( g_t \) in equation (2):

\[
g_t = \frac{A_t^{\text{aur}}}{A_t^{\text{aur}}} = \sigma \phi_t
\]  

(2)

Here, \( \sigma \) is the size of innovations and \( \phi_t \) is the innovation rate. This equation implies a positive relationship between \( g_t \) and the innovations rate \( \phi_t \). In the empirical application in the next section the latter is proxied by the rate of patenting.

Finally, the growth rate of output per capita is given by equation (3):

\[
G_t = g_t + \alpha \frac{k_t}{k_t}
\]  

(3)

In a steady state, the growth rate of capital, \( \frac{k_t}{k_t} \), is equal to zero and the growth rate of output per person is \( g_t \). Capital obsolescence can lead to a reversal of the positive steady-state relationship between technological progress and output growth implied by the current endogenous growth framework. Outside the steady state it is hard to derive a testable relationship between the rate of economic growth, \( G_t \), and the rate of arrival of innovations, \( \phi_t \),
since this will depend crucially on the behavior of the capital stock. Capital obsolescence accelerates along with the innovation rate creating substantial time-lags between the occurrence of an innovation and a possible positive impact on output growth. In the system estimation in the next section, I consider the steady state relationship of output growth with technological change by including long lags of $g_t$, along with industry-specific effects and an exogenous time trend, as explanatory variables for output growth.

The main components of the model I consider here are given by equations (1), (2), and (3). This framework deals with the Jones critique of models of R&D-induced growth but provides several testable implications which are brought to the data next. These are: (a) A positive relation between the arrival rate of innovations and R&D intensities. This is implied by equation (1). (b) A positive relation between the average rate of productivity and the arrival rate of innovations. This is implied by equation (2). (c) A positive relationship between output growth and technological progress. This is implied by equation (3).

---

9In the context of an endogenous growth model, and using implied capital obsolescence rates from Caballero and Jaffe (1993), Howitt (1997) suggests that capital obsolescence associated with rapid technological change could keep the growth rate of output below what it would have been in the absence of technological change for a period longer than a decade.
1.3 A PRELIMINARY LOOK AT THE DATA

I use annual data on patents, R&D expenditures, gross output, and productivity growth.\textsuperscript{10} Table 1.1 presents summary statistics. The patents data are patents granted allocated in the year in which the application was filed with the US patent office. These are available for the period 1963 to 1988. I calculate the rate of patenting as the number of patents divided by the patents stock. I construct the latter as described in the appendix. Figures 1.3, 1.4, and 1.5 present the rate of patenting for aggregate manufacturing and the ten two-digit manufacturing industries in the sample. These are 20: Food and Kindred Products, 28: Chemicals and Allied Products, 30: Rubber and Plastics Products, 32: Stone, Clay, and Glass Products, 33: Primary Metal Industries, 34: Fabricated Metal Products, 35: Machinery Except Electrical, 36: Electrical Machinery, 37: Transportation Equipment, and 38: Instruments and Related Products. Table 1.2, presents the results of the stationarity tests for the rate of patenting in manufacturing and its two-digit industries with available data. The individual series appear stationary\textsuperscript{11} and a panel test that uses the Bonferroni bound implies that the null of stationarity cannot be rejected at the ten percent level of significance.

\textsuperscript{10}The sources for these data are described in the appendix.
\textsuperscript{11}There are five rejections of the null of stationarity at the five percent level of significance using Park's (1990) G(1,3) test. These are for total manufacturing, and for industries 28, 30, 32, and 34. For all of these cases Park's G(1,2) and G(1,4) tests do not reject the null of stationarity at the ten percent and five percent levels of significance respectively. The one exception is industry 34 for which Park's G(1,4) test rejects the null of stationarity.
<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>std dev</th>
<th></th>
<th></th>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RDY</td>
<td>RP</td>
<td>TBK</td>
<td>GY</td>
<td>RDY</td>
<td>RP</td>
<td>TBK</td>
<td>GY</td>
<td></td>
</tr>
<tr>
<td>3: Total Manufacturing</td>
<td>0.028</td>
<td>0.069</td>
<td>0.024</td>
<td>0.024</td>
<td>0.005</td>
<td>0.011</td>
<td>0.022</td>
<td>0.052</td>
<td></td>
</tr>
<tr>
<td>20: Food &amp; Kindred Products</td>
<td>0.003</td>
<td>0.074</td>
<td>0.010</td>
<td>0.019</td>
<td>0.001</td>
<td>0.017</td>
<td>0.020</td>
<td>0.023</td>
<td></td>
</tr>
<tr>
<td>28: Chemicals &amp; Allied Products</td>
<td>0.042</td>
<td>0.079</td>
<td>0.016</td>
<td>0.030</td>
<td>0.008</td>
<td>0.012</td>
<td>0.044</td>
<td>0.058</td>
<td></td>
</tr>
<tr>
<td>30: Rubber &amp; Plastics Products</td>
<td>0.010</td>
<td>0.074</td>
<td>0.004</td>
<td>0.041</td>
<td>0.003</td>
<td>0.009</td>
<td>0.030</td>
<td>0.087</td>
<td></td>
</tr>
<tr>
<td>32: Stone, Clay &amp; Glass Products</td>
<td>0.010</td>
<td>0.074</td>
<td>0.007</td>
<td>0.011</td>
<td>0.003</td>
<td>0.012</td>
<td>0.014</td>
<td>0.065</td>
<td></td>
</tr>
<tr>
<td>33: Primary Metal Industries</td>
<td>0.003</td>
<td>0.070</td>
<td>-0.002</td>
<td>0.019</td>
<td>0.000</td>
<td>0.015</td>
<td>0.031</td>
<td>0.023</td>
<td></td>
</tr>
<tr>
<td>34: Fabricated Metal Products</td>
<td>0.045</td>
<td>0.066</td>
<td>0.007</td>
<td>0.008</td>
<td>0.005</td>
<td>0.010</td>
<td>0.014</td>
<td>0.038</td>
<td></td>
</tr>
<tr>
<td>35: Machinery Except Electrical</td>
<td>0.166</td>
<td>0.063</td>
<td>0.019</td>
<td>0.013</td>
<td>0.070</td>
<td>0.011</td>
<td>0.026</td>
<td>0.061</td>
<td></td>
</tr>
<tr>
<td>36: Electrical Machinery</td>
<td>0.163</td>
<td>0.073</td>
<td>0.020</td>
<td>0.019</td>
<td>0.031</td>
<td>0.015</td>
<td>0.016</td>
<td>0.050</td>
<td></td>
</tr>
<tr>
<td>37: Transportation Equipment</td>
<td>0.262</td>
<td>0.064</td>
<td>-0.002</td>
<td>0.015</td>
<td>0.061</td>
<td>0.011</td>
<td>0.019</td>
<td>0.106</td>
<td></td>
</tr>
<tr>
<td>38: Instruments &amp; Products</td>
<td>0.040</td>
<td>0.082</td>
<td>0.020</td>
<td>0.026</td>
<td>0.010</td>
<td>0.014</td>
<td>0.024</td>
<td>0.052</td>
<td></td>
</tr>
</tbody>
</table>

Table 1.1: Summary Statistics over 1969-88, for R&D over Gross Output (RDY), the number of patents over the stock of patents (RP), the growth rate of technology (TBK), and the growth rate of output (GY).
The R&D data include research and development expenditures by "Federally Funded Research and Development Centers" (FFRDC) which are administered by industry. These are available for 1957 to 1992. For the purposes of this study, I use R&D expenditures weighted by gross output. The latter ratio is often referred to in the literature on R&D as "R&D intensity". I present R&D intensities for aggregate manufacturing and the ten two-digit manufacturing industries in my sample in figures 1.6, 1.7, and 1.8. In table 1.2, I present the results of the stationarity tests for the R&D intensities in manufacturing and its two-digit industries for which data are available. The individual industry variables appear to be stationary\textsuperscript{12} and a panel test that uses the Bonferroni bound implies that the null of stationarity cannot be rejected even at the ten percent level of significance.

Technological change is usually proxied by Total Factor Productivity (TFP) growth. Under the assumptions of constant returns to scale, perfect competition in the inputs and outputs markets, instantaneous adjustment of all inputs (long-run equilibrium), correct aggregation, and correct measurement of the several inputs and outputs, TFP growth measures exactly the exogenous shifts in the production function and is thus identical to the "true"

\textsuperscript{12}There are only three rejections of the null of stationarity, one for industry 30 using Park's G(1,2) test, one for industry 34 using Park's G(1,3) test, and one for industry 33 using Park's G(1,4) test. For the first case, the null of stationarity could not be rejected at the five percent significance level using the G(1,3) or G(1,4) tests, for the second case the null of stationarity could not be rejected at the five percent significance level using the G(1,2) or the G(1,4) tests, and for industry 33 the null of stationarity could not be rejected at the five percent significance level using the G(1,2) or the G(1,3) tests.
technology shock. In the presence of non-constant returns to scale, imperfect competition, factor adjustment costs, aggregation bias, and measurement errors for input and output quantity and quality, the degree of cyclicality and persistence of measured TFP growth will not generally coincide with the cyclicality and persistence of the technology shock.

Basu, Fernald, and Kimball (1998) use Jorgenson's quality adjusted gross output data\textsuperscript{13} and consider adjustments for non-constant returns to scale, imperfect competition, cyclical factor utilization, and aggregation effects. The resulting fully corrected estimate of technological change (TBK) in Basu, Fernald, and Kimball (1998) removes the contemporaneous procyclical bias leading to nearly zero contemporaneous correlation between these estimates of technological progress and output, and to negative contemporaneous correlation with employment.

One would expect the adjusted proxy to enable an improved assessment of the relation between technological change and innovative activity. Thus, I use the Basu, Fernald, and Kimball (1998) fully corrected technological progress estimate. This is available for the period 1950 to 1989. Moreover, I calculate a gross-output based measure of TFP growth from the Jorgenson data on capital, labor, and intermediate inputs, and using a translog index similar to the one described in appendix A which allows for time-varying input shares of capital, labor, energy, and intermediate inputs. I use Jorgenson's gross

\textsuperscript{13}For a detailed description of this dataset see Jorgenson, Gollop, and Fraumeni (1987).
output data for US manufacturing industries for the period 1950 to 1989 to calculate output growth. Augmented Dickey-Fuller and Weighted Symmetric (tau) tests for TBK, TFP, and output growth, show that the null of a unit root is easily rejected for most industries, and a panel unit root test using the Bonferroni bound implies that the joint hypothesis of a unit root null for the panel can be rejected at the five percent level of significance in favor of the alternative hypothesis of a stationary process.

Figure 1.3: The Rate of Patenting in US Manufacturing
### R&D Intensity

<table>
<thead>
<tr>
<th></th>
<th>G(1,2)</th>
<th>G(1,3)</th>
<th>G(1,4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3: Total Manufacturing</td>
<td>0.189</td>
<td>0.167</td>
<td>0.174</td>
</tr>
<tr>
<td>20: Food &amp; Kindred Products</td>
<td>0.553</td>
<td>0.274</td>
<td>0.181</td>
</tr>
<tr>
<td>28: Chemicals &amp; Allied Products</td>
<td>0.192</td>
<td>0.101</td>
<td>0.162</td>
</tr>
<tr>
<td>30: Rubber &amp; Plastics Products</td>
<td>0.027*</td>
<td>0.084</td>
<td>0.148</td>
</tr>
<tr>
<td>32: Stone, Clay &amp; Glass Products</td>
<td>0.336</td>
<td>0.584</td>
<td>0.354</td>
</tr>
<tr>
<td>33: Primary Metal Industries</td>
<td>0.082</td>
<td>0.163</td>
<td>0.026*</td>
</tr>
<tr>
<td>34: Fabricated Metal Products</td>
<td>0.459</td>
<td>0.024*</td>
<td>0.058</td>
</tr>
<tr>
<td>35: Machinery Except Electrical</td>
<td>0.057</td>
<td>0.101</td>
<td>0.146</td>
</tr>
<tr>
<td>36: Electrical Machinery</td>
<td>0.263</td>
<td>0.427</td>
<td>0.168</td>
</tr>
<tr>
<td>37: Transportation Equipment</td>
<td>0.283</td>
<td>0.193</td>
<td>0.166</td>
</tr>
<tr>
<td>38: Instruments &amp; Products</td>
<td>0.541</td>
<td>0.268</td>
<td>0.357</td>
</tr>
</tbody>
</table>

### Rate of Patenting

<table>
<thead>
<tr>
<th></th>
<th>G(1,2)</th>
<th>G(1,3)</th>
<th>G(1,4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3: Total Manufacturing</td>
<td>0.654</td>
<td>0.042*</td>
<td>0.089</td>
</tr>
<tr>
<td>20: Food &amp; Kindred Products</td>
<td>0.521</td>
<td>0.117</td>
<td>0.225</td>
</tr>
<tr>
<td>28: Chemicals &amp; Allied Products</td>
<td>0.129</td>
<td>0.024*</td>
<td>0.055</td>
</tr>
<tr>
<td>30: Rubber &amp; Plastics Products</td>
<td>0.953</td>
<td>0.033*</td>
<td>0.039*</td>
</tr>
<tr>
<td>32: Stone, Clay &amp; Glass Products</td>
<td>0.663</td>
<td>0.038*</td>
<td>0.061</td>
</tr>
<tr>
<td>33: Primary Metal Industries</td>
<td>0.904</td>
<td>0.051</td>
<td>0.112</td>
</tr>
<tr>
<td>34: Fabricated Metal Products</td>
<td>0.309</td>
<td>0.033*</td>
<td>0.071</td>
</tr>
<tr>
<td>35: Machinery Except Electrical</td>
<td>0.563</td>
<td>0.061</td>
<td>0.127</td>
</tr>
<tr>
<td>36: Electrical Machinery</td>
<td>0.399</td>
<td>0.059</td>
<td>0.097</td>
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<tr>
<td>37: Transportation Equipment</td>
<td>0.667</td>
<td>0.095</td>
<td>0.192</td>
</tr>
<tr>
<td>38: Instruments &amp; Products</td>
<td>0.918</td>
<td>0.061</td>
<td>0.129</td>
</tr>
</tbody>
</table>

Table 1.2: P values for the stationarity null (G test, Park 1990)

### Notes:

* * Reject the Null of stationarity at the five percent level of significance.

R&D intensity (RDY) is the fraction of output spent on research and development. This is available for 1957-89.

The rate of patenting (RP) is given by the number of patents over the stock of patents. This is available for 1963-88.

*I would like to thank Masao Ogaki for providing the programs for performing the G tests.
Figure 1.4: The Rate of Patenting in US Manufacturing.
Figure 1.5: The Rate of Patenting in US Manufacturing
Figure 1.6: R&D Intensity in US Manufacturing
Figure 1.7: R&D Intensity in US Manufacturing
Figure 1.8: R&D Intensity in US Manufacturing
1.4 EMPIRICAL ANALYSIS AND RESULTS

Here, I estimate a system of equations that relates R&D, patents, technological change, and output growth. Equations (1S), (2S), and (3S) form the basis of a system that relates in turn R&D to the rate of innovation or patenting, the rate of innovation to technological progress, and technological progress to the growth of output. This is essentially the value-added from using an endogenous growth model in asking the questions relating to R&D, patents and productivity. Again, one has to take into account that the relations between these variables are usually medium to long-run rather than contemporaneous or short-run ones, and thus should hold only with a lag.

The three basic equations I consider are

\[ \log \phi_{it} = \log \lambda_i + \tau t + \sum_{i=1}^{6} \gamma_i \log(n_{it-i}) + u_{it} \]  
(1S)

\[ g_{it} = \psi_i + \sum_{i=1}^{6} \sigma_i \phi_{it-i} + v_{it} \]  
(2S)

\[ G_{it} = \alpha_i + \theta t + \sum_{i=1}^{6} \zeta_i g_{it-i} + e_{it} \]  
(3S)

where \( u_{it}, v_{it}, \) and \( e_{it} \) are stationary errors\(^\text{15}\). I estimate this system of equa-

\(^{15}\)To the extent that some of the explanatory variables cannot be convincingly shown to be either I(0) or I(1), the analysis of Kocharlakota and Yi (1997) becomes relevant. They conduct their analysis assuming that the error term is stationary or independent of the stochastic process generating their explanatory variables, and further that their variables have bounded support. In their application, their explanatory variable is given by the share of public capital over output whereas here my explanatory variables include
tions applying iterated SUR estimation to a panel of ten industries for the period 1969 to 1988, for a total of two-hundred observations. The Newey-West (1987) heteroskedasticity and autocorrelation consistent covariance matrix with three lags is used to obtain consistent standard errors.

Equation (1S) is a logarithmic linearization of equation (1) which assumes \( \phi(n_t) = n_t^\gamma \) as the functional form for the R&D production function, where \( n_{it} \) stands for R&D intensity and \( \phi_{it} \) for the rate of patenting in industry \( i \) at period \( t \). The industry-specific constants \( \log \lambda_i \) stand for the log of an industry's research productivity but might also be capturing industry-specific differences in the propensity to patent. Moreover, I consider a common trend term for equation (1S) to capture possible changes of the propensity to patent over time.\(^1\) Such changes are not part of the basic theoretical specification from equation (1) but make sense in an empirical context. Finally, for some formulations I impose the restriction \( n_{it} = n_t \) on equation (1S) in order to capture spillover effects from aggregate manufacturing R&D to the individual industries innovation production.

Based on Fuller, Hasza, and Goebel (1981), they point out that "under these assumptions OLS provides consistent estimates of the sums of coefficients and standard inference procedures can be used, keeping in mind that the inference is conducted conditional on the particular realization of the variables, regardless of the stochastic processes generating the policy variables."

\(^1\)The estimates are obtained using the LSQ command in TSP which allows simultaneous iteration on the parameters and the residual covariance matrix.

\(^1\)This is suggested by the finding of a negative trend coefficient in Pakes and Griliches (1984) which points to a falling propensity to patent. Here, I confirm this result and find a negative and highly significant coefficient for the time trend.
In going from the theoretical equation (2) to the empirical specification (2S) I make the assumption that the aggregate relation from the former equation is reflected in the behavior of the average manufacturing industry I consider here. The justification for looking at average-manufacturing-industry relations using two-digit industry data from US manufacturing rather than considering aggregate manufacturing data is that doing so can improve the power of the tests. The restriction $\sigma_i = \sigma$ is imposed on equation (2S) to limit the number of parameters to be estimated.\(^{18}\) The industry-specific effects $\psi_i$ added to equation (2S) capture the effect on technological change of heterogeneity among the industries due to factors other than the rate of innovation.

As an extension to the basic framework, I consider the direct effect of the R&D ratio on technological change by adding the term $\sum_{i=1}^{6} s_i n_{it-1}$ to the right-hand side of equation (2S). This direct effect of R&D on technology is in addition to the indirect effect through the impact of R&D on patents which in turn enter equation (2S). Some innovations are not patented, and for such cases the link between R&D and technological change will not be captured by the indirect effect of R&D on technological change through its effect on patenting. It is thus essential to add a term for the direct effect of R&D in order to avoid misspecification. Finally, preliminary testing suggested

\(^{18}\)For six lags and ten industries the formulation with $\sigma_{i,t}$ rather than $\sigma_i$ would require sixty instead of six parameters for the latter formulation. The estimates of the sum of coefficients for the lags of the parameter $\sigma$ are not sensitive to this restriction.
that a time trend need not be included in equation (2S) since it was always estimated to be statistically indistinguishable from zero.\footnote{Including a time trend led to a statistically insignificant effect of patenting when the first three lags are considered, but a positive and strongly significant effect beyond the first three years.}

The variable \( G_{it} \) in equation (3S) stands for the growth rate of gross output in industry \( i \) at time \( t \). The industry-specific effects, \( \alpha_i \), in equation (3S) are meant to capture time-invariant heterogeneity among the industries which affects their output growth. A common trend is added to capture the effect on output growth of exogenous time-varying factors. The other parameter estimates are not sensitive to the inclusion of this time trend. Nevertheless, this time trend is estimated to be positive and statistically significant.

In table 1.3, I present results for the basic system of equations (1S), (2S), and (3S), as well as results for modifications of these equations. Estimates from single equations estimation are presented in the last two columns of the table. All results are obtained using the total of business and federal R&D expenditures data, and the Basu, Fernald, and Kimball (1998) fully adjusted technological change proxy (TBK). Results which use only data for TFP growth as the proxy for technological change are reported in table 1.5.\footnote{Results which use data for business R&D are similar to the ones presented here and are not reported.}

The estimates from the first equation of the system relating R&D intensity to the rate of patenting show that the former has a strong long-run impact
on the rate of innovation. Furthermore, as shown in the first row of column II, aggregate manufacturing R&D seems to have a strong positive impact on the rate of patenting implying technology spillovers across manufacturing industries. An interesting finding is that lags longer than two years are often positive and statistically significant. This suggests that the lag between research and invention might be longer than 1.34 years reported in Pakes and Schankerman (1984) or 1.6 years reported in Pakes and Griliches (1984.) Moreover, the finding of a positive sum of R&D coefficients in the latter paper was due to a large contemporaneous effect which might be due to reverse causality, whereas here I exclude the contemporaneous effect in estimating a strong positive impact of R&D on patenting. Finally, the finding of a strong time-series relationship between R&D and patenting is in contrast to the existing literature's findings summarized in Griliches (1990.)

The estimates from the second equation suggest a strong long-run impact of R&D intensity on technological progress, and a strong long-run impact of the rate of patenting on technological progress when one ignores the short-run effect of the first three years. The first result confirms the results in

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21 When I include both aggregate manufacturing R&D and individual industry R&D in the same equation, the former remains positive and statistically significant whereas the latter is now positive but statistically insignificant. This reinforces the argument that aggregate R&D spillovers matter for the innovation rate of individual industries.

The estimates of the impact of individual R&D and aggregate manufacturing R&D on the rate of patenting become larger when I include lags of technological progress. The latter are estimated to have a statistically significant negative impact on the rate of patenting suggesting that the difficulty of innovation might be increasing with technological progress.

These results are available from the author upon request.

22 For example, the fifth lag is always positive and, in most cases, strongly significant.
### Table 1.3: Coefficients’ sum of parameters

<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>II</th>
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<th>s.eq. (IV)</th>
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<td>$\sum_{i=1}^{6} \gamma_{t-i}$</td>
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<td>0.57</td>
<td>0.17</td>
<td>0.57</td>
<td>0.17</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
<td>(3.85)***</td>
<td>(4.49)***</td>
<td>(4.90)***</td>
<td>(4.63)***</td>
<td>(2.29)***</td>
<td>(6.31)***</td>
</tr>
<tr>
<td>$\sum_{i=1}^{6} s_{t-i}$</td>
<td></td>
<td></td>
<td>0.17</td>
<td></td>
<td>0.17</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(4.58)***</td>
<td></td>
<td>(5.03)***</td>
<td>(2.79)***</td>
</tr>
<tr>
<td>$\sum_{i=1}^{6} \sigma_{t-i}$</td>
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<td>0.25</td>
<td>0.18</td>
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<tr>
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<td>(2.17)**</td>
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<tr>
<td>$\sum_{i=4}^{6} \sigma_{t-i}$</td>
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<td>0.50</td>
<td>0.65</td>
<td>0.63</td>
<td>0.43</td>
<td>0.58</td>
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<tr>
<td></td>
<td>(4.45)***</td>
<td>(4.33)***</td>
<td>(5.63)***</td>
<td>(5.29)***</td>
<td>(1.92)**</td>
<td>(2.49)***</td>
</tr>
<tr>
<td>$\sum_{i=3}^{6} \xi_{t-i}$</td>
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<td>0.89</td>
<td>0.49</td>
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<tr>
<td></td>
<td>(2.59)***</td>
<td>(2.94)***</td>
<td>(3.59)***</td>
<td>(3.83)***</td>
<td>(1.14)</td>
<td>(1.14)</td>
</tr>
</tbody>
</table>

**Notes:**

*: Test of the hypothesis that the parameter equals zero given in brackets.

*: p-value of hypothesis test <0.10, **: p-value <0.05, ***: p-value <0.01

$\gamma$: Parameter for the impact of R&D intensity on the Rate of Patenting.

$S$: Parameter for the direct impact of R&D intensity on Technological Change.

$\sigma$: Parameter for the impact of the Rate of Patenting on Technological Change.

$\xi$: Parameter for the impact of Technological Change on Output Growth.


I: Basic formulation from equations (15), (25), and (35).

II: Impose $\Pi_{L} = \Pi_{C}$ on equation (15) for basic formulation.

III: Add $\sum_{l=1}^{6} S_{l} \Pi_{L} - l$ to right-hand side of equation (25) for basic formulation.

IV: Add $\sum_{l=1}^{6} S_{l} \Pi_{C} - l$ to right-hand side of equation (25) for II. s.eq.: single equations estimation.
some of the earlier work summarized in Nadiri (1993), whereas the latter result deviates from the findings of Kortum (1993.) In the case of the rate of patenting, the sum of coefficients becomes more highly significant when we consider lags longer than three indicating that the impact of patenting on technological progress occurs with a lag. This is a plausible result. If one considers that the two-digit industries are rather broad categorizations, then one should expect that firms within any one industry will need some time before experiencing technological gains as spillovers from patents of other firms within the industry.

A problem with patents as a proxy for innovation is that each patent is treated as if it incorporated the same value whereas this is likely to be different for different patents or products and possibly changing over time. This would make it difficult to uncover the relationship between the “true” rate of patenting and technological change. Caballero and Jaffe (1993) estimate an increasing “size” of patents until 1970 but a falling one thereafter. Kortum (1993) uses panel data in an endogenous growth framework and considers the relation between productivity growth and the rate of patenting. He does not find the positive relationship I estimate here using the fully corrected proxy of technological change, and proposes that the value of patents might have risen as an explanation for the increasing R&D expenditures per patent he finds. This might indeed be behind the difficulty in capturing the relation between patents and technological change.
Pakes and Griliches (1980, p.378) argue that, “patents are a flawed measure (of innovation output); particularly since not all innovations are patented...”.

This is why I allow for a direct effect of R&D on technological change in addition to the indirect effect of R&D on technological change through its impact on patenting. Moreover, the propensity to patent in an industry is likely to vary across different industries which is why I allow for industry-specific effects. Finally, the propensity to patent might vary over time for exogenous reasons rendering patents a problematic measure of the behavior of innovation over time.\(^{23}\) This is why I allow for an exogenous trend in the equation relating patenting to R&D. However, it becomes evident from all the above that one should treat patents with caution and try to account for all the aforementioned problems before attempting to relate patents to innovation and technological progress. In particular, one should include a direct effect of R&D on technological progress as in specifications (III) to (IV) in order to avoid misspecification and, furthermore, one should incorporate long lags of the rate of patenting in attempting to explain technological progress.

The third equation relating technological progress to output growth implies a strong long-run impact of technological progress on output growth. The parameter estimates from the three equations imply that the null hypothesis that growth is not induced by R&D can be rejected. This suggests the plausibility of R&D-induced growth in US manufacturing even when

\(^{23}\)Griliches (1990) suggests rising costs of patenting as an explanation for a decline in the number of patents.
productivity growth appears stable while R&D expenditures have been increasing over time.

Comparing specifications (II) and (IV) which impose the restriction $n_{it} = n_t$ on equation (1S) with specifications (I) and (III) which consider individual industry R&D, we can see that spillovers from aggregate manufacturing R&D on the individual industries innovation output appear to be important. The specifications which impose the above restriction give sums of coefficients which are larger than the sum of coefficients for individual industry R&D.

The estimates obtained using TFP growth (reported in table 1.5) are for the most part lower than those obtained by using the fully adjusted proxy of technological change. The sum of coefficients for the effect of patenting on TFP growth is now statistically indistinguishable from zero for most specifications. The fact that TFP growth is a procyclical measure that relates more to the business cycle rather than to technology might account for the difference in the results obtained when using this proxy of technological change in studying technology and growth. It might be that the failure of much of the previous research to find the positive relationships uncovered here is partly due to the use of inappropriate proxies for technological change.

In table 1.4, I present the results from the estimation of a system which includes autoregressive lags in each of the three equations of interest. Such autoregressive lags might capture interesting dynamics and correct the model for deviations from the long-run equilibrium relationship which might be

40
important for the current application. Nevertheless, dynamic models of panel data are faced with biased estimation problems. Nerlove (1971) discusses these in detail. Such problems become extreme in applications to classic panel data with short time series (usually less than ten observations) and broad cross sections (see Nickell 1981). The bias goes away asymptotically. Nevertheless, such bias would still be too important to ignore in applications with twenty or so time-series observations. Using industry-specific constants the estimates of the autoregressive lags would be downwardly biased leading to an upward bias for the coefficients of the other right-hand side variables. On the other hand, using a common constant instead of industry-specific effects would have the opposite effect. Here, I apply Anderson and Hsiao's (1982) instrumental variables approach to a first-differenced formulation of the three equations in the system. The basic formulation for the dynamic first-differenced system of equations is

\begin{align}
\Delta \log \phi_{it} &= \tau + \sum_{i=1}^{6} \gamma_i \Delta \log(n_{it-1}) + \sum_{i=1}^{6} \rho_i \Delta \log(\phi_{it-1}) + \varepsilon_{it} \\
\Delta g_{it} &= \sum_{i=1}^{6} \sigma_i \Delta \phi_{it-1} + \sum_{i=1}^{6} \nu_i \Delta g_{it-1} + \eta_{it}, \quad \sigma_{it} = \sigma_t \\
\Delta G_{it} &= \theta + \sum_{i=1}^{6} \xi_i \Delta g_{it-1} + \sum_{i=1}^{6} \zeta_i \Delta G_{it-1} + \omega_{it}
\end{align}

where \( \Delta x_t = x_t - x_{t-1} \) for any variable \( x \), and \( \varepsilon_{it}, \eta_{it}, \) and \( \omega_{it} \) are stationary variables.

\(^{24}\text{See also Holtz-Eakin, Newey, and Rosen (1988).}\)
unobservable errors. I estimate the above system using instrumental variables. A heteroskedasticity-consistent covariance matrix (Robust White) is used. I use the instruments \( Z_i = (y_{t-2}, y_{t-1}, x_{t-2}, x_{t-1}) \), where \( y \) and \( x \) stand respectively for the dependent and explanatory variables of each equation in the system.

The results from the instrumental variables estimation of the autoregressive specification are consistent with the previous findings presented in table 1.3. I present the results from the estimation of this system using instruments \( Z_1 \) in table 1.4. These results are obtained using the total of business and federal R&D expenditures data, and the Basu, Fernald, and Kimball (1998) fully adjusted technological change proxy (TBK). The conclusions from the estimation of the “levels” specification appear robust to the dynamic first-differenced specification I consider here, with the exception of the effect of patenting on productivity growth which remains positive but is now statistically insignificant unless we consider lags longer than three years. The other important change is that, due to larger standard errors, the direct impact of R&D intensity on technological progress in now statistically significant at the ten percent level rather than at the one percent level even though the estimates are greater now than they were before.

\(^{25}\)To the extent that some of the variables used in the estimation cannot be convincingly shown to be stationary, the first-differenced formulation is a check for the robustness of the results obtained with the previous estimation, since one can expect the first-differenced data to be free of unit roots.

\(^{26}\)Again, using business R&D leads to higher estimates for R&D but leaves the rest of the results intact.
Results for TFP growth as the proxy for technological change are presented in table 1.5. The estimates of the relationship between technological progress and the rate of patenting or the direct effect of R&D intensity are now statistically insignificant, and estimates for the effect of technological change on output growth are now smaller. Again, this could be attributed to the failure of TFP growth to capture technological progress.

In the last two columns of tables 1.4 and 1.6 I present the results from the estimation of individual equations analogous to those used in the system estimation. The estimates are statistically insignificant with the exception of specification (I) in table 1.4, for which the sum of coefficients for the rate of patenting for lags four to six is significant at the five percent level. Results from the estimation of individual equations analogous to those used in the system estimation for the specification without autoregressive lags, are presented in tables 1.3 and 1.5. Again, the estimates from the single equations estimation have much higher standard errors leading to estimates which are usually less statistically significant than the estimates from the system estimation. In the case of table 1.3, most estimates of the relations of interest remain positive and statistically significant with the notable exception of the estimate of the relation between technological progress and output growth which is now statistically indistinguishable from zero. In the case of table 1.5, where I replace “TBK” by “TFP” growth, most estimates become statistically indistinguishable from zero for the single equations estimation.
Overall, the system improves estimation efficiency and in certain cases provides quite different parameter estimates from those given by estimating single equations.

1.5 CONCLUSION

Growth theory has made significant advances over the last decade. One of the most interesting contributions is the Aghion and Howitt model that predicts a higher rate of output growth for societies that generate higher R&D intensity. This framework emphasizes the role of endogenous R&D and patenting activity on productivity and ultimately economic growth. I view the link as being inherently dynamic and sequential: from R&D intensity to patenting, from patenting to productivity enhancement, and from productivity growth to output growth.

I look for evidence of R&D-induced growth in US manufacturing. I derive and estimate the implications of the Schumpeterian framework of endogenous growth as a system of inter-related equations which relates R&D, patenting, technological change, and output growth. A simple version of this model of Schumpeterian endogenous growth implies contemporaneous relationships for the variables of interest whereas the empirical specification I consider here allows for lagged relationships, taking into account that the essence of these growth models relates to medium to long-run rather than contemporaneous or short-run relationships. Consistent with the idea that individual
<table>
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<th>s.eq. (IV)</th>
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<td>( \sum_{i=1}^{6} \gamma_{t-i} )</td>
<td>0.80 (2.91)***</td>
<td>1.33</td>
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<td>( \sum_{i=1}^{6} s_{t-i} )</td>
<td>[ \begin{array}{c} \sum_{i=1}^{6} \sigma_{t-i} \end{array} ]</td>
<td>0.46 (1.36)*</td>
<td>0.45 (1.46)*</td>
<td>-0.60 (-0.12)</td>
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<tr>
<td>( \sum_{i=4}^{6} \sigma_{t-i} )</td>
<td>0.93 (2.25)**</td>
<td>0.93 (2.36)**</td>
<td>1.16 (2.72)**</td>
<td>1.15 (2.67)**</td>
<td>0.94 (1.68)**</td>
<td>0.63 (0.19)</td>
</tr>
<tr>
<td>( \sum_{i=1}^{6} \xi_{t-i} )</td>
<td>5.69 (2.46)**</td>
<td>5.33 (2.41)**</td>
<td>5.41 (2.50)**</td>
<td>5.01 (2.31)**</td>
<td>2.90 (0.99)</td>
<td>2.90 (0.99)</td>
</tr>
</tbody>
</table>

Table 1.4: Coefficients’ sum of parameters using instruments \( Z \)

Notes:

- t-test of the hypothesis that the parameter equals zero given in brackets.

* p-value of hypothesis test <0.10, ** p-value<0.05, *** p-value<0.01

\( \gamma \): Parameter for the impact of R&D intensity on the Rate of Patenting.

\( S \): Parameter for the direct impact of R&D intensity on Technological Change.

\( \sigma \): Parameter for the impact of the Rate of Patenting on Technological Change.

\( \xi \): Parameter for the impact of Technological Change on Output Growth.

A heteroskedasticity-consistent covariance matrix is used to obtain consistent standard errors. Using the total of business and federal R&D expenditures, and Basu, Ferraadi, and Kimball’s (1998) fully adjusted technological change proxy for 10 industries \( \times \) 19 years (1970-88).

I: Basic formulation from equations (1D), (2D), and (3D).

II: Impose \( \Pi_{it} = \Pi \) on equation (1D) for basic formulation.

III: Add \( \sum_{i=1}^{6} S_{i} \Delta N_{it-i} \) to right-hand side of equation (2D) for basic formulation.

IV: Add \( \sum_{i=1}^{6} S_{i} \Delta N_{it-i} \) to right-hand side of equation (2D) for II. s.eq.: single equations estimation.
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<td>0.17</td>
<td>0.58</td>
<td>0.17</td>
<td>0.62</td>
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<tr>
<td></td>
<td>(3.57)**</td>
<td>(8.73)***</td>
<td>(4.31)***</td>
<td>(9.67)***</td>
<td>(2.29)**</td>
<td>(6.31)***</td>
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<td>$\sum_{t=1}^{6} \sigma_{t-1}$</td>
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<td>(2.28)**</td>
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<td>(2.13)**</td>
<td>(2.68)***</td>
<td>(3.04)***</td>
<td>(3.44)***</td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
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Table 1.5: Coefficients’ sum of parameters with TFP growth.

Notes:

- * p-value of hypothesis test <0.10, ** p-value<0.05, *** p-value<0.01, ! negative estimate.

$\gamma$: Parameter for the impact of R&D intensity on the Rate of Patenting.

$S$: Parameter for the direct impact of R&D intensity on TFP growth.

$\sigma$: Parameter for the impact of the Rate of Patenting on TFP growth.

$\xi$: Parameter for the impact of TFP growth on Output Growth.

The Newey-West covariance matrix with three lags is used to obtain autocorrelation-and-heteroskedasticity-consistent standard errors. Using business and federal R&D expenditures and TFP growth for 10 industries x 20 years (1969-88).

I: Basic formulation from equations (15), (25), and (35).

II: Impose $\eta_{t} = \eta_{t}$ on equation (15) for basic formulation.

III: Add $\sum_{i=1}^{6} S_{i}\eta_{t-i}$ to right-hand side of equation (25) for basic formulation.

IV: Add $\sum_{i=1}^{6} S_{i}\eta_{t-i}$ to right-hand side of equation (25) for II.

s.eq.: single equations estimation.

46
Table 1.6: Coefficients’ sum of parameters with TFP growth
(using instruments Z_i.)

Notes:

1. t-tests of the hypothesis that the parameter equals zero given in brackets.

   * p-value of hypothesis test < 0.10, ** p-value < 0.05, *** p-value < 0.01, ! negative estimate.

   \( \gamma \): Parameter for the impact of R&D intensity on the Rate of Patenting.

   \( S \): Parameter for the direct impact of R&D intensity on TFP growth.

   \( \sigma \): Parameter for the impact of the Rate of Patenting on TFP growth.

   \( \xi \): Parameter for the impact of TFP growth on Output Growth.

A heteroskedasticity-consistent covariance matrix is used to obtain consistent standard errors. Using the total of business and federal R&D expenditures, and TFP growth for 10 industries \( \times \) 19 years (1970-88).

I: Basic formulation from equations (1D), (2D), and (3D).

II: Impose \( \Pi_{1k} = \Pi_k \) on equation (1D) for basic formulation.

III: Add \( \sum_{l=1}^{6} S_l \Delta \Pi_{1k} - 1 \) to right-hand side of equation (2D) for basic formulation.

IV: Add \( \sum_{l=1}^{6} S_l \Delta \Pi_{1k} - 1 \) to right-hand side of equation (2D) for II. s.eq.: single equations estimation.
industries can draw from an aggregate pool of knowledge, I consider the effect of total manufacturing innovative activity variables on the average industry’s technological progress.

I find robust evidence of positive effects of R&D on future economic growth. The lags are substantial with significant impacts on output often arriving beyond five years after the R&D expenditure. Using two-digit industry data from US manufacturing, I find evidence for positive impact of R&D intensity on the rate of patenting, of the rate of patenting and R&D intensity on technological change, and of technological change on output growth.

The estimates from the first equation of the system relating R&D intensity to the rate of patenting show that the former has a strong long-run impact on the latter. Furthermore, aggregate manufacturing R&D seems to have a strong positive impact on the rate of patenting implying technology spillovers across manufacturing industries. Lags of R&D longer than two years often have a strong positive effect on patenting. This suggests that the lag between research and invention might be longer than 1.34 years reported in Pakes and Schankerman (1984) or 1.6 years reported in Pakes and Griliches (1984.)

The estimates from the second equation suggest a strong long-run impact of R&D intensity on technological progress, and a strong long-run impact of the rate of patenting on technological progress when one excludes the short-run effect of the first three years. The first result confirms the results in some
of the earlier work summarized in Nadiri (1993), whereas the latter result deviates from the findings of Kortum (1993). Finally, the third equation relating technological progress to output growth implies a strong long-run impact of technological progress on output growth. The estimates from the three equations imply that the null hypothesis that growth is not induced by R&D can be rejected. This suggests the plausibility of R&D-induced growth in US manufacturing even when productivity growth appears stable while R&D expenditures have been increasing over time.

I find that considering long lags, aggregate manufacturing spillovers, and adjustments to the usual proxy of technological progress to remove spurious\textsuperscript{27} procyclicality, are all important in uncovering the relationships between the variables of interest I consider here. Moreover, it is evident that the system estimation implied by a model of R&D-induced growth improves the efficiency of estimation and that in some cases it provides parameter estimates which are quite different from those given by the estimation of single equations.

The above findings suggest that the model considered here can be a useful template for studying growth in advanced economies like the US. A direct extension of this work would be to study the relation between R&D, patents, productivity, and output growth for a group of OECD countries in order to assess the relevance of this class of models for countries other than the tech-

\textsuperscript{27}“Spurious” in the sense that such cyclicalities are unrelated to technical change which is what the TFP growth proxy is meant to measure when used in growth applications.
nological leader. Moreover, the study of the impact of R&D performed by the US (the technological leader) or by OECD countries close to the technology frontier on technological progress and economic growth in countries which are further behind the frontier, is likely to be a fruitful area for future research.
CHAPTER 2

R&D-INDUCED GROWTH IN THE OECD?

2.1 INTRODUCTION

During the second half of the last decade several papers have addressed the question of testing endogenous growth theory based on its implications about convergence (Evans 1996a), and the relation of output growth with government-related variables (Kocherlakota and Yi 1997), money (Evans 1996b), investment and R&D expenditures (Jones 1995a,b). With the exception of Kocherlakota and Yi (1997) the evidence from these papers appears to be against the empirical relevance of endogenous growth theory. Dinopoulos and Thompson (1997) perform a direct evaluation of and provide evidence for the empirical relevance of an augmented version of Romer's (1990) model of endogenous growth proposed in Dinopoulos and Thompson (1996).

In this chapter, I implement tests of endogenous growth theory based on a simple model of R&D-induced growth from Aghion and Howitt (1998). This framework deals with most of the empirical critiques that have been raised to
this date as explained in Howitt (1998, 1999), but implies testable relations
between innovative activity, technological change, and output growth. Unlike
the earlier version of endogenous growth models which implied scale effects,
this framework remedies the problem and implies a relation between R&D
intensity\textsuperscript{28} and economic growth rather than between R&D expenditure levels
and economic growth.

I use data for a group of OECD countries to estimate a system implied
by a model of R&D-induced growth which relates R&D intensity, productivity,
and economic growth. The OECD accounts for ninety percent of R&D
expenditures in the world.\textsuperscript{29} The rest of the world can thus be best thought
of as an importer of technologies developed in the OECD. In this case, R&D-
induced growth in the OECD would mean productivity and output growth
for the rest of the world.\textsuperscript{30}

Griliches (1980a,b), Mansfield (1988), and Griliches and Mairesse (1990)
study the R&D-productivity relation. More recently, Keller (1998) uses a
panel of industries and countries to study the role of interindustry and inter-
national technology flows in the OECD. Finally, in the first chapter of this
dissertation I use US manufacturing industry data to estimate a system of
equations implied by a model of R&D-induced growth. The results of the

\textsuperscript{28} R&D intensity is given by the fraction of GDP that is attributed to research and
development expenditures.

\textsuperscript{29} Reported by Acemoglu and Zilibotti (1999).

\textsuperscript{30} Bayoumi, Coe, and Helpman (1999) provide simulation results suggesting the impor-
tance of such R&D spillovers for developing countries.
first chapter suggest that R&D-induced growth is consistent with evidence from US manufacturing. The extent to which the latter conclusion is specific to the US which happens to be the "technological leader" or can be applied to a broader group of countries which are close to the technological frontier is the main focus of this chapter.

Part of the value added of my approach to the existing literature is that using a relatively larger time series dimension, I consider the lags between R&D and productivity, and productivity and output growth, in the chain of events giving rise to economic growth.

I perform the statistical analysis using aggregate data across thirteen OECD countries, and two-digit manufacturing industry data for seven OECD countries for the period 1973 to 1991. The comparison between the aggregate data results and the industry-level results from the R&D-intensive manufacturing sector can be instructive about the economywide relevance of studies of the manufacturing sector.

Regressing productivity growth on lags of R&D intensity, and output growth on lags of productivity growth should give nonzero sums of the slope coefficients for models of R&D-induced growth. A zero sum of slope coefficients for either of the two equations would imply non-rejection of the null hypothesis that growth is not induced by R&D. I find evidence of positive long-run impact of the explanatory variables for both equations. The null hypothesis that growth is not induced by R&D is therefore rejected for this
group of OECD countries. Results are stronger when estimating a system of equations implied by a model of endogenous growth rather than estimating single equations, and when estimating aggregate relations rather than industry-level relations. The latter result, combined with the strong effect of aggregate R&D on industry-level patenting rates reported in the first chapter for the US, suggests the possibility of aggregate R&D spillovers. The conclusions are robust for a variety of specifications.

In the next section, I describe the data and in the third section I present the empirical analysis and results. The final section concludes.

2.2 DATA

I perform the statistical analysis using aggregate data across thirteen OECD countries. These are Australia, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Sweden, the UK, and the US. I check the robustness of the aggregate results by using data across seven two-digit manufacturing industries for seven OECD countries for which all data are available. These are Canada, Denmark, France, Germany, Japan, Sweden, and the US. The two-digit manufacturing industries are: Food, Beverages, and Tobacco (31), Textile, Wearing apparel and Leather Industries (32), Paper and Products, Printing and Publishing (34), Chemicals and Chemical Petroleum, Products made of Coal, Rubber, and Plastic (35), Non-metallic Mineral Products except Products of Petroleum and Coal (36),
Basic Metal Industries (37), and finally, Fabricated Metal Products, Machinery, and Equipment (38). I do not consider industry 33, Wood and Wood Products, since the required R&D data are not available for all of these countries. The R&D data for the period 1973 to 1993 come from the 1998 OECD ANBERD database. GDP data were obtained from the 1994 OECD International Sectoral and STAN Databases for the period 1970 to 1991. Total Factor Productivity (TFP) data in levels were obtained from the 1994 OECD International Sectoral database for the period 1970 to 1991 and were used to construct TFP growth rates. A description of how the TFP data were constructed using constant shares of capital and labor inputs, is given in the explanatory section of the OECD International Sectoral Database.

For the purposes of this study, I use R&D expenditures divided by gross domestic product (GDP). This ratio is often referred to in the literature as the R&D intensity. R&D intensities for a subgroup of the thirteen OECD countries (the G7) are presented in figure 2.1. It can be seen from this picture that R&D intensities vary across countries and time. I present the results of Park's (1990) G(1,2), G(1,3), and G(1,4) stationarity tests for these data in table 2.1. The aggregate economy R&D intensities across the thirteen OECD countries appear to be stationary. A panel test that uses the Bonferroni bound implies that the null of stationarity cannot be rejected.

\[ \text{Bonferroni bound}^{31} \text{ implies that the null of stationarity cannot be rejected} \]

\[ ^{31}\text{Using a Bonferroni bound, one rejects the null hypothesis at the 5 percent level of significance for a panel of n countries or industries if one can reject the null hypothesis at the 5/n level of significance for any of the n countries or industries} \]
at the ten percent level of significance for the $G(1,2)$, $G(1,3)$, or $G(1,4)$
tests. The $G(1,4)$ test does not reject the null of stationarity at the five
percent level of significance for any one country. The $G(1,3)$ test rejects the
null of stationarity at the five percent level of significance for two of the
thirteen countries, Finland and Germany. The $G(1,2)$ test rejects the null of
stationarity at a five percent significance level for Australia and Germany.
There is no country for which the $G(1,2)$, $G(1,3)$, and $G(1,4)$ tests all reject
the null of stationarity, and there is only one country, Germany, for which
two of these three tests reject the null of stationarity at a five percent level.

In table 2.2, I present stationarity tests for seven two-digit manufacturing
industries across the seven OECD countries for which data are available. A
panel test that uses the Bonferroni bound implies that the null of stationarity
cannot be rejected at a five percent significance level for the $G(1,2)$, $G(1,3)$,
or $G(1,4)$ tests. However, for some industries in certain countries there is
evidence against the stationarity null. For example, in industry 36 of Den­
mark the $G(1,2)$, $G(1,3)$, and $G(1,4)$ tests all reject the null of stationarity
at a five percent significance level. In industries 32, 36, and 37 of France
and industry 35 for Germany the $G(1,2)$, $G(1,3)$, and $G(1,4)$ tests reject the
null of stationarity at the ten percent level. For this reason and to address
the problem of biased estimation in dynamic panels, I consider in the next
section a differenced specification.

GDP growth and TFP growth series for a subgroup (the G5) of the thir-
teen countries in the sample are shown in figures 2.2 and 2.3 respectively. It can be seen that these series exhibit greater variability over the cycle compared to that for the R&D intensities shown in figure 2.1. Moreover, the apparent existence of a common business cycle across these countries implied from figures 2.2 and 2.3 means that it makes sense to use time-specific dummies in the econometric analysis of the next section since that analysis aims at capturing the long-run relation between economic growth, productivity growth, and R&D intensity.

2.3 EMPIRICAL ANALYSIS AND RESULTS

I consider a model of R&D-induced growth based on the model in chapter twelve of Aghion and Howitt (1998). This simple model abstracts from international technology spillovers and considers that for developed OECD countries own-country R&D determines productivity growth which in turn determines output growth for each country. This assumption is made in order to investigate the relevance of a basic R&D model of endogenous growth and is not meant to imply that international technology spillovers are unimportant for the OECD countries in this sample. Keller (1998) finds that about sixty percent of the total productivity effect originates from domestic R&D and the rest is due to international technology spillovers.

The main components of the model assumed to apply for every country are given by
\[ g_t = \beta \phi \left( \frac{R_t}{A_t^{\text{max}}} \right), \phi' > 0, \phi'' \leq 0 \] (1)

\[ G_t = g_t + \alpha \frac{\dot{k}_t}{k_t} \] (2)

Equation (1) implies a positive relationship between technological change given by \( g_t \) and the adjusted level of R&D at time \( t \) given by \( n_t \). In equation (1) \( \beta = \sigma \lambda, \sigma \) is the innovation size, \( \lambda > 0 \) is the flow probability of an innovation, and \( \phi \) gives the relation between R&D inputs and innovation output. Research intensity is given by \( n_t = \frac{R_t}{A_t^{\text{max}}} \) with \( R_t \) the total amount of final output invested in R&D at date \( t \). \( A_t^{\text{max}} \) is the leading-edge productivity parameter at date \( t \) and division by this indicates that the cost of further advances increases proportionately to technological advances as a result of increasing complexity.

Equation (2) implies a positive long-run relationship between economic growth given by \( G_t \), and technological change given by \( g_t \). The term \( \frac{\dot{k}_t}{k_t} \) captures the extent to which the economy's capital stock is away from its steady-state value. In the long-run the second term on the right hand side of the equation disappears and economic growth is solely driven by technological progress.

The empirical specification I consider below allows for lagged relationships between the variables of interest, taking into account that the essence of these growth models relates to medium to long-run rather than contemporaneous
Figure 2.1: R&D Intensities for US, Japan, Canada, Germany, France, Italy, and the UK.
<table>
<thead>
<tr>
<th>Country</th>
<th>G(1,2)</th>
<th>G(1,3)</th>
<th>G(1,4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.039*</td>
<td>0.086</td>
<td>0.162</td>
</tr>
<tr>
<td>Canada</td>
<td>0.607</td>
<td>0.078</td>
<td>0.141</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.124</td>
<td>0.058</td>
<td>0.113</td>
</tr>
<tr>
<td>Finland</td>
<td>0.359</td>
<td>0.034*</td>
<td>0.074</td>
</tr>
<tr>
<td>France</td>
<td>0.598</td>
<td>0.245</td>
<td>0.419</td>
</tr>
<tr>
<td>Germany</td>
<td>0.020*</td>
<td>0.039*</td>
<td>0.087</td>
</tr>
<tr>
<td>Italy</td>
<td>0.086</td>
<td>0.088</td>
<td>0.175</td>
</tr>
<tr>
<td>Japan</td>
<td>0.276</td>
<td>0.093</td>
<td>0.177</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.194</td>
<td>0.198</td>
<td>0.105</td>
</tr>
<tr>
<td>Norway</td>
<td>0.635</td>
<td>0.487</td>
<td>0.105</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.062</td>
<td>0.059</td>
<td>0.122</td>
</tr>
<tr>
<td>UK</td>
<td>0.079</td>
<td>0.211</td>
<td>0.308</td>
</tr>
<tr>
<td>US</td>
<td>0.963</td>
<td>0.092</td>
<td>0.188</td>
</tr>
</tbody>
</table>

Table 2.1: P-values for the Null of stationarity using Park’s (1990) G test.

Notes:

* Reject the stationarity null at the five percent significance level.
<table>
<thead>
<tr>
<th>Country</th>
<th>ISIC</th>
<th>31</th>
<th>32</th>
<th>34</th>
<th>35</th>
<th>36</th>
<th>37</th>
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<td>Canada</td>
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<tr>
<td>G(1,2)</td>
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<td>.725</td>
<td>.117</td>
<td>.145</td>
<td>.388</td>
<td>.349</td>
<td>.172</td>
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<tr>
<td>G(1,3)</td>
<td>.197</td>
<td>.371</td>
<td>.144</td>
<td>.188</td>
<td>.133</td>
<td>.457</td>
<td>.221</td>
<td></td>
</tr>
<tr>
<td>G(1,4)</td>
<td>.201</td>
<td>.289</td>
<td>.276</td>
<td>.263</td>
<td>.147</td>
<td>.618</td>
<td>.185</td>
<td></td>
</tr>
<tr>
<td>Denmark</td>
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</tr>
<tr>
<td>G(1,2)</td>
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<td>.663</td>
<td>.415</td>
<td>.042*</td>
<td>.009*</td>
<td>.242</td>
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<td>G(1,3)</td>
<td>.348</td>
<td>.075</td>
<td>.181</td>
<td>.090</td>
<td>.016*</td>
<td>.057</td>
<td>.013*</td>
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<td>.103</td>
<td>.301</td>
<td>.156</td>
<td>.019*</td>
<td>.109</td>
<td>.029*</td>
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</tr>
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<td>France</td>
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<td>.013*</td>
<td>.154</td>
<td>.064</td>
<td>.021*</td>
<td>.077</td>
<td>.711</td>
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<td>.064</td>
<td>.159</td>
<td>.070</td>
<td>.023*</td>
<td>.085</td>
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<td>.030*</td>
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<td>.104</td>
<td>.057</td>
<td>.122</td>
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<tr>
<td>Germany</td>
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<tr>
<td>G(1,2)</td>
<td>.034*</td>
<td>.146</td>
<td>.050*</td>
<td>.009*</td>
<td>.033*</td>
<td>.089</td>
<td>.064</td>
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<tr>
<td>G(1,3)</td>
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<td>.137</td>
<td>.036*</td>
<td>.093</td>
<td>.234</td>
<td>.146</td>
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<td>G(1,4)</td>
<td>.177</td>
<td>.165</td>
<td>.197</td>
<td>.067</td>
<td>.167</td>
<td>.205</td>
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<tr>
<td>Japan</td>
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<tr>
<td>G(1,2)</td>
<td>.578</td>
<td>.468</td>
<td>.145</td>
<td>.559</td>
<td>.032*</td>
<td>.240</td>
<td>.058</td>
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<tr>
<td>G(1,3)</td>
<td>.018*</td>
<td>.346</td>
<td>.032*</td>
<td>.296</td>
<td>.064</td>
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<td>.052*</td>
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<tr>
<td>G(1,4)</td>
<td>.042*</td>
<td>.183</td>
<td>.076</td>
<td>.480</td>
<td>.112</td>
<td>.435</td>
<td>.115</td>
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<tr>
<td>Sweden</td>
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<td>G(1,2)</td>
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<td>.136</td>
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<td>G(1,3)</td>
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<td>G(1,4)</td>
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<td>.224</td>
<td>.712</td>
<td>.688</td>
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<td>.150</td>
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<tr>
<td>US</td>
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<td>G(1,2)</td>
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<td>G(1,3)</td>
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<td>.071</td>
<td>.666</td>
<td>.135</td>
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<td>.082</td>
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<td>G(1,4)</td>
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<td>.151</td>
<td>.437</td>
<td>.216</td>
<td>.207</td>
<td>.159</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.2: P-values for the Null of stationarity for R&D/GDP for the period 1973-93 using Park's (1990) G test.

Notes:

* Reject the stationarity null at the five percent significance level.

Figure 2.2: GDP growth for US, Japan, Canada, Germany, and France
Figure 2.3: TFP growth for US, Japan, Canada, Germany, and France
or short-run relationships.\textsuperscript{32} I perform iterated SUR estimation\textsuperscript{33} on the empirical model

\begin{align*}
g_{it} &= \psi + \psi_i + \psi_t + \sum_{r=1}^{l} \beta_r n_{it-r} + v_{it} \quad (3) \\
G_{it} &= \alpha + \alpha_i + \alpha_t + \sum_{r=1}^{l} \xi_r g_{it-r} + e_{it} \quad (4)
\end{align*}

where the subscript \textit{i} stands for country \textit{i}, \textit{g}_{it} is TFP growth, \textit{G}_{it} is the growth rate of gross domestic product, \textit{n}_{it} is R&D intensity, \textit{v}_{it} and \textit{e}_{it} are unobservable stationary errors, \psi_i and \alpha_i are dummy variables specific to each country, and \psi_t and \alpha_t are dummy variables specific to each time period. The parameter \beta captures the impact of R&D intensity on productivity growth, and the parameter \xi captures the impact of productivity growth on output growth. For each equation I set the parameters for the first country and time period equal to zero and include a constant, \psi or \alpha. The Newey-West (1987) heteroskedasticity and autocorrelation consistent covariance matrix with three lags is used to obtain the standard errors. Time-specific dummies are included in order to avoid biasing the results due to the presence of a common business cycle. Country-specific dummies are included in equations (3) and (4) so as to capture variation across countries not attributable to

\textsuperscript{32}The empirical specification for the relation of productivity growth with R&D intensity makes the simplifying assumption that \(\sigma(\frac{R&D}{L}) = n_i^\gamma\), \(\gamma = 1\). This assumption makes it possible to consider a linear relation between technological change and the lags of R&D intensity.

\textsuperscript{33}The estimates are obtained using the LSQ command in TSP which allows simultaneous iteration on the parameters and the residual covariance matrix.
R&D intensity or productivity growth.

For specifications (I) to (III), I set the number of lags, $l$, equal to one. For specification (I) I use annual data for the period 1974 to 1990 across the thirteen OECD countries shown in table 2.1, for a total of 221 observations. The parameter estimates are shown in row (I) of table 2.3 and are positive and statistically significant.

As a robustness check, I average the data for periods of three years each. I do this to limit the problem of spurious procyclicality that might be present in the proxy of productivity growth. I estimate the above system for five three-year periods between 1976 to 1990 for a total of 65 observations (specification II) and using total manufacturing data for the same period (specification III). The parameter estimates and t-statistics for these two regressions are presented respectively in rows (II) and (III) of table 2.3. The system estimation implied by a model of R&D-induced growth gives positive and statistically significant parameter estimates for specifications (II) and (III).

Next, I consider extending specification (I) to include three lags ($l=3$) of the explanatory variables (specification IV) and to include six lags ($l=6$) of the explanatory variables (specification V). The justification for looking at additional lags of the explanatory variables comes from the observation that growth relates to medium to long-run rather than contemporaneous or short-run relationships. The sum of the parameter estimates and t-statistics for lags one to three and one to six for each of these two samples are pre-
sented respectively in rows (IV) and (V) of table 2.3. Once more, the system estimation implied by a model of R&D-induced growth gives positive and statistically significant parameter estimates consistent with a long-run impact of R&D on productivity and output growth. Interestingly, the estimation of the individual equations for specification (V) fails to uncover the accumulated long-run impact of R&D on productivity and output growth.

To check the robustness of these results, I consider an alternative proxy of technological change from Imbs (1998) which purges spurious procyclicality from the Solow Residual by allowing for factor hoarding. I use an economywide sample from eight countries for the period 1976 to 1989 taking three lags of the explanatory variables for a total of 112 observations. I report the results of this estimation in row (VI) and results using unadjusted Solow residuals from Imbs (1998) in row (VII). Using the adjusted proxy again gives positive estimates for $\beta$ and $\xi$. However, the parameter estimate for $\xi$, although positive, is not statistically significant at conventional levels of confidence. Using the unadjusted Solow Residual for the same group of countries and the same time period gives bigger estimates than Imbs adjusted proxy of technological progress for both parameters of interest. In contrast, in the first chapter I find that Basu, Fernald, and Kimball's (1998) methodology of adjusting the Solow residual to account for demand-induced cyclicalities,

---

34 "Spurious" in the sense that such cyclicalities are unrelated to technical change which is what the TFP growth proxy is meant to measure when used in growth applications.

35 These are Australia, Canada, France, Germany, Italy, Japan, the UK, and the US.

36 It is statistically significant only at a fifteen percent level of significance.
provides proxies of technological progress which are more strongly related to future output growth than the unadjusted residuals are for US manufacturing industries. The degree to which this is due to the different samples used (OECD aggregate data versus US manufacturing industries) or due to the methodology of Basu, Fernald, and Kimball (1998) being superior to that of Imbs (1998) can only be investigated by applying the former methodology to OECD data. Unfortunately, the methodology of Basu, Fernald, and Kimball is more demanding on data than Imbs' methodology which makes it difficult to apply for a broad OECD sample.

Overall, the parameter estimates presented in table 2.3 are consistent with R&D-induced growth in the OECD countries. Moreover, the results are usually stronger when estimating a system of equations as implied by a model of endogenous growth rather than estimating single equations as done in much of the previous work on R&D and productivity. Finally, both conclusions are robust across the eight different specifications I consider.

To further check the robustness of these results, I consider a dynamic first-differenced specification which includes autoregressive lags for the following two equations:

---

37 Such autoregressive lags might capture interesting dynamics and correct the model for deviations from the long-run equilibrium relationship. Nevertheless, dynamic models of panel data are faced with biased estimation problems. Such problems become extreme in applications to panel data with short time series. The bias goes away asymptotically. However, such bias would still be too important to ignore in applications with twenty or so time-series observations. Anderson and Hsiao (1982) propose first-differencing and using lagged levels as instruments.
Table 2.3: Results from estimation of equations (3) and (4) with aggregate data

Notes:

1. Tests of the hypothesis that the parameter equals zero given in brackets.

2. $p$-value of hypothesis test $< 0.10$. ** $p$-value of hypothesis test $< 0.05$. *** $p$-value of hypothesis test $< 0.01$

$\beta$: Parameter for the impact of R&D intensity on TFP growth.

$\xi$: Parameter for the impact of TFP growth on Output Growth.

For (IV), (VI), and (VII) I report the sum of the estimated parameters of lags one to three, and for (V) the sum of lags one to six respectively.

The Newey-West covariance matrix with one lag for specifications (II), and (III), and three lags for specifications (I), (IV), (V), (VI), and (VII), is used for obtaining heteroskedasticity-consistent and autocorrelation-robust standard errors.

(I) Aggregate economy, taking one annual lag of the explanatory variable, a total of 221 observations from thirteen countries for the period 1974 to 1990.

(II) Aggregate economy, taking one three-year period lag of the explanatory variable, a total of 65 observations from thirteen countries and five three-year periods between 1976 and 1990.
(III) Manufacturing sector, taking one three-year period lag of the explanatory variable, a total of 65 observations from thirteen countries and five three-year periods between 1976 and 1990.

(IV) Aggregate economy, taking three annual lags of the explanatory variable, a total of 195 observations from thirteen countries for the period 1976 to 1990. Reporting the sum of parameter estimates for three lags.

(V) Aggregate economy, taking six annual lags of the explanatory variable, a total of 156 observations from thirteen countries for the period 1979 to 1990. Reporting the sum of parameter estimates for six lags.

(VI) Aggregate economy using adjusted proxies of technological change from Imbs (1998), taking three annual lags of the explanatory variable, a total of 112 observations from eight countries for the period 1977 to 1989. Reporting the sum of parameter estimates for three lags.

(VII) Aggregate economy using Solow Residuals from Imbs (1998), taking three annual lags of the explanatory variable, a total of 112 observations from eight countries for the period 1977 to 1989. Reporting the sum of parameter estimates for three lags.
### Table 2.4: Results from system estimation of level and first-differenced specifications using aggregate data.

<table>
<thead>
<tr>
<th></th>
<th>( \beta )</th>
<th>( \xi )</th>
</tr>
</thead>
<tbody>
<tr>
<td>(I)</td>
<td>0.550 (1.13)</td>
<td>0.571 (13.89)***</td>
</tr>
<tr>
<td>(II)</td>
<td>3.616 (8.55)***</td>
<td>0.229 (1.62)*</td>
</tr>
<tr>
<td>(III)</td>
<td>1.152 (5.53)***</td>
<td>0.145 (1.55)*</td>
</tr>
<tr>
<td>(IV)</td>
<td>1.512 (3.24)***</td>
<td>0.945 (9.33)***</td>
</tr>
<tr>
<td>(VI)</td>
<td>0.782 (1.29)*</td>
<td>0.326 (2.10)**</td>
</tr>
<tr>
<td>(VII)</td>
<td>1.606 (2.91)***</td>
<td>0.584 (2.72)***</td>
</tr>
</tbody>
</table>

**Notes:**

- t-tests of the hypothesis that the parameter equals zero given in brackets.

- * p-value of hypothesis test <0.10, ** p-value of hypothesis test <0.05, *** p-value of hypothesis test <0.01

- \( \beta \): Parameter for the impact of R&D intensity on the TFP growth.

- \( \xi \): Parameter for the impact of TFP growth on Output Growth.

- For (IV), (VI), and (VII) I report the sum of the estimated parameters of lags one to three, and for (V) the sum of lags one to six respectively.

- I do not consider first-differenced specifications for (V) because the samples are small.

- A Robust-White covariance matrix is used for obtaining heteroskedasticity-consistent standard errors.

- (I) Aggregate economy, taking one annual lag of the explanatory variable, a total of 208 observations from thirteen countries for the period 1975 to 1990.

- (II) Aggregate economy, taking one three-year period lag of the explanatory variable, a total of 52 observations from thirteen countries and four three-year periods between 1979 and 1990.

- (III) Manufacturing sector, taking one three-year period lag of the explanatory variable, a total of 52 observations from thirteen countries and four three-year periods between 1979 and 1990.
(IV) Aggregate economy, taking three annual lags of the explanatory variable, a total of 182 observations from thirteen countries for the period 1970 to 1990. Reporting the sum of parameter estimates for three lags.

(VI) Aggregate economy using adjusted proxies of technological change from Imbs (1998), taking three annual lags of the explanatory variable, a total of 104 observations from eight countries for the period 1978 to 1989. Reporting the sum of parameter estimates for three lags.

(VII) Aggregate economy using Solow Residuals from Imbs (1998), taking three annual lags of the explanatory variable, a total of 104 observations from eight countries for the period 1978 to 1989. Reporting the sum of parameter estimates for three lags.
\[
\Delta g_{it} = \Delta \psi_i + \sum_{r=1}^{l} \beta_r \Delta n_{it-r} + \sum_{r=1}^{l} \nu_r \Delta g_{it-r} + \eta_{it}
\]

(5)

\[
\Delta G_{it} = \Delta \alpha_t + \sum_{r=1}^{l} \xi_r \Delta g_{it-r} + \sum_{r=1}^{l} \zeta_r \Delta G_{it-r} + \varepsilon_{it}
\]

(6)

where \(\Delta x_t = x_t - x_{t-1}\) for any variable \(x\), \(\eta_{it}\) and \(\varepsilon_{it}\) are stationary unobservable errors\(^3\), \(\Delta \alpha_t\) and \(\Delta \psi_t\) are time dummies, and \(\beta_t\) and \(\xi_t\) are again the parameters of interest. A heteroskedasticity-consistent covariance matrix (Robust White) is used to obtain the standard errors.

Similarly to Beck, Levine, and Loayza (1999), I use GMM to estimate a system composed of the equation in levels and its first-differenced formulation.\(^3\) Lagged levels of the variables are used as instruments for the regression in differences (as suggested by Anderson and Hsiao 1982) and the most recent lagged difference is used as instrument for the regression in levels. My conclusions regarding the sign of the parameters of interest remain unchanged. The parameter estimates presented in table 2.4 are consistent with R&D-induced growth in the OECD.\(^4\)

Considering panel data across the industries of each country can potentially improve the power of the tests. Moreover, the comparison between the aggregate data results and the industry-level results from the R&D-intensive

\(^3\)To the extent that any variables used in the estimation cannot be convincingly shown to be stationary the first-differenced formulation is also a check for the robustness of the previous results, since one can expect the first-differenced data to be free of unit roots.

\(^4\)Arellano and Bover (1995) propose such an estimator in order to reduce the potential biases and imprecision associated with the difference estimator.

\(^4\)However, the estimate of the parameter \(\beta\) for the dynamic specification (I) is not statistically significant at conventional levels of confidence.
manufacturing sector can be instructive about the economy-wide relevance of studies of the manufacturing sector like Mansfield (1988), and my first chapter.

I now assume that equations (3) and (4) apply to each industry. Here, I consider only the own-industry effect on productivity and output growth, abstracting from the important question of interindustry R&D spillovers. This enables a striking comparison with the aggregate data results which provide much stronger evidence for R&D-induced growth suggesting the possibility of R&D spillovers at the aggregate level.

I use data across seven manufacturing industries for the seven OECD countries shown in table 2 for which the data are available over the period 1973 to 1991. I include industry-specific dummies to capture variation across industries not attributable to R&D intensity or to productivity growth.

The parameter estimates and t-statistics from estimating equations 3 and 4 using these data are presented in table 2.5, and those using the dynamic specification from equations 5 and 6 are presented in table 2.6. Again, the system estimation implied by a model of R&D-induced growth gives positive estimates for the parameters of interest. However, the estimates of parameter $\beta$ for specifications (II) and (III) are not statistically significant at conventional levels of significance. The estimation of the dynamic specification gives similar results.

The smaller parameter estimates obtained using the industry data com-
pared to those for the economy-wide data suggests that industry-level studies might be underestimating the impact of R&D on growth when interindustry spillovers are not taken into account. The results are consistent with the idea that individual industries can draw from an aggregate pool of knowledge and do not depend only on the private knowledge generated by their own R&D expenditures.

2.4 CONCLUSION

I estimate a system implied by a model of R&D-induced growth that relates R&D intensity, productivity, and economic growth. Aggregate data across thirteen OECD countries and two-digit manufacturing industry data for seven OECD countries for the period 1973 to 1991 are employed in this analysis. The regression of productivity growth on lags of R&D intensity and the regression of output growth on lags of productivity growth should give nonzero sums of the slope coefficients for models of R&D-induced growth. A zero sum of slope coefficients for either of the two equations would imply non-rejection of the null hypothesis that growth is not induced by R&D.

---

41 Holding \( \lambda \) constant, the smaller estimates for \( \beta = \sigma \lambda \) might be explained by smaller size (\( \sigma \)) of individual industry relative to aggregate innovations.
Table 2.5: Estimation of equations (3) and (4) with manufacturing industry data.

<table>
<thead>
<tr>
<th></th>
<th>single equation</th>
<th>system estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta$</td>
<td>$\xi$</td>
</tr>
<tr>
<td>(I)</td>
<td>0.291 (2.55)***</td>
<td>0.017 (0.42)</td>
</tr>
<tr>
<td>(II)</td>
<td>0.288 (2.10)**</td>
<td>-0.091 (-1.12)</td>
</tr>
<tr>
<td>(III)</td>
<td>0.214 (1.64)*</td>
<td>0.159 (2.08)***</td>
</tr>
</tbody>
</table>

Notes:

- t-tests of the hypothesis that the parameter equals zero given in brackets.
- * p-value of hypothesis test <0.10, ** p-value of hypothesis test <0.05, *** p-value of hypothesis test <0.01

$\beta$: Parameter for the impact of R&D intensity on TFP growth.

$\xi$: Parameter for the impact of TFP growth on Output Growth.

The Newey-West covariance matrix with one lag for specification (III), and three lags for specifications (I) and (II) is used for obtaining heteroskedasticity-consistent and autocorrelation-robust standard errors.

(I) 852 observations from 7 industries, 7 countries, and 16 years for 1974 to 1991. Taking one annual lag of the explanatory variable.

(II) 784 observations from 7 industries, 7 countries, and 16 years for 1975 to 1991. Taking 3 annual lags of the explanatory variable. Reporting the sum of parameter estimates for the three lags.

(III) 245 observations from 7 industries, 7 countries, and 5 three-year periods between 1976 and 1990. Taking a three-year lag of the explanatory variable.
Table 2.6: Estimation of each parameter from a system composed of the level and first-differenced specifications of each equation. Using manufacturing industry data.

Notes:

T-tests of the hypothesis that the parameter equals zero given in brackets.

* p-value of hypothesis test <0.10, ** p-value of hypothesis test <0.05, *** p-value of hypothesis test <0.01

$\beta$: Parameter for the impact of R&D intensity on TFP growth.

$\xi$: Parameter for the impact of TFP growth on Output Growth.

For the differenced specifications, a Robust-White covariance matrix is used to obtain heteroskedasticity-consistent standard errors.

(1) 833 observations from 7 industries, 7 countries, and 17 years for 1975 to 1991. Taking one annual lag of the explanatory variable.

(II) 735 observations from 7 industries, 7 countries, and 15 years for 1977 to 1991. Taking 3 annual lags of the explanatory variable. Reporting the sum of parameter estimates for the three lags.

(III) 196 observations from 7 industries, 7 countries, and 4 three-year periods between 1979 and 1990. Taking a three-year lag of the explanatory variable.
The system estimation provides evidence of positive long-run impact of the explanatory variables for both equations. The null hypothesis that growth is not induced by R&D is therefore rejected for this group of OECD countries. Results are stronger when estimating a system of equations implied by a model of endogenous growth rather than estimating single equations as done in previous work on the link between R&D and productivity growth. Moreover, the results are stronger when estimating aggregate relations rather than industry-level relations, suggesting the possibility of spillovers from aggregate R&D. The conclusions are robust for a variety of specifications.

The above findings suggest that models of R&D-induced growth are consistent with the experience of countries close to the technology frontier. This suggests that such models could serve as empirical templates to assess the potential of different policies in inducing growth for these countries. Moreover, to the extent that technologies developed in the R&D-intensive countries flow across national borders, models of R&D-induced growth will have important implications about the policies that governments and other institutions should be undertaking in order to promote growth in less developed countries that do not perform intensive R&D. Empirical work on the impact of R&D on world economic growth and the channels through which this takes place, is bound to be a fruitful area for future research.
CHAPTER 3

R&D-INDUCED PRODUCTIVITY AND INTERNATIONAL PRICES

3.1 INTRODUCTION

Models of R&D-induced growth predict that the intensity of innovation-related activity over time as measured by the stock of Research and Development should largely determine the productivity level.\footnote{For example, see Kortum (1997) and Keller (1998).} I construct and estimate a model that explores the relationship between R&D-induced productivity and prices. Productivity is determined by the accumulated stock of R&D in the manufacturing sector. I interpret the stock of R&D to be a measure of the stock of technically useful knowledge in the domestic economy. It will then serve as an adequate proxy of the productivity level of the domestic economy if the real world is well characterized by models of "R&D-induced" or "idea-based" growth. Productivity differences across countries in turn induce negative cross-country price differences for manufacturing goods.
I also consider an extension of the model with a non-tradeables sector that does not perform R&D. In this model, there is a positive relation between productivity differences and price differences across countries.

I use a broad cross-section of prices in Germany, France, Italy, the UK, the Netherlands, and Denmark to look at the relation between commodity-specific real exchange rates and cross-country productivity differences as proxied by differences in R&D stocks. I classify individual goods into traded and nontraded goods categories to distinguish between the effects on the price differences of traded and nontraded goods.

Straus (1996) uses aggregate time-series data for the traded and nontraded goods sectors across seven OECD countries and finds that cross-country differences in relative productivity for traded goods have a cointegrating relationship with the real exchange rate. Canzoneri, Cumby, and Diba (1996) use aggregate time-series data for the traded and nontraded goods sectors across thirteen OECD countries and find that relative labor productivity in the traded goods sector appears to be cointegrated with the relative price of nontraded goods in a country, thus reconfirming a basic premise of the Balassa-Samuelson hypothesis. Further, they find that PPP does not appear to hold for the tradeable goods sector. The latter finding contradicts a second component of the Balassa-Samuelson hypothesis and is consistent with much of the empirical work on PPP. Isard (1977), Giovannini (1988), and Knetter (1993) find that violations of PPP persist over time even
for tradeable goods at high SIC levels, and Crucini, Telmer, and Zachariadis 
(1999) find evidence for large deviations from the law of one price (LOP) 
by looking at a cross-section of individual goods prices in thirteen European 
countries.

This chapter makes two main contributions to the existing literature. 
First, it highlights the relevance of models of R&D-induced growth to interna­
tional macroeconomic issues. There is no previous attempt to my knowledge 
to relate a model of R&D induced growth to international price differences. 
In doing so, this chapter provides a justification for the use of R&D stocks 
as an indirect proxy of productivity that is free of the usual problems associ­
ated with direct measures of labor productivity or total factor productivity.43 
Second, in contrast to previous work on international productivity and price 
differences, the empirical part of this chapter uses a disaggregated dataset of 
individual prices rather than using aggregate price indices. This allows for a 
more careful study of the role of tradeability in determining price differences 
across locations.

Direct measures of productivity face several problems. To calculate pro­
ductivity levels one usually makes the assumption that at some initial date 
the countries in the sample have identical productivity levels, and then accu­
mulates these levels to the present by using measures of productivity growth. 
Measures of productivity growth in turn face the problem of being driven

43See the discussion below.
by demand-induced cyclical ity which renders them problematic proxies of technological change. To correct for this cyclicity Basu, Fernald, and Kimball (1998) propose a methodology that accounts for imperfect competition, non-constant returns to scale, and aggregation problems. Nevertheless, this methodology is data intensive and requires information that is not available for the group of countries in my sample. Finally, studies like Canzoneri, Cumby, and Diba (1996) which use labor productivity ignore variations in capital and intermediate inputs that might be important in determining the level of productivity. The use of R&D stocks to instrument for productivity provides an alternative that avoids most of these problems and serves as a robustness check for previous work that has used direct measures of productivity.

I find that countries with higher R&D stock have lower prices of traded goods. The law of one price therefore fails for tradeables since the prices of manufactures in countries with high R&D stocks lie below those with lower stocks. Moreover, I find that countries with high R&D stocks have higher price ratios of non-traded relative to traded goods. Nevertheless, depending on the relative size of the traded sector, high productivity countries can have lower overall price levels. This contrasts markedly with the Balassa-

\footnote{GDP per capita differences between countries would imply differences in preferences across countries. Different demand elasticities combined with some market segmentation would imply a role for price discrimination across locations. Another explanation for price differences across countries would be the existence of trade impediments for tradeable goods.}
Samuelson hypothesis. The finding that traded goods price differences across countries are negatively related to relative productivity differences is consistent with other empirical evidence on the apparent failure of LOP for traded goods (Crucini, Telmer, and Zachariadis 1999.) The finding regarding the implied relation between the relative price of nontraded goods with the productivity of traded relative to nontraded goods is consistent with a basic premise of the Balassa-Samuelson hypothesis and with Canzoneri, Cumby, and Diba (1996).

In the next section, I briefly describe the data. In the third section, I present a framework which allows for R&D-induced growth and in the fourth section I describe the empirical analysis and results for this basic model. In the fifth section, I consider an extension of the model and describe some additional results. The final section briefly concludes.

3.2 DATA

I use Eurostat Survey prices of household goods and services across six European countries in 1980 and in 1985. For a detailed description of the

---

45The Balassa (1964) and Samuelson (1964) hypothesis states that countries with higher relative productivity for traded goods will have a higher price level than other countries. This is because in the Balassa-Samuelson framework higher productivity in the traded goods sector leads to higher wages and higher prices in the non-traded sector. Assuming purchasing power parity for traded goods holds the overall price level will be higher in countries with higher prices for nontraded goods.

46Thus, an essential component of the Balassa-Samuelson hypothesis appears to be empirically relevant using two distinct proxies of productivity and price data which differ in several dimensions.
price data see Crucini, Telmer, and Zachariadis (1999). For 1980, there are 46 non-tradeable commodity prices and 241 traded goods prices, and for 1985 there are 85 non-tradeable commodity prices and 339 traded goods prices which are available for all six countries. In figures 3.1 and 3.2, I present for each country the log deviations from German traded and nontraded goods prices respectively in 1980. In figures 3.3 and 3.4, I present the same information for traded and nontraded goods prices respectively in 1985. The log deviations from German prices are presented in ascending order. Points below the zero line indicate goods for which a price is lower in Germany. Germany is the country with the highest stock of R&D among the six countries in the sample for both 1980 and 1985. It becomes apparent that most traded goods had a lower price for Germany in both 1980 (53 percent) and 1985 (60 percent.) Comparing figures 3.2 and 3.4 to figures 3.1 and 3.3 respectively, log price deviations for nontraded goods appear to be displaced upwards relative to those of traded goods in both 1980 and 1985.\footnote{For 1980, 63 percent of non-traded goods prices were higher in Germany compared to 47 percent for traded goods. For 1985, 48 percent of non-traded goods prices were higher in Germany compared to 40 percent for traded goods.}
Figure 3.1: 1980 German Real Exchange Rates for Traded Goods with five other EC Countries (Goods sorted separately for each country by degree of deviation from Germany.)
Figure 3.2: 1980 German Real Exchange Rates for Nontraded Goods with five other EC Countries (Goods sorted separately for each country by degree of deviation from Germany.)
Figure 3.3: 1985 German Real Exchange Rates for Traded Goods with five other EC Countries (Goods sorted separately for each country by degree of deviation from Germany.)
Figure 3.4: 1985 German Real Exchange Rates for Nontraded Goods with five other EC Countries (Goods sorted separately for each country by degree of deviation from Germany.)
I construct the R&D capital stock as a proxy of the knowledge stock for each of the six European countries in the sample using twelve percent as the rate of depreciation for this stock. This depreciation rate of 0.1 is based on the findings of Nadiri and Prucha (1993) and is also used by Bernstein (1996). The equation is

\[ H(R_j) = R_j + (1 - 0.1) \times H(R_{j-1}) \]

with \( R_j \) standing for R&D expenditures in constant prices and \( H(R_j) \) standing for the implied stock of knowledge in country \( j \). The benchmark value for this stock is obtained by assuming a steady state for the benchmark year. This implies \( H(R_0) = \frac{R_0}{0.12} \), where the denominator is the sum of the assumed rate of depreciation and the growth rate. I use the 1997 ANBERD data from the OECD. This provides R&D expenditures at current prices in national currencies. I use the 1994 OECD STAN data to construct deflators from value-added output for each industry and country, and use this to obtain R&D expenditures in constant 1985 prices. Finally, I use the yearly US dollar exchange rates for each currency to convert R&D expenditures in constant 1985 prices to a common currency. In figures 3.5 and 3.6, I present respectively the 1980 and 1985 R&D stocks in millions of SUS for the total economy and for the manufacturing (traded) and service (nontraded) sectors. Germany has the highest stock of R&D (or knowledge) followed by France and the UK. For each of the six countries in the sample, it becomes apparent
that most of R&D is performed in the manufacturing sector.

In figure 3.7, I present the Gross Domestic Product per Capita in constant $US (base 1985) for 1980 and 1985 for each of the six countries. The latter data are taken from the Penn World Tables.

Figure 3.5: 1980 R&D stocks in millions of constant $US (base 1985.)
Figure 3.6: 1985 R&D stocks in millions of constant $US (base 1985.)
Figure 3.7: 1980 and 1985 GDP per capita in constant $US (base 1985.)
3.3 THE MODEL

I consider first a simple model for which productivity is determined by R&D performed in the domestic economy. The model considered here assumes a perfectly competitive final goods sector in each country that uses labor and capital. Capital flows freely across countries so that the interest rate is equalized internationally. Productivity differences between the countries exist due to different domestic stocks of knowledge which do not diffuse across countries and the price of the final good is not equalized across countries. Instead, it is cheaper in the most productive country.

The model presented here is a variant of the Schumpeterian framework of Aghion and Howitt (1998). The innovation process uses final output to produce inventions which can be thought of as new forms of capital services that benefit the domestic economy. Two simplifying assumptions are made about the creation of new technologies: there are no international spillovers of knowledge and there is a scale effect so that countries with higher accumulation of R&D are presumed to have higher levels of productivity.

The production function for final goods in each country is given by

\[ Y_t = (A_t L_t)^{1-\alpha} K_t^\alpha \]  

\[ Y_t^* = (A_t^* L_t^*)^{1-\alpha^*} K_t^{*\alpha^*} \]

\[ 48 \text{This is an extreme assumption made for simplicity. Similar results would follow if there was incomplete diffusion of knowledge between countries.} \]

92
where $Y_t$, $A_t$, $L_t$, and $K_t$ stand for output, technology level, labor input, and capital input, and the superscript * indicates the foreign country. The rate of technological progress for the domestic economy is given by $\frac{\dot{A}_t}{A_t} = \sigma \lambda \frac{R_t}{A_t}$, where $\sigma$ stands for innovation size and $\lambda$ stands for research productivity both assumed to be time-invariant. Here, I have assumed constant returns to R&D so that technological progress is proportional to R&D-intensity and the level of technology is proportional to the stock of knowledge implied by the accumulated stock of R&D expenditures. In the current framework, the stock of R&D can be interpreted as the stock of knowledge in the domestic economy. The latter implies the productivity level for the domestic economy as in models of "R&D-induced" or "idea-based" growth. The level of technology for the domestic economy as of period $t$ will thus be given by

$$A_t = \int_{s=0}^{t} \dot{A}_s \, ds = \sigma \lambda \int_{s=0}^{t} R_s \, ds$$

(2)

Setting the value of the marginal product of capital equal to the world interest rate, and the value of the marginal product of labor equal to the wage rate, I obtain conditions (3) and (4):

$$P_t \alpha A_t^{1-\alpha} k_t^{\alpha-1} = r_t$$

(3)

$$E_t P_t^* \alpha^* A_t^{1-\alpha^*} k_t^{\alpha^*-1} = r_t$$

(3*)
\[ P_t(1 - \alpha)A_t^{1-\alpha}k_t^\alpha = w_t \quad (4) \]

\[ E_t P_t^* (1 - \alpha^*)A_t^*^{1-\alpha^*}k_t^*{\alpha^*} = E_t w_t^* \quad (4^*) \]

where \( k_t = K_t / L_t \) is the capital-labor ratio.

The real exchange rate for any individual commodity at time \( t \) is defined as

\[ Q_t = \frac{P_t}{E_t P_t^*} \quad (5) \]

where \( E \) is the number of units of home currency a unit of the foreign currency can be exchanged for (or the nominal exchange rate of the foreign currency.) The Law of One Price (LOP) would imply that \( Q \) equals one for any one good. It follows that Purchasing Power Parity holds on aggregate if the LOP holds for every commodity. The LOP fails to the extent that country-specific differences exist between countries. For example, GDP per capita differences between countries would imply differences in preferences across countries. Different demand elasticities combined with some market segmentation would imply a role for price discrimination across locations. Another explanation for price differences for tradeable goods would be the existence of trade impediments for international trade.\(^9\)

\(^9\)The basic Balassa-Samuelson framework assumes that PPP holds for traded goods in which case \( Q \) would equal one for any one commodity. Allowing for factors which may cause PPP to fail, then the prices for manufactures may differ between countries with different levels of R&D stocks. The prediction would be that more productive countries would have lower prices for manufacturing goods relative to those in countries with lower productivity. Intuitively, in a world without any trade the more productive country would
Plugging equations (3) and (3*) into the equation for the real exchange rate given in (5), assuming the share of capital is identical for the final goods sector across countries so that \( \alpha = \alpha^* \), and using expressions (4) and (4*) then

\[
Q_t = \left( \frac{A_t}{A_t^*} \right)^{\alpha-1} \left( \frac{w_t}{E_t w_t^*} \right)^{1-\alpha} \quad (6)
\]

Finally, using expression (2) while assuming that innovations' size and research productivity are identical across countries so that \( \sigma = \sigma^* \) and \( \lambda = \lambda^* \), we get

\[
Q_t = \left( \frac{\int_{s=0}^{t} R_s ds}{\int_{s=0}^{t} R_s^* ds} \right)^{\alpha-1} \left( \frac{w_t}{E_t w_t^*} \right)^{1-\alpha} = \left( \frac{H(R_t)}{H(R_t^*)} \right)^{\alpha-1} \left( \frac{w_t}{E_t w_t^*} \right)^{1-\alpha} \quad (7)
\]

In the empirical application, I proxy \( H(.) \) with the accumulated stock of R&D so that \( H(R_t) = \sum_{s=0}^{t} R_s \).

Equation (7) implies a relation between the real exchange rate and cross-country productivity. On the one hand, Balassa and Samuelson's framework assumes that traded goods will flow freely and thus have identical prices across countries. The in-between case of goods that are traded but face transportation costs would then be compatible with lower prices for these goods in the more productive country. Countries with a higher stock of R&D will be more productive relative to countries with lower stocks of R&D so that a higher stock of R&D will be associated with lower manufacturing prices relative to low-productivity countries, at the same time that higher productivity raises the prices of non-tradeable services relative to those in less productive countries. In addition, even when transportation costs between countries remain fixed over time the changing pattern of exports and imports due to changing relative productivities between the countries will have an impact on the time-series behavior of the real exchange rate for any pair of countries.
country differences in accumulated R&D expenditures. Taking logs and defining $\zeta = \alpha - 1$ then expression (8) can be written as

$$\log Q = \zeta \left[ \log(H(R)/w) - \log(H(R^*)/E_t w^*) \right]$$

(8)

3.4 THE EMPIRICAL ANALYSIS

Using a large cross-section of individual goods' prices across six European countries for 1980 and for 1985, I look at the relationship of differences in the accumulated stock of knowledge and commodity-specific real exchange rates between countries.

I use OLS to estimate an empirical specification of equation (8) assumed to hold for every final good $i$ and every $jk$ pair of countries,

$$q_{ijk} = \zeta h_{jk} + u_{ijk}$$

where $q_{ijk} = \log(\pi_{ij})-\log(\pi_{ik})$ stands for log price differences (or individual log real exchange rates) between countries $j$ and $k$ for commodity $i$, $\pi_{ij}$ and $\pi_{ik}$ are the prices of commodity $i$ in country $j$ and $k$ converted to US dollars, $\chi$ is a constant term, $u_{ijk}$ is an error term, $h_{jk} = \log(H(R_j)/\omega_j)-\log(H(R_k)/\omega_k)$ is the cross-country difference between R&D stocks in US dollars divided by the wage in US dollars, and $\zeta$ the parameter capturing the effect of differences in the knowledge stock on cross-country price differences.\(^{50}\)

\(^{50}\)This specification may well suffer from endogeneity problems since wages are likely to
As a robustness check, I consider a specification that allows GDP per capita as an explanatory variable for price differences not explained by technology. This extends the empirical specification beyond the narrowly defined structural link between R&D and price differences considered above. GDP per capita can be thought of as a proxy for demand-induced effects on prices which become more important in the presence of some form of imperfect competition. I use the log of differences in GDP per capita. The estimated parameter should capture the impact of demand differences on cross-country price differences.

I report estimates and t-statistics for the impact of differences in technology and differences in GDP per capita on cross-country price differences in table 3.1. Considering bilateral price differences for manufactured goods between the six countries provides 1205 observations in 1980 (for 241 traded goods prices), and 1695 observations in 1985 (for 339 traded goods prices.) The analysis is performed separately for each cross-section at a point in time in order to make use of all the commodity prices in each of the two years, and to avoid comparability problems of similar goods between the two samples.

The estimates presented in table 3.1 suggest that the economywide stock of domestic R&D is negatively related with price differences of traded commodities. Countries with higher productivity have lower prices of tradeable goods. Nevertheless, since the estimates obtained here are similar to those from the specification in section 3.5 which does not include wages, we can be confident that the results here are not driven by biases associated with the endogeneity of wages.
goods. Moreover, differences in GDP per capita have a strong statistically
significant positive impact on cross-country price differences. That is, richer
countries have higher prices of traded commodities.

3.5 EXTENSIONS OF THE MODEL

I extend the model of the previous section to include a nontraded goods
sector in addition to the manufactured goods sector. I consider the basic
Balassa-Samuelson framework modified so that R&D is performed in the
economy. The model considered here assumes two perfectly competitive final
goods sectors in each country, services which is the non-tradeables sector and
uses only labor inputs\(^5\), and manufacturing which is the tradeables sector
and uses both labor and capital. Labor flows freely across sectors and capital
flows freely across countries so that wages are equalized across the sectors of
the domestic economy and the interest rate is equalized across countries.\(^6\)

\(^5\) Alternatively, one could allow for labor and capital to be used in both sectors and
assume the nontraded sector to be labor intensive.

\(^6\) This means that supply is so elastic that demand has no effect on the relative price
of non-traded goods. The finding that GDP per capita differences are important in deter-
mining price differences suggests that the assumption of perfect intrasectoral mobility of
labor is rather simplistic.

Here, my intention is to build a simple model to examine the impact of relative productivity
differences on cross-country price differences. I then extend the empirical specification
to allow for the importance of demand in order to check the sensitivity of the results.
Table 3.1: Explaining cross-country price differences of manufactures.

Notes:

t-statistics in parentheses

* the estimate is statistically significant beyond the one percent level.
The model presented here is a variant of the Schumpeterian framework of Aghion and Howitt (1998). The innovation process uses only the manufacturing sector's final output to produce inventions which can be thought of as new forms of capital services that benefit the domestic manufacturing sector.\textsuperscript{53} As a result, the productivity level of the manufacturing sector is increasing over time while the productivity level of services remains constant over time. Finally, there are no international spillovers of knowledge and there is a scale effect so that countries with higher accumulation of R&D are presumed to have higher levels of productivity.

The production functions for tradeables and non-tradeables in each country are given respectively by

\begin{align*}
Y_T &= (A_T L_T)^{1-\alpha} K_T^\alpha \\
Y_N &= A_N L_N
\end{align*}

where $Y_T$, $A_T$ ($A_N$), $L_T$ ($L_N$), and $K_T$ stand for output, technology level, labor input, and capital input, and the subscripts $T$ and $N$ indicate the tradeables and non-tradeables sectors respectively. The innovation process uses the manufacturing sector's final output to produce inventions which can be thought of as new forms of capital services that benefit the domestic manufacturing sector.\textsuperscript{54} The rate of technological progress in the manufacturing

\textsuperscript{53}Thus, technological progress is induced by R&D performed for the domestic manufacturing sector. The data suggest that about eighty percent of R&D across OECD countries is performed within the manufacturing sector.

\textsuperscript{54}Thus, the aggregate level of technology grows at the rate $g_t = (1-\beta)\frac{A_T}{A_T}$ where $(1-\beta)$
sector is \( \dot{A}_T = \sigma \lambda \frac{R_T}{A_T} \), where \( \sigma \) stands for innovation size and \( \lambda \) stands for research productivity both assumed to be time-invariant. Again, I assume constant returns to R&D so that technological progress is proportional to R&D-intensity, and the level of technology is proportional to the stock of knowledge implied by the accumulated stock of R&D expenditures. The level of technology in the manufacturing sector as of period \( t \) is thus given by

\[
A_T(t) = \int_{s=0}^{t} \dot{A}_T(s) \, ds = \sigma \lambda \int_{s=0}^{t} R_T(s) \, ds \tag{E2}
\]

Setting the value of the marginal product of capital equal to the world interest rate, and the value of the marginal product of labor in each sector equal to the wage rate, I obtain conditions (E3) to (E5):

\[
\alpha A_T^{1-\alpha} k_T^{\alpha - 1} = r_t \tag{E3}
\]

\[
(1 - \alpha) A_T^{1-\alpha} k_T^\alpha = w_t \tag{E4}
\]

\[
P_t A_N = w_t \tag{E5}
\]

where \( k_T = K_T/L_T \) is the capital-labor ratio in manufacturing, and \( P_t = \frac{P_N}{P_T} \) is the relative price of services.

Solving equation (E3) for \( k_T \) gives \( k_T = r_t^{\frac{1}{\alpha-1}} A_T^{\frac{1}{\alpha-1}} \). Substituting for \( k_T \) in equation (E4) gives \( w_t(r_t, A_T) = (1 - \alpha) \alpha^{\frac{1}{\alpha-1}} r_t^{\frac{\alpha}{\alpha-1}} A_T \). Finally, is the output share of the manufacturing sector in the domestic economy.
substituting the latter expression for $w_t$ in expression (E5), the relative price of services is given by

$$\frac{P_N}{P_T} = (1 - \alpha)\alpha^{\frac{1}{1-\alpha}}r_t^{\frac{\alpha}{1-\alpha}}\frac{A_{T_t}}{A_N}$$

(P)

so that the relative price of non-tradeables to tradeables is greater the greater is the accumulation of R&D in the traded goods sector.

The price level for any one country is given by weighting tradeables and non-tradeables prices as follows,

$$P = P_N^\beta P_T^{1-\beta}$$

(E6)

$$P^* = (P_N^*)^\beta (P_T^*)^{1-\beta}$$

where $\beta = \beta^*$ stands for the output share of the non-tradeables sector in the economy.

Defining the real exchange rate for any tradeable commodity as

$$X = \frac{P_T}{E_t P_T}$$

(E7)

where $P_T$ stands for the price of tradeables, the LOP fails (or $X$ deviates from one) for any one commodity to the extent that country-specific differences or trade impediments exist between countries.

Plugging equations (E6) and (E7) into the equation for the real exchange rate given by $S_t = \frac{p_t}{E_t p_t}$, we get $S = \frac{X^P_T P_T^{\beta} P_N^{1-\beta}}{(P_N^*)^\beta (P_T^*)^{1-\beta}} = X^{(P_N^*/P_T^*)^\beta} \frac{(P_N^*/P_T^*)^{\beta}}{(P_N^*/P_T^*)^{1-\beta}}$ and letting $\beta$, the output share of non-tradeables in the economy, be identical
across countries,

\[ S = X \left( \frac{P_N}{P_T} \right)^{\beta} \]  

(E8)

Using the expression for the relative price of non-tradeables given by (P), expression (E8) can be rewritten in terms of relative productivity,

\[ S = X \left( \frac{1 - \alpha}{1 - \lambda} \frac{\rho^{\alpha} \sigma^{\lambda}}{\rho^{\alpha} \sigma^{\lambda}} \frac{A_{Tt}}{A_{Nt}} \right)^{\beta} \]

and assuming the share of capital is identical for the tradeables sector across countries so that \( \alpha = \alpha^* \), then

\[ S = X \left( \frac{A_{Tt} / A_N}{A_{Tt}^* / A_{Nt}^*} \right)^{\beta} \]  

(E9)

Assuming that the level of technology in the non-tradeables sector is similar across countries so that \( A_N = A_N^* \), and using expression (E2) while assuming that innovation size and research productivity are identical across countries so that \( \sigma = \sigma^* \), and \( \lambda = \lambda^* \), we get

\[ S = X \left( \frac{\int_{s=0}^{T} R_{Ts} ds}{\int_{s=0}^{T} R_{Ts}^* ds} \right)^{\beta} = X \left( \frac{H(R_{Tt})}{H(R_{Tt}^*)} \right)^{\beta} \]  

(E10)

In the empirical application, I proxy \( H() \) with the accumulated stock of R&D so that \( H(R_{Tt}) = \sum_{s=0}^{t} R_{Ts} \).

The above expression implies a relation between real exchange rates and cross-country differences in accumulated R&D expenditures of the manufacturing sector. Taking logs, expression (E10) can be written as

\[ \text{One of the postulates of the Balassa model (and consistent with the Baumol-Bowen effect) is that productivity levels for non-tradeables are closer across countries than those for tradeables. As shown in table 3.3, for 1985 the mean of absolute differences across countries for R&D stocks in manufacturing was 1.35 compared to 0.89 for services. For 1980, the mean was 1.5 for manufacturing compared to 0.73 for services.} \]
\[ s = x + \beta (h(RD_T) - h(RD^*_T)) \]  

(E11)

where the small letters denote the natural logs of the corresponding variables.

The log real exchange rate, \( s \), from equation (E11) reflects a weighted average of the commodity-specific real exchange rates of goods found in any two economies. In the Balassa-Samuelson framework, this is predicted to have a positive relation with productivity differences across countries. This is because of the assumption that non-tradeables prices go up in the country with higher relative productivity, while the prices of tradeables are equalized across countries.

Here, I partition the goods into two sets, tradeables and non-tradeables, and look at the commodity-specific real exchange rates rather than considering a weighted average. Motivated by the findings in the previous section that show cross-country price differences for traded goods to have a negative relation with productivity differences, I estimate an empirical specification of equation (E11) separately for the set of traded and for the set of non-traded goods. This specification is assumed to hold for every good \( i \) and every country pair \( jk \) so that

\[ s_{ijk} = x + \zeta h_{jk} + u_{ijk} \]

where \( s_{ijk} = \log(\pi_{ij}) - \log(\pi_{ik}) \) stands for log price differences (or individual log real exchange rates) between countries \( j \) and \( k \) for commodity \( i \), \( \pi_{ij} \) and

104
\( \pi_{ik} \) is the price of commodity \( i \) in country \( j \) and \( k \) respectively converted to US dollars, \( u_{ijk} \) is an error term, \( \tau \) is a constant term directly implied by equation (E11), \( h_{jk} = \ln(H(R_j^T)) - \ln(H(R_k^T)) \) is the cross-country difference between the stocks of R&D in the manufacturing sector, and \( \zeta \) the parameter capturing the effect of knowledge stock or productivity differences on cross-country price differences.\(^{56}\) Again, in order to extend the empirical specification beyond a narrowly defined structural link between R&D and price differences, I use log differences in GDP per capita as an explanatory variable for price differences not explained by technology.

Considering bilateral price differences between the six countries for non-traded and for traded goods provides 230 and 1205 observations (for 46 non-tradeable commodity prices and 241 traded goods prices respectively) in 1980, and 425 and 1695 observations (for 85 non-tradeable commodity prices and 339 traded goods prices respectively) in 1985. I perform separate OLS regressions of non-tradeables and tradeables price differences on R&D stock and GDP per capita differences and report estimates and t-statistics in column (I) of table 3.2.

Again, a higher knowledge stock is found to be associated with lower individual exchange rates for tradeables. Moreover, comparing the estimates for the impact of productivity on tradeables prices with those for the impact \(^{56}\)The knowledge stock can also be seen as a proxy for the relative productivity of manufactures to services as long as the potential of the latter to benefit from a greater stock of knowledge is smaller than is the case for manufactures.
of productivity on non-tradeables prices it appears that the relative price of non-tradeables to tradeables is increasing with productivity. Finally, the results reported in column (I) of table 3.2 imply that higher productivity is associated with higher individual exchange rates for non-tradeables once we control for GDP per capita differences. The latter result does not necessarily imply a higher overall real exchange rate for the more productive countries since the prices of tradeables are lower there.

The results for the impact of differences in GDP per capita on cross-country price differences are consistent with those presented in table 3.1. Differences in GDP per capita have a strong statistically significant positive impact on cross-country price differences for traded manufactured goods but also for non-traded services. The estimates for the impact of differences in GDP per capita on cross-country price differences for non-tradeables are higher than for tradeables. GDP per capita should proxy for demand-induced effects on prices which will be important in the presence of some form of imperfect competition. The fact that markets are more segmented for non-tradeables than for tradeable commodities implies that we should expect such effects to be stronger for non-tradeables prices as evidenced in the results.

In column (II) of table 3.2, I present additional estimates from an alternative specification. Specification (II) considers dependence of relative non-tradeables prices on the R&D stock of manufacturing relative to the R&D stock in the service sector so that \( h_{jk} = \ln\left(\frac{H(R^T)}{H(R^S)}\right) - \ln\left(\frac{H(R^T)}{H(R^S)}\right) \). This
specification relaxes the assumption that productivity enhancing R&D is accumulated only in the manufacturing sector. The evidence from table 3.3 suggests that there are greater differences in R&D-implied traded goods productivity across countries than in non-traded goods productivity, so that we can expect the former differences to drive the relation between price differences and $h_{jk}$ as defined in specification (II). The estimates in column (II) give evidence of a positive relation between productivity and the relative price of nontraded goods to traded ones.

3.6 CONCLUSION

I construct a model where productivity is determined by the accumulation of R&D stock in the manufacturing sector. Productivity differences across countries are predicted to have a negative relation with cross-country price differences of manufacturing goods.

I use a broad cross-section of prices in six European countries to look at the relation between commodity-specific real exchange rates and cross-country productivity differences proxied by differences in R&D stocks. I find that individual real exchange rates of traded goods are negatively related to cross-country knowledge stock differences. The law of one price can fail even for tradeables and the lower prices for manufactures in the country with higher productivity will remain below those of the second country.
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<table>
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Table 3.2: Explaining cross-country price differences.

Notes:

* t-statistics in parentheses
* the estimate is statistically significant beyond the one percent level.
** the estimate is statistically significant beyond the five percent level.
*** the estimate is statistically significant beyond the ten percent level.

(1) $h_{jk} = \ln(H(R_j^T)) - \ln(H(R_k^T))$ (11) $h_{jk} = \ln\left(\frac{H(R_j^T)}{H(R_k^T)}\right) - \ln\left(\frac{H(R_j^T)}{H(R_k^T)}\right)$

108
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<th>maximum</th>
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Table 3.3: Absolute R&D stock differences of 5 EC countries from Germany.
An extension of the model which considers a non-tradeables sector, implies instead a positive relation between productivity differences and price differences across countries. I find that countries with higher productivity have a higher relative price of nontraded relative to traded goods.\footnote{The latter finding is consistent with a basic premise of the Balassa-Samuelson hypothesis and with Canzoneri, Cumby, and Diba (1999). Given smaller cross-country productivity differences in the nontraded sector across countries, those countries with a higher knowledge stock and thus higher productivity for manufactures will tend to have higher prices for nontraded commodities. Given a certain degree of intrasectoral labor mobility, this could arise due to upward pressure on the wages of the nontraded sector as the traded sector becomes more productive.} Once again, I find that countries with higher productivity have lower prices for traded goods. The finding that prices of manufactures remain cheaper in the more productive countries flies in the face of PPP and can reverse the usual Balassa-Samuelson result\footnote{The Balassa-Samuelson hypothesis states that countries with higher relative productivity for traded goods will have a higher price level. This is because higher productivity and wages in the traded goods sector imply, here, higher wages and prices in the nontraded goods sector. Assuming purchasing power parity for traded goods holds, the overall price level would then be higher in countries with higher prices for nontraded goods.} of a higher overall price level for higher productivity countries.
APPENDIX

DATA SOURCES AND CONSTRUCTION FOR CHAPTER 1

The ESRC Data Archive provided US patents data for 1963-88.\textsuperscript{59} US R&D data for 1957-92 were compiled by Bruce Grimm and Carol Moylan of the BEA (R&D Satellite Account.) Basu, Fernald, and Kimball provided estimates of the technological change component of TFP growth for US Manufacturing for 1950-89 and the Jorgenson input and output data for the US economy for 1948-89. I calculate the unadjusted measure of TFP growth using the Jorgenson gross output data and a translog index allowing for time-varying input shares.

I construct the stock of patents as a proxy of the knowledge stock using a knowledge obsolescence rate of seven percent.\textsuperscript{60} The benchmark year (1963) stock is given by the number of patents over the depreciation rate.\textsuperscript{61} I accumulate this up to 1988 using $\text{STOCK}_t = \text{PAT}_t + (1 - 0.07) \times \text{STOCK}_{t-1}$.

\textsuperscript{59}These data were collected by the US Department of Commerce and compiled by R. A. Wilson (1991).
\textsuperscript{60}This is this century's average annual rate of technological obsolescence estimated by Caballero and Jaffe (1993).
\textsuperscript{61}The growth rate for the patents ranged from positive to negative values over the period so that the average was close to zero.
PAT is the number of patents and STOCK the implied knowledge stock. The rate of patenting is the number of patents for any one year divided by the stock of patents.

TFP growth is $\delta(TFP^i_t) = \delta(Y^i_t) - \delta(K^i_t) - \delta(L^i_t) - \delta(M^i_t) - \delta(E^i_t)$. $\delta(.)$ is the log difference so that $\delta(Y^i_t) = \ln Y^i_t - \ln Y^i_{t-1}$ and $\delta(X^i_t) = \ln X^i_t - \ln X^i_{t-1}$ for inputs $X=K, L, M, E$. $K^i_t$ and $P^i_{Kt}$ stand respectively for net capital stock quantity and price of capital in sector $i$ at time $t$. The labor quantity for each sector $i$ is $L^i_t$ and the price of labor is $P^i_{Lt}$. The quantities and prices for intermediates and energy inputs are given respectively by $M^i_t$, $P^i_{Mt}$ and $E^i_t$, $P^i_{Et}$. $Y^i_t$ is real gross output and $P^i_{Yt}$ is its price. The weight for each input $X$ is given by $S^i_{Xt} = \frac{1}{2} (S^i_{Xt} + S^i_{Xt-1})$ where $S^i_{Xt} = \frac{P^i_{Xt}X^i_t}{P^i_{Yt}Y^i_t}$ is the value share of input $X$ in the value of output or the value share of input $X$ in the value of total cost, $S^i_{Xt} = \frac{P^i_{Xt}X^i_t}{TC^i_t}$. The value of total cost is $TC^i_t = P^i_{Lt}L^i_t + P^i_{Kt}K^i_t + P^i_{Mt}M^i_t + P^i_{Et}E^i_t$. Under zero profits, $TC^i_t = Y^i_t$ and input shares in cost will equal input shares in the value of output.\footnote{Input shares equal input elasticity with respect to output when the assumptions of constant returns to scale, competitive behavior, and optimal choice of factors of production hold at producer's equilibrium. The sum of the input shares and the sum of the elasticities equal one under constant returns to scale.} I use input shares in the value of total cost to construct total factor productivity growth ("TFP") with the Jorgenson data.
References


113


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