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Endogenous Growth and Learning-By-Doing Spillovers

by

Shamika Sirimanne

A thesis submitted to
the Faculty of Graduate Studies and Research
in partial fulfilment of
the requirements for the degree of

Doctor of Philosophy

Department of Economics
Carleton University
Ottawa, Ontario

July 2001

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the Faculty of Graduate Studies and Research
acceptance of the thesis,

"Endogenous Growth and Learning-By-Doing Spillovers"

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in partial fulfilment of the requirements
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July 2001

Dedication

TO MY PARENTS, G. W. SIRIMANNE AND LEELA SIRIMANNE,
AND TO MY HUSBAND, KEITH FORBES.

Abstract

This thesis investigates the relationship between learning-by-doing spillovers and productivity growth. We develop an endogenous growth model that allows for differential spillovers across sectors. Using this model, we examine the contribution of national and international spillovers to the productivity growth of a country.

The empirical results show that learning spillovers are important in determining productivity growth. It is found that both domestic and international spillovers depend on the skill intensity of a sector: that is, the higher the skill intensity of a sector, the larger will be the spillovers. In both cases, significant spillovers exist only in high-skill-intensive manufacturing sectors. The above results hold true for a country despite its stage of development or the size of its economy. The empirical results also show that greater openness to international trade leads to a higher dissemination of international knowledge.

We find several other important empirical implications of learning-by-doing spillovers. The first concerns the postulation of learning-by-doing theories that large countries would have a substantial growth potential over small countries. We do not find empirical evidence to support the notion that larger countries tend to grow faster. Second, with regard to international spillovers, we find that the foreign knowledge stock affects the productivity growth of a country only when interacted with a measure of openness. Our results indicate that the contribution of foreign knowledge to productivity growth is higher, the more open a country is to foreign trade. Third, regarding the best channel through which foreign-knowledge is transferred, we find that any one of the bilateral trade measures (imports, exports, or total trade) gives rise to broadly similar results.

Acknowledgements

I would like to thank Professors Ehsan Choudhri and Larry Schembri for their guidance to complete this thesis. Thanks are also due to all my teachers at Carleton and Ottawa Universities, fellow graduate students, and support staff in the Economics Department of Carleton University. They made my residence at Carleton a productive and a very pleasant experience.

Table of Contents

Acceptance sheet	ii
Dedication	iii
Abstract	iv
Acknowledgements	v
Table of contents	vi
List of tables	viii
List of charts	ix
 Chapter 1: Endogenous Growth and Learning-By-Doing Spillovers: Introduction	 1
Chapter 2: National Spillovers from Learning-By-Doing: The Model	9
Basic Model of National Spillovers	12
Alternative Versions of National Spillovers	14
Summary	17
Chapter 3: Empirical Models and Data	19
Empirical Models	19
Data	22
Chapter 4: Empirical Results	29
Model I (with Country Size)	30
Model II (without Country Size)	34
National Spillovers -- Summary	42
Chapter 5: International Spillovers from Learning-By-Doing: The Model	45
Aggregate Model	50
Sectoral Model	55
Chapter 6: Empirical Models and Data	58
Empirical Models	58
Data	60
Chapter 7: Empirical Results	68
Aggregate Model	69
Sectoral Model with International Spillover Effects	76

Sectoral Model with International & National Spillover Effects	80
International Spillovers -- Summary	83
Chapter 8: Conclusion	86
Appendix 1: Empirical Analysis.	89
Appendix 2: Data	126
Bibliography	143

List of Tables

Table 1: Evolution of Sectoral Composition between 1971-75 and 1986-1990	27
Table 2: Regression Results for Model I	32
Table 3: Regression Results for Model II	36
Table 4: Average Share of Imports from the G-7 Countries, 1971-75 and 1986-1990 .	63
Table 5: Average share of exports to the G-7 countries, 1971-75 and 1986-1990	64
Table 6: Regression Results for the Aggregate Model	70
Table 7: Simulation Results for India and Turkey	72
Table 8: Aggregate Model with Learning and R&D Spillovers	74
Table 9: Regression Results for the Sectoral Model--International Spillovers	77
Table 10: Regression Results for Sectoral Model--National & International Spillovers .	81

List of Charts

Chart 1: Total Factor Productivity growth for selected countries	26
Chart 2: Simulation results for Ecuador using Model II.	38
Chart 3: Simulation results for India using Model II.	41
Chart 4: Evolution in available foreign knowledge stock for selected countries	66
Chart 5: Evolution in available foreign knowledge stock with openness factor	67
Chart 6: Simulation results for India using Sectoral Model	80

Chapter 1

Endogenous Growth and Learning-By-Doing Spillovers: Introduction

The neoclassical growth theory, as formulated by Solow (1956, 1957) and Swan (1956), predicts that in the absence of exogenous technological progress, growth of per capita income would fall to zero in the long run, as capital per worker increased over time. For example, if investment increases because of an investment subsidy policy, it will lead to additional growth for a time. However, as the ratio of capital per worker increases over time, the marginal product of capital will decline, and the economy will converge back to long-run equilibrium, with productivity growth (and growth of per capita income) equal to the rate of exogenous technological progress. Consequently, the investment subsidy will have no impact on long-run economic growth.

The endogenous-growth literature pioneered by Romer (1986, 1987, 1990a), Lucas (1988, 1993), and Helpman and Grossman (1991), on the other hand, distinguishes itself from neoclassical growth by emphasizing that economic growth is an endogenous outcome of an economic system and not a result of factors outside the system. This idea is usually incorporated into endogenous-growth models by generating a strong, positive spillover effect from other economic activities that will offset any propensity to diminishing returns of the type that is integrated into the neoclassical models.¹ The

¹Endogenous growth literature based on the AK model does not rely on spillovers to offset the tendency for diminishing returns. Note that in the simplest version of the model, A is a positive constant that reflects the level of technology, and K represents capital. Given output per capita is $y = Ak$ (where k is per capita capital), the marginal product of capital is constant at the level A . This way, the AK model delivers endogenous growth by avoiding diminishing returns

sources of spillover effects are commonly identified as occurring through learning-by-doing, human capital accumulation, and/or research and development (R&D) activities.

In the empirical testing of these models, it is common to find a spillover term such as aggregate cumulative output, if the cause of spillovers is learning-by-doing; aggregate human capital or R&D stock, if the cause of spillovers is human capital accumulation or R&D activities, respectively.² Since the focus has been on an economy-wide spillover term, these studies have not investigated whether the spillovers differ between sectors. In other words, could on-the-job learning in the computer industry give rise to different spillovers than on-the-job learning in the apparel industry? If different sectors are capable of generating different spillovers, then their contribution to economic growth would also differ. In this thesis we explore whether such sectoral differences play an important role in the growth process.

We focus on the spillover effects of learning-by-doing as the source of continuous growth. Empirical work on learning-by-doing spillovers is limited. Most studies concentrate on the learning-by-doing benefits that are internalized by the firms in terms of reduction in the unit cost of production (Wright 1936; Ghemawat 1985; Argote and Epple 1990; Mishina 1999; and Wright 1999). However, in the context of sustained growth, it is important to determine whether part of these learning benefits spill over to other firms, hence benefiting the economy as a whole.

to capital in the long-run (see Barro and Sala-i-Martin (1994) for a discussion).

²Early empirical studies include Romer 1989 and 1990b; Backus, Kehoe, and Kehoe 1992; Mankiw, Romer, and Weil 1992; and Coe and Helpman 1994.

The study by Backus, Kehoe, and Kehoe (1992) analyses the impact of learning-by-doing spillovers on growth.³ They, however, assume spillovers are similar across industries. Assuming there are significant spillovers across industries within a country, the authors take the total output of the country as the relevant measure of the variable that generates learning-by-doing spillovers. The implication is that countries with larger output will benefit from higher learning spillovers, and hence will grow the fastest. However, they find little empirical evidence to support this hypothesis.

The authors consider an alternative version in which there are no inter-industry spillovers but each industry generates the same within-industry spillovers. They consider the total output of the country weighted by an index for sectoral specialization as the relevant variable in this case. The implication of this version is, that all else being equal, a country that is able to specialize more will grow faster. Note that according to this model, a country could choose to increase specialization in any sector, and the benefits will be the same, regardless of the sector chosen. This implies that countries with larger industries would grow faster. The authors, also, find little empirical evidence to support this hypothesis.

One reason for this lack of empirical support for their model might be the assumption that each and every sector's capability of generating spillovers is the same. To explain this possibility, we will allow different sectors or industries to have different spillover effects. If spillovers are different, it would mean that the composition of output,

³In addition to learning-by-doing effects, the authors also consider scale economies from investment in human capital and from development of specialized inputs to production. They develop theoretical models based on all three sources of scale economies.

and not just the size of output, will be important for economic growth. In fact, Pack (1994) criticizes the empirical work on endogenous growth that neglect the output composition effect. He asks: "What would Japan's GDP per-capita have been if it had not been able to move from agriculture and low-quality textiles to chemicals, metal-based products, and electronics?" Furthermore, he inquires whether some of the growth attributed to investment and education may simply reflect the fact that they facilitate a change in the composition of production. As in the case of Japan, evidence from the fast growing, newly industrialized countries in East Asia indicates that these countries have indeed experienced remarkable changes in the composition of production mix during the last three decades. Over time, they have managed to move towards more sophisticated production activities (Chenery, Robinson, and Syrquin 1986; Lucas 1993). For example, consider the economic growth stories of South Korea and the Philippines. In the early 1960s, there were striking similarities between South Korea and the Philippines in their production and export mixes (Lucas 1993). Since the 1960s, South Korea has pursued a rigorous, selective industrial strategy and has encouraged those industries or sectors that are relatively high-skill-intensive.⁴ South Korea has become a major producer and exporter of increasingly sophisticated manufactured goods and has enjoyed rapid economic growth. The same is not true for the Philippines, however. In early 1970s, for instance, the share of high-skill-intensive manufacturing production in gross domestic product (GDP) for both countries was around 9%. By the late 1980s, this share doubled in

⁴ Korean industrial policy appears to have encouraged resource shifts towards capital- and technology-intensive sectors and away from low-skill-labour-intensive sectors. Highly promoted industries included iron and steel, metal products, machinery, electronics, and industrial chemicals (World Bank 1993).

Korea to 18%, while it lagged at 10% in the Philippines.⁵ If higher-skill-intensive activities can indeed generate higher learning-by-doing spillovers, then part of the high growth enjoyed by South Korea could be attributed to the change in the composition of production.

Do different sectors or industries generate different spillovers, so that the composition of output matters in determining productivity growth of a country?⁶ The first part of this thesis is devoted to finding an answer to this question. We develop a learning-by-doing model which extends the Backus, Kehoe, and Kehoe (1992) framework by allowing for sectoral differences in learning spillovers. As in their study, we assume in this part of the thesis that spillovers operate within national borders. In the empirical analysis that follows, we test whether some sectors are able to generate higher learning spillovers, and if so, whether the spillovers change over time. We also investigate the hypothesis suggested by the learning-by-doing literature that spillovers depend on a scale variable, so that larger countries stand to gain more from learning spillovers than do smaller countries.

We make use of an improved data set for the empirical investigation. First, we use detailed industry-level output data, whereas Backus, Kehoe, and Kehoe (BKK) relied on export data as a proxy for industrial output data. Second, we construct a data series for

⁵Please refer to Appendix 2 for other country examples regarding the changes in the composition of output over time.

⁶One could question whether the causality operates the other way around. That is, economic growth tends to cause changes in the composition of output instead of the latter causing economic growth. Denison (1967, 1985), who investigates the direction of causality, finds strong evidence to support the view that the shifts in production structure do explain part of economic growth.

total factor productivity growth, while BKK simply used the growth of aggregate output as a proxy for productivity growth. Note that these two series coincide only when steady-state properties are imposed. This research is based on a developing country sample that consists of 20 countries. For industrial countries, spillovers from other sources, particularly through R&D may also be important, whereas in developing countries that undertake little R&D activities, learning-by-doing spillovers may play a key role in driving long-run growth.

The empirical results show that the sectoral composition of output is clearly important, since learning spillovers significantly differ across sectors. We find that the higher the skill intensity of a sector, the higher will be the learning spillovers. However, learning spillovers are statistically significant only in the high-skill-intensive manufacturing sector. Moreover, this sector seems to maintain its superior ability to contribute to productivity growth over time. All of these results hold true for a country regardless of its stage of development or the size of its GDP. Our results do not support the hypothesis that larger countries tend to grow faster.

We have so far focussed on learning-by-doing spillovers that operate within national borders. However, as Baldwin and Krugman (1988, 176) argue, “the ability of firms to learn from each other is not noticeably restricted by national boundaries.” The implication is that knowledge can be as easily obtained from firms outside the country as from firms within the country, so that learning is international in scope. Therefore, in the second part of the research, we extend our work on national spillovers to analyse the role of

international spillovers from learning-by-doing in determining the rate of productivity growth.

Current empirical work on international spillovers is limited. The key contributions to the literature consider the impact of international R&D spillovers on the total factor productivity of a country (Coe and Helpman 1994; Coe, Helpman, and Hoffmaister 1995; and Bayoumi, Coe, and Helpman 1999). Except for a few industry-specific studies (Irwin and Klenow 1994; Gruber 1998), the role of learning-by-doing as a source of international spillovers has not been examined. In the second part of the thesis, we attempt to fill this void by studying the role of international learning spillovers in determining productivity growth.

For this purpose, we extend the national spillover model by incorporating international spillovers from knowledge gathered in foreign countries. The empirical results indicate that international spillovers from learning-by-doing play a significant role in determining productivity growth. We also find that the foreign knowledge stock affects the productivity growth of a country only when interacted with a measure of openness. Our results indicate that the contribution of foreign knowledge to productivity growth is higher, the more open a country is to foreign trade. This research also indicates that a country's trading partner could be a factor in determining the amount of spillovers, and, hence, productivity growth.

With regard to the magnitude of international spillovers, our research shows that it depends on the skill intensity of a sector; so that, the higher the skill intensity, the higher the spillovers will be from international knowledge. As in the case of national spillovers,

statistically significant international spillovers are present only in the high-skill-intensive manufacturing sector. These results on sectoral differences of spillover structures hold true regardless of the size of the country or its stage of economic development.

Finally, we combine the national and international spillover models. The conclusions remain the same regarding the relationship between the magnitude of spillovers and the skill-intensity of a sector. In the combined model, the high-skill intensive manufacturing sector tend to generate statistically significant spillovers both in the case of national and international spillovers.

The remainder of the thesis consists of two parts followed by a conclusion. In the first part, Chapters 2 to 4 deal with national spillovers from learning-by-doing. In Chapter 2, we develop the theoretical model that defines the relationship between productivity growth and national spillovers. In Chapter 3, we discuss the empirical methodology and data, followed by the empirical results in Chapter 4. The second part of the thesis, Chapters 5 to 7, deals with international spillovers. In Chapter 5, we develop the theoretical model of international spillovers through learning-by-doing. Chapter 6 discusses the empirical methodology and data. Chapter 7 presents the empirical results. A brief set of concluding remarks follows in Chapter 8.

Chapter 2

National Spillovers from Learning-By-Doing: The Model

The potential for learning-by-doing spillovers to account for economic growth was first introduced by Arrow (1961). More recent theoretical work on the subject includes Boldrin and Scheinkman (1988), Lucas (1993, 1994), Stokey (1988) and Young (1991).

The empirical work on learning-by-doing spillovers is, however, limited. Most of the studies focus on micro-level learning benefits that are internalized by firms in the form of reduction in the unit cost of production. The earliest micro-level study of learning-by-doing benefits was done by Wright (1936) for aeroplane-frame production. He observed that productivity had been increasing with cumulative output. Later, others confirmed similar firm-level relations for other industries (Mishina 1999; Liberman 1984; and see Argote and Epple 1990, for a list of related studies). The focus of these micro-level studies, however, is not to find out whether there are externalities from learning-by-doing that would spill over to other industries (or firms), thereby making these benefits readily appropriable by outsiders to the firm. If there are such spillovers, then they can be linked to sustained productivity growth of an entire economy. Argote and Epple (1990) presuppose the existence of spillovers across firms.⁷ More recent micro-level studies by Gruber (1998) on the semi-conductor industry finds supporting evidence for learning-by-doing spillovers, although internalized learning benefits tend to outweigh spillovers.

⁷They also argue that the experience gained in one product may increase the productivity of related products. Stokey (1988) and Young (1991), develop theoretical models that capture this effect.

None of these studies, however, investigates the link between learning spillovers and the productivity of an whole economy. The key contribution to the empirical work on the relation between learning-by-doing and long-run economic growth comes from Backus, Kehoe, and Kehoe (1992) (BKK). The study assumes that learning spillovers are identical across industries. Assuming that there are no inter-sectoral spillovers, the authors use the total output of the country weighted by an index for sectoral specialization as the relevant variable for measuring learning-by-doing spillovers. According to this model, all else being equal, a country that is able to specialize more will grow faster. Given the assumption of identical learning spillovers, a country could choose to increase specialization in any sector, and the benefits will be the same. In other words, the model implies that those countries with larger industries would grow faster.⁸ However, they find little empirical evidence to support this hypothesis.⁹

The authors do not investigate whether spillovers from learning-by-doing are different across industries or sectors. In fact, this issue has not been addressed in the literature. Industry-level studies that concentrate only on learning benefits that are internalized (i.e., do not consider spillovers), show that their benefits vary widely from industry to industry (Ghemawat 1985; Argote and Epple 1990; Hannah 1999; and Wright 1999). Relatively higher learning opportunities are found in industries where there is a

⁸Note that the authors do not investigate the role of international spillovers.

⁹The authors develop an alternative model to consider the possibility of having significant spillovers across industries within a country. In this case, they use the total output of the country to measure learning-by-doing spillovers. The implication of this model is that countries with larger output will benefit from higher learning spillovers, and, hence, will grow the fastest. They find, however, little evidence to support this hypothesis.

greater potential for improvement in the products and processes than in those industries that do not possess such characteristics. For instance, manufacturing activities, which usually exhibit greater potential for such improvements, are found to be superior in generating learning benefits when compared with service activities such as raw material purchasing, marketing, sales, and distribution. In fact, industry-level studies done by Ghemawat (1985) and Argote and Epple (1990) find learning benefits to be small or virtually nonexistent in non-manufacturing activities, particularly in the above-mentioned service sectors. Within the manufacturing sector itself, learning potential is higher in high-skill-intensive sectors or industries that are operating at the scientific frontiers and have more room for improvement and innovation.

Since these studies show that the internalized part of learning benefits tend to vary across industries, it is reasonable to expect that spillover benefits from learning would also differ across industries. Similarly, since internalized learning benefits appear to depend on the skill-intensity of an industry, it may be the case that a similar relation can be found with regard to spillovers from learning.

The first part of this thesis explores these possibilities by developing and testing a model that allows for such sectoral differences in learning spillovers. At first, we assume that spillovers operate within national borders. (The issue of international spillovers is taken up in Chapter 5.) The basic model of learning-by-doing spillovers is developed in Section 2.1. This model is also used to develop a test to examine the BKK assumption of uniform spillovers. Then we introduce two extensions of the basic model to relax the assumption of the learning-by-doing theory that large countries tend to gain more from

learning spillovers (Section 2.2.1), and to introduce the possibility of inter-sectoral spillovers (Section 2.2.2).

2.1 Basic Model of National Spillovers

We introduce a learning-by-doing model based on the BKK framework. As mentioned above, however, we allow for different learning spillovers across sectors. It is assumed that there are n sectors, each producing according to a simple production function,

$$Y_i = A_i F_i, \quad i = 1, 2, \dots, n \quad (1)$$

where Y_i represents sector i 's total output, and $F_i [= F_i(K_i, L_i)]$ represents a composite index of capital and labour inputs.¹⁰ (Note that the time subscripts are dropped for simplicity.) The variable A_i measures the spillover effects of learning-by-doing in sector i . It is assumed, initially, that the learning is sector-specific. Following BKK, it is assumed that A_i at time t depends on the cumulative output of sector i up to that time:

$$A_i = \exp\left(\int_{-\infty}^t \beta_i Y_i(\tau) d\tau\right) . \quad (2)$$

Since we assume that learning spillovers are sector-specific, note that (2) implies that the experience gathered in a particular sector cannot be appropriated by another.¹¹

¹⁰BKK introduce a Cobb-Douglas production function. In the empirical work, we also assume a Cobb-Douglas production technology. Chapter 3 provides more details on this issue.

¹¹We will relax this assumption below when we study the inter-sectoral spillover effects.

Given that the rate of growth of aggregate output, $\dot{Y}/Y$, is the weighted average of the growth rates of individual sectors, we have

$$\dot{Y}/Y = \sum_i^n Y_i/Y (\dot{Y}_i/Y_i) . \quad (3)$$

Since (1) and (2) imply that $\dot{Y}_i/Y_i = \beta_i \dot{Y}/Y + \dot{F}_i/F_i$, (3) can be rewritten as

$$\dot{Y}/Y = Y \sum_i^n \beta_i (Y_i/Y)^2 + \sum_i^n Y_i/Y (\dot{F}_i/F_i) . \quad (4)$$

The first term on the right-hand side represents the rate of growth of total factor productivity or $\dot{A}/A$ (Note that $\dot{A}/A = \dot{Y}/Y - \sum_i Y_i/Y (\dot{F}_i/F_i)$). It captures the contribution of learning spillovers to growth. The second term is the direct contribution of capital and labour inputs (via the composite factor index) to growth. Since it is the first term that is of interest to this study, we isolate it by rearranging (4) and expressing the total factor productivity (TFP) growth of the economy as

$$\dot{A}/A = Y \sum_i^n \beta_i (Y_i/Y)^2 . \quad (5)$$

Note that the right hand side of (5) includes a scale effect, as well as a sectoral composition effect. The scale effect is represented by the aggregate output variable, which indicates that the higher the aggregate output of a country, higher would be total factor productivity growth. The term, $\sum_i \beta_i (Y_i/Y)^2$, represents the composition effect. It implies that if a particular sector generates relatively higher learning spillovers (i.e., has larger β_i 's), then a higher rate of TFP growth can be achieved by transferring resources to that

sector. As discussed at the beginning of this section, high-skill-intensive sectors with more learning opportunities are expected to display higher learning spillovers. In other words, we expect that the learning coefficients, the β_i 's, to be relatively larger in these sectors compared to those of relatively low-skill-intensive sectors.

In contrast, the BKK model, which is based on the assumption that learning coefficients are uniform across sectors (i.e., $\beta_i = \beta$ for all i), does not allow for the possibility of differential learning spillovers. Hence, a country could choose to increase specialization in any sector, and the benefits will be the same, regardless of the sector chosen.

In the empirical analysis, we divide the economy into three sectors: high-skill-intensive manufacturing, low-skill-intensive manufacturing, and non-manufacturing.¹² We also consider a broader classification with two sectors: manufacturing and non-manufacturing.

2.2 Alternative Versions of National Spillovers

Two alternative models of learning spillovers are developed below. In the first we remove the country-size effect of learning spillovers to avoid the implication of (5) that, given all else is equal, larger countries (with larger outputs) tend to grow faster. In the second alternative model, we relax the assumption that learning spillovers are sector-specific by allowing for inter-sectoral spillovers.

¹² A discussion of the sectoral definitions and data issues can be found in Appendix 2.

2.2.1 Country-Size Effects Removed

The positive relation between the level of aggregate output and the rate of growth of TFP, as seen in (5), carries the somewhat unwelcome implication that a large country like India or China would have a substantial growth potential over a small country like Singapore or Taiwan. Lucas (1994) suggests that it is an implication of the learning-by-doing theories, which one would want to dispose.

As a way of eliminating the country-size effect, Barro and Sala-i-Martin (1994) propose the use of average output per worker rather than the aggregate output as the scale variable.¹³ Following this approach, we develop a model that eliminates the country-size effect by assuming that sectoral spillovers depend on the average output-per-worker of a sector, rather than the aggregate output. In this version, the spillover index in (2) is modified as

$$A_i = \exp\left(\int_{-\infty}^t \beta_i y_i(\tau) d\tau\right),$$

where $y_i = Y/L_i$. The rate of growth of TFP is thus determined as

$$\dot{A}/A = y \sum_i \beta_i (Y_i/Y)^2 (L/L_i), \quad (6)$$

where y represents per capita income (Y/L).

As another approach for removing the country-size effect, Lucas (1993) suggests that one could assume that each country has a number of viable economic regions (or city

¹³ Similarly, Lucas (1988), who assumes that the learning spillover is a result of human capital accumulation, defines that each worker benefits from the average level of human capital in the economy, rather than from the aggregate stock of human capital.

states) that are roughly the same size. Moreover, the number of regions is proportional to the labour force. Therefore, doubling the labour force, while keeping the size of each region fixed, means doubling the number of regions that are subject to learning spillovers. Accordingly, if we define regional output of sector i as $\hat{Y}_i$, then the regional spillover term for sector i can be expressed as

$$A_i = \exp\left(\int_{-\infty}^t \beta_i \hat{Y}_i(\tau) d\tau\right), \quad (7)$$

where $\hat{Y}_i = Y/R$; and R represents the number of regions. Assuming that the number of regions is proportional to the labour force, we can replace R with L (by appropriate normalization) and have $\hat{Y}_i = Y/L$. The corresponding TFP growth relation for the regional economy is now expressed as

$$\dot{A}/A = \gamma \sum_i^n \beta_i (Y_i/Y)^2. \quad (8)$$

By assuming TFP growth to be similar across regions, we can interpret (8) as describing the rate of growth of TFP for the whole economy.

2.2.2 Inter-sectoral Spillover Effect

Thus far, our model has assumed that learning-by-doing spillovers are sector-specific. According to the anecdotal evidence presented by Rosenberg (1982), however, there appear to be substantial spillovers of knowledge across industries, with innovations originating in one sector finding new applications in other industries. The widespread use of computer-chip technology in other industries is a prime example of this phenomenon.

Jaffe (1986) shows that the number of patents a firm secures is based not only on its own R&D efforts, but also on the R&D efforts of its technical neighbours. Although no formal empirical analysis of inter-sectoral spillovers through learning-by-doing has been undertaken, Young (1991) argues that it is reasonable to assume that advances in managerial and production experience of one industry would have applications in others. Therefore, if learning spillovers spread across industries or sectors within a country, the function determining A_i in (2) can be redefined as

$$A_i = \exp\left(\int_{-\infty}^t \sum_{k=1}^n \beta_{ik} Y_k(\tau) d\tau\right), \quad (9)$$

where β_{ik} represents the learning resulting in sector i as a result of activities in the sector k . Then the rate of growth of TFP becomes

$$\dot{A}/A = Y \sum_{i=1}^n \sum_{k=1}^n \beta_{ik} (Y_k/Y) (Y_i/Y). \quad (10)$$

Note that the composition effect now depends on the shares of output in sectors i and k , and it is different from (5), where there are no inter-sectoral spillover links.

2.3 Summary

This chapter has extended the growth model formulated by BKK by allowing different sectors to have different learning capabilities. In our extended model, the sectoral composition of output plays an important role in determining productivity growth of a country. If relatively higher learning opportunities are available in high-skill-intensive

sectors when compared with those of low-skill-intensive sectors, the model predicts that a country that has a relatively high proportion of high-skill-intensive output will, *ceteris paribus*, enjoy higher productivity growth. We also modified the basic model to remove the country-size effect in learning spillovers and to take into account inter-sectoral spillovers. In the next chapter we develop the empirical versions of the learning spillover models and then discuss data issues.

Chapter 3

Empirical Models and Data

In this chapter, we present the testable versions of the theoretical models developed in Chapter 2. We then discuss data sources and the construction of the variables for estimation purposes. Some interesting features of data are also highlighted at the end.

3.1 Empirical Models

The empirical versions of the basic model and the alternative models that remove the country-size effect and allow for inter-sectoral spillovers are discussed below. Note that the learning-by-doing models we develop in Chapter 2 are capable of explaining only a part of TFP growth. Therefore, we introduce an intercept term to capture the influence of other factors on TFP growth.

After adding an intercept term, α ,¹⁴ and an error term to (5), the testable version of the basic spillover model for TFP growth in country j can be defined as

$$\dot{A}^j/A^j = \alpha + Y^j \sum_i^n \beta_i (Y_i^j/Y^j)^2 + \epsilon^j. \quad (11)$$

Recall that in Chapter 2, we considered two alternative spillover models [see (6) and (8)] that remove the country-size effect in learning spillovers. The lack of sectoral-level labour data, however, prevents us from estimating the relationship in (6). In empirical work,

¹⁴We later allow the intercept term to vary across countries and across time. We also explore whether the intercept term is randomly distributed.

therefore, we focus only on the relation given in (8) and consider the following testable version of (8):

$$\dot{A}^j/A^j = \alpha + y^j \sum_i^n \beta_i (Y_i^j/Y^j)^2 + \epsilon^j . \quad (12)$$

In the empirical work that follows, we consider a three sector economy: high-skill-intensive manufacturing (hs), low-skill-intensive manufacturing (ls), and non-manufacturing sectors (nm). Thus, $i = \text{hs, ls, nm}$. Alternatively, we also consider a two-sector economy with manufacturing (mn) and non-manufacturing (nm) sectors (in this case $i = \text{mn, nm}$). As discussed in Chapter 2, learning coefficients, β_i 's, are presumed to depend on the skill orientation of a sector, so that higher skill intensive sectors would produce bigger learning coefficients. Each learning coefficient is expected to be equal to or greater than zero ($\beta_i \geq 0$), since it is reasonable to assume that there would not be any negative learning spillovers. Note that the BKK version is a special case with $\beta_i = \beta$. And the regression equation (11) becomes

$$\dot{A}^j/A^j = \alpha + \beta Y^j \sum_i^n (Y_i^j/Y^j)^2 + \epsilon^j . \quad (13)$$

In the empirical work, we will test the BKK model by developing a specialization index weighted by the country-size as in (13). We call this index the BKK index. BKK develop a similar index, although they test it against the GDP growth. Moreover, they use export shares instead of output shares to measure the specialization index.

The empirical version of the inter-sectoral spillover model in (10) for country j can be described as

$$\dot{A}^j/A^j = \alpha + Y^j \sum_i^n \sum_k^n \beta_{ik} (Y_k^j/Y^j)(Y_i^j/Y^j) + \epsilon^j. \quad (14)$$

However, in the econometric analysis, the above specification of learning spillovers gives rise to an identification problem regarding the across-sector learning effects. For example, it is not possible to differentiate between the spillovers generated in sector k as a result of activities in sector i , from the spillovers generated in the latter sector as a result of the activities in the former sector. One way to overcome this problem is by imposing further restrictions on the direction of spillovers. For example, it can be assumed that lower-skill-intensive sectors benefit from the learning experience of the relatively higher skill-intensive sectors, but not vice versa. Since the data for our study are aggregated into three broad sectors, we argue below that our empirical models based on regressions (11) and (12) are able to account for much of the inter-sectoral spillovers.

In this respect, even though productivity gains from learning accumulated in a particular industry may diffuse to many other sectors, the major part of the gains will generally accrue in the initial sector. Jaffe (1986) finds that major beneficiaries are closely related industries, and most of them fall within a broad industry cluster defined at a two-digit level International Standard Industry Classification (ISIC). For example, learning acquired in spinning activities may improve weaving, knitting, and textile production, which all fall within the same two-digit level industry classification. Similarly, electrical

industrial machinery, radio and television, and electrical appliances that are combined at the two-digit ISIC level, will each benefit from the others' activity. Conversely, it is reasonable to assume that the learning occurring in spinning may not greatly benefit the electrical appliances, since the two are not closely related industries. This suggests that if related sectors are grouped together, then there is a high likelihood that the inter-sectoral spillovers are already captured within these groups. Since we have divided the economy into three broad sectors with similar skill intensities, it would appear safe to assume that related sectors are brought together at this level of aggregation. Thus, we will not take up the issue of inter-sectoral learning spillovers in the econometric work in Chapter 4.

Nonetheless, inter-sectoral spillovers deserve more investigation, and should be undertaken with industry data defined at a much more disaggregated level than that of our research. Further restrictions on the direction of spillovers may also be necessary to carry out the econometric testing.

3.2 Data

A panel data set for 20 developing countries covering the period from 1970 to 1990 is used to estimate the relationship between the rate of growth of TFP and learning spillovers. The country sample is limited to those for which adequate manufacturing data are available at a detailed sectoral level for the entire period. The sectoral-level manufacturing data, reported at three-digit ISIC levels, are obtained from the United Nations Industrial Development Organization's (UNIDO) International Yearbook of Industrial Statistics, and United Nations National Accounts Statistics: Main Aggregates and Detailed Tables. By using sectoral output data, we have addressed one of the

limitations of the BKK data set that uses export data as a proxy for calculating the sectoral production shares.

The series for real GDP per capita and data on capital and labour are taken from the World Bank's World Tables, East Asian Miracle Data Base (World Bank), and the Summers and Heston data set (Penn World Table (Mark 5.6) data set).

For each variable, non-overlapping five-year averages for 1971-75, 1976-80, 1980-85, and 1986-90 are computed. We focus on five-year averages rather than making use of annual data. First of all, the use of yearly time spans may give more weight to the short-term disturbances, and consequently becomes inappropriate for studying the causes of long-run TFP growth. Longer time spans, on the other hand, are less influenced by business cycle fluctuations (Islam 1995). The empirical studies by Islam (1995) and Knight (1993) that investigate long-run economic growth also use five-year averages. Furthermore, for some variables and countries, data are missing for several periods. This is particularly the case for physical capital and industry-level output data. The average values for longer time intervals may, in that case, provide reasonable approximations. We also apply the full set of annual time series data on the regressions in (11) and (12) for comparison purposes. (These results appear in Appendix 1.) The conclusions with regard to the differences in sectoral learning effects are similar to those derived by using the 5-year intervals.

3.2.1 TFP growth series

Recall that the rate of TFP growth for the aggregate economy is

$$\dot{A}/A = \dot{Y}/Y - \sum_i Y_i/Y (\dot{F}_i/F_i). \quad (15)$$

where $\dot{F}/F_i$ measures the sectoral contribution of capital and labour inputs to productivity growth. Since sectoral-level input data for labour and capital are not available for several countries in the sample, we use aggregate measures of capital and labour instead, by replacing $\sum_i (Y/Y) \dot{F}/F_i$ with $\dot{F}/F$. Then we measure the rate of TFP growth as

$$\dot{A}/A = \dot{Y}/Y - \dot{F}/F. \quad (16)$$

To understand the difference between (15) and (16), note that we can express

$$\frac{\dot{F}}{F} = \sum_i \frac{F_i}{F} \frac{\dot{F}_i}{F_i}.$$

The term on the right hand side is different from $\sum_i (Y/Y) \dot{F}/F_i$, in that it uses F_i/F instead of Y_i/Y as weights. Since $Y/Y = (A/A) (F/F)$, the definition in (16) that is used to construct the TFP growth series omits the influence of the sectoral share of productivity, A_i/A .

To construct the $\dot{F}/F$ series, we follow BKK by assuming Cobb-Douglas production technology. Following Fischer (1993), the share of capital in output is taken as 40%, the

estimate commonly used in the case of developing countries (e.g., see Islam 1995).¹⁵ The rate of growth of TFP for country j is thus estimated as

$$\dot{A}^j/A^j = \dot{Y}^j/Y^j - 0.4(\dot{K}^j/K^j) - 0.6(\dot{L}^j/L^j) .$$

Note that by using the TFP growth series, we address another limitation of the BKK study, which uses the growth of aggregate output as a proxy for TFP growth. These two series coincide only when steady-state properties are imposed. Chart 1 illustrates TFP growth series for some of the countries in the sample. Observe that these data exhibit substantial fluctuations over time.

¹⁵We are considering a production function that is based on two inputs: capital and labour. As such, we have not differentiated between physical and human capital. One could wonder whether the series of TFP growth rates constructed may be affected by this omission. Fischer (1993) specifically deals with this issue. Following Mankiw, Romer and Weil (1992) he incorporates human capital into the production function in addition to physical capital and labour. The TFP growth series is then constructed by imposing coefficients used in Mankiw, Romer, and Weil paper, as follows.

$$\dot{A}^j/A^j = \dot{Y}^j/Y^j - \frac{1}{3}(\dot{K}^j/K^j) - \frac{1}{3}(\dot{L}^j/L^j) - \frac{1}{3}(\dot{HK}^j/HK^j) ,$$

where HK represents the human capital stock. He uses data for 68 countries for the period of 1961 to 1988 to calculate the TFP growth series. This series is then compared with TFP growth series calculated by using only capital and labour data (the shares of capital and labour in total output are taken as 40% and 60%, respectively). The two series are highly correlated with a pairwise R^2 value exceeding 0.98. As a result, Fischer chooses to use the TFP growth series calculated using capital and labour data in his paper. We follow Fischer's approach in our research.

Chart 1: Trends in TFP Growth

Chart 1: Total Factor Productivity growth for selected countries between 1971-90.
Source: Appendix 2

3.2.2 Evolution of sectoral shares

Finally, a preliminary analysis of the available data reveals quite interesting information about the changes in the sectoral composition of output over time. The changes in sectoral output shares in GDP between the 1971-75 and 1986-90 periods for some of the countries in the sample are reported in Table 1. Note that in several countries, significant changes in the structure of production have taken place between the two periods. It is particularly interesting to note that it is the fast growing newly industrialized countries such as Korea, Malaysia, Indonesia, Mexico, and Singapore that have undergone

tremendous changes in sectoral shares. Over time, these countries have managed to achieve a remarkable increase in the share of high-skill-intensive production in GDP.¹⁶ In contrast, countries with a relatively low growth record during the two decades--for example, Argentina, Chile, India, Peru, and the Philippines--have not experienced a similar structural change towards manufacturing, and within manufacturing, towards high-skill-intensive activities. Note also that Korea, Peru, and the Philippines all had similar production structures in the early 1970s, but only Korea managed a significant change in the direction of high-skill sectors.

Table 1: Evolution of Sectoral Composition between 1971-75 and 1986-1990

Country	Share of high-skill-intensive sector in GDP*		Share of low-skill-intensive sector in GDP*	
	1971-1975	1986-1990	1971-1975	1986-1990
Argentina	14.1%	14.2%	15.8%	13.5%
Chile	7.7%	5.3%	16.3%	13.4%
Ecuador	4.1%	7.3%	12.5%	13.3%
Hong Kong	10.2%	9.3%	16.6%	9.8%
India	6.1%	8.9%	8.9%	9.3%
Indonesia	2.1%	6.1%	6.9%	12.0%
Korea	9.4%	17.6%	15.0%	13.6%
Malaysia	7.2%	12.7%	8.9%	11.0%
Mexico	7.4%	12.2%	16.2%	12.4%
Panama	6.0%	2.4%	9.3%	5.2%
Peru	9.7%	10.6%	15.8%	15.1%
Philippines	8.8%	9.9%	15.4%	15.2%
Singapore	16.9%	22.0%	6.3%	4.5%

Source: Appendix 2

*Appendix 2 contains a discussion on how three-digit ISIC industries are divided in to high-skill-intensive and low-skill-intensive sectors.

¹⁶Hong Kong is the only exception, which may be partly due to its city-state nature. The data show a rapid increase in the service sector (considered non-manufacturing here), which naturally undermined the share of the manufacturing sector.

In the next chapter we formally investigate whether high-skill-intensive sectors are indeed capable of generating higher spillovers. If so, then changes in the composition of output towards high-skill-intensive sectors would contribute to higher growth.

Chapter 4

Empirical Results

In this chapter we discuss the empirical results of learning-by-doing models. A panel data set for 20 countries for 1970 to 1990 is used to estimate the regression equations (11) and (12).¹⁷ As discussed earlier, the regression equation (11) includes both the sectoral composition and country-size effects in determining learning spillovers, while the country-size effect is removed in (12). Accordingly, in the rest of this chapter we will call (11) “Model I”, and (12) “Model II”.

As discussed in Chapter 3, the constant term, α , allows for the influence of other factors on TFP growth. We introduce time and country specific intercept terms to accommodate for these factors. to take care of the impact of these exogenous changes.¹⁸ Since time effects are found to be significant in both models, all regressions reported here include time effects. However, country effects are significant only in Model I. Therefore, in the case of Model II, we focus on the results of the ordinary least squares (OLS) procedure that exclude country effects. For each regression, a random effects specification

¹⁷Regression results have been corrected for heteroskedasticity and autocorrelation problems (for details, refer to Appendix 1, Section 1).

¹⁸With regard to time effects, since our data set consists of four time periods (1971-75, 1976-80, 1980-85, and 1986-90) we introduce three dummy variables to take care of the possible shifts to the intercept term over time. Likewise, with regard to country-specific effects, since we have 20 countries, 19 dummy variables are introduced to take care of the shifts in the intercept term across countries. With regard to the sectoral variables, however, F-tests on both Models I and II indicate that sectoral learning effects are similar across countries and time (see Appendix 1, Section 1).

was also considered, but the test results rejects the model (refer to Appendix 1, Section 2, for details).¹⁹

4.1 Model I (with Country Size)

Table 2 presents the results of Model I. As mentioned above, all regression results include unreported time and country specific fixed effects. The first column of Table 2 reports the results of the regression when the economy is divided into three sectors: high-skill-intensive manufacturing, low-skill-intensive manufacturing, and non-manufacturing sectors. As the results indicate, learning spillovers differ between sectors. Sectors with higher skill intensity tend to generate relatively more learning spillovers. Statistical tests demonstrate that spillover effect of the high-skill-intensive-sector is significantly different from that of the low-skill-intensive sector.²⁰ Note from Table 2, however, that only the

¹⁹Random effects model assumes that country effects are not fixed, but drawn from a common distribution. As an alternative pooling technique, we also experimented with a cross-sectionally heteroskedastic and time-wise autoregressive model as described by Kmenta (1986). It was found to be not relevant for this study, since heteroskedasticity and autocorrelation problems are not present in the error terms of both models.

To investigate whether simultaneity bias has affected the results, we applied instrumental variable estimation to both models using the lagged values of the sectoral indexes. Results are similar to what is reported in this section. Refer to Section 3 of Appendix 1 for more details and the results of this method. Finally, we apply the panel data techniques discussed above to the total data set, consisting of annual data for 18 years for 21 countries. The results from this estimation are consistent with the results reported here (Appendix 1).

²⁰The results of the t-tests of the hypothesis that the spillover effects are the same between sectors with different skill intensity are as follows (the test statistic is given in brackets with “*” indicating that the null hypothesis is rejected at 5% significance level):

- (i) $\beta_{hs} = \beta_{ls}$: (t-statistic = 2.92*)
- (iii) $\beta_{nm} = \beta_m$: (t-statistic = 3.14*)

We also test whether the spillovers in low-skill insensitive and non-manufacturing sectors are insignificant by testing $\beta_{oth} = \beta_{ls} = 0$: ($F_{(2, 34)} = 2.01$).

high-skill-intensive manufacturing sector generates significant learning spillovers.

Similarly, when the economy is divided into two sectors, the results in column 2 of Table 2 indicate that significant spillovers exist only in the manufacturing sector.

The next step is to test the validity of the BKK assumption that spillovers are similar across sectors. We use two different tests. In the first, we make use of the BKK index (sectoral specialization index weighted by the country-size) developed in (13). The results of the BKK model, which appear in the third column of Table 2, indicate that the BKK index is not statistically significant, and consequently cannot satisfactorily explain the variation in TFP growth. This result is, in fact, similar to what they obtain in their study. They find that the specialization index used in their study (which is based on export data) weighted by the country size is not able to account for cross-country differences in growth rates of per capita GDP. The second test, perhaps a more direct test on the uniformity of spillovers, is to use an F-test to investigate whether the learning effects are similar across sectors. We test the superiority of the restricted BKK model (where $\beta_i = \beta$ for all i) against the unrestricted three-sector model using an F-test. The test statistic at 5.11 (distributed with 2 and 54 degrees of freedom in the numerator and denominator, respectively) is significant at a 5% level, thus rejecting uniform spillover effects.

Table 2: Regression Results for Model I

(t-statistics in parentheses)

Dependent variable: Growth rate of TFP

Independent Variable ²	3-sector model	2-sector model	BKK model	3-sector model (compare with Model II) ¹
High-skill sector index	0.123 E-03 (2.46)*	-	-	0.945E-03 (2.25)*
Low-skill sector index	0.301 E-04 (0.29)	-	-	0.120E-04 (1.66)
Non-manufacturing sector index	-0.482 E-06 (-0.78)	-0.606E -06 (-0.82)	-	0.178E-06 (0.62)
Manufacturing sector index		0.205 E-04 (1.91)*	-	
BKK index		-	0.829 E-06 (1.35)	
Number of observations	80	80	80	80
R ²	0.534	0.525	0.501	0.212
Adjusted R ²	0.318	0.312	0.301	0.148
Std. Error of Regression	0.02	0.021	0.022	0.023
Time-specific effects	yes	yes	yes	yes
Country -specific effects	yes	yes	yes	no

* Test statistic is significant at the 5% significance level. The t-statistics are heteroskedastic-consistent.

Notes:

1. The regression results exclude country-specific effects. We will use these results to compare Model I with Model II which also excludes country-specific effects. The relatively low values of R² and adjusted R² are because of the exclusion of these country-specific effects that are accounted for by 19 dummy variables for the 20 countries in the sample.

2. The regression equation for Model I as expressed in (11) is as follows:

$$\dot{A}^j / A^j = \alpha + Y^j \sum_i^n \beta_i (Y_i^j / Y^j)^2 + \epsilon^j .$$

In the three-sector version, $i = \text{hs, ls, nm}$. Accordingly, high-skill sector index is defined as $Y(Y_{\text{hs}}/Y)^2$, low-skill sector index is defined as $Y(Y_{\text{ls}}/Y)^2$, and so forth. Similarly, in the two-sector version $i = \text{mn, nm}$, and non-manufacturing sector index, for example, is defined as $Y(Y_{\text{nm}}/Y)^2$. The BKK index is derived by assuming all $\beta_i = \beta$.

Regarding the interpretation of the coefficients in Table 2, recall that they are a product of both output composition and scale effect (see the expression in (11), in Chapter 3). Our primary interest is to examine what happens to the TFP growth of a country when the sectoral composition of output changes, given that other factors remain constant.²¹ We undertake a simulation exercise for this purpose. Ecuador is chosen for the exercise, since it more or less exhibits the average features of the rest of the countries in the sample. For example, its real GDP per capita and sectoral composition of output are closer to the average values computed for all the countries in the sample. The share of the high-skill manufacturing sector is approximately 7% of GDP, while respective shares of low-skill and non-manufacturing sectors are 13% and 80%.

The results of the simulation exercise illustrate the importance of composition effect in determining TFP growth. In the case of Ecuador, if the share of the high-skill-intensive manufacturing sector is doubled from its present level of 7% of GDP to 14% by transferring resources from the low-skill-intensive manufacturing sector, it will add slightly less than half of a percent to its TFP growth rate (in other words, TFP growth will increase from its present 1.88% to 2.28%), provided that the aggregate output remains constant. Instead, if resources are transferred from the non-manufacturing sector, the increase in TFP growth will be even higher as the learning coefficient of the non-manufacturing sector is lower than that of the low-skill-intensive sector. In this instance, the change in output composition will add slightly more than half of a percent to TFP growth.

²¹For example, we assume that changes in sectoral composition will not change the aggregate output.

The learning-by-doing model we developed in Chapter 2 specifies that the relationship between sectoral shares and the rate of growth of TFP is non-linear. In quantitative terms for Ecuador, it means that if the share of the high-skill-intensive manufacturing sector is increased further from 14% to 28%, for example, by transferring resources from the low-skill-intensive manufacturing sector, it will add approximately 2% to Ecuador's TFP growth (in this case, the growth rate of TFP will increase from 2.28% to 4.32%). These results indicate that the larger the share of high-skill-intensive sector, the larger the benefits would be from further shifts of resources towards this sector.²²

4.2 Model II (without Country Size)

Table 3 presents the results of Model II. An F-test reveals that country-specific effects are not significant in this model. However, time-specific effects are still statistically significant. Therefore, the results reported in Table 3 and the discussion of these results below are based on the regression analysis that excludes country-specific effects.

As discussed in Chapter 2, the regression Model I has the undesirable implication that larger countries would grow faster. Consequently, the regression Model II is introduced as an alternative, in which the country-size effect is removed by using per capita income to weigh the sectoral composition indexes. It is interesting to investigate, however, whether Model II, which is more appealing theoretically, also performs better empirically. We compare the three-sector version of Model II reported in the first column

²²More simulation experiments are undertaken in the next section when we test Model II.

of Table 3 with the results of the three-sector version of Model I reported in the last column of Table 2 (note that both cases exclude country-specific effects). A comparison based on adjusted R^2 and standard error of regression indicates that Model II indeed performs better.

We also consider another test to compare the performance of the two models. Recall that both models attempt to explain the variation in TFP growth, but the explanatory variables differ based on the way sectoral indexes are constructed. As a result, one model cannot be expressed as a restriction of the other, making these competing models non-nested. We apply two non-nested model tests to determine which set of regressors has more explanatory power.²³ They are Davidson and MacKinnon's (1981) J-test, and an extended version of the likelihood ratio test proposed by Cox (1961, 1962). More details on these tests and the computation procedures appear in the Appendix I (Section 2). Both test results indicate that Model II better explains the variations in TFP growth. In other words, we do not find empirical evidence to support the notion of Model I that larger countries tend to grow faster.

Examining the results of Model II, we find the empirical findings are generally similar to those for Model I, with the following three factors clearly discernible for

²³For this exercise, we use the versions of the two models that include time-specific effects but no country-specific effects. We also use the version with both time- and country-specific effects, and the test results show that Model II outperforms Model I (see Appendix 1, Section 2).

Table 3: Regression Results for Model II

(t-statistics in parentheses)

Dependent variable: Growth rate of TFP

Independent variable**	3-sector model	2-sector model	BKK model	Difference b/w coeff. of high- & low- income countries	Difference b/w coeff. of 1970s & 1980s
Constant	160 (2.32)*	150 (2.42)*	150 (2.34)*	-64.6 (-0.43)	-170 (-1.46)
High-skill sector index	0.740 (3.08)*	-		6.15 (1.61)	-0.894 (1.55)
Low-skill sector index	0.402 (0.49)	-		-0.691E-02 (-0.20E-02)	-1.61 (-0.82)
Non-Manufacturing sector index	-0.0161 (-1.79)	-0.0164 (-1.88)		-0.721E-02 (-0.21)	0.0136 (0.67)
Manufacturing sector index	-	0.673 (2.44)*			-
BKK index	-	-	-0.00473 (-0.581)		0.209 E -06 (0.86)
Number of observations	80	80	80	80	80
R ²	0.228	0.205	0.172	0.279	0.171
Adjusted R ²	0.194	0.163	0.127	0.175	0.089
Std. Error of regression	0.022	0.022	0.023	0.023	0.024
Likelihood ratio test (for stability)				$\chi^2(4) = 3.78$	$\chi^2(4) = 8.55$
Time-specific effects	yes	yes	yes	yes	yes
Country- specific effects	no	no	no	no	no

* Test statistic is significant at the 5% significance level. The t-statistics are heteroskedastic-consistent.

Notes:

1. The regression equation for Model II as expressed in (12) is as follows:

$$\dot{A}^j/A^j = \alpha + y^j \sum_i^n \beta_i (Y_i^j/Y^j)^2 + e^j.$$

In the three-sector version, $i = \text{hs, ls, nm}$. Accordingly, high-skill sector index is defined as $y(Y_{\text{hs}}/Y)^2$, low-skill sector index is defined as $y(Y_{\text{ls}}/Y)^2$, and so forth. Similarly, in the two-sector version $i = \text{mn, nm}$, and non-manufacturing sector index, for example, is defined as $y(Y_{\text{nm}}/Y)^2$. The BKK index is derived by assuming all $\beta_i = \beta$.

the three-sector model (see column 1 of Table 3): learning effects are markedly different across sectors;²⁴ the magnitude of the learning effects is positively related to the skill intensity of the sector; and only the high-skill-intensive sector is capable of generating statistically significant learning effects. When the economy is divided into two sectors (manufacturing and non-manufacturing), again it is evident that the size of learning coefficients are positively related to the skill intensity of a sector and the learning effects differ across sectors (see column 2 of Table 3).²⁵ In addition, only the manufacturing sector is capable of generating significant spillovers.

As explained in Section 4.1, we use two methods to test the validity of the BKK assumption of uniform spillovers. In the fourth column of Table 3, we report the outcome of the BKK model, by constructing a specialization index weighted by per capita income (i.e., modified BKK index that excludes the country-size effect).²⁶ This index does not produce statistically significant results. We also undertake an F-test to investigate the superiority of the BKK model against the three-sector model. The test statistic (which is

²⁴The relevant t-tests are as follows (The test statistic is given in parentheses, with “*” indicating that the null hypothesis is rejected at 5% significance level):

(i) $\beta_{hs} = \beta_{ls}$: (t-statistic = 4.52*)
 (iii) $\beta_{oth} = \beta_{ls} = 0$: ($F_{(2, 73)} = 1.63$)

²⁵We test the null hypothesis: $\beta_{nm} = \beta_m$. The t-statistic at 3.34 rejects the null hypothesis at 5% significance level.

²⁶Model I is the most appropriate in comparing the BKK claim, since BKK's explanatory variable includes the country size.

Chart 2: Simulation results for Ecuador using Model II. They show the impact of moving resources from non-manufacturing and low-skill-intensive to high-skill-intensive sector.

distributed with 2 and 73 degrees of freedom in the numerator and denominator, respectively) at 4.52 rejects the notion of uniform spillovers at the 5% significance level.

The next step is to investigate how the changes in the sectoral composition of output affect TFP growth (see Chart 2). In the case of Ecuador, for example, if the share of high-skill-intensive sector is doubled from its present level of 7% to 14% by transferring resources from the low-skill-intensive sector, it will add another 0.33% to its TFP growth (in this case, TFP growth will increase from the estimated 1.48% to 1.81%). On the other hand, if the resources are moved from the non-manufacturing sector to the high-skill-intensive sector, the gain will be higher with 0.58% added to the TFP growth rate

(reflecting the rate of growth of TFP increasing from the estimated 1.48% to 2.06%). As Chart 2 illustrates, a change in the output composition towards higher skill-intensive sectors will clearly benefit productivity growth.

Chart 2 also illustrates the non-linear relationship between sectoral shares and TFP growth that we discussed in Chapter 3. It means that those countries with larger share of output in the high-skill sector would stand to benefit more from further sectoral shifts towards this sector. For example, if the high-skill sector's share doubles further from 14% to 28% in Ecuador by moving resources out of the low-skill-intensive sector, it will add another 1.7% to Ecuador's TFP growth (from 1.81% to 3.51%).²⁷

It is also interesting to observe that while a change in the composition of output towards high-skill-intensive sectors clearly increases the growth potential, the magnitude of this increase depends on the initial per capita income (see the testable version of Model II given in the expression (12) in Chapter 3). Let's take the case for India, for example, to demonstrate this fact. Even though the sectoral composition is very much similar to that of Ecuador, with high-skill- and low-skill-intensive sectors accounting for 8% and 10% of output at the end of sample period, respectively, the level of per capita income is much lower in India at US\$350 than Ecuador's at US\$1400. As Chart 3 illustrates, if India manages to double the share of its high-skill-intensive sector from its present level (i.e., at the last sample period) of 8% to 16%, by moving resources out of the non-manufacturing sector, it will add 0.19% to its TFP growth rate (so that the estimated

²⁷Note that these results are comparable with those of Model I. It seems that the composition effect has more influence on TFP growth compared to the country-size effect. The latter does not appear to have a significant influence on learning spillovers.

TFP growth rate will increase from 1.45% to 1.64%). If, on the other hand, resources are moved out of the low-skill-intensive manufacturing sector, then the additional gain is lower at 0.12% (with TFP growth increasing from 1.45% to 1.57%). Observe that similar changes in the composition of output in two countries give rise to different results. It is clear that Ecuador, with a higher per capita income, gains more in terms of TFP growth.

Thus far, we have established the importance of the composition of output in determining productivity growth. Next, we investigate two additional issues: Do learning coefficients differ across countries depending on the stage of development? Are the learning coefficients stable over time?

With regard to the first issue, we ask, in the case of a low-income country, whether spillover benefits from high-skill-intensive sectors are different from those of a relatively higher income country. We apply Model II to two groups of countries by separating the current sample into high- and low-income countries. Those countries that fall below the median average real per capita income level for the period under study are considered the low-income group, while those above the median are considered high-income countries. The cut-off level of income is approximately US\$1,400. Then we perform a likelihood ratio test to see whether the results are significantly different between the two groups. The fourth column of Table 3 reports the differences between coefficients for the two groups, with t-statistics in parentheses. Differences found between the two sets of coefficients are small and statistically insignificant at the 5% level. The likelihood ratio test statistic at 3.78 (distributed as a chi-square with 4 degrees of freedom) accepts the null hypothesis that coefficients are equal across the two income groups (at the 5% significance level). In

terms of learning spillovers, then, despite the stage of development, those countries that specialize in higher skill industries can be expected to benefit in terms of higher productivity growth.

Chart 3: Simulation results for India using Model II. They show the impact of moving resources from non-manufacturing and low-skill-intensive to high-skill-intensive sectors. The Y-axis is to the same scale as Chart 2.

Finally, we investigate the second issue: that is whether different sectors are associated with permanently different learning potential over time. More specifically, this will require us to test the hypothesis that learning coefficients are stable over time against the alternative hypothesis that they tend to vary. We develop a likelihood ratio test to investigate the possibility of decade-to-decade stability of the sectoral learning

coefficients. The last column of Table 3 reports the differences of the sectoral coefficients in the 1980s when compared to those of the 1970s. Very small differences are found between the coefficients, and, more important, all of them are statistically insignificant at the 5% level. The likelihood ratio test statistic, which is distributed as chi-square with 4 degrees of freedom, is equal to 8.55 and accepts the hypothesis (at a 5% significance level) that learning coefficients are stable across the two decades. This indicates that the high-skill-intensive sector has a tendency to maintain its ability to generate higher spillovers over time.

4.3 National Spillovers -- Summary

This study formalizes and tests the implications of endogenous growth theory by empirically investigating the relationship between productivity growth and learning-by-doing spillovers. Consistent with the theoretical discussion in Chapter 3, learning spillovers tend to differ between sectors, such that, the higher the skill intensity of a sector, the greater its ability to generate learning spillovers. Significant spillovers are, however, found only in the high-skill-intensive manufacturing sector. These empirical results clearly show that the composition of output matters in determining long-run productivity growth.

With regard to the robustness of our results, note that apart from the regression results reported in Tables 2 and 3, we have experimented with several alternative versions of the models by using different empirical methodologies (see footnote 17). The outcome of these procedures appear in Appendix 1. They include the applications of random-effect specification, instrumental variable estimation, and the Kmenta (1986) procedure. In

addition, we also applied the full time-series data set to Models I and II. The results consistently support the findings of this research on the nature of learning spillovers, thus providing further proof regarding the robustness of our results.

We undertook several simulation exercises to quantify the productivity gains from the changes in the composition of output. The simulation results also indicate that while a change in the composition of output towards high-skill-intensive sectors clearly increases the growth potential, the magnitude of this increase depends on initial conditions. First, those countries that already have larger sectoral shares in high-skill-intensive activities appear to benefit more from moving resources towards this sector. Second, those countries with higher initial per capita income tend to gain more from the movements of resources to higher skill-intensive activities.

The empirical results indicate, however, that the learning effects remain similar, despite a country's stage of development. Furthermore, they do not change over time. These two factors suggest that no matter what the stage of development, policies that encourage high-skill-intensive activities will always be beneficial in terms of increased productivity growth in the long run. However, it should be noted that such a policy may have costs in terms of market distortions that we do not study here. Finally, we do not find empirical evidence to support the notion that larger countries tend to grow faster. In fact, the learning-by-doing spillover model that excludes the country-size effect tends to perform better empirically than the model that includes this effect.

Thus far, this study has considered only the impact of spillovers generated within national borders. In the next chapters, we extend the learning-by-doing model we have developed in Chapter 2 to incorporate international spillovers.

Chapter 5

International Spillovers from Learning-By-Doing: The Model

In the first part of this thesis, we explored the relationship between productivity growth and national spillover effects from learning-by-doing. Empirical evidence presented in Chapter 4 indicates that national learning-by-doing spillovers are clearly important, and sectors with high-skill intensity tend to display a superior ability in generating learning spillovers compared with the relatively low-skill-intensive activities. If spillovers exist within national borders, it is difficult to believe that all such knowledge is solely confined within a country. As Baldwin and Krugman (1988, 176) argue, “the ability of firms to learn from each other is not noticeably restricted by national boundaries.” The implication is that knowledge is as obtainable across firms within a country as across countries, so that learning may become international in scope. Therefore, this part of the thesis extends our work on national spillovers to analyse the role of international learning spillovers in determining productivity growth of a country.

There is little empirical work on the international spillovers of knowledge. The key early contributions to this literature are by Coe and Helpman (1993) (CH) and Coe, Helpman and Hoffmaister (1995) (CHH). Both studies consider the impact of international spillovers from R&D on the domestic total factor productivity. In CH, the foreign-knowledge stock is represented by the cumulative R&D expenditures of a country’s trading partners. The empirical results show that foreign R&D, as well as domestic R&D, have a positive influence on domestic productivity levels. They also find that in the case of smaller countries, foreign R&D is more important than domestic R&D stock in

determining productivity gains. In larger countries, on the other hand, the domestic R&D stock is found to be more important.

While the empirical analysis in CH is based on a sample of industrial countries, in CHH the same methodology is applied to a sample that consists of 77 developing countries. The authors find that there are significant R&D spillovers from industrial countries to developing countries.

More recent research on international spillovers reconfirms the findings of CH and CHH. The R&D is commonly considered to be the source of spillovers in these studies (Bayoumi, Coe, and Helpman 1999; Gustavsson, Hansen and Lundberg 1999).²⁸ They largely follow the methodology in CH, but use different data sets in empirical analyses.

However, the role of learning-by-doing as a source of international knowledge spillovers has not been studied, except for a few industry-specific studies (Irwin and Klenow 1994; Gruber 1998). Irwin and Klenow (1994), for example, study the semiconductor industry. Their study is based on quarterly firm-level data, over the period 1974-92 for eight generations of dynamic random access memory (DRAM) semiconductors. They find that in six out of eight cases, learning spilled over just as much between firms in different countries as between firms within the same country.

These micro-level studies, however, do not investigate whether international spillovers from learning are capable of driving sustained growth of an entire economy. Our research is an attempt to fill this void. The main objective of this part of our study is to extend the sectoral spillover model developed in Chapter 2 to incorporate international

²⁸See Bernstein (1994, 1998), and Brecher, Choudhri and Schembri (1996), for empirical studies on R&D spillovers between Canada and the United States.

spillovers from learning-by-doing. We examine whether international learning spillovers are an important source of productivity growth. We then analyse whether significant differences exist between sectors in their capacity to generate international spillovers. The extended version of the sectoral spillover model (called the Sectoral Model below) is also used to analyse the relative contribution of national and international spillovers to productivity growth. In addition, we address several related issues: Do small countries benefit more from international spillovers compared to large countries? Do countries with higher degrees of openness benefit more from international spillovers? Does the composition of trade matter in determining the productivity growth?

Before exploring sector-level international spillovers, however, we need to explore the channels through which knowledge transmits across borders. This is a new issue that we are confronted with in dealing with international spillovers. Unlike in the case of domestic knowledge stock, knowledge accumulated in a foreign country may not be as readily accessible because it may depend on contacts the home country has with the foreign country. Case studies of Japan (Lockwood 1954) and South Korea (Rhee, Ross-Larson, and Purcell 1984), for example, describe the importance of international trade as a medium of knowledge transfer.²⁹ Grossman and Helpman (1991) present theoretical arguments that relate productivity to trade volumes. They argue that if the residents of a country interact with foreign counterparts, they may get opportunities to learn technical

²⁹ In addition, other activities, in particular Foreign Direct Investment (FDI), are also known to have a role in transferring knowledge. This is an issue Hejazi and Safarian (1996) consider in their work. Their research attempts to capture the spillover benefits gained by the OECD countries from the R&D activities in the United States through trade and FDI channels. Bende-Nabende (1999) undertakes an econometric investigation for the ASEAN countries of the impact of FDI and its spillover effects on economic growth.

information that may contribute to their country's general knowledge. These opportunities may not arise if the country opts for economic isolation. The interactions that contribute to the domestic knowledge stock may increase with the number of commercial transactions between domestic and foreign agents. One way to enter into such commercial transactions is through international trade. The authors identify four specific ways in which international trade brings knowledge diffusion (Grossman and Helpman (1991), Section 6.5). First, international trade enables a country to employ a large variety of intermediate products and capital equipment embodying foreign knowledge, which will, in turn, enhance the productivity of domestic resources. Second, international trade provides the channels of communication that stimulate the learning of production techniques, product design, organizational and managerial methods, and market conditions. Third, these types of international contacts allow a country to imitate foreign technologies and products, and adapt these to suit domestic conditions. Imitation has played a major role in the economic development of Japan, and the Southeast Asian newly industrialized countries (see Rhee, Ross-Larson, and Purcell 1984; and CHH). Finally, international trade can increase a country's productivity in the development of new technologies (or the imitation of existing technologies), thereby indirectly raising the productivity of the entire economy.

Knowledge diffusion through international trade could be expected to come as a result of engaging either in import activities, export activities, or both. In the empirical literature, however, it is common to find that import activities are being considered the main channel of knowledge transfer. Yet, export activities are also known to transfer knowledge across borders, particularly through the last three mechanisms explained

above.³⁰ Rhee, Ross-Larson, and Purcell (1984), who surveyed a large number of Korean exporters, find foreign buyers and foreign suppliers as important sources for technical knowledge. Chuang (1998), who studied how international trade promotes access to knowledge gathered in foreign countries, finds that both exports and imports are equally important as sources of learning.

As part of our contribution to the literature on international spillovers, we intend to explore various channels through which international knowledge is transferred to determine which best explains these transfers.³¹ For this purpose, we consider a simplified version of the Sectoral Model that assumes away the sectoral differences in international spillovers. This model, which we call the Aggregate Model, is also used to investigate whether international spillovers from learning-by-doing exist in the first place, and the role of R&D spillovers *vis-à-vis* the learning spillovers.³²

³⁰ A large body of empirical work that links export performance and long-run economic growth finds that there is a positive link between economic growth and export expansion (Feder 1983; Balassa 1978; Krueger 1980; Bhagwati and Srinivasan 1978). Since exports are part of the aggregate output, one could argue that this positive link may be merely capturing this relation. However, these studies find that, in addition, export activities also generate positive externalities. Introducing a slight variation to this general theme, we investigate whether the positive relation observed between exports and growth is partly due to the role of exports in transmitting foreign knowledge. If so, then higher exports will lead to higher growth.

³¹ The role of investment, the other main channel through which international knowledge is transmitted, has been studied extensively in the literature of foreign direct investment (FDI). While it is important, we will not pursue it, since we do not have data to carry out an empirical verification.

³² As an interesting side issue, a slight variation of the Aggregate Model is used to investigate whether the capacity of foreign countries to generate spillovers differs.

In the rest of this chapter, we develop the Aggregate and Sectoral Models. Chapter 6 discusses the empirical version of the models and data issues. Chapter 7 presents the empirical results and a conclusion to the research on international spillovers.

5.1 Aggregate Model

We extend the national spillover model introduced in Chapter 2 to explore the role of international spillovers through learning-by-doing. In the Aggregate version of the model considered in this section, however, we assume away the sectoral differences in spillovers. The latter issue is taken up in Section 5.2.

Recall in Chapter 2, we consider the cumulative output of the home country to be the source of national learning spillovers. By extension then, it is the cumulative output of the foreign country that becomes the source of international spillovers. However, as explained at the beginning of this chapter, the extent to which the home country may benefit from the foreign knowledge stock depends on the trading relations between the two countries. In other words, more trade leads to more opportunities for the home country to acquire knowledge transfers from the foreign country. The model developed below is based on these assumptions.

We define aggregate output as $Y = A F$, where A captures learning-by-doing spillovers, and $F [= F(K, L)]$ represents a composite index of the contribution of capital and labour inputs to output.³³ It is assumed that the spillover term, A , at time t depends on the foreign knowledge stock, X^* :

³³As in Chapter 2, time subscripts are dropped for simplicity.

$$A = \exp\left(\int_{-\infty}^t \beta^* X^*(\tau) d\tau\right), \quad (1)$$

where X^* is a trade weighted sum of trading partners' output

$$X^* = \sum_g w_g Y_g^*, \quad (2)$$

where Y_g^* is the aggregate output in foreign country g , and w_g is a trade weight for country g . The definition of X^* is quite similar to that of CH, except that we use foreign output instead of the R&D stock (see below in Section 5.1.1 for a discussion of R&D spillovers). We use three kinds of alternative trade weights based on the bilateral shares of imports, exports, and total trade to capture the channels-of-knowledge transmission. For instance, when imports are used as the weight, we have

$$w_g = \frac{M_g}{M}, \quad (3)$$

where M is home country's total imports and M_g represents imports from country g . This relation implies that the higher the share of imports from country g , the higher will be the spillover benefits from this trading partner.

Note that the above definition of X^* uses weights that sum to one. As such, this index may not adequately capture the benefits of a country's openness to trade that we discussed above. In other words, if two countries have the same composition of trade (i.e., similar bilateral trade shares), then the country that engages in more trade relative to its GDP, and as a result has a more open economy, may be expected to benefit more from foreign knowledge. CH discuss the importance of having a measure of openness interacting with

the R&D variable in their model (see also Chuang 1998; Gustavsson, Hanson, and Lundberg 1999; and Bayoumi, Coe, and Helpman 1999). Accordingly, an alternative version of X^* can be developed by introducing a measure of openness, so that,

$$X^* = \sum_g \mu w_g Y_g^* . \quad (4)$$

The term μ measures the openness of the home country.³⁴ We consider both measures of X^* in our empirical analysis in Chapter 7. Once X^* is defined, given that $\dot{Y}/Y = \dot{A}/A + \dot{F}/F$, the rate of growth of aggregate output becomes

$$\frac{\dot{Y}}{Y} = \beta^* X^* + \frac{\dot{F}}{F} . \quad (5)$$

As in Chapter 2, we are interested in an expression for TFP growth, $\dot{A}/A$. Noting that $\dot{A}/A = \dot{Y}/Y - \dot{F}/F$, we rearrange (5) to isolate TFP growth:

$$\frac{\dot{A}}{A} = \beta^* X^* . \quad (6)$$

In the empirical analysis that follows, the above specification (6), due to its simplicity (i.e., in the absence of sectoral shares), is used to investigate which mechanism best explains the transmission of foreign knowledge. As a side issue, a slight variation of this model is used to explore whether the capacity of foreign countries to generate spillovers differs. Note that the current specification of $\beta^* X^*$ indicates that this capacity is equal across countries. If we assume away the uniformity then (6) becomes

³⁴In Chapter 6, we discuss possible measures of openness.

$$\frac{\dot{A}}{A} = \sum_g \beta_g^* X_g^* . \quad (7)$$

5.1.2 Learning-By-Doing and R&D Spillovers

The international spillover model discussed above considers learning-by-doing spillovers as the factor that drives the productivity growth of the economy. As CH, CHH, and others demonstrate, R&D could be another source of spillovers driving productivity growth. Our sample, however, consists of developing countries that do not undertake significant R&D spending on their own. In 1990 close to 92% of world's R&D expenditures took place in the Group of Seven countries (UNESCO 1993).³⁵ The implication is that national R&D spillovers (i.e., spillovers from domestic R&D efforts) may not be a major factor in determining TFP growth in developing countries. When it comes to international spillovers, however, R&D activities in foreign countries may have an impact on productivity growth, as demonstrated by CH and CHH studies.

Therefore, it may be interesting to incorporate possible spillovers via this source of knowledge into our international learning spillover model. To do this, we modify the Aggregate Model as follows: we assume there are two sources of international knowledge spillovers, learning-by-doing and R&D. Recall that we consider the cumulative output of the foreign country to be the source of learning spillovers. In the CH and CHH studies, the

³⁵We refer to 1990 data because our sample is from 1970-1990. Prior to the 90s the R&D expenditures of the Group of Seven (G-7) countries were even higher. The G-7 includes Canada, France, Germany, Italy, Japan, the United Kingdom and the United States.

cumulative R&D expenditures of the foreign country is assumed to represent the foreign-knowledge stock that gives rise to international spillovers. We follow this definition of R&D spillovers in extending the Aggregate Model. All other assumption made in Section 5.1 remain the same: for example, we assume away the sectoral differences in spillovers. As before, the variable A measures the spillover effects:

$$A = \exp\left(\int_{-\infty}^t \beta^* X^*(\tau) d\tau + \int_{-\infty}^t \psi^* R^*(\tau) d\tau\right), \quad (8)$$

where X^* and R^* represent the foreign knowledge stocks pertaining to learning-by-doing and R&D spillovers, respectively. We have already discussed the definition of X^* in Section 5.1. The definition of R^* in (8) is very similar to that of X^* : R^* is the sum of trade weighted R&D expenditures of foreign countries:

$$R^* = \sum_g w_g RD_g^*, \quad (9)$$

where, RD_g^* is the R&D expenditures in foreign country g . We also consider an alternative R^* definition when the trade weighted RD^* in (9) is interacted with an openness measure, μ (Note that CH and CHH consider similar definitions). Given that $\dot{A}/A = \dot{Y}/Y - \dot{F}/F$, we solve for the reduced form equation that measures the rate of growth of TFP:

$$\frac{\dot{A}}{A} = \beta^* X^* + \psi^* R^* \quad (10)$$

5.2 Sectoral Model

The Sectoral Model is a direct extension of the national learning-by-doing model introduced in Chapter 2. We use it to explore the possible sectoral differences in international spillovers, as well as to investigate the relative contribution of national and international spillovers to productivity growth.³⁶

As in Chapter 2, it is assumed that there are n sectors, and the output in sector i is given by $Y_i = A_i F_i$, with $i = 1, 2, \dots, n$. The term A_i captures the spillovers for sector i , whereas $F_i [= F_i(K_i, L_i)]$ represents a composite index of capital and labour inputs.³⁷ It is assumed that learning effects are sector-specific. Therefore, the term A_i at time t depends on the foreign knowledge stock in sector i ,

$$A_i = \exp\left(\int_{-\infty}^t \beta_i^* X_i^*(\tau) d\tau\right), \quad (11)$$

with X_i^* defined for each sector as

$$X_i^* = \sum_g w_{ig} Y_{ig}^*. \quad (12)$$

The Y_{ig}^* is the output in sector i in foreign country g , and w_{ig} represents the bilateral trade share for country g in sector i . This means that if imports are used as the weight,

³⁶Note that the national spillover effect is suppressed for the time being, and will be introduced at the end of Section 5.2.

³⁷ As in Chapter 2, the time subscripts are dropped for simplicity in presentaion.

$$w_{ig} = \frac{M_{ig}}{M_i}, \quad (13)$$

where M_i is the home country's imports of industry or sector i and M_{ig} is imports of industry or sector i 's goods from country g . As in Section 5.1, we consider an alternative version of X_i^* by interacting it with a sectoral openness index.

Considering that $\dot{Y}_i/Y_i = \beta_i^* X_i^* + \dot{F}/F_i$, and the rate of growth of aggregate output is the weighted average of growth rates of individual sectors, we have

$$\dot{Y}/Y = \sum_i^n \beta_i^* (Y_i/Y) X_i^* + \sum_i^n Y_i/Y (\dot{F}_i/F_i) \quad (14)$$

As in Chapter 2, we express (14) in terms of TFP growth as follows:

$$\dot{A}/A = \sum_i^n \beta_i^* (Y_i/Y) X_i^* \quad (15)$$

The expression in (15) indicates that given the foreign knowledge stock, X_i^* , if a particular sector generates higher international spillover effects (i.e., β_i^* s), the home country can achieve higher productivity growth by allocating more resources to this sector.

The model so far has not considered the national learning spillovers developed in Chapter 2. Once they are incorporated, (15) can be written as

$$\dot{A}/A = \sum_i^n \beta_i^* (Y_i/Y) X_i^* + Y \sum_i^n \beta_i (Y_i/Y)^2 \quad (16)$$

Note that the second term on the right-hand side of (16) represents the national spillover expression developed in Chapter 2. The Sectoral Model in (16) also enables us to

disentangle the role of national and international learning spillovers in determining the productivity growth.

As seen from the empirical evidence in Chapter 4, with regard to national learning spillovers, the degree of skill intensity of a sector determines the magnitude of spillover effects. Accordingly, we may also expect that international learning effects, β_i^* s, will be higher in relatively high-skill-intensive sectors. As in the first part of this research, we divide the economy into three sectors in the empirical analysis: high-skill-intensive manufacturing, low-skill-intensive manufacturing, and non-manufacturing sectors. We anticipate manufacturing sectors that are relatively more skill-intensive to display higher spillover effects than non-manufacturing activities.³⁸ Within manufacturing activities, the high-skill-intensive sector is expected to account for higher learning spillovers compared to the high-skill-intensive sector. The next step is to set out the empirical models, select data, and construct the foreign knowledge stock variables introduced in this chapter.

³⁸ Chapter 2 discusses why manufacturing activities are deemed to be relatively more skill-intensive than non-manufacturing activities.

Chapter 6

Empirical Models and Data

In this chapter we present the empirical versions of the Aggregate and Sectoral Models developed in Chapter 5. There is a brief discussion of the data sources and the construction of the variables for estimation purposes (details are provided in Appendix 2). Finally we highlight some interesting features of the data.

6.1 Empirical Models

The empirical versions of the Aggregate and Sectoral Models are presented below. As discussed in Chapter 3, these models are able to explain only part of the productivity growth. Hence, we add an intercept term to the regression equations to capture the impact of exogenous factors on TFP growth. The testable version of the Aggregate Model in (6) for the rate of growth of TFP for country j , after incorporating an intercept term, α , and the error term ϵ^j , can be expressed as³⁹

$$\frac{\dot{A}^j}{A^j} = \alpha + \beta \cdot X^{*j} + \epsilon^j . \quad (17)$$

The empirical version of (7) that considers the possibility of different spillover coefficients for different foreign countries becomes

³⁹In the next chapter we test whether country-specific and time-specific constant (i.e., intercept) terms are indeed warranted. Other hypotheses regarding the constant term are also tested.

$$\frac{\dot{A}^j}{A^j} = \alpha + \sum_g \beta_g^* X_g^{*j} + \epsilon^j . \quad (18)$$

The empirical version of the model in (10) that combines learning and R&D spillovers can be expressed as follows:

$$\frac{\dot{A}^j}{A^j} = \alpha + \beta^* X^{*j} + \psi^* R^{*j} + \epsilon^j . \quad (19)$$

This model is used to compare the results of learning spillovers against R&D spillovers, and to investigate whether our results on learning spillovers are robust when another possible source of international externalities is introduced.

The empirical version of the Sectoral Model presented in (15) takes the following form:

$$\dot{A}^j/A^j = \alpha + \sum_i^n \beta_i^* (Y_i^j/Y^j) X_i^{*j} + \epsilon^j . \quad (20)$$

Finally, the testable version of (16) that incorporates both national and international spillovers can be defined as

$$\dot{A}^j/A^j = \alpha + Y^j \sum_i^n \beta_i (Y_i^j/Y^j)^2 + \sum_i^n \beta_i^* (Y_i^j/Y^j) X_i^{*j} + \epsilon^j . \quad (21)$$

We consider an economy with three sectors: high-skill-intensive manufacturing (hs), low-skill-intensive manufacturing (ls), and non-manufacturing (nm) sectors. Alternatively, a two-sector economy is also considered, consisting of manufacturing and non-

manufacturing activities. All learning coefficients are expected, both at national and international levels, to take values equal to or greater than zero, since it is reasonable to expect that learning would not create negative externalities. Furthermore, we expect the value of learning coefficients to be positively related to the skill intensity of a sector.

6.2 Data

Here we briefly discuss how the aggregate and sectoral-level foreign-knowledge stocks (X^* and X_i^* , respectively) are constructed. Foreign-knowledge stock is a product of foreign output and bilateral trade shares. Recall that we also introduce an alternative version of the foreign-knowledge stock where it is interacted with an openness index. The details on other variables, such as TFP growth and sectoral shares of output that were used in the first part of the thesis, can be found in Chapter 4 and in Appendix 2.

With regard to the foreign output (Y_g^* and Y_{ig}^*), we consider only the output of the Group of Seven (G-7) countries because of data limitations. The data are taken from the OECD STAN database, using data at three-digit level International Standard Industry Classification (ISIC). The series is then converted into US\$, using the exchange rates reported in the IMF's International Financial Statistics. The output data are reported in 1985 constant prices. The fact that we focus on the output from the G-7 means that the knowledge generated in non-G-7 countries has not been taken into account. However, this omission may not be significant, since most of the knowledge activities take place in the G-7 countries. For example, with regard to knowledge generated through R&D activities, G-7 countries alone accounted for about 92% of total world R&D expenditure in 1990 (UNESCO 1993). Moreover, since the G-7 accounted for approximately 65% of world

output in 1990 (World Bank 1993), we can safely assume that the majority of knowledge through learning-by-doing is generated in these countries. There is another reason why the omission of spillovers from the non-G-7 countries may not significantly affect our results. Much of the trade of the developing countries in the sample takes place with G-7 countries, and thus the bulk of international spillover benefits to these developing countries would be channelled through their dealings with G-7 countries.

With regard to bilateral trade shares, note that we use three alternative trade weights--imports, exports, and total trade--to test for the channel that best explains foreign knowledge transfers. Since we use only G-7 countries' output to account for the international knowledge, w_g in the Aggregate Model, for example, is constructed using bilateral trade shares of the developing countries in the sample with G-7 countries. A similar approach is used to construct w_{ig} for the Sectoral Model, with bilateral trade share indexes developed at a sector level. Trade data are obtained from Statistics Canada's World Trade Data Base. Data are defined at a two-digit level Standard International Trade Code (SITC) classification system for 68 product categories. The product categories under the SITC classification system are then matched with the industry categories under the ISIC system.⁴⁰

With regard to the openness index, μ , we follow Dinopoulos and Thompson (2000) by defining it as the ratio of total trade to GDP (i.e., $\{\text{Exports} + \text{Imports}\}/\text{GDP}$).⁴¹ The data are obtained from the Summers and Heston data set (Penn World Table (Mark 5.6) data

⁴⁰Note that the ISIC classification is used to measure the sectoral shares of output, Y/Y . Appendix 2 compares the ISIC and SITC classification systems.

⁴¹CH use a slightly narrower definition of μ , based on the ratio of imports to GDP.

set). Because of the lack of sectoral data on openness, μ is also used in the Sectoral Model. The R&D expenditure data are taken from the OECD's Main Science and Technology Indicators. These data are reported in US\$ and in 1985 constant prices.

Finally, having discussed data sources, we take a look at the behaviour of some of the variables we constructed in this part of the research. In particular, a preliminary analysis of the evolution of trade patterns and knowledge stock over time reveals quite interesting information.

6.2.1 Evolution of trade patterns

As mentioned, the foreign-knowledge stock is constructed using three alternative weights, representing bilateral import, export, and trade shares. For some countries in the sample, Table 4 illustrates the average value of w_g 's for the periods 1971-75 and 1986-90,⁴² when imports are used as the weight. Meanwhile, Table 5 illustrates w_g 's based on export data for the same periods (Appendix 2 shows data for all countries). A comparison of the two tables indicates a possible similarity between export and import patterns. If a country tends to export more to a particular G-7 trading partner, it is generally the case that imports from the same G-7 partner are also relatively higher. This suggests that the empirical analysis on the most appropriate channel of knowledge transfer (i.e., imports, exports or total trade) might produce similar results. Nonetheless, this point is examined further in the empirical section.

⁴²The two data points correspond the first and last periods of our sample.

Table 4: Average Share of Imports from the G-7 Countries, 1971-75 and 1986-1990

Import Country	Period	EXPORT COUNTRY						
		Canada	France	Germany	Italy	Japan	UK	USA
		(as percentages)						
Argentina	1971-75	5.12	7.45	20.98	11.71	7.72	8.88	38.15
	1986-90	2.06	9.98	22.02	11.84	11.84	0.79	41.47
Brazil	1971-75	5.02	7.81	19.7	7.78	13.61	8.97	37.11
	1986-90	5.55	7.65	16.44	5.28	12.17	6.05	46.86
Ecuador	1971-75	2.07	2.79	13.45	4.22	18.43	6.2	52.83
	1986-90	3.79	3.52	11.4	6.15	17.08	5.54	52.52
Guatemala	1971-75	2.71	2.51	14.27	2.47	15.88	5.82	56.35
	1986-90	2.62	2.55	8.86	4.12	9.82	3.01	69.01
India	1971-75	10.75	5.14	17.65	4.05	15.47	18.88	28.06
	1986-90	3.15	8.98	17.25	4.34	20.74	21.59	23.95
Indonesia	1971-75	1.79	2.92	13.65	2.29	46.5	5.88	26.96
	1986-90	3.46	5.6	12.2	3.25	48.65	5.56	21.29
Korea	1971-75	3.41	3.67	6.06	1.21	51.86	3.95	29.84
	1986-90	3.51	2.93	6.43	1.9	47.44	2.52	35.27
Malaysia	1971-75	1.85	3.59	10.47	2.66	37.37	23.45	20.6
	1986-90	2.01	2.93	7.88	2.66	42.85	8.02	33.66
Mexico	1971-75	5.82	5.49	12.98	3.09	7.61	4.71	60.31
	1986-90	2.3	2.15	5.32	1.35	5.68	1.86	81.34
Philippines	1971-75	3.21	2.03	6.96	1.31	40.43	6.23	39.83
	1986-90	2.69	3.19	9.69	1.42	39.3	4.98	38.72
Turkey	1971-75	2.32	10.93	29.81	16.74	5.7	14.97	19.54
	1986-90	2.01	9.96	32.47	14.15	8.34	11.37	21.7

Source: Appendix 2

Another interesting observation arising from Tables 4 and 5 concerns the evolution of trading alliances and increased regionalism over time. The data show that, for most countries, trading relations with the United Kingdom, both for exports and imports, have declined. Regarding imports, the largest drop is reported for Malaysia, from 23% to 8%,

between 1970 and 1990. The United States, on the other hand, has seen its share of trade with the majority of these countries increase in terms of both imports and exports.

Table 5: Average share of exports to the G-7 countries, 1971-75 and 1986-1990

Export Country	Period	IMPORT COUNTRY						
		Canada	France	Germany	Italy	Japan	UK	USA
		(as percentages)						
Argentina	1971-75	1.39	14	19.01	12.19	13.61	11.89	27.92
	1986-90	2.41	8.12	23.77	12.71	11.86	3.63	37.5
Brazil	1971-75	4.4	12.07	20.97	10.59	12.18	11.97	27.84
	1986-90	4.02	8.02	13.46	8.47	13.27	6.18	46.57
Ecuador	1971-75	3.74	2.38	13.92	4.73	14.77	0.46	60
	1986-90	1.16	1.42	6.09	2.43	3.94	0.69	84.26
Guatemala	1971-75	2.18	1.16	18.63	5.64	12.1	4.71	55.58
	1986-90	2.79	1.77	11.06	6	5.21	1.83	71.33
India	1971-75	4.78	7.29	9.4	5.43	19.14	30.56	23.39
	1986-90	2.06	5.44	14.11	5.92	21.34	13.09	38.03
Indonesia	1971-75	0.57	4.83	18.6	4.63	32.49	4.72	34.18
	1986-90	0.81	3.02	4.9	1.75	60.88	3.04	25.59
Korea	1971-75	7.3	1.68	6.75	1.87	42.22	4.97	35.21
	1986-90	4.58	2.99	6.22	1.79	28.1	4.54	51.79
Malaysia	1971-75	4.99	8.89	13.33	8.84	22.07	17.82	24.05
	1986-90	2	3.98	8.54	2.38	36.63	8.66	37.81
Mexico	1971-75	4.52	2.27	5.47	2.97	11.25	1.53	72
	1986-90	3.48	2.79	2.17	0.68	7.12	1.27	82.49
Philippines	1971-75	1.72	2.74	15.95	1.39	18.05	4.42	55.72
	1986-90	2.16	3.08	8.38	1	27.74	6.38	51.26
Turkey	1971-75	0.41	13.43	37.76	16.09	3.76	11.19	17.37
	1986-90	0.97	11.22	44.46	15.53	2.1	10.96	14.75

Source: Appendix 2

Over time, Latin American countries in particular, have strengthened their ties with the United States which is the largest importer and exporter to almost all of the countries in the region. In East Asia, on the other hand, Japan has a much stronger position as the

largest importer to most countries in the region, including Indonesia, South Korea, Malaysia, and the Philippines.

6.2.3 Evolution of foreign knowledge stock

It is also interesting to examine the behaviour of the foreign-knowledge stock over time. We use the Sectoral Model to provide some examples. Chart 4 illustrates, for countries randomly selected from the sample, the upward trend in the high-skill-intensive foreign-knowledge stock (X^*_{hs}) when the bilateral import share is used as the weight (see Appendix 2 for more country illustrations). (The openness index, μ , is not included.) Note, however, that those countries that pursued outward-oriented development and trade strategies seem to have gained more from foreign knowledge over time. As Chart 4 illustrates, in Malaysia and South Korea, for example, foreign knowledge stock more than tripled from 1974 to 1992. In contrast, countries such as India and Turkey, which followed relatively more inward-oriented development and trade strategies, experienced relatively slower growth in foreign-knowledge stock in the high-skill-intensive manufacturing sector. Note also from Chart 4 that X^*_{hs} in India, Indonesia, Malaysia and Brazil were quite similar in magnitude in the mid-1970s, but increasingly diverged over time, with those who followed relatively inward-oriented trade and development strategies experiencing slower growth in foreign-knowledge stock. In Chart 5, we present the values for X^*_{hs} once it is interacted with the openness index, μ . The divergence between the two groups of countries becomes even more pronounced.

Chart 4: Trends in Available Foreign Knowledge

Chart 4: Evolution in available foreign knowledge stock for selected countries between 1974-92. Source: Appendix 2.

In the next chapter we formally test how the foreign knowledge stock and the resultant international spillovers contribute to productivity growth of the home country. First, we test the Aggregate Model to find out whether there exist significant international spillovers from learning-by-doing. Then the Sectoral Model is used to investigate whether the magnitude of spillovers are positively related to the skill-intensity of a sector. Finally,

we combine the international and national spillover models to test the validity of sectoral differences in spillover capabilities.

Chart 5: Evolution in available foreign knowledge stock with openness factor included for the same period and countries as Chart 4. Source: Appendix 2.

Chapter 7

Empirical Results

As in the first part of the thesis on national spillovers, a panel data set for 20 developing countries for the period of 1970-90 is used to carry out the empirical analysis of international spillovers. First, we estimate the Aggregate Model in (17) to investigate whether international spillovers play a significant role in determining the TFP growth. We also use this model to investigate the alternative mechanisms of knowledge diffusion (i.e., imports, exports, and total trade). A few other variations of the Aggregate Model are introduced to address issues such as differential spillovers across the G-7 countries (18), and R&D spillovers (19).

We use the Sectoral Model in (20) to look for sectoral differences in international spillovers. Finally, we test the extended version of Sectoral Model presented in (21), which incorporates both the international and national spillovers. The Sectoral Model is also used to investigate the possible relationship between international spillovers and the country size, and the relative importance of national and international spillovers as a source of productivity growth.

As in the case of the national spillover model in Chapter 4, we introduce time-specific and country-specific dummy variables to capture the impact of exogenous factors on TFP growth. Since these two effects are found to be statistically significant in both the Aggregate and Sectoral Models, they are included in all of the regression results reported below.

7.1 Aggregate Model

Table 6 presents the results when the bilateral import share is used as the weight in constructing the foreign-knowledge stock variable, X^* . We find the empirical results to be quite similar when the other two alternative weights (bilateral exports and bilateral trade shares) are used. (Appendix 1, Section 6, presents the results when these alternative weights are used.) This result is not surprising, since we found in Chapter 6 that import and export patterns tend to be similar. Therefore, with regard to the most appropriate channel through which spillover effects are transmitted, it appears that all three mechanisms produce similar results. Since it is common to find the bilateral import share used in other studies in constructing the foreign-knowledge stock (including in the CH and CHH studies), we focus on the results with import weights in the rest of this chapter.

In column 1 of Table 6, we use the foreign-knowledge stock variable given in equation (2) to explain the variation in the rate of TFP growth (we call this variable X'^1). In column 2, we use the alternative measure in equation (4), which is constructed by interacting X'^1 with the openness measure, μ (we call this variable X'^2). According to the results reported in the first column, the foreign-knowledge stock, as represented by X'^1 , does not contribute significantly to TFP growth. Neither does this variable display the expected sign. Similar results are reported by CHH, when they use their version of the foreign-knowledge stock that is based on the foreign R&D stock weighted by bilateral import shares. However, when we use X'^2 , the resultant coefficient reported in the second column has the correct sign and is also statistically significant at the 5% significance level.

Table 6: Regression Results for the Aggregate Model

(t-statistic in parentheses)

Dependent variable: Growth rate of TFP

Independent Variable ¹					
X^{*1}	-0.614E-04 (-0.32)		-0.926E-04 (-0.49)		0.204E-03 (-1.02)
X^{*2}		0.721E-06 (3.49)*			0.877E-06 (2.62)*
μ			2.64 (1.48)	2.57 (1.48)	
Number of observations	80	80	80	80	80
R ²	0.502	0.524	0.512	0.506	0.534
Adjusted R ²	0.301	0.328	0.315	0.319	0.323
Std. Error of Regression	0.021	0.02	0.021	0.021	0.02
Time-specific effects	yes	yes	yes	yes	yes
Country-specific effects	yes	yes	yes	yes	yes

*Test statistic is significant at the 5% significance level. The t-statistics are heteroskedastic-consistent.

Notes:

1. The regression equation for Aggregate Model given in (17) is as follows:

$$\frac{\dot{A}^j}{A^j} = \alpha + \beta \cdot X^{*j} + \epsilon^j.$$

Recall we define two alternative versions of the foreign knowledge stock, X^* . The variable X^{*2} is constructed by interacting the knowledge stock with the openness index, μ , while X^{*1} excludes μ . For an explanation of X^{*1} and X^{*2} , see also expressions (2) and (4) in Chapter 5, respectively.

One could argue that X^{*2} may merely be capturing the contribution of openness to productivity growth. Contrary to this notion, note that the openness index, μ , by itself (column 4), or in combination with X^{*1} (column 3), does not produce statistically

significant results. Several other studies that investigate evidence for international spillover effects find similar empirical results (CH; CHH; Coe, Helpman, and Hoffmaister 1995). Hence, in the rest of this chapter, we use the definition of X^2 in analysing international spillovers.

The coefficient for X^2 in column 2 implies that if the foreign-knowledge stock increases, it will increase the rate of productivity growth in the home country. We perform several simulation exercises on India and Turkey to quantify this effect. These countries have had relatively more inward-oriented trade and growth strategies compared to the other countries in the sample, and as a result, they may yield interesting results when exposure to foreign-knowledge is increased. In the case of India, the results show that if India's foreign-knowledge stock increases by US\$10 billion (or 0.5%), it will add about 0.025% to India's TFP growth. In the case of the Turkey, an increase in knowledge stock by US\$10 billion (or 0.62%) will add 0.05% to the TFP growth. The differential effect between the two countries is partially to do with the fact that Turkey has had a relatively more open economy than that of India.

The Aggregate Model can be used to illustrate that, all else being equal, a developing country that is more open to foreign trade derives a larger marginal benefit from increases in the foreign-knowledge stock. The simulation exercises in Table 7 attempt to quantify the benefits of openness. For example, if India and Turkey increase their openness to the average level for the sample for the last period 1986-90 (i.e., 75%), it will add a further 0.81% and 0.37% to the rate of growth of TFP in India and Turkey, respectively.

Table 7: Simulation Results for India and Turkey*
TFP growth and percentage change from baseline

(Openness index (%): (Import + Export)/GDP India: 16.63%, Turkey: 42.96%

		India	Turkey
		TFP Growth (%)	TFP Growth (%)
Base case (0)	<i>Initial prediction of the model</i>	2.54	2.58
Simulation:			
Scenario (1)	Increase openness by 50%	2.66	2.83
Scenario (2)	Increase openness by 100%	2.78	3.08
Scenario (3)	Increase openness to the average level for the sample 75%	3.35	2.95
Scenario (4)	Trade only with the United States	2.73	3.17
Scenario (5)	(4) plus (3)	4.20	3.97
Scenario (6)	Trade only with Japan	2.67	3.02
Scenario (7)	(6) plus (3)	3.94	3.71

*Initial data correspond to the last period for the sample: 1986-1990.

We also experiment by changing a country's trading alliances to determine how much the country stands to gain by switching towards trading partners with larger stocks of knowledge. For example, if both India and Turkey were to import only from the United States--the G-7 country with the highest knowledge stock--it would add 0.19% to India's productivity growth and 0.59% to Turkey's. Growth predictions are higher for Turkey, since it has had a higher degree of openness than did India. Note, however, that the objective of this exercise is to quantify the spillovers benefits, and therefore, drawing any policy conclusions based on these results need to take into account other costs that may be associated with a change in policy.

7.1.2 Differential Spillover Effects

The empirical analysis has thus far been based on the assumption that the capability to generate international spillovers is equal across all foreign countries. As discussed in Chapter 5, it would be interesting to see whether the spillover structure differs among the foreign countries. To do this, we use the extended version of the Aggregate Model presented in (18) in Chapter 6 where we use X_g^* to measure foreign country g 's knowledge stock. However, the analysis reveals a serious multicollinearity problem in the knowledge stock of the G-7 countries, particularly among the European countries. As a result, the investigation of the possibility for differential spillover capabilities will not be pursued further in this research (see Appendix 1, Section 6.4 for regression results and a discussion).

7.1.3 Learning -By-Doing and R&D Spillovers

Finally, we test the extended version of the Aggregate Model that incorporates the spillovers from leaning-by-doing and R&D. The regression results of (19) are reported in Table 8.

The first column of Table 8 reproduces the results of the Aggregate Model in Table 6 (column 2). It shows that the knowledge stock variable, X^{*2} is capable of producing statistically significant contribution to TFP growth. In the second column we present the results of the regression in (19) that combines both learning and R&D spillovers. First of all, observe that the addition of the R&D variable has not changed the statistical significance or the magnitude of the coefficient of X^{*2} . It further proves that our

Table 8: Aggregate Model with Learning and R&D Spillovers
(t-statistic in parentheses).

Dependent variable: Growth rate of TFP

Independent variable ¹					
X ^{*2}	0.721E-06 (3.49)*	0.713E-06 (3.03)*			0.514E-04 (1.073)
R ^{*1}		-0.197E-04 (-0.57)	-0.217E-04 (-0.65)		
R ^{*2}				0.220E-04 (2.00)*	0.187E-04 (0.379)
Number of observations		80	80	80	80
R ²	0.524	0.525	0.506	0.518	0.52
Adjusted R ²	0.328	0.319	0.303	0.305	0.31
Std. Error of Regression	0.021	0.021	0.022	0.022	0.021
Country-specific effects	Yes	Yes	Yes	Yes	Yes
Time-specific effects	Yes	Yes	Yes	Yes	Yes

* Test statistic is significant at 5% significance level. The t-statistics are heteroskedastic-consistent.

Notes:

1. The regression equation that incorporates spillovers from R&D is as follows:

$$\frac{\dot{A}^j}{A^j} = \alpha + \beta \cdot X^{*j} + \psi \cdot R^{*j} + \epsilon^j .$$

The variable X^{*2} represent the foreign knowledge stock that gives rise to learning-by-doing spillovers. The foreign knowledge stock that is the source of R&D spillovers is defined as R^{*}. Note we consider two versions for R^{*}: The R^{*1} is constructed as in equation (9) in Chapter 5, without the openness measure. The R^{*2} includes μ (these variables are consistent with the definitions for X^{*1} and X^{*2}).

explanation of international spillovers is robust in the presence of another source of spillovers. Second, note that the R&D variable, R^{*1}, is neither statistically significant nor carries the correct sign. Also, observe from the third column that R^{*1} tested on its own is not capable of explaining the variation in TFP growth. In fact, CH and CHH find similar

results in their studies. They find that the R&D-based knowledge variable generates statistically significant results only when interacted with an openness measure.

To address this concern, we create R^{**} that takes into consideration the openness factor (a similar definition to that of X^{**}). In the fourth column we report the results when R^{**} variable is considered on its own. Consistent with CH and CHH studies, the variable is statistically significant--albeit marginally. The next step is to combine both X^{**} and R^{**} together. The results are produced in the last column.

Unfortunately, the results are not encouraging for either of the variables. Further investigation into the cause of this result reveals that the two variables are highly correlated (with a simple correlation coefficient of 0.95). The similarity of the way the two measures are calculated is the main reason for this high correlation. Recall both variables are weighted by the same openness index and bilateral trade shares. Also, in general, the R&D spending and the output (which is the basis of learning spillovers) of G-7 countries tend to be positively associated: for example, the United States and Japan that have higher GDP values are the countries that also undertake higher R&D expenditures. The presence of such a strong multicollinearity problem may have caused the unsatisfactory results in column 5. Consequently, it is not possible to derive any reasonable conclusions from the results in column 5.

Nonetheless, if one would want to compare the results of the R&D spillover model against the learning spillover model, a simple method would be to examine the general explanatory power of the two alternative models as reported in columns 3 and 1, respectively. For example, statistical indicators such as R^2 , adjusted R^2 , and the standard

error of regression demonstrate that the learning-by-doing model is superior to the R&D model. However, this is not the best test to compare the models. Further modifications to the models, either by introducing instrumental variables, or by altering the basic features of the model are necessary to pass any judgement. We do not intend to delve in to this matter further. However, we would like to emphasize the fact that the learning model we develop does consistently produce significant results even when other variables are introduced may simply demonstrate that our results are robust.

7.2 Sectoral Model with International Spillover Effects

The results of the Aggregate Model show that international learning spillovers have a significant impact on productivity growth of an economy. The Sectoral Model goes one step further to investigate whether these spillovers are linked to the skill-intensity of a sector. Recall with regard to national spillovers, the empirical results show that there is a strong positive relationship between learning spillovers and skill-intensity. In this section we consider only the international part of learning spillovers. In Section 7.3 we incorporate national spillovers.

Table 9 reports the results of the Sectoral Model. As anticipated, the magnitude of international spillover effects is positively related to the skill intensity of a sector. The results of the three-sector model (columns 1 and 2) illustrate that spillovers from the knowledge stock in the high-skill-intensive manufacturing sector are larger than those of the other two sectors.⁴³ In fact, except for the high-skill-intensive sector, none of the other

⁴³We undertake two F-tests to determine whether spillover effects are different across sectors. The test statistic is given in parentheses, with “*” indicating that the null hypothesis is

sectors exhibits statistically significant results. Also, when the economy is divided into two sectors (columns 3 and 4), the relatively more skill-intensive manufacturing sector displays higher international spillover effects.

Recall from Chapter 5 that the sectoral knowledge indexes are a product of bilateral trade shares, home country's output shares, sectoral foreign output, and an openness measure. Therefore, to interpret the values of sectoral coefficients reported in Table 9 (by isolating the contribution of various variables to TFP growth), we have to carry out some simulation exercises. We consider two types of simulation experiments. First, we investigate the impact on productivity growth as a result of a change in the composition of imports. Second, we analyse the impact of changing trading partners on productivity growth.

The empirical results confirm that, all else being equal, increases in high-skill-intensive imports will contribute to higher TFP growth, the next task is to quantify these gains. Again, we use India to carry out a few simulation exercises to gauge the impact on TFP growth when high-skill-intensive imports from the United States are increased. High-skill-intensive products imported from the United States amount to 16% of India's imports from the G-7 countries.⁴⁴ Simulation results presented in Chart 6 show that if these imports are increased from 16% to 20% by reducing the share of low-skill-intensive imports from the United States, the TFP growth rate would increase from 2.62% (as predicted by the

rejected at the 5% significance level.

- (i) $\beta_{nm}^* = \beta_{ls}^* = 0; F_{(2, 54)} = 0.32$
- (ii) $\beta_{nm}^* = \beta_{ls}^* = \beta_{hs}^*; F_{(3, 53)} = 3.98^*$

⁴⁴At the end of the sample period, 1990.

model) to 2.67%. Moreover, the increase in the TFP growth rate would be slightly higher at 2.68%, if the imports of non-manufacturing goods from the United States are reduced, instead of the imports of low-skill-intensive products.

Table 9: Regression Results for the Sectoral Model—International Spillovers
(t-statistics in parentheses)

Dependent variable: Growth rate of TFP

Independent Variable ¹	3-sector model		2-sector model		Difference b/w coeff. of large and small countries
High-skill sector index - International	0.826E-02 (3.55)*	0.627E-02 (2.96)*			-0.474 E-02 (-0.75)
Low-skill sector index - International	0.662E-02 (0.52)				-2.28 E-02 (-0.44)
Non-manufacturing sector index - International	0.116E-02 (-1.79)		0.171E-02 (0.78)		-0.520 E-02 (-0.67)
Manufacturing sector index - International			0.551E-03 (1.17)	0.633E-03 (2.08)*	
Number of observations	80	80	80	80	80
R ²	0.538	0.529	0.533	0.528	0.58
Adjusted R ²	0.331	0.33	0.325	0.328	
Std. Error of regression	0.02	0.02	0.021	0.02	0.021
Likelihood ratio test					$\chi^2(3)=5.7$
Country-specific effect	yes	yes	yes	yes	yes
Time-specific effect	yes	yes	yes	yes	yes

*Test statistic is significant at 5% significance level. The t-statistics are heteroskedastic-consistent.

Notes:

1. The regression equation for the Sectoral Model is described in (20) as follows:

$$\dot{A}^j/A^j = \alpha + \sum_i^n \beta_i^* (Y_i^j/Y^j) X_i^{*j} + \epsilon^j.$$

Note that in the three-sector version $i = \text{hs, ls, and nm}$. The high-skill sector index (international), for example, is defined as $(Y_{\text{hs}}/Y) X_{\text{hs}}^{*2}$.

In the second exercise, we explore what happens if India switches trading partners. As in the above example, if high-skill-intensive imports are increased from 16% to 20%, but the increase is achieved now by reducing low-skill-intensive imports from the United Kingdom, then India stands to gain more in terms of productivity growth (see Chart 6). It will add 0.09% to TFP growth by increasing it to 2.71% from the initial 2.62%. As emphasised earlier, these simulation exercises are used to provide a sense of the magnitude of learning spillovers. They cannot be taken as specific policy directions, without further analysis of economic costs that may occur in changing policies.

When investigating national spillovers in Chapter 4, we concluded that spillover effects do not depend on the size of the country. We investigate whether this holds true for international spillovers. For this purpose, we divide the sample into two groups, based on the country size. Those countries that fall below the median real GDP for the period under study are considered small countries. The cut-off level of income is US\$52.3 billion.⁴⁵ The results reported in the last column of Table 6 show that the differences between coefficients for large and small countries are quite small and not statistically significant. A likelihood ratio test is carried out to evaluate the hypothesis that the coefficients across the two groups are equal. The test statistic, which follows a Chi-squared distribution with three degrees of freedom, is below the critical value of 7.81 (at the 5% significance level). Therefore, the null hypothesis that the coefficients are equal is accepted. This result indicates that international spillovers do not depend on the size of the country.

⁴⁵To capture the differences between the largest and smallest countries, we introduce a dummy variable that takes the value of one for the small countries, and zero otherwise.

Chart 6: Simulation results for India using Sectoral Model showing the impact of changes in the structure of trade on the TFP growth.

7.3 Sectoral Model with International & National Spillover Effects

In this section, we estimate the regression equation (21) that combines international and national spillovers. The results are presented in Table 10. A comparison of the results of the combined spillover model with those of the national spillover model in Chapter 4 (Table 2) and international spillover model in Chapter 7 (Table 9) indicate that the

Table 10: Regression Results for Sectoral Model--National & International Spillovers
(t-statistics in parentheses)

Dependent variable: Growth rate of TFP

Independent Variable ¹	3-sector model		2-sector model		Difference b/w coeff. of large and small countries
High-skill sector index - international	0.506 E-02 (2.65)*	0.574 E-02 (2.58)*			-0.101 (-1.30)
Low-skill sector index - international.	0.242 E-03 (1.22)				-2.28 E-02 (-0.45)
Non-manufacturing sector index - international.	-0.329 E-02 (-0.24)		0.233 E-02 (1.02)		-0.821 E-02 (-1.02)
Manufacturing sector index - international.			0.540 E-02 (2.01)*	0.658 E-03 (3.46)*	
High-skill sector index- national	0.196 E-03 (2.15)*	0.101 E-02 (2.54)*			0.156 E-02 (1.22)
Low-skill sector index- national	0.555 E-04 (0.98)				-0.081 E-02 (-0.65)
Non-manufacturing sector index- national	-0.143E-06 (-0.22)		-0.317E-06 (-0.42)		0.248E-05 (0.28)
Manufacturing sector index- national			0.194E-04 (1.83)**	0.153E-04 (2.15)*	
Number of observations	80	80	80	80	80
R ²	0.562	0.555	0.557	0.55	0.628
Adjusted R ²	0.335	0.357	0.33	0.35	
Std. Error of regression	0.02	0.02	0.021	0.02	0.021
Likelihood ratio test					$\chi^2(6) = 10.59$
Country-specific effects	yes	yes	yes	yes	yes
Time-specific effects	yes	yes	yes	yes	yes

* Test statistic is significant at 5% significance level. The t-statistics are heteroskedastic-consistent.

** Test statistic is significant at 10% significance level.

Notes:

1. The results of the combined national and international model are presented above. The combined model is given in the expression (21):

$$\dot{A}^j/A^j = \alpha + Y^j \sum_i \beta_i (Y_i^j/Y^j)^2 + \sum_i \beta_i^* (Y_i^j/Y^j) X_i^{*j} + e^j.$$

For example, in the three-sector version, the high-skill sector index (international) is defined as $(Y_h/Y)X_h^{*2}$, and the high-skill sector index (national) is defined $Y(Y_h/Y)^2$.

combined model performs better than the others in terms of statistical indicators such as R^2 , adjusted R^2 , and the standard error of regression.

Regarding the magnitude of spillovers, the results confirm that it depends on the skill intensity of a sector. Moreover, in the three-sector model, results consistently show that it is only the high-skill-intensive manufacturing sector that is capable of generating statistically significant spillover effects (Table 10, column 1 and 2). This is true in the case of both national and international spillovers. The results of the two-sector model also illustrate that only the relatively higher-skill-intensive manufacturing sector generates significant spillovers (columns 2 and 3).

Recall that CH find national R&D spillovers to have a much larger impact on the level of TFP in larger countries compared to those of smaller countries. Accordingly, in the case of smaller countries, it is the foreign R&D spillovers that have a greater impact on productivity (with a few notable exceptions⁴⁶). We investigate whether these conclusions hold true in the case of learning-by-doing spillovers. For this purpose, we divide the sample into two groups: large and small countries. The last column of Table 10 reports the differences between the coefficients for the two groups of countries (the definition of large and small countries is the same as the one used earlier in Section 7.2).

The differences observed between the coefficients are small, and statistically insignificant (at the 5% significance level). We undertake a likelihood ratio test to test the

⁴⁶ From the 15 countries that were considered as small countries, four (Australia, Finland, New Zealand, and Spain) exhibited a greater impact from national R&D spillovers than from international spillovers.

hypothesis that the coefficients across the two groups are equal. The test statistic, which follows a Chi-squared distribution with six degrees of freedom, is below the critical value of 12.59 (at the 5% significance level). Therefore, the null hypothesis that the coefficients are equal is accepted.

7.4 International Spillovers -- Summary

We investigated the impact of international spillovers on productivity growth by using the Aggregate and Sectoral Models presented in Chapter 6. First, using the Aggregate Model, we investigated whether there are significant international spillovers, and if so, what is the channel through which spillovers are transmitted. The results indicate that international spillovers are important in determining TFP growth. The foreign-knowledge stock appears to affect a country's productivity growth only when interacted with a measure of openness. Our results also indicate that the effect of foreign-knowledge on TFP growth is higher, the more open a country is to foreign trade. A country's trading partner could be a factor in determining the amount of spillovers, and hence productivity growth; because the effect of foreign trade on TFP growth is higher, the larger the knowledge stock of the trading partner. With regard to the best channel through which foreign-knowledge is transferred, we find that any one of the bilateral trade measures (imports, exports, or total trade) gives rise to broadly similar results.

An extension to the Aggregate Model is used to investigate whether the contribution of each G-7 country's knowledge stock to productivity growth of the home country is the same. However, due to multicollinearity problems, we could not come to any conclusions

on this issue. Finally, we use the Aggregate Model to combine learning and R&D spillovers. The regression results show that learning spillovers remain statistically significant when R&D spillovers are taken into account. This provides further evidence on the robustness of our learning-by-doing spillover model.

In the second part of the empirical analysis, the Sectoral Model is introduced to capture the sectoral differences in spillovers. At first, only the international spillover effects are considered, and the empirical results show that spillovers are positively related to the skill intensity of a sector. Also, in the three-sector model, only the high-skill-intensive manufacturing sector is capable in generating statistically significant spillover effects. This means that the composition of imports matters in determining productivity growth. Moreover, our results indicate that international spillovers do not depend on the size of the country.

Finally, we use the Sectoral Model to investigate the effects of both the national and international spillovers. The combined spillover model performs better than the models that test the roles of national or international spillovers, separately. With regard to sectoral variations in spillovers, the empirical results are quite strong in verifying that higher skill-intensive sectors generate higher spillovers, in cases of both national and international spillovers. We find that statistically significant spillover effects, both at national and international levels, exist only in the high-skill-intensive manufacturing sector. Furthermore, these results also hold true regardless of the size of a country. The latter test also proves the robustness of the results.

On the issue of robustness, we would like to emphasize that we have tested several variations of Aggregate and Sectoral models and arrived at similar conclusions. These include regression models with alternative knowledge transfer mechanisms, R&D spillovers, national spillovers, and models that divide the sample into different country categories. Furthermore, as an alternative to panel data analysis, we make use of the full set of time-series data to test the two models. All different variations to the models consistently demonstrate that international spillovers from learning-by-doing are statistically significant, spillovers depend on the skill-intensity of a sector, and only high-skill-intensive manufacturing sectors generate significant spillovers that drive productivity growth of a country.

Chapter 8

Conclusion

Endogenous growth literature identifies that spillovers from economic activities may drive long-run growth. The commonly recognized sources of knowledge spillovers are R&D activities, human capital accumulation, and learning-by-doing. Even though the theoretical work on the relationship between learning-by-doing spillovers and sustained economic growth goes back to the Arrow's seminal paper in 1961, learning-by-doing spillovers have received the least attention in the empirical literature on endogenous growth. This thesis endeavours to fill this void.

We formalize and test the implications of endogenous growth theory by investigating the relationship between productivity growth and learning-by-doing spillovers. The model we develop allows for differential spillovers across sectors. This is the first research that explores the sectoral differences in learning-by-doing spillover capabilities. Using the sectoral model, we consider the contribution of both national and international spillovers to the productivity growth of a country. This is also the first research to examine the role of international spillovers from learning-by-doing in determining the productivity growth of a country.

The empirical results show that learning spillovers are important in determining the productivity growth of a country. The most important finding of the research is regarding the sectoral differences in learning spillovers. Empirical results demonstrate that the ability to generate learning spillovers differs between sectors. Both domestic and international spillovers depend on the skill intensity of a sector; that is, the higher the skill intensity of a

sector, the larger will be the spillovers. In both cases, we find statistically significant spillovers only in the high-skill-intensive activities. Furthermore, the high-skill-intensive activities seem to maintain their superior ability to contribute to productivity growth over time, regardless of the stage of development of a country.

With regard to the robustness of the results, we have experimented with different empirical methodologies, used different data sets and made use of additional explanatory variables, including R&D expenditures, exogenous technology spillover term, and lagged values of the explanatory variables. The results consistently support the findings of this research on the nature of learning spillovers, thus providing proof on the robustness of our results.

The other findings of this thesis relate to the relationship between country-size effect and learning spillovers, and several interesting outcomes from the research on international spillovers.

As Lucas (1994) points out, one weakness of the learning-by-doing theories is the implication that large countries would have a substantial growth potential over small countries. To address this issue, we develop and test a model that excludes the country-size effect, as part of our research on national spillovers. We do not find empirical evidence to support the notion that larger countries tend to grow faster. In fact, we find that the learning-by-doing spillover model that excludes the country-size effect tends to perform better empirically, compared to the model that includes the country-size effect.

With regard to international spillovers, we find that the foreign knowledge stock affects the productivity growth of a country only when interacted with a measure of

openness. Our results indicate that those countries that are more open to foreign trade gain more from foreign knowledge in terms of productivity growth.

Our research on international spillovers also demonstrates that a country's trading partner could be a factor in determining the amount of spillover benefits. The reason is that the effect of foreign trade on TFP growth is higher, the larger the knowledge stock of the trading partner. However, it should be noted that such policy changes may involve some costs, and quantifying those is beyond the scope of thesis. With regard to the best channel through which foreign-knowledge is transferred, we find that any one of the bilateral trade measures (imports, exports, or total trade) gives rise to broadly similar results.

The findings of this thesis regarding the sectoral differences in spillovers demonstrate that the composition of output matters in determining productivity growth. A country that promotes higher skill intensive activities, regardless of its size and stage of its development, may stand to gain more from learning-by-doing spillovers. (It should be emphasised, however, that such policies may also involve some costs.) Thus, this thesis provides an answer to Pack's (1994) question that we quoted in the introduction in Chapter 1: "What would Japan's GDP per capita have been if it had not been able to move from agriculture and low-quality textiles to chemicals, metal-based products, and electronics?" Regarding further extension of our research, it may be interesting to examine whether there are sectoral differences in spillovers from human capital accumulation.

Appendix 1: Empirical Analysis

1 National Spillovers: Preliminary Tests on Stability Across Time

In this section we consider whether the pooling of time series and cross section data is appropriate and beneficial in the present study. The theoretical justification given for pooling is that the estimators from a pooled model will, in general, be more efficient than those based on individual time series (Nerlove 1966, Baltagi and Griffin 1983). Furthermore, panel data make it possible to observe simultaneously the differences in behaviour over cross-sectional units and over-time for a given cross-sectional unit. As such, panel data provide additional observations and new sources of variation in the independent variables and more degrees of freedom. In principle, this fact should lead to more efficient estimators (Judge *et al.* 1985). Also, in the present study, the fact that we do not have enough time series data for individual countries makes it necessary for us to work with a panel data set. In this section, we test the stability of intercept and slope coefficients across time to see whether data can be pooled. The stability of intercept and coefficient across countries is another factor that determines the poolability of data. This issue is examined in Section 2.

The data consist of four time periods (1971-75, 1976-80, 1980-85, and 1986-90) and 20 countries. The stability across time reduces to the question, whether the parameters of the productivity growth equation vary from one year to another over the four time periods. A Chow-test was performed by running four separate regressions corresponding to the

four periods, and then comparing the results with the restricted pooled model, where all periods are combined. The resulting F-statistics are reported in Tables A.1 and A.2 for Models I and II, respectively. At the 5% significance level, the test statistic for Model I rejects the stability across time for all coefficients, while the test statistic for Model II marginally accepts stability.

Table A.1: Tests for Stability: Model I

Test Description	Test Statistic
F stat. for stable intercept term over-time	$F_{(12,64)} = 2.25^*$
F stat. for stable slopes over-time	$F_{(9,64)} = 1.23$

* test statistic is significant at 5% significance level.

Table A.2: Tests for Stability: Model II- country size removed

Test Description	Test Statistic
F-statistic for stable intercept term over time	$F_{(12,64)} = 1.64$
F-statistic for stable slopes over time	$F_{(9,64)} = 0.675$

* Test statistic is significant at the 5% significance level.

A further test was undertaken on each of Model I and II to check the stability of slopes, while allowing intercepts to vary. The restricted model, in this instance, is the pooled model with dummy variables to account for the variation in the slope coefficients over time. The F-statistics reported in Tables A.1 and A.2 clearly indicate that there are no significant changes in slope variables across time both in the case of Model I and Model II.

As a result, throughout this thesis, we have introduced dummy variables to capture the possible shifts over time in the intercept term. Historically, the five-year time intervals considered appear to represent markedly different events, and this fact could be the reason for the shift in the intercept term over time. Note that the first period, 1971-75, roughly corresponds to the oil shock, the third period from 1980-85 coincides with the Latin American debt crisis and falling commodity prices, whereas the fourth period from 1986-90 corresponds to the productivity slow-down in the industrial countries. Therefore, it is reasonable to expect the presence of significant structural shifts across time (i.e. change in intercept term), and as a result it may be necessary to account for these shifts, accordingly.

2 National Spillovers: Selection of the Panel Data Estimation Technique

In this section we deal with the problem of selecting the appropriate panel data estimation technique for Models I and II. The three main estimation techniques considered are: pooled regression (classical ordinary least squares procedure), fixed effect model, and random effect model. First, we appraise the selection procedure for Model I which incorporates both the scale effect and the sectoral composition effect in explaining long-run productivity growth. Afterwards, we consider Model II, which excludes the scale effect by removing the country-size. As an alternative, we apply all these techniques to the full time series data set. We also consider Kmenta's cross-sectionally heteroskedastic and time-wise autoregressive model in estimating Models I and II. A brief summary of the statistical findings and conclusions drawn will follow at the end of Section 2.

2.1 Model I

In a combined time series and cross-section framework, the “stacked” regression equation can be written for the Model I as

$$\dot{A}_t^j / A_t^j = \alpha_t + \beta_{hs} S_{hs,t}^j + \beta_{ls} S_{ls,t}^j + \beta_{nm} S_{nm,t}^j + \epsilon_t^j, \quad (A1)$$

where, $j = 1, \dots, J$, $t = 1, \dots, T$, and where j denotes the j 'th country and t denotes t 'th time period. The economy is divided into three sectors: high-skill intensive manufacturing (hs), low-skill-intensive manufacturing (ls), and non-manufacturing (nm) sectors; and S_{hs} , S_{ls} , and S_{nm} represent the sectoral indexes, respectively. The β 's represent the learning effects of the respective sectors. Recall that the explanatory variables, S 's, in Model I include both scale effect and sectoral composition effect in explaining total factor productivity growth. For example, the sectoral index for sector i , in country j for period t is, $S_{i,t}^j = Y_t^j (Y_{i,t}^j / Y_t^j)^2$, where $i = hs, ls, nm$. The first term on the right hand side, Y_t^j , is the aggregate output that captures the scale effect, while the second term represents the compositional effect.

The basic learning-by-doing model we introduced in Chapter 2 explains only part of the productivity growth. Therefore, we have included an intercept term, α , to capture the impact of exogenous variables that may influence the long-run growth (see Barro 1991 and Barro and Lee 1994 for similar treatments). The estimation techniques, which are considered below, offer different interpretations of the behaviour of the intercept term across countries.

Several studies utilizing panel data have used *a-priori* reasoning to determine a

specification of the individual country-specific effects (Reder and Neumann 1980, Swindinsky and Vanderkamp 1982, Nehru and Dhareshwar 1994). Instead, in our research, we let the sample data to determine the best panel data technique. We have experimented with three different techniques to estimate the relationship between TFP growth and sectoral composition of output. They include: the basic pooled regression model; the fixed effect model, using dummy variables; and, finally, the random effect model, using generalized least squares (GLS). In the pooled regression technique, a common intercept term is assumed for all countries; while in the fixed effect framework, the intercept term is allowed to vary between countries. The random effect model, on the other hand considers the intercept term to be drawn from a random distribution. Therefore, the choice of the estimation technique depends on the behaviour of error term ¹, ϵ_i^j .

1) Pooled Regression²

In the basic pooled regression model, corresponding to (A1), ϵ_i^j 's are assumed to be independently and identically distributed, with zero mean and variance σ_ϵ^2 . The term α is the common intercept and, in this model, it is assumed that there are no across-country differences. This is the classical regression model and, hence, ordinary least squares (OLS) procedure is applied to the model. The results appear in Table A.3.³ (Note that throughout

¹ Problems of autocorrelation and heteroskedasticity are not present in the error term. For more details on the appropriate tests, refer to the section on Kmenta procedure, below.

²The pooled regression model represents ordinary least squares applied to the pooled data. The two terms are being used interchangeably in this Appendix.

³ The OLS model has been extended to include $T-1$ dummy variables to take care of the time-specific effect. The extended model is,

the paper, we have used time dummy variables to take care of the differences between different time periods. The estimates for the dummy variables do not appear in the Tables.)

2) Fixed Effect Model

To estimate the relation between TFP growth and sectoral composition of output, a fixed effect model is used, with the following specification:

$$\frac{\dot{A}_t^j}{A_t^j} = \alpha^j + \beta_{hs} S_{hs,t}^j + \beta_{ls} S_{ls,t}^j + \beta_{nm} S_{nm,t}^j + \epsilon_t^j. \quad (A2)$$

It is assumed that each country has a country-specific intercept term, which may or may not be correlated with the sectoral indexes. For example, the term α^j captures the individual effect for country j . The model can be estimated using the least squares dummy variable method (LSDV). The results are reported in Table A.3.

3) Random Effect Model

We consider a one-way random effect model⁴. In this version, the country-specific constant terms are assumed to be randomly distributed. A random effect model (i.e., a

$$\frac{\dot{A}_t^j}{A_t^j} = \alpha + \lambda_t + \beta_{hs} S_{hs,t}^j + \beta_{ls} S_{ls,t}^j + \beta_{nm} S_{nm,t}^j + \epsilon_t^j$$

An F-test has been undertaken to verify the validity of the time-specific effect, as represented by this model, against a restricted model without time dummy variables. The test results show that there are significant changes in intercept terms across time (5-year periods).

⁴In the two-way random effect model, a randomly distributed time-specific term is introduced. It is typical of panel data studies to ignore this time-specific effect (Baltagi 1995). Following Knight *et al.* (1993), in order to eliminate the time effects, we removed the time means from each variable using $T-1$ dummy variables. The method is compatible with OLS and LSDV models estimated above, since all these models include time dummy variables.

variance-component model) is particularly appropriate when the sample of cross-section units are drawn from a large population. The model specification is as follows:

$$\dot{A}_t^j / A_t^j = C + \beta_{he} S_{he,t}^j + \beta_{le} S_{le,t}^j + \beta_{nm} S_{nm,t}^j + \epsilon_t^j + u^j. \quad (A3)$$

The u^j term is the random disturbance characterizing the j 'th country observation and is assumed to be constant through time. Further assumptions regarding the error term are made:

1. $E(\epsilon_t^j) = E(u^j) = 0$
2. $E(\epsilon_t^{j2}) = \sigma_\epsilon^2$
3. $E(u^{j2}) = \sigma_u^2$
4. $E(\epsilon_t^j, u^m) = 0$, for all j , t , and m
5. $E(u^j, u^m) = 0$, if $j \neq m$
6. $E(\epsilon_t^j, \epsilon_\tau^m) = 0$, if $t \neq \tau$

According to these assumptions, the random effect estimator is a generalized least squares (GLS) estimator. Also, note from the fourth assumption that the model treats individual country effects as uncorrelated with other regressors. Several methods have been suggested for the estimation of this GLS estimator (Swamy and Arora 1972, Wallace and Hussain 1969, Amemiya 1971). These procedures differ with respect to the estimators of the variance components σ_ϵ^2 and σ_u^2 , and the corresponding weight, θ , used for the computation of GLS model.

We employ the widely-used Swamy and Arora (1973) procedure to compute the variance-components estimator. (The methodology is detailed in Greene 1990, and Baltagi 1995.) Accordingly, in the first stage, two regressions are run to obtain estimates of the variance components (from the corresponding mean square residuals) of the regressions. The first regression is the fixed-effect or "within" regression, which has been already

computed in the earlier section. The second regression is the “between” regression, which specifies the same relationship as explained by the pooled (or OLS) regression, but now the relation is between the individual means. With regard to the “between” regression, the independent variable is defined as the mean of the TFP growth rate for each country. The explanatory variables are defined similarly.⁵ In the next step in computation, the variance component estimator is computed by estimating the relative importance of “between” and “within” variation of the disturbance u_i and ϵ_{it} , then combining the “within” and “between” estimators optimally by using this estimated ratio, θ , as the weight. It can be shown that this GLS estimator is a matrix of-weighted average of the within and between estimators. It is important to notice that,

$$\theta = \frac{\sigma_u^2}{\sigma_u^2 + T\sigma_\epsilon^2} . \quad (A4)$$

If there is no variation across countries in u_i , then σ_u^2 will be zero, and GLS collapses to OLS. It implies that the value of θ equals unity in (A4). If, on the other hand, all variation across countries is due to the different u_i 's, then σ_ϵ^2 will be zero, and the fixed effect model would be appropriate. The corresponding θ , in this case, equals zero.⁶ The results of random effect model, with the value of estimated θ , appear in tables A3 and A4.

⁵Note that, now, the number of observations are limited to number of countries, 20, in this case.

⁶The latter result would also hold, if $T \rightarrow \infty$, because then the unobserved u_i becomes observable.

Fixed Effect versus Pooled Regression (or OLS)

To check the superiority of fixed effect model over the pooled regression model, a simple F-test is undertaken to test the null hypothesis that there are no unobserved country-specific factors significantly affecting the TFP growth. In other words, we test that the coefficients of the $N-1$ (19 in this case) dummy variables are zero, by comparing the restricted pooled regression with the unrestricted fixed effect model. The test statistic is computed as,

$$F = \frac{(SSR_{PR} - SSR_{FE})/19}{SSR_{FE} / 54}$$

Where SSR_{PR} and SSR_{FE} represent sum of squared errors of the pooled regression and the fixed effect model, respectively. The test-statistic reported in Tables A.3 shows that for Model I the null hypothesis is rejected at the 5% significance level. Thus, for Model I the evidence is in favour of a fixed effect specification.

Fixed Effect versus Random Effect

Recall one of the crucial assumptions (Assumption 4) of the random effect model is that the unobservable country-specific effects are not correlated with the explanatory variables, say X 's (i.e., $E(u^j / X_i^j) = 0$). Then, under the null hypothesis of no correlation between the country-specific effects and the sectoral indexes, both the fixed effect model and the random effect model will give consistent estimates. However, the random effect estimator is asymptotically efficient, since it is a GLS estimator; while the fixed effect estimator becomes inefficient.

Under the alternative hypothesis, however, the GLS estimates become biased and inconsistent. Note that, if the country-specific effects are correlated with the sectoral indexes, then the parameter estimates for the OLS applied to the pooled data set also become biased and inconsistent. However, the estimates of the fixed effect model remain unbiased and consistent. This is because, with the use of country dummy variables, the fixed effect model is capable of averaging out the unobservable country-specific effect, μ (Hausman 1978, Baltagi 1995).

We used the Hausman Specification Test to check the validity of the null hypothesis. For Model I, the test yields a test statistic of 133, which follows a chi-squared distribution with two-degrees of freedom. The critical value at 5% is 5.99, hence, the null hypothesis that the individual effects are uncorrelated with the sectoral indexes is rejected. The test results indicate only the fixed effect estimates will be unbiased and consistent. Therefore, in the main body of the paper, we focus on the results of this procedure.

In summary, we have considered three panel data techniques for Model I: pooled regression (OLS), fixed effect model, and random effect model. A simple F-test revealed the superiority of fixed effect model as opposed to the pooled regression (OLS). The result of the Hausman test shows evidence of possible correlation of the regressors with the error term. This evidence renders both pooled regression (or OLS) and the GLS estimates biased and inconsistent. Therefore, we choose the fixed effect model as the appropriate model for further work. Hence, only fixed effect estimates are reported in the main body of the paper.

Table A.3: Regression Results for Model I

(t-statistics in parenthesis).

Dependent variable: Growth rate of TFP.

Independent Variable	Pooled (OLS)	Fixed Effect	Random Effect
Constant	130 (2.43)*		132 (2.38)*
High-Skill (β_{hs})	0.945 E -04 (1.99)*	0.123 E-03 (2.46)*	0.977 E-04 (1.72)
Low-Skill (β_{ls})	-0.120 E -03 (-2.36)*	0.301 E-04 (0.29)	-0.107 E-03 (-1.22)
Non-Manufacturing (β_{nm})	0.179 E -06 (0.62)	-0.482 E-06 (-0.78)	0.115 E-06 (0.24)
Number of observations	80	80	80
R ²	0.213	0.534	0.37
Std. Error of Regression	0.023	0.02	0.024
F-statistic: pooled vs. fixed		F (19, 54) = 2.96*	
Hausman specification test: fixed vs. random			$\chi^2 (2)=133.07^*$
Value of θ : (pooled=1, fixed=0)			0.48

* Test statistic is significant at the 5% significance level. The t-statistics are heteroskedastic-consistent.

2.2 Model II

The learning-by-doing model, introduced in Model I, takes both scale (reflected by the country-size) and composition effects into account in explaining the variation in TFP growth. The model predicts, that given all else is equal, larger countries will tend to grow relatively faster. As explained in the text, this prediction may raise some questions. As an alternative, in Model II, we remove country-size from the relationship. In this section, we determine the most appropriate panel data technique for Model II. The exercise is similar

to that of Model I. Since, the statistical details of various techniques and appropriate tests have been already examined, the following discussion is limited to selecting the most appropriate technique for Model II.

In a combined time series and cross-section framework, the “stacked” regression equation can be written for the model in Model II as

$$\dot{A}_t^j / A_t^j = \alpha + \beta_{hs} s_{hs,t}^j + \beta_{ls} s_{ls,t}^j + \beta_{nm} s_{nm,t}^j + \epsilon_t^j, \quad (A5)$$

with $j = 1, \dots, J$, $t = 1, \dots, T$, and where j denotes the j 'th country and t denotes t 'th time period. The economy is divided into three sectors: high-skill-intensive manufacturing (hs), low-skill-intensive manufacturing (ls) and non-manufacturing (nm) sectors. The sectoral index for sector i , in country j for period t is, $s_{i,t}^j = y_t^j (Y_{i,t}^j / Y_t^j)^2$, where $i = hs, ls, nm$. Observe that the country-size effect is removed by using the per capita output, y_t , instead of the aggregate output, Y_t . The sectoral index represents the composition effect. Similar to Model I, we have included an intercept term, α , to capture the impact of exogenous variables that may influence the long-run growth. The results of pooled regression (OLS), fixed effect, and random effect models are reported in Table A.4.⁷

⁷ Problems of autocorrelation and heteroskedasticity are not exhibited in the error term. For more details on the appropriate tests, refer to the section on Kmenta procedure, below.

Table A.4: Regression Results for Model II: Country Size Removed
(t-statistics in parenthesis).

Dependent variable: Growth rate of TFP

Independent Variable	Pooled (OLS)	Fixed Effect	Random Effect
Constant	160 (2.32)*	-	160 (2.07)*
High-skill (β_{hs})	0.740 (3.08)*	0.993 (2.42)*	0.769 (2.01)*
Low-skill (β_{ls})	0.402 (0.49)	-0.605 (-0.35)	0.213 (0.27)
Non-manufacturing (β_{nm})	-0.0161 (-1.79)	0.904 E-03 (0.03)	-0.139 (-1.35)
Number of observations	80	80	80
R ²	0.228	0.527	0.357
Std. error of regression	0.022	0.020	0.024
F-statistic: pooled vs. fixed		F (19, 54) = 1.70	
Hausman specification test: fixed vs. random			$\chi^2 (3) = 1.78$
Lagrange multiplier: random vs. pooled	$\chi^2 (1) = 2.70$		
Value of θ : (pooled=1, fixed=0)			0.57

* Test statistic is significant at the 5% significance level. The t-statistics are heteroskedastic-consistent

Pooled (OLS) versus Fixed Effect

To check the superiority of the fixed effect model over the pooled regression model, a simple F-test is undertaken to test the null hypothesis that there are no unobserved country-specific factors significantly affecting the TFP growth. The test, identical to a joint test, compares the restricted pooled regression with the unrestricted fixed effect model to demonstrate that the coefficients of $N-1$ (19 in this case) dummy variables are zero. The

test statistic reported in Table A.4 shows that the fixed effect model is not superior to the pooled regression model in explaining the variation of the TFP growth rates, at the 5% significance level for Model II. Thus, the null hypothesis is accepted.

Fixed Effect versus Random Effect

In Model II, the Hausman specification test statistic is 1.78, and it follows a chi-squared distribution with two-degrees of freedom (Table A.4). The critical value at 5% is 5.99. The null hypothesis that the individual effects are uncorrelated with the sectoral indexes is accepted. Based on this evidence, we decided in favour of the random effect specification, when compared to the fixed effect model. We still have to decide whether the GLS estimates from random effect model is superior to OLS estimates from the pooled regression model.

Pooled Regression (OLS) versus Random Effect

We compare the pooled regression with the random effects in order to choose the most appropriate estimate. The correct test is to investigate whether individual country effects do exist. If they do not exist, then the $\sigma_u^2 = 0$ (see the description of random effect model and its properties discussed earlier). For this purpose, we use the Lagrange multiplier statistic developed by Breusch and Pagan (1980). Under the null hypothesis, $H_0: \sigma_u^2 = 0$, Lagrange multiplier statistic is,

$$LM = \frac{JT}{2(T-1)} \left[\frac{\sum_j \left(\sum_i e_i^j \right)^2}{\sum_j \sum_i e_i^{j^2}} - 1 \right]^2$$

Under the null hypothesis LM is distributed as chi-squared with one-degree of freedom and the critical value at 5% level is 3.84. And the test statistic for Model II is 2.70, which is not significant at the 5% level. The OLS is favoured over GLS. Recall the methodology on the computation of random effect model, where we observe that, if there is no significant individual variation across countries, the value of θ will be closer to unity, and GLS applied to random effect model gives similar results to OLS applied to pooled model.

A careful examination of Table A.4's contents reveals that the coefficient values are similar in pooled and random effect models and the value of θ is indeed closer to unity, and, therefore, closer to the pooled than the fixed effect specification. Furthermore, from the values of t-statistics for individual coefficients and the standard error of regression, it can be concluded that the random effect model has not led to an increase in efficiency. This evidence supports the use of the OLS over the GLS method. As a result, in the main body of the paper we report the results of the pooled regression for Model II.

To summarise the discussion on Model II, we have considered three panel data techniques: pooled regression, fixed effect model, and random effect model. A simple F-test revealed the superiority of pooled regression as opposed to the fixed effect model. A comparison of pooled regression with the random effect model shows the former is more appropriate. In other words, we do not observe significant individual variations across countries (LM test) to justify the use of random effect estimates. Furthermore, from the values of t-statistics for individual coefficients and standard error of regression, we conclude that the random effect model does not lead to an increase in efficiency. Hence,

we choose pooled regression as appropriate when compared to random effect model to be reported in the main body of the paper.

2.3 Comparison of Model I and Model II

Model I, which incorporates both country-size and compositional effects in explaining the variation in the TFP growth, has one undesirable property. It is the implication that a large country, like India, will grow faster than small countries, like Singapore and Taiwan. In Model II, we remove the country-size effect. The purpose of this section is to see which model performs better, empirically.

Both models attempt to explain the variation in the same dependent variable, the rate of growth of TFP, but the explanatory variables differ. Because of the use of different set of regressors, Model I cannot be written as a restriction of Model II, and as a results the two competing models fall into a non-nested model category. We apply two non-nested model tests to determine which of the two possible sets of regressors has more explanatory power. The first test is the J-test introduced by Davidson and MacKinnon (1981), and the second is the Cox-test proposed in his work in 1961 and 1962.

The J-test

For the clarity of exposition, we express the fixed effect model for Model I in matrix form

$$Y = Z\theta + \epsilon_1,$$

where, Y is a 80×1 vector of the dependent variable (rate of growth of TFP), Z is a 80×23 matrix containing an intercept term, three sectoral indexes, and 19 country dummies for 20 countries, and θ is a 23×1 vector of coefficients and ϵ_1 is a 80×1 vector of error term.

There are 4 time periods for the 20 countries. Similarly, Model II can be expressed as

$$Y = X\beta + \epsilon_0,$$

where, similar to the earlier case, Y is a 80×1 vector of dependent variable (rate of growth of TFP), X is a 80×23 matrix containing an intercept term, three sectoral indexes (as in Model II), and 19 country dummies, and β is a 23×1 vector of coefficients and ϵ_0 is a 80×1 vector of error term. For Model II, the fixed effect model results are used for comparison purposes.

We test the null hypothesis that Model II has the correct set of regressors as opposed to Model I:

$$H_0: Y = X\beta + \epsilon_0$$

$$H_1: Y = Z\theta + \epsilon_1$$

To apply the J-test, first, Model I is estimated and the fitted values ($Z\theta$) are recovered.

Then the Model II is run with these fitted values as an additional regressor. The new model becomes,

$$Y = (1-\gamma)X\beta + \gamma (Z\theta) + \epsilon$$

Testing the null hypothesis, H_0 amounts to testing that $\gamma = 0$ (the null hypothesis therefore is that $H_0: \gamma = 0$). A simple t-test is applied to the coefficient of the fitted values of Model I, γ , to check the validity of the null hypothesis. The resultant t-statistic is 1.54, and at the 5% significance level, we accept the H_0 in favour of H_1 . However, this is not conclusive enough to determine that Model II performs better than Model I, because testing H_0 versus H_1 , could give rise to four possible outcomes:

1. Both models are accepted
2. Both models are rejected

3. Model I is accepted in favour of Model II
4. Model II is accepted in favour of Model I

Only in 3 and 4, do we have an unambiguous statement about which is the best model. The outcome in 2 is not applicable in the present case, since Model II has been already accepted over Model I. However, the outcome in 1 is still a possibility. To avoid ambiguity, we test the hypothesis that Model I has the correct set of regressors, as opposed to Model II, by running the regression,

$$Y = (1-\delta)Z\theta + \delta (X\beta) + \epsilon.$$

As above, a t-test is applied to δ and the resultant test statistic is 3.5, and is significant at 5% level. Thus, the null hypothesis is rejected. The results of two tests indicate a clear preference for Model II over Model I. Therefore, the empirical results do support a theoretical preference for a model in which the country size is removed.

Cox Test

As an alternative to the J-test, we apply the Cox test, which is an extension of the likelihood ratio test, to choose between Models I and II. The Cox statistic, q , which is used to test the hypothesis that X is the correct set of regressors, and Z is not, follows a standard normal distribution. That is,

$$q = \frac{c_{12}}{[Est.Var(c_{12})]^{1/2}},$$

where,

$$c_{12} = \frac{N}{2} \ln \left[\frac{s_z^2}{s_x^2 + (1/n)\beta^1 X^1 (I - Z(Z^1 Z)^{-1} Z^1) X \beta} \right] = \frac{N}{2} \ln \left[\frac{s_z^2}{s_x^2} \right],$$

and,

$$Est.Var(c_{12}) = \left| \frac{s_x^2}{s_x^4} \right| \beta^1 X^1 (I - Z(Z^1 Z)^{-1} Z^1) (I - X(X^1 X)^{-1} X^1) (I - Z(Z^1 Z)^{-1} Z^1) X \beta.$$

Note that N represents the number of observations and equal to $J * T$. The resultant Cox statistic, q , equals -0.005, and is not statistically significant at the 5% significance level. Thus, we accept the null hypothesis that Model II regressors represent the correct set of regressors (X).

We also reverse the hypotheses to check if the null hypothesis that Z is the correct set of regressors and X is not (i.e., Model I is better than II). The corresponding Cox statistic, q , equals -4.83, and, thus, the null hypothesis is soundly rejected at the 5% significance level. The above results further confirm that the regressors in Model II are preferable to that of Model I in explaining the variation in TFP growth.

3 National Spillovers: Alternative Methods of Pooling

In this section, we test three alternative pooling techniques: Kmenta's cross-sectionally heteroskedastic, and time-wise autoregressive model; pooled regression (or OLS), with annual data instead of 5-year averages used in the earlier section; and an instrumental variable method introduced to take care of the possible simultaneity bias in

data. These procedures are also the tests of robustness of Model I and Model II results reported in the earlier section.

3.1 Cross-Sectionally Heteroskedastic and Time-wise Autoregressive Model

As an alternative to the pooling techniques evaluated above, we experiment with a method proposed by Kmenta (1986). Kmenta describes a cross-sectionally heteroskedastic and time-wise autoregressive model. The basic assumptions about the error term, ϵ_t^j , (in Equations A1 and A5) are as follows:

1. $E(\epsilon_t^j) = 0$. Allow for heteroskedasticity
2. $E(\epsilon_t^j \epsilon_t^m) = 0$, for $j \neq m$. Rule out seemingly unrelated regression
3. $\epsilon_t^j = \rho \epsilon_{t-1}^j + v_t^j$. First order autoregression⁸

The feasible GLS estimators of the regression coefficients are obtained in two steps. First, OLS residuals are used to compute consistent estimates of ρ , which are then used to transform the variables. In the final step, GLS is applied to the transformed model. The results appear in Table A.5, along with the value of the AR(1) coefficients, ρ 's.

As can be seen, learning coefficients for the high-skill-intensive sector are consistently positive and statistically significant, while the other two sectors do not generate significant spillovers. Note that the AR(1) coefficients are very small, at 0.195 and 0.167 for Model I and II, respectively. Thus, the correlation of the residuals across time seems to be negligible.

⁸ One can also let the autoregressive parameter ρ , to vary across cross sections, then, Assumption 3 will be modified as $\epsilon_t^j = \rho^j \epsilon_{t-1}^j + v_t^j$. Since, we do not have enough time series observations, stable ρ^j 's cannot be obtained.

In addition, the presence of heteroskedasticity (Assumption 1) is tested using a White test on the OLS residuals from Model I and II. To compute the White test, the squared OLS residuals is regressed on a constant, all explanatory variables and their cross-products. Under the null hypothesis of no homoscedasticity, the test statistic, $JT(R^2)$ is distributed as a Chi-squared with ten-degrees of freedom. In Models I and II, the White test statistics are 5.76 and 6.52, respectively; and the critical value at the 5% significance level is 11.07, so we accept the null hypothesis. As an alternative test, we perform a modified Wald test and the results favour the homoskedasticity assumption. The sample under study consists of a relatively homogeneous group of low- to medium-income

Table A.5: Regression Results: Kmenta Procedure
(t-statistics in parenthesis).

Dependent variable: Growth rate of TFP

Independent Variable	Model I	Model II
Constant	300 (4.81)*	110 (3.39)*
High-skill (β_{hs})	0.859E-04 (2.13)*	1.43 (2.67)*
Low-skill (β_{ls})	-0.993E-04 (-1.75)	1.62 (1.05)
Non-manufacturing (β_{nm})	0.194E-06 (0.62)	-0.127E-02 (0.80)
Number of observations	80	80
R^2 (Buse)	0.387	0.527
Std. error of regression	1.035	0.021
Value of ρ	0.195	0.167

* Test statistic is significant at the 5% significance level.

countries. This may partly explain the absence of heteroskedasticity in the error term.

Since, the above tests indicate that autocorrelation and heteroskedasticity do not seem to be major problems in this study, we abandon Kmenta procedure in favour of traditional techniques of pooled, fixed effect, and random effect models, which are based on the assumption of non-autocorrelated and homoskedastic disturbances.⁹

3.2 Pooling with Full Data Set

Thus far, we have arranged the panel data into 5-year intervals (1971-75, 1976-80, 1980-85, and 1986-90). There are four observations for each country, and each observation represents the average value of a variable for a given time interval. For example, the growth rate of TFP for the first period, for country j , is the average rate of growth for the period 1971-75, and so on.

It is for two reasons we have chosen to work with a shorter time series rather than utilising the full set of data. First, for some variables and some countries, data are missing for several periods. This is particularly the case for physical capital and sectoral output data. The average values for longer time intervals will, in this case, provide reasonable approximations. Second, several empirical studies on long-run growth have been using similar arrangement of data that consider longer time intervals, generally consisting five-year averages (Islam 1995, Knight 1993). Islam (1995) points out that using yearly time spans may give more weight to short term disturbances and may be inappropriate for studying causes of long-run growth. Longer, five-year time spans, on the other hand, could

⁹Note, however, that the t-statistics reported in the main body of the paper are heteroskedastic consistent estimates.

be thought to be less influenced by business cycle fluctuations.

For the sake of completeness, we apply the panel data techniques, discussed above, to the total data set. For the years for which data are missing, a simple interpolation method is used to construct missing data points. Regression results for Models I and II appear in Tables A.6 and A.7, respectively. An examination of the Tables reveals that main conclusions derived using the five-year intervals are still valid. In most cases, the learning coefficients are very similar in both cases. The standard errors of the regressions are much higher than before; while R^2 's are lower, indicating lower predictability. This may be due to the high variability in the annual data. However, the fact that even with the high volatility of annual data regression results clearly support the findings of the paper, further strengthen our conclusions regarding the importance of sectoral composition of output in determining productivity growth.

3.3 Instrumental Variable Estimation

In both models considered here, the rate of growth of TFP is regressed on a sectoral composition index, which in turn is weighted by the aggregate output, in the case of Model I, and per capita output in Model II. Since the regressors themselves are endogenous, there could be a possibility that they are contemporaneously correlated with the disturbance terms. If so, this will create a simultaneous bias that will render least squares estimates (both pooled (OLS) and fixed effect) bias and inconsistent. The possibility is remote, since we deal with growth variables rather than level variables, and we use the rate of TFP growth rather than the rate of growth of output. Also, the regressors are expressed as complex composition indexes and may not be significantly correlated with the disturbance

term.

Table A.6: Regression Results for Model I: Complete Time Series Data Set
(t-statistics in parenthesis)

Dependent variable: Growth rate of TFP

Independent Variable	Pooled (OLS)	Fixed Effect	Random Effect	Kmenta Procedure**
Constant	260 (3.92)*		260 (2.69)*	210 (3.02)*
High-skill (β_{hs})	0.139 E -03 (3.44)*	0.135 E-03 (2.37)*	0.146 E-03 (2.53)*	0.153E-03 (3.14)*
Low-skill (β_{ls})	-0.169 E -03 (-2.92)*	-0.174E-03 (-1.29)	-0.177 E-03 (-2.30)*	-0.189E-03 (-3.27)*
Non-manufacturing (β_{nm})	0.22 E -06 (0.77)	0.111 E-05 (1.11)	0.257 E-06 (0.589)	0.245E-06 (0.93)
Number of observations	360	360	360	360
R ²	0.135	0.224	0.178	
Buse raw moment R ²				0.231
Std. error of regression	0.042	0.041	0.043	1.01
F-statistic: pooled vs. fixed		$F_{(19,320)} = 1.95^*$		
Hausman Specification Test: fixed vs. random			$\chi^2(2) = 1.51$	
Value of θ : (pooled=1, fixed=0)			0.51	

* Test statistic is significant at the 5% significance level. The t-statistics are heteroskedastic-consistent.

** AR(1) parameter is set to vary across cross sections so that Assumption 3 is modified as $\epsilon_i^j = \rho^j \epsilon_{i-1}^j + v_i^j$.

Table A.7: Regression Results for Model II: Complete Time Series Data Set
(t-statistics in parenthesis).

Dependent variable: Growth rate of TFP

Independent Variable	Pooled (OLS)	Fixed Effect	Random Effect	Kmenta Procedure**
Constant	190 (2.99)*	-	180 (1.81)	
High-Skill (β_{hs})	1.58 (2.63)*	2.43 (1.88)	1.67 (1.99)*	1.12 (1.98)*
Low-Skill (β_{ls})	1.95 (1.25)	1.82 (0.47)	1.49 (0.99)	0.956 (0.63)
Non-Manf (β_{nm})	-0.959E-02 (-0.49)	0.0447 (0.84)	-0.206E-02 (-0.08)	-0.593E-03 (-0.24)
No. of observations	360	360	360	360
R ²	0.134	0.217	0.168	
Buse Raw Moment R ²				0.233
Std. Error of Regression	0.042	0.041	0.043	1.012
F-statistic: pooled Vs. Fixed		$F_{(19,320)} = 1.79^*$		
Hausman Specification Test: Fixed Vs. Random			$\chi^2(3) = 2.68$	
Value of θ : (pooled=1, fixed=0)			0.56	

* test statistic is significant at 5% significance level. The t-statistics are heteroskedastic-consistent.

** AR(1) parameter is set to vary across cross sections so that Assumption 3 is modified as $\epsilon_{it}^j = \rho^j \epsilon_{it-1}^j + v_{it}^j$.

To be cautious, however, we investigate whether the simultaneity bias has affected the main results derived in the paper regarding the sectoral composition output and growth. We propose to use instrumental variable (IV) estimation that uses the lagged values of the regressors as instrumental variables. It is a reasonable proposition, since we have already determined that there is no serial correlation in both models. (In the presence of serial correlation, the notion that the lagged endogenous variables are predetermined loses its validity.) The results of the IV procedure for Model II are reported in Table A8.

The results are consistent with those reported in the main body of the thesis. They confirm that the composition of output matters in determining TFP growth, with the high-skill-intensive sector displaying statistically significant contribution to TFP growth.

Table A.8: Instrumental Variable Estimation for Model II

(t-statistics in parenthesis)

Dependent variable: Growth rate of TFP

Independent Variable	Pooled (OLS)	Fixed Effect	Random Effect
Constant	91.4 (1.32)	-	160 (2.07)*
High-skill (β_{hs})	2.46 (2.38)*	7.18 (2.86)*	0.769 (2.01)*
Low-skill (β_{ls})	2.22 (1.30)	-2.45 (-0.65)	0.213 (0.27)
Non-manufacturing (β_{nm})	-0.0433 (-1.41)	-0.0120 (-1.82)	-0.0139 (-1.35)
Number of observations	60	60	60
R ²	0.292	0.716	0.552
Std. error of regression	0.022	0.017	0.022
F-statistic: pooled vs. fixed		F (19, 35) = 2.751	
Hausman specification test: fixed vs. random			$\chi^2 (2) = 4.854$
Value of θ : (pooled=1, fixed=0)			0.35

* Test statistic is significant at the 5% significance level. The t-statistics are heteroskedastic-consistent.

To summarise, we applied in this section several alternative econometrics techniques to Model II. First, as an alternative pooling technique, we experimented with a cross-sectionally heteroskedastic and time-wise autoregressive model, as described by Kmenta. However, individual tests on the presence of auto-correlation and heteroskedasticity in the error term applied to each model suggest that in this study these problems are not present.

Then, we applied the panel data techniques discussed above to the total data set

consisting of annual data for the 20 countries. Even though the high variability in the annual data seems to cause some loss of efficiency in the estimates, the main conclusions derived using five-year intervals in terms of differential spillover effects are still valid. It is important to note that even with the high volatility, regression results further strengthen our conclusions regarding sectoral composition of output and long-run growth. The results from the use of the full data set and Kmenta procedure clearly show that there are significant differences in learning effects across sectors and that high-skill-intensive sectors are superior in generating learning spillovers. This evidence shows the robustness of the results of our model. Finally, in order to control for a potential problem of simultaneity bias we have used the instrumental variable estimation technique to test both Models I and II. The results again show that main results derived in the study are not distorted by the possible simultaneity bias.

4 National Spillovers: Exogenous Technological Change

In this section, we consider an alternative spillover structure where the spillovers of sector i , A_i , is taken to be exogenous. Then

$$A_i = \exp(\lambda_i t) ,$$

where λ_i represents the exogenous learning effect that is sector specific in nature. Consequently, the rate of growth of aggregate output becomes

$$\dot{Y}/Y = \sum_i^n \lambda_i (Y_i/Y) + \sum_i^n Y_i/Y (\dot{F}_i/F_i) .$$

The empirical version of rate of growth of TFP for country j is now

$$\dot{A}^j/A^j = \alpha^j + \sum_i^n \lambda_i (Y_i^j/Y^j) + \epsilon^j .$$

This version has been directly tested assuming that there are no country-specific effects, so that $\alpha^j = \alpha$. The results, with t-statistics in parenthesis, are given below:

$$\dot{A}^j/A^j = \begin{matrix} 0.180 \\ (0.37) \end{matrix} - \begin{matrix} 0.078 \\ (-0.16) \end{matrix} (Y_h^j/Y^j) - \begin{matrix} 0.232 \\ (-0.46) \end{matrix} (Y_L^j/Y^j) - \begin{matrix} 0.166 \\ (-0.35) \end{matrix} (Y_{nm}^j/Y^j) .$$

None of the coefficients are statistically significant and the results are relatively unsatisfactory in terms of standard error of the regression (SER = 0.023) and R-squared statistics ($R^2 = 0.191$), when compared to the endogenous spillover structure considered in Chapter 2 and tested in Chapter 4.

We also test an unrestricted version where both exogenous and endogenous spillovers are present (by adding exogenous spillovers to the Model I with learning spillovers). An F-test is carried out to see the superiority of this unrestricted model over the restricted Model I. The resultant F-statistic is 0.218; and is distributed with 3-degrees of freedom in the numerator, and 70-degrees of freedom degrees of freedom in the denominator. The critical value at the 5% level is 2.74, and the null hypothesis that λ_i 's are individually and jointly equal to zero is accepted. The results show that the unrestricted model does not add statistically significant information in explaining the rate of growth of TFP. These results further strengthen the validity of endogenous, learning-by-doing spillover structure tested in Chapter 4.

5 Summary: National Spillover Models

Before moving on to the next section on international spillovers, we summarise the discussion on the national spillover model. First we considered whether the intercept term and slope coefficients are stable across time. The test results show that slope coefficients remain unchanged, but the intercept term does vary across time. As a result, throughout the study we allow for the possibility of a changing intercept term over time. The second consideration was the selection of the appropriate panel data estimation technique. In other words, we investigated the country-specific effects and their influence on the intercept term. We considered three basic panel data techniques: pooled regression (OLS), fixed effect model, and random effect model. For Model I, statistical evidence shows that the fixed effect model is superior to other two techniques. For Model II, where the country-size is removed, statistical evidence favours pooled regression. Based on the above analyses, in the case of Model I, we choose the outcomes of fixed effect model, while for case Model II, pooled regression model was chosen. These results are reported in Chapter 4.

Various other alternative econometric testings, as well as specifications, have been tried and are outlined in the Section 3 and 4 of this Appendix. These results consistently show that the results of Model I and II that are reported in Chapter 4 are robust.

We also carried out several specific tests to investigate which model (I or II) better explains the variation in TFP growth. Recall that the Model I, which incorporates both the country-size and composition effects in explaining the variation in the TFP growth, has

one undesirable property, since it implies that larger countries will grow faster than smaller countries. To rectify this problem, in Model II we remove the country-size effect. We used two types of tests applicable in testing non-nested models (J-test and Cox test) to investigate which model performs better empirically. Both test results clearly show that the empirical performance of Model II is superior to that of Model I.

6 International Spillovers

In this section we discuss the statistical issues regarding the testing of international spillovers from learning-by-doing. As in the case of national spillover discussion in Section 1 of this Appendix, first, we consider whether the pooling of time series and cross section data is appropriate and beneficial in the international spillover research (Section 6.1). In Section 6.2 we experiment with three panel data techniques: pooled regression (OLS), random effect and fixed effect models. In Section 6.3 we report the results of the analysis on what is the mechanism that best explains knowledge transfers across countries (the main body of the thesis reports the results when imports are considered to be the appropriate mechanism, and here we report the results of other possible mechanisms). In Section 6.4 we test whether different foreign countries are capable of generating different spillovers. Finally, in Section 6.5 we combine spillovers from learning-by-doing and R&D.

6.1 Stability Across Time

As in the case of national spillover model, several preliminary tests are undertaken

for the Aggregate and Sectoral models of international spillovers. Among them is the test for stability across time. As in the earlier case where national spillovers were tested, the data consist of four time periods (1971-75, 1976-80, 1980-85, and 1986-90) and 20 countries. An F-test is undertaken to compare the restricted model with the unrestricted model (with dummy variables added for time periods).¹⁰ The results of the F-test are reported in Table A.9 for the Aggregate Model. At the 5% significance level, the test statistic for each variation of the model is larger than the critical value 2.76, thus, rejecting the stability across time.

Table A.9: Tests for Stability Across Time: Aggregate Model

Description of the model	Test Statistic
Aggregate model (with X^{*1})	$F_{(3, 61)} = 6.88^*$
Aggregate model (with X^{*2})	$F_{(3, 61)} = 7.34^*$
Aggregate model (with X^{*1} and μ)	$F_{(3, 60)} = 7.22^*$
Aggregate model (with μ)	$F_{(3, 61)} = 7.34^*$

* Test statistic is significant at the 5% significance level.

Also, in the case of the Sectoral Model, results are similar to that of Aggregate Model, indicating time dummies characterize significant variations across time. As a result, throughout this study, each regression contains non-reported time dummy variables. This approach is consistent with the research on the national spillover effects. The intuitive justification was discussed in the Section 2 of this appendix.

¹⁰We have used the fixed effect model throughout the paper, the reason for which will be discussed below. Hence the rationality to perform the stability across time based on the fixed effect model.

6.2 Techniques of Panel Data Analysis

We consider three panel data techniques for both the Aggregate and Sectoral Models: pooled regression, fixed effect model, and random effect model. A simple F-test reveals the superiority of the fixed effect model as opposed to pooled regression. (The F-statistics are significant at the 5% significance levels for almost all the cases considered.) We also compute the Hausman test statistic to investigate the superiority of the fixed effect model in relation to the random effect model. The results show that there are instances where there could be possible correlation between the regressors and the error term. This evidence render both pooled regression (OLS) and the random effect estimates biased and inconsistent. Therefore, we choose fixed effect model as appropriate. Hence, the fixed effect estimates are reported in the main body of the paper. The fixed effect specification shows that exogenous country specific effects are important in explaining the variation in TFP growth across countries.

6.3 Alternative Mechanisms of Knowledge Spillovers

One objective of the empirical analysis is to determine the mechanisms through which international spillovers are transmitted. Following the theoretical literature on the issue (see Chapter 5), we identify three possible mechanisms: bilateral imports, exports, and trade. The Aggregate Model is used to identify the best mechanism. The results reported in Tables A.10 and A.11 are when the bi-lateral exports and trade are considered to be the vehicles of international spillovers, respectively. Corresponding results when imports are used are reported in Chapter 7. There is a striking similarity in the results. The magnitude of

the coefficients, as well as the resultant statistics of the regressions are similar, indicating all three alternative mechanisms tend to produce similar results, so that either one of them is equally suited in explaining the underlying spillover mechanism. The similarity rises from a trend that we identify in Chapter 6 in analysing data patterns. There we noted that imports and export patterns of the countries in the sample are closely linked, such that, if a country is exporting a larger proportion of its exports to a particular G7 country, it is generally the case that larger proportion of that country's imports are also from the same G7 country.

Table A.10: Regression Results for the Aggregate Model with Bilateral Exports as Weights (t-statistic in parentheses).

Dependent variable: Growth rate of TFP

Independent variable	1	2	3
X^{*1}	0.124E-03 (0.848)	0.819E-04 (0.55)	
X^{*2}			0.722E-06 (2.19)*
μ		2.36 (1.30)	
Number of observations	80	80	80
R^2	0.509	0.523	0.528
Std. error of regression	0.021	0.021	0.020
F-statistic for all $\alpha^j = \alpha$	1.997*	1.6	1.725**

*Test statistic is significant at the 5% significance level. The t-statistics are heteroskedastic-consistent.

**Test statistic is significant at the 10% significance level.

Table A.11: Regression Results for the Aggregate Model with Bilateral Trade as Weights (t-statistic in parentheses).

Dependent variable: Growth rate of TFP

Independent variable	1	2	3
X^{*1}	-0.645E-04 (-0.31)	-0.113E-03 (-0.55)	
X^{*2}			0.690E-06 (2.68)*
μ		2.72 (1.47)	
Number of observations	80	80	80
R^2	0.504	0.522	0.524
Std. error of regression	0.021	0,021	0.020
F stat for all $\alpha^j = \alpha$	1.766*	1.458	1.697**

*Test statistic is significant at the 5% significance level. The t-statistics are heteroskedastic-consistent

** Test statistic is significant at the 10% significance level.

6.4 Differential Spillover Effects

In this section we analyse whether the capability to generate spillovers differs between the G7 countries. If two countries possess similar amounts of stocks of knowledge and similar trading patterns with a third country, we will inquire whether the two countries would generate the similar amount of spillovers in the third country. If there are discernible differences among the G7 countries in their capabilities in generating spillovers, the conclusions we draw in the Aggregate Model will have to be reinterpreted carefully. For instance, in the Aggregate Model, we find that it is beneficial for a developing country to trade with those G7 countries with a relatively larger stock of knowledge. However, if the G7 countries will have different spillover structures, this notion might have to be re-evaluated. It might be possible for a G7 country with a relatively smaller stock of

knowledge to generate larger spillover effects, which may give rise to a superior spillover structure than a country with a larger stock of knowledge.

For the purpose of this inquiry we construct knowledge stocks for each G7 country. For example, the available knowledge stock to the developing country j from the G7 country g is

$$X_g^{*2j} = \mu w_g Y_g^* ,$$

where the weight, w_g , is j 's bilateral import share from country g , and μ represents an openness index for j . The results are reported in the last column of Table A.12. The results are not encouraging since only Japan seems to create statistically significant spillovers, while the United States display a negative spillover effect consistently.

In another variation of the experiment, we investigate whether the results will improve if the developing country sample is divided into regional groupings: Asia and Latin America. This was thought to give a better representation of the current trading relations. For example, Latin American countries predominantly trade with the United States while Asian countries engage in more trade with Japan. The results for Asian and Latin American samples are reported in Table A.12 and there is no significant improvement in the results.

Table A.12: Spillover Differences Between G7: with Bilateral Imports As Weights
(t-statistic in parentheses).

Dependent variable: Growth rate of TFP

Variable	Asia = X ²	L. America =X ²	Total Sample =X ²
Canada	0.181E-03 (1.13)	-7.895E-05 (-0.40)	7.341E-05 (0.67)
France	-3.80E-05 (-0.55)	4.040E-05 (0.63)	-3.272E-05 (-0.83)
Germany	-1.281E-05 (-0.62)	4.794E-06 (0.12)	1.757E-05 (1.02)
Italy	5.327E-05 (1.86)	-0.146E-03 (-2.60)	-2.539E-05 (-0.82)
Japan	9.073E-07 (0.85)	3.507E-07 (0.18)	1.712E-06 (2.63)*
UK	8.149E-06 (0.96)	1.9571E-04 (1.32)	1.035E-05 (1.35)
USA	-6.955E-07 (-0.52)	5.137E-08 (0.040)	-1.368E-06 (-1.94)*
Number of observations	36	44	80
R ²	0.404	0.445	0.32
Std. error of regression	0.022	0.022	0.022

* test statistic is significant at 5% significance level. The t-statistics are heteroskedastic-consistent.

** test statistic is significant at 10% significance level.

We find that there is a serious multicollinearity problem among the knowledge stocks of the G-7 countries, particularly prevalent among the European countries (Table A.13). This may have affected the results of the analysis. We do not intend to pursue this line of thought further, though the issues is of some interest.

Table A.13: Correlation Coefficients Matrix - X_t

	<i>Canada</i>	<i>France</i>	<i>Germany</i>	<i>Italy</i>	<i>Japan</i>	<i>UK</i>	<i>USA</i>
<i>Canada</i>	1						
<i>France</i>	0.77348	1					
<i>Germany</i>	0.72443	0.94414	1				
<i>Italy</i>	0.65611	0.86737	0.86902	1			
<i>Japan</i>	0.64137	0.59488	0.59238	0.49726	1		
<i>UK</i>	0.66377	0.85839	0.8392	0.80315	0.50258	1	
<i>USA</i>	0.73866	0.75876	0.75487	0.63634	0.80266	0.66796	1

Appendix 2: Data

1 National Spillovers

A sample of 20 developing countries has been used in the empirical analysis of this study. The selection is based on the availability and quality of data, particularly regarding sectoral-level manufacturing data. Summers and Heston (1989) categorize the 139 countries in their database according to the quality of each country's data. The 44 developing countries that receive a C- grade or better are initially considered in our research. Since our study is based on the industry-level data that are known to have relatively high variability in quality, the selection of the best countries becomes particularly important. From the 44 countries, only 20 countries have got adequate, annual, time-series data for manufacturing output at 3-digit ISIC level (International Standard Industry Classification) and international trade data at 2-digit SITC levels (Standard International Trade Code) for the period 1970-90. Thus, our sample consists of 20 countries. They are Argentina, Bolivia, Chile, Colombia, Ecuador, El Salvador, Guatemala, Hong Kong, India, Indonesia, Israel, South Korea, Malaysia, Mexico, Panama, Peru, Philippines, Singapore, Turkey, and Venezuela.

Several countries in the sample do not have a complete set of data for the period of 1970-90. A complete listing of data availability for industry-level output data is reported in Table B1. The values for missing years are constructed by using a simple straight-line interpolation. Since, data is arranged using non-overlapping, five-year averages for the periods 1971-75, 1976-80, 1980-85, and 1986-90, the problems arising from incomplete

Table B.1: Availability of industry data at three-digit ISIC level

Country	Periods for which data are available	Country	Periods for which data are available
Argentina	1971-1990	Israel	1970-79, 1983-92
Bolivia	1970-1990	South Korea	1970-91
Chile	1970-1986, 1989-1991	Malaysia	1970-74, 1976-79, 1981-91
Colombia	1970-1991	Mexico	1970-92
Ecuador	1970-1989	Panama	1970-79, 1981-85, 1987-89
El Salvador	1970-1985	Peru	1970-88
Guatemala	1971-72, 1974-75, 1977-89	Philippines	1970-77, 1979-89
Hong Kong	1973-74, 1976-91	Singapore	1970-92
India	1970, 1973-90	Turkey	1970, 1972-91
Indonesia	1970-73, 1975-89	Venezuela	1970-79, 1981-92

data is mitigated to a great extent. Industry-level manufacturing data at the three-digit ISIC level are obtained from several issues of UNIDO's *International Yearbook of Industrial Statistics*. There are 28 industry categories at this level of aggregation (see List 1). We divide these industries into two categories based on the skill-intensity of the industry as high-skill- and low-skill-intensive sectors (Table B2). This sectoral classification conforms with UNIDO (1981) guidelines and discussions we have had with Industry Canada staff on this issue.

Table B.2: Division of industries into high-skill and low-skill-intensive sectors

Sector	ISIC
High-skill-intensive manufacturing	342, 351, 352, 353, 354, 355, 356, 369, 371, 372, 381, 382, 383, 384, 385, 390
Low-skill-intensive manufacturing	311, 313, 314, 3321, 322, 323, 324, 331, 332, 341, 361, 362

Note that UNIDO only reports the data for manufacturing industries. As a result, this source is used to calculate the share of each sector i in total manufacturing, i.e., Y_i/Y_{mf} where Y_{mf} refers to the total output of manufacturing activities. However, for this study we require each sector's share in the total output of the country, i.e., Y_i/Y . Fortunately, the United Nations' National Accounts Statistics-Main Aggregates and Detailed Tables provide the share of manufacturing activities in the total output, i.e., Y_{mf}/Y . This is combined with the UNIDO data to calculate the sectoral shares in the total output. So that,

$$\frac{Y_i}{Y} = \frac{Y_i}{Y_{mf}} \frac{Y_{mf}}{Y}$$

As for the non-manufacturing share of the output, Y_{nm}/Y , this is taken from the UN National Accounts Statistics. The shares of high-skill- and low-skill-intensive manufacturing sectors, for the first and last sample periods, are illustrated in Table B3. Note

Table B.3: Evolution of Sectoral Composition between 1971-75 and 1986-90

Country	Share of high-skill-intensive sector		Share of low-skill-intensive sector	
	1971 - 1975	1986-1990	1971 - 1975	1986-1990
Argentina	14.1%	14.2%	15.8%	13.5%
Bolivia	1.9%	6.2%	11.8%	8.8%
Chile	7.7%	5.3%	16.3%	13.4%
Colombia	6.7%	8.2%	13.7%	12.8%
Ecuador	4.1%	7.3%	12.5%	13.3%
El Salvador	5.1%	7.5%	15.2%	10.0%
Guatemala	4.6%	5.0%	11.1%	10.5%
Hong Kong	10.2%	9.3%	16.6%	9.8%
India	6.1%	8.9%	8.9%	9.3%
Indonesia	2.1%	6.1%	6.9%	12.0%
Israel	10.7%	11.6%	11.4%	10.0%
Korea	9.4%	17.6%	15.0%	13.6%
Malaysia	7.2%	12.7%	8.9%	11.0%
Mexico	7.4%	12.2%	16.2%	12.4%
Panama	6.0%	2.4%	9.3%	5.2%
Peru	9.7%	10.6%	15.8%	15.1%
Philippines	8.8%	9.9%	15.4%	15.2%
Singapore	16.9%	22.0%	6.3%	4.5%
Turkey	7.5%	10.4%	11.9%	12.0%
Venezuela	7.8%	9.7%	8.6%	11.5%

Source: UNIDO's International Yearbook of Industrial Statistics (several years) and United Nations' National Accounts Statistics-Main Aggregates and Detailed Tables

that fast growing newly-industrialized countries like South Korea, Malaysia, Mexico, and Singapore have seen tremendous increases over time in the shares of their high-skill-intensive sectors. The only fast growing country that has not seen a substantial increase in the high-skill-intensive share is Hong Kong. Due to its special city-state nature it may not exhibit the general trends observed for the group. On the other hand, countries like India, Argentina, and several other Latin American countries have seen relatively smaller increases in the share of the high-

skill sector's production over time. Most of the countries in this group have deliberately pursued inward-oriented development strategies well in to the 1970s and 1980s, and, as a result, may not have created an incentive structure to encourage high-skill-intensive activities (Kruger 1980; Chenery, Robinson, and Syrquin 1986). In the cases of India, Argentina, Chile, Columbia, Guatemala, and Peru the production structure has not experienced much change. It is also interesting to note that South Korea, the Philippines and Peru had similar output shares in the high-skill sectors in early 1970s; and later on, only South Korea has managed to substantially increase its share of high-skill-intensive activities, and emerge as a fast growing newly industrialized country. Both the Philippines and Peru experienced a slower evolution of their production mix, as well as relatively slower growth performance than compared to South Korea.

1.2 Total Factor Productivity Growth

The dependent variable of the learning-by-doing model is the rate of growth of total factor productivity. TFP growth for the aggregate economy is, $\dot{A}/A = \dot{Y}/Y - \sum_i Y_i/Y (\dot{F}_i/F_i)$, where $\dot{F}_i/F_i$ represents the contribution of capital and labour inputs to sector i 's productivity growth. Since, sectoral-level input data for labour and capital are not available for several countries in the sample, we use aggregate measures of capital and labour instead, by replacing $\sum_i (Y_i/Y) \dot{F}_i/F_i$ with $\dot{F}/F$, where $F = \sum_i F_i$. Since,

$$\frac{\dot{F}}{F} = \sum_i \frac{F_i}{F} \frac{\dot{F}_i}{F_i},$$

it is different from $\sum_i (Y_i/Y) \dot{F}_i/F_i$ because the weights used to measure the sectoral input growth are different. Note, also, that $\dot{Y}/Y = (\dot{A}/A) (\dot{F}/F)$, and the difference between the two measures is that the weight we use excludes the sectoral share of productivity, $\dot{A}/A$. Consequently, in the empirical work that follows, we calculate the rate of TFP growth as $\dot{A}/A = \dot{Y}/Y - \dot{F}/F$.

In order to construct the $\dot{F}/F$ series, following BKK, we assume Cobb-Douglas production technology. Following Fischer (1993), the share of capital in output is taken as 40%, since it is commonly estimated in the case of developing countries (also in Islam, 1995).¹¹ The rate of growth of TFP for country j is, thus, estimated as

$$\dot{TFP}^j / TFP^j = \dot{Y}^j / Y^j - 0.4(\dot{K}^j / K^j) - 0.6(\dot{L}^j / L^j)$$

The data are obtained from the World Bank's World Tables and East Asian Miracle Database, and Summers and Heston data set (Penn World Table (Mark 5.6) data set). The

¹¹We are considering a production function that is based on two-inputs: capital and labour. As such, we have not differentiated between physical and human capital. One could wonder whether the series of TFP growth rates constructed may be affected by this omission. Fischer (1993) specifically deals with this issue. Following Mankiw, Romer, and Weil (1992) he incorporates human capital into the production function, in addition to physical capital and labour. The TFP growth series is then constructed by imposing coefficients used in the Mankiw *et al* paper as follows:

$$\dot{TFP}^j / TFP^j = \dot{Y}^j / Y^j - \frac{1}{3}(\dot{K}^j / K^j) - \frac{1}{3}(\dot{L}^j / L^j) - \frac{1}{3}(\dot{HK}^j / HK^j),$$

where HK represents the human capital stock. He uses data for 68 countries for the period 1961-88 to calculate the TFP growth series. This series is then compared to the TFP growth series calculated by using only capital and labour data (the shares of capital and labour in total output are taken as 40% and 60%, respectively). The two series are highly correlated with a pairwise R^2 value exceeding 0.98. As a result, Fischer chooses to use the TFP growth series calculated using capital and labour data. We follow Fischer's approach in our research.

series of annual TFP growth rates constructed in this manner is illustrated in the Charts 1 and 2 for a few representative countries in the sample. Observe the volatility of annual data series: no discernible trend can be identified across countries, though the volatility of TFP growth seem to be relatively higher among Latin American countries when compared to Asian countries. However, the volatility in the annual time series makes our decision to use 5-year averages justifiable. Furthermore, it is more appropriate to use data for longer time intervals since we are interested in long-run relationships that would require a TFP growth measure that may average out the cyclical changes observed in the annual data series.

Chart 1: Trends in TFP Growth

Source: World Bank's World Tables (several years), East Asian Miracle Database (World Bank) (several years), and Summers and Heston data set

2 International Spillovers

The second part of our research deals with foreign-stock of knowledge and the impact of the international spillovers on TFP growth. Two types of data sources are primarily used to construct the series of sectoral international knowledge indexes: sectoral output data for the G-7 countries (Canada, France, Germany, Italy, Japan, United Kingdom, and United States); and bilateral trade data of the countries in the sample and their G-7 trading partners.

2.1 Sectoral Output for G-7

We consider only the output of the G-7 countries to measure the foreign output Y_g^* and Y_{ig}^* in the Aggregate and Sectoral Models, respectively. Consequently, the knowledge generated in the non-G-7 countries has not been taken into account. However, this omission is likely not be significant, since most of the knowledge activities take place in the G-7 countries. For example, with regard to knowledge generated through R&D activities, G-7 countries alone accounted for about 92% of total world R&D expenditure in 1990, whereas other OECD countries and developing countries accounted for 4% each (UNESCO 1993). Furthermore, since the G-7 accounted for approximately 65% of world output in 1990 (World Bank 1993), and given that the cumulative output is the source of learning-by-doing spillovers, we can safely assume that the majority of knowledge through learning-by-doing is also generated in these countries. There is another reason why the omission of the spillovers from the non-G-7 countries may not affect our results significantly. Much of trade of the developing countries in the sample--an important channel for spillovers-- takes

place with the G-7 countries, indicating that the majority of international spillover benefits to these developing countries accrue through their dealings with the G-7 countries.

The G-7 sectoral output data are obtained from the OECD's STAN database for 1970-92 at the three-digit ISIC levels. The real industrial output was then calculated by using industrial price indexes, with the base period set in 1985. The data series are also converted into US dollars with the conversion rates given in IMF's publication *International Financial Statistics*. As explained above with regard to national spillover research, we broadly divide the output, recorded at three-digit level industries, into three sectors: high-skill-intensive manufacturing, low-skill-intensive manufacturing, and non-manufacturing sectors. The sectoral classification follows the same groupings for domestic output used in the first part of our study.

2.2 International Trade Data

The second type of data required to construct the foreign stock of knowledge is bilateral trade data. For the sample countries and the G-7 trading partners, trade data are obtained from Statistics Canada's World Trade Data Base (WTDB). The trade data is aggregated at the two-digit SITC level, with 68 commodity categories at this level of aggregation. Our subsequent sectoral classification of the data into high-skill-, low-skill-intensive, and non-manufacturing follow guidelines suggested by UNIDO (1981). With regard to identifying commodities in the non-manufacturing sector, we follow the common practice of categorizing those commodity groups that fall within 0 to 5 of the one-digit SITC, and 63, 64 and 68 of the two-digit SITC as non-manufacturing. The division of two-

digit commodity categories into three broad sectors is given in Table B4 (definitions of commodity categories appear in List 2):

Table B.4: Sectoral division of trade data

Sector	SITC
High-skill-intensive manufacturing:	69,71,72,73, 75, 76, 77, 87, 88, 51, 52, 53, 54, 55, 56, 59, 74, 78, 79
Low-skill-intensive manufacturing:	58, 62, 67, 66, 61, 65, 81, 82, 83, 84, 85, 89
Non-manufacturing:	00,01, 02, 03, 04,05, 06, 07, 08, 09, 11, 12, 21, 22, 23, 24, 25, 26, 27, 28, 29, 32, 33, 34, 35, 41, 42, 43, 63, 64, 68
Residual:	93, 94, 95, 97, and 9X

Note that the UNIDO (1981) guidelines on skill-intensity of sectors are based on the two-digit SITC levels that account for 68 product categories. Whereas, at the three-digit ISIC level there are only 28 industries. Concordance between the two standards was established and used to produce the final list. This exercise facilitates compatibility between the industry data and the international trade data.

2.3 Foreign Knowledge Stock

The available foreign knowledge stock for each sector is computed as the weighted average of each G-7 country output. We use three alternative weights: bilateral import, export, and trade shares. For example, when imports are used as the weight, the foreign stock of knowledge in sector i , X_i^* , becomes

$$X_i^* = \sum_g \frac{M_{ig}}{M} Y_{ig}^*,$$

where M represents the total imports from G-7 and M_{ig} the imports from sector i of the G-7 country, g . Y_{ig}^* stands for sector i 's output in country, g . For comparison purposes, Charts 3 and 4 illustrate the available foreign-knowledge stock for a few representative developing countries in the sample, for high-skill- and low-skill-intensive manufacturing sectors. Table B5 illustrates the evolution in foreign-knowledge stock for high-skill-intensive sectors for all countries in the sample.

Table B5: Evolution of Foreign Knowledge Stock: High-Skill Sector (in US\$ billion)

	1971-75	1986-90
Argentina	376.14	770.19
Bolivia	422.55	812.69
Chile	475.18	835.10
Ecuador	416.55	771.05
El Salvador	415.09	749.29
Guatemala	438.49	643.28
Hong Kong	233.01	711.04
Israel	338.86	532.11
Mexico	289.75	858.65
Panama	359.23	1208.99
Peru	395.55	677.43
Philippines	383.42	790.34
Singapore	347.29	962.88
Venezuela	326.70	819.15

For the high-skill sector, a positive trend can be observed in the foreign-knowledge stock over time. The highest gains over time are evident in Hong Kong and Panama, where the high-skill knowledge stocks have increased four-folds. Singapore, South Korea, and

Malaysia have experienced increases of more than three-folds over the same period. On the other hand, lowest gains in terms of foreign knowledge stocks in high-skill sectors have been reported by Turkey, India, Guatemala, and El Salvador. The fact that is clearly emerging, when the trends are carefully observed, is that all the Newly Industrialized Countries (NICs) have experienced significant gains in foreign knowledge in the high-skill-intensive sectors. Whereas, countries like India, Turkey, Guatemala, Bolivia, and Peru have reported relatively lower gains. The main reason is that while most of the latter group of countries have had largely closed economies, the former group pursued more openness to trade, and consequently had access to ideas and knowledge generated in foreign countries. It is also interesting to notice that India, Indonesia, Malaysia, and Mexico all reported similar stocks of foreign knowledge in early 1970s, but diverged sharply in the ensuing period. Note that Hong Kong's foreign knowledge stock at the initial period is much less than the above mentioned countries.

Chart 4 illustrates, for the same countries in Chart 3, the trends in available stock of knowledge in low-skill-intensive sectors. Unlike in the high-skill sectors there are no discernible trends in the evolution of the stock of knowledge. A few countries, Guatemala, South Korea, and Philippines, have experienced a doubling of foreign knowledge in this sector, when the first and last periods are compared, but by no means do they amount to a consistent pattern. Meanwhile, in Argentina, Bolivia, Ecuador, and Hong Kong, the stock of knowledge largely remained constant between the two periods.

**Chart 3: Trends in Available Foreign
High-Skilled Knowledge Stock**

Source: OECD STAN Database (several years), World Trade Database (several years), IMF International Financial Statistics (several years)

**Chart 4: Trends in Available Foreign
Low-Skilled Knowledge Stock**

Source: OECD STAN Database (several years), World Trade Database (several years), IMF International Financial Statistics (several years)

List 1: Industry Classification at three-digit ISIC Level

ISIC	Industry	ISIC	Industry
311	Food Products	354	Petroleum, Coal Products
313	Beverages	355	Rubber Products
314	Tobacco	356	Plastic Products n.e.c.
321	Textiles	361	Pottery, China, etc
322	Wearing Apparel	362	Glass & Products
323	Leather & Products	369	Non-Metal Products n.e.c.
324	Footwear	371	Iron & Steel
331	Wood Products	372	Non-ferrous Metals
332	Furniture & Fixtures	381	Metal Products
341	Paper & Products	382	Machinery n.e.c.
342	Printing, Publishing	383	Electrical Machinery
351	Industrial Chemicals	384	Transport Equipment
352	Other Chemical Products	385	Professional Goods
353	Petroleum Refineries	390	Other Industries

List 2: Description of SITC coding at two-digit level (Revision IV)

SITC	Description	SITC	Description	SITC	Description
01	Meat & Meat Preparations	34	Gas, Natural & Manufac.	72	Machinery Specialized
02	Dairy Products & Birds Eggs	41	Animal Oils & Fats	73	Metal Working Machinery
03	Fish, Crustaceans, Molluscs	42	Fixed Vegetable Oils & Fats	74	General Indust. Mach. & Equip. & Parts
04	Cereals & Preparations	43	Animal Vegetable Oils, Fats, Waxes	75	Office Mach. & Auto. Data Proc. Equip.
05	Vegetables & Fruit	51	Organic Chemicals	76	Telecom. & Sound Recording App.
06	Sugar, Preparations & Honey	52	Inorganic Chemicals	77	Elec. Mach., App. & Appliances
07	Coffee, Tea, Cocoa, Spices	53	Dyeing, Tanning & Colouring Materials	78	Road Vehicles
08	Feeding Stuff for Animals	54	Medicinal & Pharm. Prods	79	Other Transport Equip.
09	Misc. Edible Products	55	Essential Oils & Perfume	81	Sanitary Plumbing, Heat. & Light. Fix.
11	Beverages	56	Fertilizers, Manufactured	82	Furniture & Parts
12	Tobacco & Manufactures	58	Artif. Resins, Plastic Mat.	83	Travel Goods, Hand Bags Etc.
21	Hides, Skins & Fur Skins, Raw	59	Chemical Materials & Prod.	84	Apparel & Clothing Access.
22	Oil Seeds & Oleaginous Fruit	61	Leather, Leather Manuf.	85	Footwear
23	Crude Rubber	62	Rubber, Manufactures	87	Prof., Scientific & Control. Instruments
24	Cork & Wood	63	Cork & Wood Manufactures	88	Photog. App., Optical Goods, Watches
25	Pulp & Waste Paper	64	Paper, Paper Board, Paper Pulp	89	Misc. Manufactured Articles
26	Textile Fibres & Their Wastes	65	Textile Yarn, Fabrics,	93	Special Transactions & Commodities
27	Crude Fertilizers	66	Non-metallic Mineral Manuf.	94	Animals, Live
28	Metalliferous Ores & Metal Scrap	67	Iron & Steel	95	Armoured Vehicles, Arms. & Ammunition
29	Crude Animal & Vegetable Mat.	68	Non-ferrous Metals	97	Gold, Non-monetary
32	Anthracite / Peat	69	Manufactures of Metal		
33	Petroleum, Petrol Products & Related	71	Power Generating Machinery & Equip		

Bibliography

- Aghion, P. and Howitt, P. (1992). "A Model of Growth Through Creative Destruction," *Econometrica* 60, 323-51
- Amemiya, T. (1971). "The Estimation of the Variances in a Variance-Component Model," *International Economic Review* 12, 1-13
- Argote, L. and Epple, D. (1990). "Learning Curves in Manufacturing," *Science* 247, 920-24
- Arrow, K.J. (1961). "The Economic Implications of Learning-by-doing," *Review of Economic Studies* 29, 155-73
- Backus, D., Kehoe, P., & Kehoe, T. (1992). "In Search of Scale Effects in Trade and Growth," *Journal of Economic Theory* 58, 377-409
- Balassa, Bela (1978). "Exports and Economic Growth: Further Evidence," *Journal of Development Economics* 5 (2) June, 181-89
- Baldwin, Richard E. & Krugman, Paul R. (1988). "Market Access and International Competition: A Simulation Study of 16K Random Access Memories." In Robert C. Feenstra, ed. *Empirical Methods for International Trade*, Cambridge, MA: MIT Press
- Baltagi, Badi H. & Griffin, J. M., (1983). "Gasoline Demand in the OECD. An Application of Pooling and Testing Procedures," *European Economic Review* 22, 117-37
- Baltagi, Badi H. (1995). *Econometric Analysis of Panel Data*. New York: John Wiley & Sons, Inc.
- Barro, R. (1991). "Economic Growth in a Cross Section of Countries," *Quarterly Journal of Economics* 106 (2), 407-43

- 1997. **Determinants Of Economic Growth: A Cross-countries Empirical Study.** Cambridge, MA: MIT Press
- Barro, R. & Sala-i-Martin, X. (1995). **Economic Growth.** New York: McGraw-Hill, Inc.
- Bayoumi, Tamin, Coe, David T., & Helpman, H. (1999). "R&D Spillovers and Global Growth," *Journal of International Economics* 47 (2) April, 399-428
- Bende-Nabende, Anthony (1999). **FDI, Regionalism, Government Policy and Endogenous Growth: A Comparative Study of the ASEAN-5 Economies, with Development Policy Implications for the Least Developed Countries.** Aldershot, U.K.
- Bernstein, Jeffery (1994) **International R&D Spillovers Between Industries in Canada and the United States.** Working Paper No. 3. Ottawa: Industry Canada
- (1998) **Inter-Industry and U.S. R&D Spillovers, Canadian Industrial Production and Productivity Growth.** Working Paper No. 19. Ottawa: Industry Canada
- Bernstein, Jeffery & Mohnen, Pierre (1994) **International R&D Spillovers Between U.S. and Japanese R&D Intensive Sectors.** Working Paper No. 4682. Cambridge, MA: National Bureau of Economic Research
- Bernstein, Jeffery & Yan, Xiaoyi (1995) **International R&D Spillovers Between Canadian and Japanese Industries.** Working Paper No. 5401 Cambridge, MA: National Bureau of Economic Research
- Bhagwati, Jagdish N. & Srinivasan, T.N. (1978) "Trade Policy and Development," In Rudger Dornbusch & Jacob A. Frenkel, eds. **International Economic Policy: Theory and Evidence.** Baltimore, MD: Johns Hopkins University Press
- Boldrin, Michele & Scheinkman, Jose A. (1988). "Learning-by-Doing, International Trade and Growth: A Note." In Santa Fe Institute Studies in the Sciences of Complexity, **The Economy as an Evolving Complex System, 285-300**

- Brecher, Richard A., Choudhri, Ehsan U., & Schembri, Lawrence L. (1996) "International spillovers of knowledge and sectoral productivity growth: some evidence for Canada and the United States," *Journal of International Economics*, 40 299-311
- Breusch, T. S. & Pagan, A.R. (1980). "The Lagrange Multiplier Test and Its Applications to Model Specification in Econometrics," *Review of Economic Studies* 47, 239-53
- Cardellichio, P. A. (1990). "Estimation of Production Behaviour Using Pooled Micro data," *Review of Economics and Statistics* 72, 11-18
- Chenery, H., Robinson, S., & Syrquin, M. (1986). *Industrialization and Growth: A Comparative Study*. New York: Oxford University Press,
- Chuang, Yih-Chyi (1998). "Learning by Doing, the Technology Gap, and Growth," *International Economic Review* 39 (3) August, 697-721
- Coe, David T. & Helpman, H. (1993). "International R&D Spillovers" NBER Working Paper No. 4444, August
- Coe, David T., Helpman, H., & Hoffmaister, Alexander W. (1995). "North-South R&D Spillovers," Working Paper No. 5048, NBER, Cambridge, MA
- Cox, D. (1961). "Tests of Separate Families of Hypothesis," In *Proceedings of the 4th Berkeley Symposium on Mathematical Statistics and Probability*. Berkeley: University of California Press,
- (1962). "Further Results on Tests of Separate Families of Hypothesis," *Journal of the Royal Statistical Society, Series B* 24, 406-24
- Davidson, R. & MacKinnon, J. (1981). "Several Tests for Model Specification in the Presence of Alternative Hypothesis," *Econometrica* 49, 781-93

- Denison, Edward F. (1967). *Why Growth Rates Differ*. Washington D.C.: The Brookings Institution
- Dinopoulos, Elias & Thompson, Peter (2000). "Endogenous Growth in a Cross-Section of Countries," *Journal of International Economics* 51, 317-34
- Fagerberg, Jan (1994). "Technology and International Differences in Growth Rates," *Journal of Economic Literature* 32, September, 1147-75
- Feder, G. (1983). "On Export and Economic Growth," *Journal of Development Economics* 12, (February/April)
- Fischer, Stanley (1993). "The Role of Macroeconomics Factors on Growth," *Journal of Monetary Economics* 32, 485-512
- Ghemawat, P. (1985). "Building Strategy on the Experience Curve" *Harvard Business Review*. 63, 143-49
- Griffin, Keith & Khan, Azizur K. (1992). *Globalization and the Developing World*. Geneva: UNRISD
- Grossman, Gene M. & Helpman, Elhanan (1991). *Innovation and Growth in the Global Economy*. Cambridge, MA: MIT Press
- Gruber, Harald (1998). "Learning by Doing and Spillovers: Further Evidence for the Semiconductor Industry," *Review of Industrial Organization* 13 (6) 697-711
- Gustavsson, Patrick, Hanson, Par, & Lundberg, Lars (1999). "Technology, Resource Endowments, and International Competitiveness," *European Economic Review* Volume 43 (8) August, 1501-30
- Hannah, Leslie (1999). Marshall's "Trees" and the Global "Forest": Were "Giant Redwoods" Different? In *Learning by doing in markets, firms, and countries*. Eds. Lamoreaux,

- N.R., Raff, D.M.G., and Temin, P. Conference report (National Bureau of Economic Research). Chicago, Ill., University of Chicago Press
- Hausman, J. A. (1978). "Specification Tests in Econometrics," *Econometrica* 46, 1251-71
- Hejazi, Walid & Safarian, Edward A. (1996). "Trade Investment and United States R&D Spillovers," Working Paper. Toronto: Canadian Institute for Advanced Research
- Hsiao, C. (1986). Analysis of Panel Data. Cambridge, UK: Cambridge University Press
- Irwin, Douglas A. & Klenow, Peter J. (1994). "Learning-by-Doing in the Semiconductor Industry," *Journal of Political Economy* 102 (6), 1200-27
- International Monetary Fund (several issues). International Financial Statistics. Washington, D.C.: IMF
- Islam, Nurul (1995). "Growth Empirics: A Panel Data Approach," *Quarterly Journal of Economics*, 110 (4) November, 1127-70
- Jaffe, Adam B. (1986). "Technological Opportunity and Spillovers of R&D: Evidence From Firms' Patents, Profits, and Market Value," *American Economic Review* LXXVI (December) 984-1001
- Judge, G. G., Griffiths, W. E., Hill, R.C., Lutkepohl, H., & Lee, T. C. (1985). The Theory and Practice of Econometrics. New York: John Wiley & Sons
- Kmenta, J. (1986). Elements of Econometrics, New York: Macmillan
- Knight, Malcolm, Loayza, Norman, & Villanueva, Delano, (1993). "Testing the Neo-Classical Theory of Economic Growth: A Panel Data Approach," *IMF Staff Papers*, 40 (3) September
- Krueger, Anne O. (1980). "Trade Policy as an Input to Development," *American Economic Review*, 70 (2) May, 288-92

- Lamoreaux, Naomi R., Raff, Daniel M.G., & Temin, Peter (eds.) (1999). *Learning by Doing in Markets, Firms, and Countries*. NBER Conference Report Series. University of Chicago Press
- Lockwood, William W. (1954). *The Economic Development of Japan: Growth and Structural Change 1868-1938*. Princeton University Press
- Lucas, Robert E. (1988). "On the Mechanics of Development Planning," *Journal of Monetary Economics* 22 (1) July, 3-42
- (1993). "Making a miracle," *Econometric* 61 (2), 251-72
- Maddala, G. S. (1977). *Econometrics*. New York: McGraw-Hill
- Mankiw, N.G., Romer D., & Weil D. (1992). "A Contribution to the Empirics of Economic Growth," *Quarterly Journal of Economics* 107(2), 407-437
- Matsuyama, Kiminori (1992). "Agricultural Productivity, Comparative Advantage and Economic Growth," *Journal of Economic Theory* 58, 317-34
- Mishina, Kazuhiro (1999). *Learning by New Experiences: Revisiting the Flying Fortress Learning Curve*. In *Learning by doing in markets, firms, and countries*. Eds. Lamoreaux, N.R., Raff, D.M.G., and Temin, P.. Conference report (National Bureau of Economic Research). Chicago, Ill., University of Chicago Press
- Nehru, Vikram & Dhareshwar, Ashok (1994). "New Estimates of Total Factor Productivity Growth for Developing Countries," *Policy Research Working Paper 1313*, Washington D.C.: The World Bank
- OECD (several issues). *The OECD STAN Database for Industrial Analysis*. Paris, France: OECD
- OECD (several issues). *Main Science and Technology Indicators*. Paris, France: OECD

- Owusu-Gyapong, A. (1986). "Alternative Estimating Techniques for Panel Data on Strike Activity," *Review of Economics and Statistics* 68, 526-31
- Pack, Howard (1994). "Endogenous Growth Theory: Intellectual Appeal and Empirical Shortcomings," *The Journal of Economic Perspectives*, 8 (1) Winter, 55-72
- Reder, Melvin, & Neumann, George (1980). "Conflicts and Contracts: The Case of Strikes," *Journal of Political Economy* 88 October, 867-86
- Rhee, Yung Whee, Ross-Larson, Bruce, & Purcell, Garry (1984). *Korea's Competitive Edge: Managing the Entry into World Markets*. Baltimore: Johns Hopkins University Press for the World Bank
- Romer, Paul M. (1986). "Increasing Returns and Long Run Growth," *Journal of Political Economy* 94 (5) October, 1002-37
- (1987). "Growth Based on Increasing Returns Due to Specialization," *American Economic Review* 77 (2) May, 56-62
- (1989). "What Determines the Rate of Growth and Technological Change?," Working Papers, Macroeconomic Adjustment and Growth, Country Economics Department, WPS 279. Washington D.C.: The World Bank
- (1990a). "Endogenous Technological Change," *Journal of Political Economy* 98 (5) October, Part II, S71-S102
- (1990b). "Human Capital and Growth: Theory and Evidence," *Carnegie-Rochester Conf Ser. Public Pol.* 32 Spring, 251-86
- Rosenberg, Nathan (1982). *Inside the Black Box: Technology and Economics*. Cambridge, UK: Cambridge University Press

- Sheshinski, Eytan (1967). "Optimal Accumulation with Learning-by-doing." In Karl Shell, ed. *Essays on the Theory of Optimal Economic Growth*. Cambridge MA, MIT Press, 31-52
- Solow, Robert M. (1956). "A Contribution to the Theory of Economic Growth," *Quarterly Journal of Economics* 70 (1) February, 65-94
- (1957). "Technical Change and the Aggregate Production Function," *Review of Economics and Statistics* 39 (August), 312-20
- Statistics Canada (several years). *World Trade Database*. Ottawa: Statistics Canada
- Stokey, Nancy (1988). "Learning-by-doing and the Introduction of New Goods," *Journal of Political Economy* 96, 701-17
- Summers, R. & Heston, A. (1988). "A New Set of International Comparisons of Real Product and Price Levels: Estimates for 130 Countries, 1950-1985," *Rev. Income Wealth* 34, 1-25
- (1991). The Penn World Table (Mark 5): An empirical set of international comparisons, 1950-1988. *Quarterly Journal of Economics* 106 (2), 327-68
- Swamy, P.A., & Arora, S. S. (1972). "The Exact Finite Sample Properties of the Estimators of Coefficients in the Error Components Regression Models," *Econometrica* 40, 261-75
- Swan, Trevor W. (1956). "Economic Growth and Capital Accumulation," *Economic Record* 32 (November) 334-61
- Swidinsky, Robert, & Vanderkamp, John (1982). "A Micro-Econometric Analysis of Strike Activity in Canada," *Journal of Labor Research* 3 Fall, 455-71
- UNESCO (several years). *Statistical Yearbook*. Paris: UNESCO

- UNIDO (several years). International Yearbook of Industrial Statistics. Vienna: UNIDO
- UNIDO (1982). Changing Patterns of Trade In World Industry: An Empirical Study of Revealed Comparative Advantage. Vienna: United Nations Industrial Development Organization
- UNIDO (1981). World Industry in 1980: Regular issue of the biennial Industrial Development Survey. Vienna: United Nations Industrial Development Organization
- United Nations (several years). Year Book of International Trade Statistics. New York: United Nations,
- Wallace, T. D. & Hussain, A. (1969). "The use of Error Components Models in Combining Cross-Section and Time-Series Data," *Econometrica*, 37, 55-72
- World Bank (1987). World Development Report, 1987. New York: Oxford University Press
- (1993). World Tables 1992-93 Edition. World Bank, Washington, D.C.
- Wright, Gavin (1999). Can a Nation Learn? American Technology as a Network Phenomenon. In Learning by doing in markets, firms, and countries. Eds. Lamoreaux, N.R., Raff, D.M.G., and Termin, P. Conference report (National Bureau of Economic Research). Chicago, Ill., University of Chicago Press
- Wright, T.P. (1936). "Factors Affecting the Cost of Airplanes," *Journal of Aeronautical Science* 3, 122-28
- Young, Alwyn (1991). "Learning-by-doing and the Dynamic Effects of International Trade," *Quarterly Journal of Economics* 106, 369-405