

UNIVERSITY OF ZULULAND



TRADE, PRODUCTIVITY AND EFFICIENCY: TESTING FOR INNOVATIVE SPILLOVERS FROM ASIA'S NEWLY INDUSTRIALIZED COUNTRIES (NICS) ON MANUFACTURING IN SOUTH AFRICA

By

Brian Tavonga Mazorodze

(201640053)

Thesis

Submitted for the Degree of
Doctor of Philosophy (PhD)

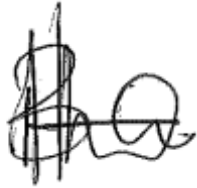
In

the Department of Economics
Faculty of Commerce, Administration and Law
University of Zululand

Supervisor: Professor D.D. Tewari

DECLARATION

I, **Brian Tavonga Mazorodze**, declare that this Doctoral thesis represents my original work, save for citations and referencing otherwise in the text. The thesis has not been submitted for the award of any degree at this or any other university.



Sign_____

Date_____

B.T. Mazorodze

CERTIFICATE OF APPROVAL

I declare that this thesis is from the student's own work and citations have been made where other sources of information have been used. The thesis is therefore submitted with my approval.

Sign _____ Date _____

Professor D.D Tewari

ACKNOWLEDGEMENTS

Firstly, I am indebted to the Almighty God for seeing me through the battles of life and guiding me up to this stage of an academic life. Secondly, my heartfelt appreciation goes to my family for their support throughout this long academic journey. Special thanks go to my brother Benson whom I prefer to call “Big Brother”. Thank you my brother for all the sacrifices you have made for me. I am thankful for your moral and financial support. As your young brother, I have little to offer in return but I can only pray that God fulfills all the desires of your heart. The study benefited from informative discussions with Professor Kulshrestha from Canada, Dr. Malachila from the International Monetary Fund and Dr. Chris Tipoy from the University of KwaZulu-Natal among many others. It comprises several chapters that have been accepted for publication in peer reviewed journals and presented at international conferences that include the Multidisciplinary Conference hosted by the University of London in Britain, the Management of Business and Legal Initiatives (MBALI) hosted by the University of Zululand and the UKZN research day. I am therefore grateful for the comments and suggestions that came out of these platforms, reviewers and participants.

I would also like to extend my gratitude to the entire Economics department at the University of Zululand. Special regards go to the head of department Professor Greyling, retired Professor Contogiannis for his comments on this work at the proposal stage and Professor Kaseeram for his priceless academic and administrative support. Often I tell my friends that universities are the same, the difference is that the university of Zululand has Professor Kaseeram. Thank you Prof. You played an important role during my stay here and I hope you will continue to do the same for other students. I would also like to appreciate the foundation I received from all my former lecturers at Midlands State University in Zimbabwe particularly Mr Charles Nyamutowa, Mr Nyasha Chipunza, Mrs Maparara and Mr Rushizha whose guidance remains an integral part of my academic career. As a Christian, I would also like to extend my gratitude to all men and women of God who have prayed for me and included me in their prayers such as Mr Isaac Mandinde and the late Mr Talksense among others.

I began my career in Zimbabwe and joined the University of Zululand for my Master’s in economics. My approach to research since then has been significantly improved by my supervisor and the former Dean of Faculty of Commerce, Administration and Law Professor Devi Datti Tewari. In our earlier meeting back in 2016, he said to me “Brian, as you will be writing your research, I want you to always remember that postgraduate research is about an idea.” I am very grateful for his piece of advice.

To Harris, Khayelihle, Sheu, Vhusi, Ruth, Minenhle, Dorcas and Makhoba, thank you very much. The same token of appreciation goes to my two brothers from another mother, Isaac Mutsau and Dr. Mavodyo. I am also grateful to the most important but often unmentioned group of professionals (the police service department) who work hard to ensure that our research is conducted at a campus that is safe and secure. Lastly, I would like to thank the University of Zululand for giving me the opportunity to conduct my postgraduate studies and funding my conference travel to the UK. Thank you UNIZULU, the university of choice.

DEDICATION

To my mother, Felistas.

TABLE OF CONTENTS

TITLE PAGE	i
DECLARATION.....	ii
CERTIFICATE OF APPROVAL	iii
ACKNOWLEDGEMENTS	iv
DEDICATION.....	v
CHAPTER 1.....	1
INTRODUCTION.....	1
1.1 BACKGROUND AND PROBLEM STATEMENT	1
1.2 RESEARCH QUESTIONS.....	5
1.3 OBJECTIVES	5
1.4 NEED FOR THE STUDY	6
1.5 CONTRIBUTION OF THE STUDY	7
1.6 DEFINITION OF KEY TERMS	9
1.7 OUTLINE OF THE STUDY	10
CHAPTER 2.....	11
THEORETICAL FRAMEWORK	11
2.1 THEORETICAL MODEL	11
2.2 APPLICATION OF THE MODEL.....	33
2.3 CONCLUDING REMARKS	20
CHAPTER 3.....	21
LITERATURE REVIEW	21
3.1 THEORETICAL LITERATURE.....	21
3.2 EMPIRICAL LITERATURE	26
3.3 CONCLUDING REMARKS	35
CHAPTER 4.....	37
IMPACT OF CHINESE, KOREAN AND JAPANESE INNOVATION SPILLOVERS ON TFP OF MANUFACTURING INDUSTRIES.....	37
4.1 BACKGROUND	37
4.2 METHODOLOGY.....	41
4.3 MEASURING INNOVATION SPILLOVERS.....	42
4.4 MEASURING TFP	43
4.5 THE MODEL	44

4.6 DATA DESCRIPTION.....	47
4.7 RESULTS AND DISCUSSION	48
4.8 CONCLUDING REMARKS	57
CHAPTER 5.....	58
CHINESE, KOREAN AND JAPANESE INNOVATION SPILL OVER EFFECT ON TFP OF SOUTH AFRICAN MANUFACTURING INDUSTRIES: A BAYESIAN ANALYSIS.....	58
5.1 BACKGROUND	58
5.2 LITERATURE REVIEW	59
5.3 METHODOLOGY.....	63
5.4 MEASURING TFP	63
5.5 INNOVATION SPILLOVERS	64
5.6 INNOVATION AND TFP GROWTH.....	64
5.7 DATA DESCRIPTION.....	67
5.8 RESULTS AND DISCUSSION	68
5.9 DIAGNOSTIC TESTS	74
5.10 CONCLUDING REMARKS	78
CHAPTER 6.....	80
THE IMPACT OF CHINESE, KOREAN AND JAPANESE INNOVATION SPILLOVERS ON MANUFACTURING LABOUR PRODUCTIVITY IN SOUTH AFRICA	80
6.1 BACKGROUND	80
6.2 LITERATURE REVIEW	82
6.3 MODEL SPECIFICATION.....	86
6.4 DATA DESCRIPTION.....	86
6.5 ESTIMATION PROCEDURE	87
6.6 RESULTS AND DISCUSSION	89
6.7 FURTHER ROBUSTNESS CHECKS	97
6.8 CONCLUDING REMARKS	99
CHAPTER 7	101
THE IMPACT OF CHINESE, KOREAN AND JAPANESE INNOVATION SPILLOVERS ON TECHNICAL EFFICIENCY OF MANUFACTURING INDUSTRIES IN SOUTH AFRICA	101
7.1 BACKGROUND	101
7.2 LITERATURE REVIEW	103
7.3 THE STOCHASTIC FRONTIER ANALYSIS.....	106
7.4 MODEL SPECIFICATION.....	110

7.5 DATA DESCRIPTION.....	113
7.6 RESULTS AND DISCUSSION	114
CHAPTER 8.....	121
THE IMPACT OF CHINESE, KOREAN AND JAPANESE INNOVATION SHOCKS ON MANUFACTURING LABOUR PRODUCTIVITY IN SOUTH AFRICA.....	121
8.1 BACKGROUND	121
8.2 LITERATURE REVIEW	123
8.3 RESEARCH METHODS	126
8.4 THE LOCAL PROJECTIONS METHOD	127
8.5 DATA DESCRIPTION.....	128
8.6 RESULTS AND DISCUSSION	128
8.7 CONCLUDING REMARKS	133
CHAPTER 9.....	134
SUMMARY, CONCLUSION AND POLICY RECOMMENDATIONS.....	134
9.1 SUMMARY	134
9.2 RESULTS AND DISCUSSION OF FINDINGS	137
9.3 POLICY IMPLICATIONS AND RECOMMENDATIONS.....	141
9.4 LIMITATIONS AND AREAS FOR FURTHER STUDY	143

ABSTRACT

This study primarily speaks to the current debate on technology transfer by testing whether Chinese, South Korean and Japanese service imports affect productivity and efficiency of South Africa's manufacturing industries through transferring innovation embodied in foreign services. This is a relatively underexplored area as previous literature on international technology transfer has given more attention on imports of physical goods.

In achieving the central aim of the analysis, the study makes several contributions to the body of knowledge. Firstly, it modifies and improves open economy endogenous growth theories by accommodating trade in services as a channel through which technology can be transferred across borders. Secondly and most importantly, it constructs a composite innovation spillover index that comprises several indicators of innovation namely R&D stock, researchers in R&D sector, trademarks and patent applications. Thirdly, it applies a Bayesian approach in one of the chapters (chapter five) which allows us to circumvent model uncertainty in the technology transfer model. Fourthly, unlike the majority of previous studies, it also focuses on technical efficiency as the outcome variable which allows us to establish not only whether Chinese, South Korean and Japanese innovation spillover pushes domestic technology frontier outwards but also how it influences the industries' movement towards the existing technology frontier. Fifthly and for the first time in literature, it examines the response of labour productivity to exogenous innovation shocks through impulse response functions derived from the local projections method.

Using the R&D stock measure and physical intermediate imports as the transmission mechanism, the study is able to first replicate the result obtained in previous studies that innovation spillovers from China, South Korea and Japan significantly influence productivity growth of manufacturing industries in South Africa and that the effect increases with institutional quality and human capital accumulation. In particular, Generalised Method of Moments (GMM) results in chapter four confirm that Chinese, South Korean and Japanese innovation spillovers raise total factor productivity of South Africa's manufacturing industries in the 0.003 – 0.012 per cent, 0.005 – 0.022 per cent and 0.0150 – 0.0151 per cent range respectively. When the study moves from the simple R&D stock measure and physical intermediate imports to a composite innovation measure and service imports as the transmission channel in chapter five based on a Bayesian analysis, the study reaches a different conclusion which is that China's imported innovation exerts a negative effect on total factor productivity of South African manufacturing industries in the -0.015 – 0.176 per cent range. For South Korea and Japan, the effect is plausible and positive in the 0.023 – 0.061 per cent and 0.132 – 0.141 per cent range respectively which is consistent with open economy endogenous growth theories.

Chapter six focuses on labour productivity in the entire manufacturing sector. Results based on the Autoregressive Distributed Lag (ARDL) model are similar to those reported in chapter five despite the use of different outcome variables (i.e. labour productivity and total factor productivity). It is confirmed that South Korean and Japanese innovation spillovers are positively associated with labour productivity and the results are robust to alternative estimators and the decomposition of the total

sample. For China, the result of a negative effect on productivity still emerges this time in the – 0.01 – 0.036 per cent range.

Chapter seven focuses on technical efficiency as the outcome variable and the results from a True-Fixed effects stochastic frontier model show that innovation spillovers from South Korea and Japan improve technical efficiency of manufacturing industries. South Korean spillovers have a larger effect (0.310 per cent) when compared with Japanese spillovers (0.129 per cent). Meanwhile, China still enters with a negative effect on technical efficiency which is akin to a positive effect on technical inefficiency.

With respect to the local projections method in chapter eight, it is empirically confirmed that productivity growth in South Africa's manufacturing sector increases with Japanese and South Korean exogenous technology spillover shocks particularly in long term horizons (above 6 quarters). For China, South Africa's productivity response is significantly negative.

At the outset, the study raises four arguments. Firstly, Chinese innovation reduces productivity growth adding to the on-going concerns of China's resource predatory presence in Africa. Secondly, innovation imported from the remaining countries particularly Japan and South Korea correlates positively with domestic productivity and the effect increases with human capital accumulation and the quality of institutions. Thirdly, despite observing a positive effect innovation from Japan and South Korea on domestic productivity, it is domestic innovation that enters with the most sizeable effect implying that foreign innovation should not substitute but rather complement domestic innovation efforts. Fourthly, trade in services plays an important role in transferring innovation across international boundaries.

As far as domestic industrial policy is concerned, the policy implication arising from this study is that service trade with Japan and South Korea is a relevant mechanism through which South Africa's manufacturing industries can make technological upgrades but that with China should be a source of concern and an important area that requires further research. Two possible explanations for China's negative effect are suggested. Firstly, China's services in Africa hardly employ domestic workers as they normally come with their own workforce. This means when Chinese services (or service providers) leave South Africa, none of their technology is left for the domestic manufacturing industries to utilise. Secondly, China has been recurrently accused of providing services in Africa at the expense of natural resource extraction. This implies that the technology effect of China might be outweighed by the resource extraction leading to an overall negative effect of Chinese presence.

For South Korea and Japan in which the technology spillover effect is positive, evidence suggest that the effect is smaller when compared to that of domestic innovation index implying that Japanese and South Korean imported innovation ought to be treated as a complement rather than a substitute of domestic innovation effort. Also confirmed is that the positive impact of imported innovation increases with human capital accumulation and institutional quality implying that domestic absorptive capacity plays a huge role in ensuring that South Africa is able to fully absorb technology coming from Japan and South Korea.

PUBLICATIONS FROM THE THESIS

- Mazorodze, B. T., and Tewari, D.D., 2018., Impact of Chinese, Korean and Japanese Innovation Spillovers on Labour Productivity in South African Manufacturing. *Journal of Economics and Behavioural Studies*, 10, pp 16 – 28.
- Mazorodze, B. T., and Tewari, D.D., 2018., The Relative effects of Domestic Innovation and Asian Innovation Spillovers on Total Factor Productivity of South Africa's Manufacturing Industries. *African Journal of Business and Economic Research*. Adonis & Abbey Publishers Ltd, 13, pp 51 – 69.
- Mazorodze, B. T., and Tewari, D.D., 2019., The Impact of Chinese, Japanese and Korea Innovation Spillovers on Total Factor Productivity of South Africa's Manufacturing Industries. A Bayesian Analysis. *Journal of Economics and Behavioural Studies*. Forthcoming.
- Mazorodze, B. T., and Tewari, D.D., 2019., The Impact of Chinese, Japanese and Korea Innovation Spillovers on Technical Efficiency of South Africa's Manufacturing Industries. *Journal of African Trade*. Forthcoming.

LIST OF TABLES

TABLE 3.1	TRADE, TECHNOLOGICAL SPILLOVERS AND PRODUCTIVITY GROWTH	34
TABLE 4.1	IM, PESARAN AND SHIN UNIT ROOT RESULTS	49
TABLE 4.2	LEVINSOHN AND PETRIN PRODUCTION RESULTS	49
TABLE 4.3	IM, PESARAN AND SHIN UNIT ROOT RESULTS	50
TABLE 4.4	PESARAN CROSS SECTIONAL DEPENDENCE TEST	50
TABLE 4.5	IMPACT OF CHINESE, KOREAN AND JAPANESE INNOVATION SPILLOVERS ON TFP – SYSTEM GMM ESTIMATES	51
TABLE 5.1	AVERAGE ANNUAL TFP GROWTH (2000 – 2015)	69
TABLE 5.2	IMPACT OF CHINESE, JAPANESE AND SOUTH KOREAN INNOVATION SPILLOVERS ON TFP: BAYESIAN RESULTS	72
TABLE 5.3	ESS SUMMARIES A	72
TABLE 5.4	ESS SUMMARIES B	73
TABLE 6.1	UNIT ROOT RESULTS	92
TABLE 6.2	BOUNDS TESTING F-TESTS FOR A LONG RUN RELATIONSHIP	92
TABLE 6.3	IMPACT OF INNOVATION SPILLOVERS ON LABOUR PRODUCTIVITY	94
TABLE 6.4	ARDL DIAGNOSTIC TESTS	97
TABLE 6.5	IMPACT OF INNOVATION SPILLOVERS ON LABOUR PRODUCTIVITY	98
TABLE 6.6	IMPACT OF INNOVATION SPILLOVERS ON LABOUR PRODUCTIVITY	99
TABLE 7.1	IMPACT OF INNOVATION SPILLOVERS ON TECHNICAL EFFICIENCY	116
TABLE 7.2	SUMMARY STATISTICS ON TECHNICAL EFFICIENCY	119
TABLE 8.1	VARIANCE OF DECOMPOSITION FOR LABOUR PRODUCTIVITY	132
TABLE 9.1	SUMMARY OF THE STUDY	135

LIST OF FIGURES

FIGURE 1.1	A COMPARISON OF INNOVATION INDICATORS IN SELECTED COUNTRIES	2
FIGURE 1.2	LAYOUT OF THE STUDY	10
FIGURE 2.1	A SCHEMATIC MODEL OF INNOVATION INDICATORS	18
FIGURE 4.1	FLOW DIAGRAM OF METHODOLOGICAL STEPS	42
FIGURE 5.1	A SCHEMATIC MODEL OF TECHNOLOGY TRANSFER THROUGH SERVICE TRADE	62
FIGURE 5.2	FLOW DIAGRAM OF METHODOLOGICAL STEPS	63
FIGURE 5.3	TFP INDICES FOR THE 16 INDUSTRIES (2000 – 2015)	70
FIGURE 5.4	BAYESIAN DIAGNOSTICS	75
FIGURE 6.1	COMPOSITE INNOVATION SPILLOVERS FROM CHINA, SOUTH KOREA AND JAPAN	91
FIGURE 6.2	AKAIKE INFORMATION CRITERION	93
FIGURE 6.3	CUSUM TEST FOR PARAMETER STABILITY	96
FIGURE 6.4	JARQUE BERA TEST FOR RESIDUAL NORMALITY	96
FIGURE 7.1	FLOW DIAGRAM OF EMPIRICAL ANALYSIS	109
FIGURE 7.2	TFE TECHNICAL EFFICIENCY OF MANUFACTURING INDUSTRIES	119
FIGURE 8.1	LOCAL PROJECTIONS IMPULSE RESPONSE FUNCTIONS WITH CONDITIONAL BANDS	131

LIST OF ABBREVIATIONS

ADF	AUGMENTED DICKEY FULLER
ANBERD	ANALYTICAL BUSINESS ENTERPRISE RESEARCH AND DEVELOPMENT
ARDL	AUTOREGRESSIVE DISTRIBUTED LAG MODEL
CCR	CANONICAL COINTEGRATING REGRESSION
DOLS	DYNAMIC ORDINARY LEAST SQUARES
FDI	FOREIGN DIRECT INVESTMENT
FMOLS	FULLY MODIFIED ORDINARY LEAST SQUARES
GDP	GROSS DOMESTIC PRODUCT
GMM	GENERALISED METHOD OF MOMENTS
ICT	INFORMATION AND COMMUNICATION TECHNOLOGIES
IDC	INDUSTRIAL DEVELOPMENT CORPORATION
OECD	ORGANISATION OF ECONOMIC, COOPERATION AND DEVELOPMENT
PCA	PRINCIPAL COMPONENT ANALYSIS
PIM	PERPETUAL INVENTORY METHOD
PP	PHILLIPS PERRON
PPP	PURCHASING POWER PARITY
R&D	RESEARCH AND DEVELOPMENT
SA	SOUTH AFRICA
SANS	SOUTH AFRICAN NATIONAL SURVEY
SYSGMM	SYSTEM GENERALIZED METHOD OF MOMENTS
TFP	TOTAL FACTOR PRODUCTIVITY
WDI	WORLD DEVELOPMENT INDICATORS

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND PROBLEM STATEMENT

Few issues are more topical in international economics than the transfer of technology across international boundaries since the ground-breaking work of Grossman and Helpman (1991). Economists generally share a common view that long-run productivity growth is sustained in countries that invest heavily in innovation as advocated by Romer (1989) but measuring it and determining how innovation transcends across international boundaries remains debatable.

The evidence presented so far both empirically and theoretically is inconclusive which makes it difficult to make policy inferences (see Mairesse., 1983, Griliches and Lichtenberg., 1984, Goto and Suzuki, 1989., Coe and Helpman., 1995., Verspagen., 1997, Los and Verspagen., 2000, Gong and Keller, 2003., Fischer *et al.*, 2006 and Griliches and Scherngell *et al.*, 2007 and more recently Nordin *et al.*, 2016, Ogawa *et al.*, 2016, Ertur and Musolesi, 2017., Kim and Park, 2017., Gioldasis *et al.*, 2018).

Empirically, there is a widespread notion that innovation is highly concentrated in rich countries¹ but can easily spread across the developing world through a variety of channels (Grossman and Helpman, 1991, Acemoglu *et al.*, 2006., and Wang and Wong, 2012). In other words, the fastest developing countries today, which are mostly in Asia (especially China and South Korea²) are arguably adopters of innovations discovered in the United States of America (USA) and other technologically better off parts of the world.

The central question is: how do developing countries adopt technology discovered in rich countries? Several channels have been suggested in the literature

¹ It is because they heavily invest in research and development.

² This is not to say, however, that China and South Korea's economic success is solely underpinned by technology imitation from the USA. There are other domestic policies that have played a huge role.

as relevant mechanisms of technology transfer and among them is international trade (Grossman and Helpman, 1991). The argument is that trade facilitates contact between domestic firms and foreign firms making it possible for the former to adopt and imitate innovation invented by the latter.

A key feature characterising global trade in recent years has been the dominance of Asian countries such as China and South Korea among others. This feature has two implications as far as the argument raised by Grossman and Helpman (1991) is concerned. Firstly, it implies that Asia is becoming better able to adopt technology from the rest of the world. Secondly, it implies that less economically developed countries such as South Africa and many other countries in Africa, can imitate some of the technologies discovered in Asia. The latter argument is plausible given that countries like China, Japan and South Korea are technologically better-off than South Africa³ as far as common technology indicators are concerned (Figure 1.1).

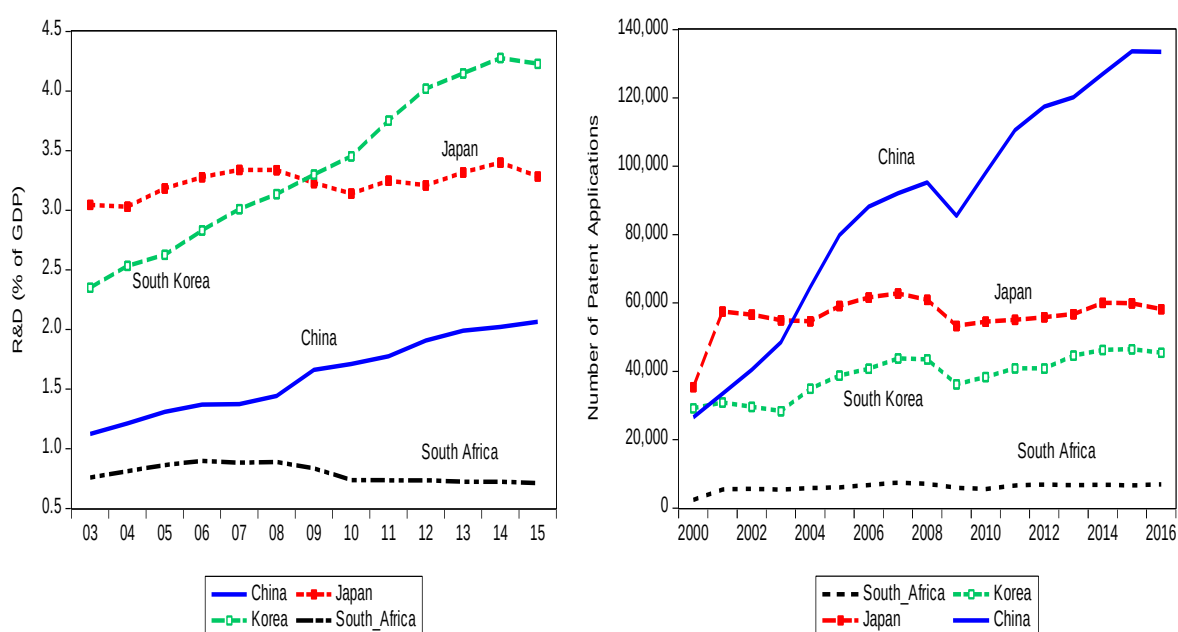


FIGURE 1.1: A COMPARISON OF INNOVATION INDICATORS IN SELECTED COUNTRIES

Source: Computed based on data from the World Development Indicators (2018).

³ A World Bank report by Dessus *et al.*, (2017) finds South Africa lagging behind other emerging markets and global technology leaders.

China, South Korea and Japan are the most industrialised economies in Asia. In terms of technological progress. Brahmbhatt and Hu (2009) argue that no other part of the developing world has seen more success in knowledge diffusion and creation over the last three decades than these three Asian economies. Adding on to that, the Economic Survey of India (2016) recently cited China, South Korea and Japan as the leading Asian economies in R&D expenditure corroborating the argument that these countries can be regarded as technology frontier economies.

The South Korean government is argued to have successfully transformed her economy within a generation from being one of the World's poorest countries to one of the richest supported by robust policymaking. Essential to note is that at the centre of this vivid transformation lies innovation (Wang, 2007). It is well documented that technological progress is the key factor that underpinned the competitiveness of South Korean exports and this consequently engineered the economy's sustained rise during its transition from a poor agricultural society post the South Korean War to a high-technology economy.

China's competitiveness on the other hand is primarily driven by processing and assembling exports combined with technologies adopted through foreign direct investment (FDI). Owing to the adoption of modern technologies, the added value of its high-tech industry increased threefold between 1995 and 2001 (Guo and N'Diaye, 2009). At the same time, its high-tech exports jumped to US\$ 67.9 billion in 2002 from only US\$ 10.1 billion in 1995 while the share of high-tech goods in its total exports rose to 20.9 percent in 2002 from only 6.8 percent in 1995 according to data from the World Bank (2018).

As argued by Xu *et al.*, (2008), China has managed to transform her economy into one of the fastest growing economies underpinned by economic reforms and a significant opening up to global trade. The significant effort to liberalize trade in China allowed her to increase productivity growth through extension of domestic markets and adoption of foreign innovation. While research effort has often focused on sources of

China's remarkable growth, it is also important to flip the question around and establish how China's technology affects productivity in other countries.

Japan on the other hand has long since been a technology economy characterised by the intensive use of robots and automotive innovation processes that make manufacturing industries productive, efficient and cost effective. Its heavy reliance on technology in manufacturing is largely driven by the acute shortage of labour given a relatively small population when compared to South Korea and China in particular. The question then becomes, can South Africa manage, through trade, to benefit from these technologically better-off Asian economies?

Empirical research probing this important question has mostly done so by assessing the impact of foreign technology indicators weighted by bilateral imports on productivity of the importing country. These studies include Apergis *et al.*, (2009), Nishioka and Ripoll (2012), Behera *et al.*, (2012), Medda and Piga (2014), Piermartini and Rubínová (2014), Bloom *et al.*, (2016) and Pradeep *et al.*, (2017). Despite this abundance of literature, there is no known empirical study that has, thus far, established the impact of innovation spillovers on productivity and efficiency in the context of South Africa and its relevant trading partners.

Such a study would be important given that raising productivity (both labour and total factor productivity) and efficiency has been one of the main challenges in South Africa's policy agenda since 1994 when the country attained independence. It is in this regard that South Africa's minister of Trade and Industry has regularly identified exploitation of existing technologies and increasing the rate of technological progress as imperative if the country is to grow sufficiently in a way that helps tame her two problems of poverty and unemployment. In this respect, a central policy question is to what extent productivity and efficiency in the country's manufacturing sector could benefit from these two growth sources namely technical progress and innovation spillovers across international borders.

1.2 RESEARCH QUESTIONS

Given the above background, this study seeks to answer the following research questions:

- i. What is the impact of Chinese, South Korean and Japanese innovation spillovers on total factor productivity of South Africa's manufacturing industries?
- ii. What is the impact of Chinese, South Korean and Japanese innovation spillovers on labour productivity of South Africa's manufacturing sector?
- iii. What is the impact of Chinese, South Korean and Japanese innovation spillovers on technical efficiency of South Africa's manufacturing industries?
- iv. Does labour productivity respond to exogenous technology spillover shocks from China, South Korea and Japan?

1.3 OBJECTIVES

Given the above research questions, the primary aim of this study is to establish the significance of technology spillovers mainly from China, South Korea and Japan on productivity and efficiency of South Africa's manufacturing industries. This is achieved by determining:

- i. the impact of Chinese, South Korean and Japanese innovation spillovers on total factor productivity of South Africa's manufacturing industries;
- ii. the impact of Chinese, South Korean and Japanese innovation spillovers on labour productivity of South Africa's manufacturing sector;
- iii. the impact of Chinese, South Korean and Japanese innovation spillovers on technical efficiency of South Africa's manufacturing industries; and
- iv. the response of labour productivity to exogenous technology spillover shocks from China, South Korea and Japan;

1.4 NEED FOR THE STUDY

The study is motivated by five main factors. The first factor relates to the debate on technology spillovers across countries which remains ongoing, inconclusive and unsettled (Medda and Piga., 2014, Piermartini and Rubínová., 2014, Bloom *et al.*, 2016 and Pradeep *et al.*, 2017). Results presented thus far do not provide a clear cut picture of how technology discovered in one country benefits other countries which necessitates further research.

Secondly, from the existing inconclusive literature (Apergis *et al.*, 2009., Nishioka and Ripoll., 2012., Behera *et al.*, 2012., Medda and Piga., 2014), there has not been any empirical attempt examining the possibility of technology spillovers between South Africa and Asia. This is despite the fact that South Africa in particular is fast becoming the destination of Asian exports. Such a study would facilitate tailor made trade and industrial policy proposals that are specific to South Africa.

Thirdly, growth in South Africa's manufacturing sector has declined sharply in recent years (Dessus, *et al.*, 2017). Particular sectors that have recorded significant TFP losses include the footwear, textiles, fiber and rubber products which are critical in generating employment. Several explanations have been proposed for the TFP decline but Adler *et al.*, (2017) attributes the decrease in capital-embodied innovation as the major reason. On the same note, Dessus *et al.*, (2017) attributes the decline in TFP to the reduction in innovation spillover effects from South Africa technological leaders but there is a lack of empirical evidence validating this proposition. The present study tests this proposition.

Fourth, there is a need to address some of the controversial methodological aspects in previous empirical work such as the appropriate mechanism through which technology is transferred from one country to another. In other words, there is a lack of clarity on whether the appropriate trade weights should be based on physical intermediate goods, capital goods and consumer goods. The conducted study fulfils this vacuum.

Fifth, understanding technology spillovers is going to be key going forward as the world slowly enters the fourth industrial revolution characterised by the fusion of technologies in manufacturing. In particular, this study is capable of shedding light on issues that may be helpful to the fourth industrial revolution and how developing countries can benefit from technology leaders.

1.5 CONTRIBUTION OF THE STUDY

The study makes the following seven contributions to the existing body of knowledge.

1. It is the first empirical work examining the relevance of technology spillovers from China, South Korea and Japan on productivity and efficiency of South Africa's manufacturing sector. A slightly similar paper by Edwards and Jenkins (2015) only examined the effect of Chinese imports on the South African manufacturing sector and did not proceed to analyse technology⁴ spillovers.
2. It constructs a composite innovation index (which has several novel features). To date, most studies (i.e. Leiva, 2014., Nordin *et al.*, 2016., Ertur and Musolesi, 2017 and Gioldasis *et al.*, 2018) have relied on R&D as a proxy for innovation but it has long been acknowledged in the literature that the use of R&D alone may be necessary but not sufficient since R&D expenditure is simply an input in the innovation creation processes. Given this inadequacy, this study proposes and constructs a novel index that comprises not only R&D stock but also trademark applications, patents and human capital in the R&D sector. This contribution is important for policy making as regularly advocated by the OECD.
3. It improves Grossman and Helpman's (1991) theory by using trade in services as a transmission channel of innovation. In early theories, the transmission channel was chiefly the flow of physical goods justified to a large extent by Adam Smith's observation that services' contribute less to economic progress relative to physical goods. The world has however significantly evolved which

⁴ Other studies measure technology using a simple time trend which can easily pick up other factors nested in the error term unrelated to technological progress.

requires theoretical modifications. Trade in services is becoming an integral element of the new globalised world and there is a wide consensus now that trade in services is crucial in the transfer of technology across countries.

4. It extends our understanding of technology spillovers by looking at their effects on technical efficiency of the manufacturing industries in the importing country as opposed to the commonly used outcome variable productivity growth. This is an attempt to complement and improve previous literature which is based on production functions in which technology advancement is assumed to raise the production frontier through technical changes. This assumption is plausible but may not be appropriate in cases where industries are operating below the existing production frontier.
5. It pioneers application of the true-fixed effects stochastic frontier model in the technology spillover literature. A leading study by Andersson and Stone (2017) that has addressed technical efficiency effects of foreign innovation has done so using the Battese and Coelli (1995) time-varying decay stochastic frontier model which, according to Greene (2005a) does not distinguish time-invariant heterogeneity from time-varying inefficiency with the resulting implication of generating biased technical efficiency scores of industries by treating unobserved heterogeneity as inefficiency.
6. It also applies, for the first time in the literature, a Bayesian analysis to establish the link between innovation spillovers and productivity growth in the hope of circumventing model uncertainties in classical econometrics. This contribution comes against the background of a recent work by Gioldasis *et al.*, (2018) which mentions a Bayesian analysis as an area of future studies.
7. Differently from previous studies, it computes the response of labour productivity to exogenous shocks in Chinese, Japanese and Korean innovation

using the local projections method which, unlike the vector autoregression, is robust to serial correlation and model misspecification (Jordà, 2009).

1.6 DEFINITION OF KEY TERMS

Key words in this study are total factor productivity, labour productivity, technical efficiency and innovation spillovers. They are defined as follows;

1. Total factor productivity is part of output that is not explained by inputs used in the production process. It is measured empirically using data envelopment analysis (in chapter five) and an algorithm devised by Levinsohn and Petrin (2003) (in chapter four).
2. Labour productivity is output per worker as in Lipsey (1999).
3. Technical efficiency is the ratio of output to potential output following Aigner *et al.*, (1977) and Coelli *et al.*, (2005). It ranges between 0 and 1 where 0 means complete inefficiency and 1 is full efficiency.
4. Innovation is proxied by a composite index comprising trademark applications, R&D stock, patents applications and the number of researchers in the R&D sector. The word composite technically means that the variable comprises many factors that are aggregated with some weights. Trade in services is used as the weight that essentially represents the mechanism through which innovation spills from China, Japan and South Korea to South Africa.

1.7 OUTLINE OF THE STUDY

The rest of the study unfolds as follows: chapter two and three provide the theoretical framework and literature review respectively; chapter four and five deal with the effect of innovation spillovers on total factor productivity; chapter six and seven deal with the impact of innovation spillovers on labour productivity and technical efficiency respectively, chapter eight analyses the response of labour productivity to Chinese, South Korean and Japanese technology shocks using impulse response functions computed by the local projections method while chapter nine provides a summary, conclusion and recommendations (Figure 1.2).

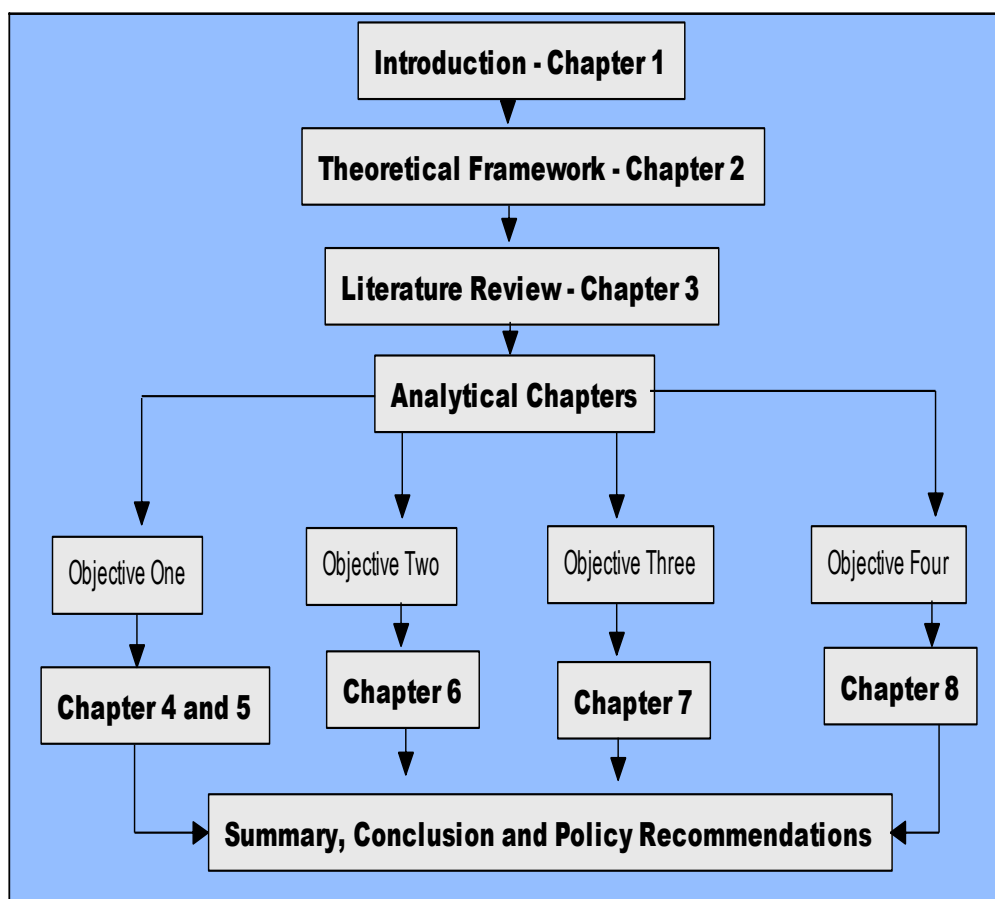


FIGURE 1.2: LAYOUT OF THE STUDY

CHAPTER 2

THEORETICAL FRAMEWORK

This chapter provides a theoretical framework that lays a foundation for the subsequent empirical exercises. The model relies heavily on open economy endogenous growth theory by Grossman and Helpman (1991) and it provides a theoretical intuition of how technological progress imported from the outside world affects productivity in the importing country. For simplicity, the analysis begins with the customary R&D measure of innovation and intermediate physical goods as the transmission channel. This simple framework can be easily modified, without loss of generality, by using instead a composite innovation measure and trade in services as the channel through which external innovation affects domestic productivity.

2.1 THEORETICAL MODEL⁵

In line with Grossman and Helpman (1991), Coe and Helpman (1995) and Coe *et al.*, (2009), consider an industry that uses (X) primary domestic inputs and (W) intermediate inputs to produce a single output (Y) . Value-added represented by (Y) , is the difference between total production (Z) and the intermediate input expenditure (expressed in terms of output price P_z);

$$\begin{aligned} Y &= Z - \sum_j P_{wj} W_j / P_z \\ &= A \cdot f(X_1, X_2, \dots, X_M, Q_1 W_1, \dots, Q_N W_N) - \sum_k P_{wj} / P_z Q_j \cdot Q_j W_j \end{aligned} \quad (2.1)$$

where A reflects neutral technology that governs the input-output relationship, $f(\cdot)$ denotes a production function, W_j is the intermediate input, P_{wj} represents the

⁵ This theoretical model is derived from Grossman and Helpman (1991), Coe and Helpman (1995) and Coe *et al.* (2009). It is however modified in latter sections to include trade in services as the transmission mechanism and not trade in physical goods.

price of the intermediate input while quality of the intermediate input is captured by index Q_j , $j \in \{1, \dots, N\}$.

The price of output, P_z , is proportional to the unit production costs, C , under the assumption of constant returns to scale.

$$P_z = 1/A C \left(P_{x,1}, P_{x,2}, P_{x,3}, \dots, P_{x,m}, P_{w,1}/Q_1 \dots P_{w,N}/Q_N \right) \quad (2.2)$$

From equation (2.2), unit costs are dependent on the quality corrected primary intermediate input prices and the level of technology used in the production process. Taking the natural logarithms of equation (2.1) and substituting equation (2.2) results in a specification that reveals the changes in value-added (in real terms) which can be attributed to three factors, namely, primary intermediate inputs, technology, and the price plus quality of intermediate inputs:

$$\begin{aligned} \Delta y &= \Delta a + \sum_l s_{x_l} \Delta x_l - \sum_j c_{wj} (\Delta p_{w,j} - \Delta q_j - \Delta p_y), \\ \sum_l s_{x_l} &= 1, \quad \sum_j c_{wj} < 1 \end{aligned} \quad (2.3)$$

where s_{x_l} represents the primary input share $l \in \{1, \dots, M\}$ on value-added, c_{wj} is a share of an intermediate input, W_j , on the total costs of production, and p_y signifies the value-added price which is essentially a weighted average of primary input prices. From the model, the first-order impact of primary intermediate inputs in efficiency units i.e. $Q_j W_j$ on valued added is, for now and for simplicity, considered small and therefore does not enter the specification for relative change of real value-added.

Total factor productivity (*TFP*) growth is defined as the difference between output growth and the contribution of primary factors of production to growth as follows:

$$\Delta TFP = \Delta y - \sum_l s_{x_l} \Delta x_l \quad (2.4)$$

$$= \Delta a - \sum_j c_{wj}(\Delta p_{w,j} - \Delta q_j)$$

where the valued added price, p_y , has been treated as the numéraire, price = 0 and the second part of the expression has been derived based on equation (2.3). This new expression indicates that TFP growth arises from improvements in the price-quality factor particularly when the supplier of the intermediate input from China, or South Korea in this case, cannot fully charge for quality improvements. The buyer of the intermediate input, in this case, from a South African industry, therefore benefits from the innovative activities done by the supplier of the intermediate input. This refers to rent spillovers.

Technically, price increases are a positive function of quality increases i.e.

$$\Delta p_{w,j} = \theta \Delta q_j, 0 \leq \theta \leq 1$$

where parameter θ measures appropriability or, similarly, the price-quality relationship. If for instance $\theta = 1$, then changes in prices will fully reflect changes in the quality so that appropriability is perfect, while a value of θ less than one signals a case where price increases by a less than proportionate change in the quality improvements.

To capture such quality improvements, the study uses R&D activity of the intermediate input supplier since R&D expenditure is plausibly meant to improve product quality and resource use efficiency. In the theoretical model therefore, quality upgrade is captured by R&D stocks in the supplier of the intermediate input and representing R&D by R , the discounted sum of past investments, $\Delta q_j = \varphi \Delta r_j$, where parameter φ is relates R&D efforts to quality upgrade. With algebraic manipulation of equation (2.4), TFP growth can be expressed as:

$$\Delta TFP = \Delta a + \varphi(1 - \theta) \sum_j c_{wj} \Delta r_j \quad (2.5)$$

Equation (2.5) suggests that TFP growth of each industry emanates from technical changes as well as changes in own R&D stocks and that of other industries.

Growth rates of R&D stocks ($R_{i,t}^d$) of other industries weighted by intermediate inputs that spillover to the buyer can be logically constructed, in line with equation (2.5), as;

$$\frac{R_{i,t}^d - R_{i,t-1}^d}{R_{i,t-1}^d} = \sum_{j=1, j \neq i}^N c_{Wji,t} \left(\frac{R_{j,t} - R_{j,t-1}}{R_{j,t-1}} \right) \quad (2.6)$$

where c_{Wji} denotes a share of intermediate inputs from j^{th} industry in the total output of industry i . Construction of foreign R&D stock ($R_{i,t}^f$) is done in the very same way to give;

$$\frac{R_{i,t}^f - R_{i,t-1}^f}{R_{i,t-1}^f} = \sum_{K=1}^K \sum_{j=1, j \neq i}^N c_{Wji,t} b_{kj,t} \left(\frac{R_{kj,t} - R_{kj,t-1}}{R_{kj,t-1}} \right) \quad (2.7)$$

where b_{kj} , measures the share of the supplying economy $k \in \{1, \dots, K\}$ given the total imports of goods produced in industry j . Noteworthy is that c_{Wji} again is the intermediate input share from industry j in the total output of industry i but this one concerns aggregate imports from all foreign (j) industries and not domestic j industry. Combining equations (2.6) and (2.7) and substituting this in equation (2.5) gives us:

$$\Delta TFP_i = \Delta a_i + \varphi(1 - \theta)\Delta r_i^d + \varphi(1 - \theta)\Delta r_i^f \quad (2.8)$$

Up to this stage, the model is only considering rent spillovers and has not accommodated knowledge spillovers. According to Griliches (1979), rent spillovers are ideas that are developed in industry j and are beneficial to production in industry i . It is reasonable to assume that knowledge spillovers are transmitted via the intermediate input channel as the buyer of the intermediate input can learn from simply examining the product that it buys from the supplier.

In addition to that, the buyer of the intermediate input can acquire the idea through communication with the supplier or through participation in international conferences. To this effect, growth of technology is considered to depend on R&D activity of the intermediate input suppliers together with own R&D as follows:

$$\Delta a_i = f(\Delta r_i, \Delta r_i^d, \Delta r_i^f) \quad (2.9)$$

Plugging this into equation (2.9) results in a new specification where growth of TFP depends on R&D activity as well as rent and knowledge spillovers. Note that the two types of spillovers are not distinguished since the study assumes that both occur through the same transmission mechanism. As a result, the study only includes a single foreign R&D stock and a single domestic R&D stock in the model which means that the quality coefficient $(1 - \theta)$ in equation (2.9) vanishes in the final specification:

$$\Delta t_i = \theta_i \Delta r_i + \theta_i^d \Delta r_i^d + \theta_i^f \Delta r_i^f \quad (2.10)$$

Own R&D stock represents an unweighted stock by measurement which is a common feature in related literature. Basing on this theoretical model, the study formulates a regression model empirically as follows:

$$\log \text{TFP}_{it} = \alpha_i + \beta_2 \log R\&D_{it}^D + \beta_3 \log R\&D_{it}^A + \varepsilon_{it} \quad (2.11)$$

where $R\&D_{it}^D$ represents both direct and indirect stock of domestic R&D, $R\&D_{it}^A$ denotes foreign stock of R&D, ε_{it} is the random disturbance term while α_i is the intercept. The interpretation of parameters, β_2 and β_3 is derived from the theoretical discussion above as; $\beta_2 = \theta_i^d$ and $\beta_3 = \theta_i^f$. The term $\theta_i \Delta r_i$ is dropped under the assumption that the direct and indirect effect of domestic R&D stock is the same.

Empirically, the most important aspect of examining the effects of innovation spillovers on TFP is to define the level of aggregation. Broadly speaking, innovation spillovers can be inter-firm (as in Medda and Piga 2014, Pradeep *et al.*, 2017 and Klein, 2017, for instance), inter-industry (as in Mehta, 2013 and Higón, 2002), or inter-sector or inter-country spillovers (as demonstrated in Coe and Helpman, 1995).

This study conducts an industry-level analysis following Mehta (2013) and Higón (2002) based on ISIC 3-digit-level industries⁶. This means that the study is interested in innovation that spills over, for example, from China's footwear industry into South

⁶ Higher digit level industries would have been more ideal but such data is not easily available in the case of South Africa.

Africa's footwear industry and the transmission channel, as will be justified shortly, is through intermediate physical and service imports.

Turning to measurement issues, several indicators have been used in the literature as proxies for innovation. Common proxies of innovation applied in most studies such as Mehta (2013), Nishioka and Ripoll (2012), Raouf *et al.*, (2015), Apergis *et al.*, (2009) and Behera *et al.*, (2012) are R&D stock and patents. The former represents an input in the innovation creation process while the latter is essentially an output indicator of innovation creation. An argument raised by Higón (2002) is that an appropriate measure of innovation and of an increase in the stock of knowledge is essentially an increase in knowledge capital that comes through new investment in R&D.

Following Keller (2010), the study firstly interacts the R&D stock (S) with intermediate import shares as follows:

$$ISP_{it}^A = \sum_{j \neq i} \frac{m_{jit}}{Y_{i,t}} \cdot S_{jt}$$

where (S_{jt}) represents industry R&D stock in the Asian economy, m_{jit} represents industry intermediate imports from economy j to economy i (South Africa) and $Y_{i,t}$ output of the exporting country. Noteworthy is that $\frac{m_{jit}}{Y_{i,t}}$ are weights which essentially capture the trade related technology diffusion channel. R&D stock is computed using the perpetual inventory method (PIM). According to PIM, R&D stock (S_t) at the start of year t equals initial stock (S_{t-1}) plus R&D expenditure during the year (R_t) adjusted for the depreciation of the beginning stock (δS_{t-1}) in which δ represents the rate of annual depreciation.

$$S_t = (1 - \delta)S_{t-1} + R_t$$

R&D stock in year S_0 is given by:

$$S_0 = R_1/(\delta + g)$$

where g denotes the average yearly growth rate of R&D. Given the fact that initial R&D stock is not observable for empirical purposes, the study has measured it on the assumption that spending on R&D and depreciation prior to the initial period is the same as the average rates after the initial period. The study has also assumed a 15 percent rate of depreciation as applied in Feldman and Kogler (2010) and Hall and Rosenberg (2010). This measure of innovation is only applied in chapter four.

In chapters five to eight of this study, the model will be modified to allow variable S to represent South Africa's composite innovation index while C , K and J represent composite innovation indices for China, South Korea and Japan respectively so that their corresponding slope parameters represent spillover effects. The composite indices are generated based on the principal component analysis which is essentially a technique that transforms the correlated indicators of innovation indicators into one index technically referred to as a principal component.

In the present case, four innovation indicators are used and these are R&D stock, the number of researchers in the R&D sector, patents and trademark applications are used and an index is computed for each economy⁷. Human capital represented by the number of researchers in the R&D sector is vital because, like R&D expenditure, it represents an important input in the discovery of knowledge and innovation. There is an established understanding that education systems which comprises researchers contribute towards research and knowledge bases.

A novel feature of this index relates to the inclusion of trademark applications which are often used by undertakings when launching new products as a novelty sign and a way of promoting new product brand with the overall aim of appropriating the benefits and rewards of their innovation effort.

⁷ When constructing the innovation index, all the indicators are first standardised in order to make the contribution comparable.

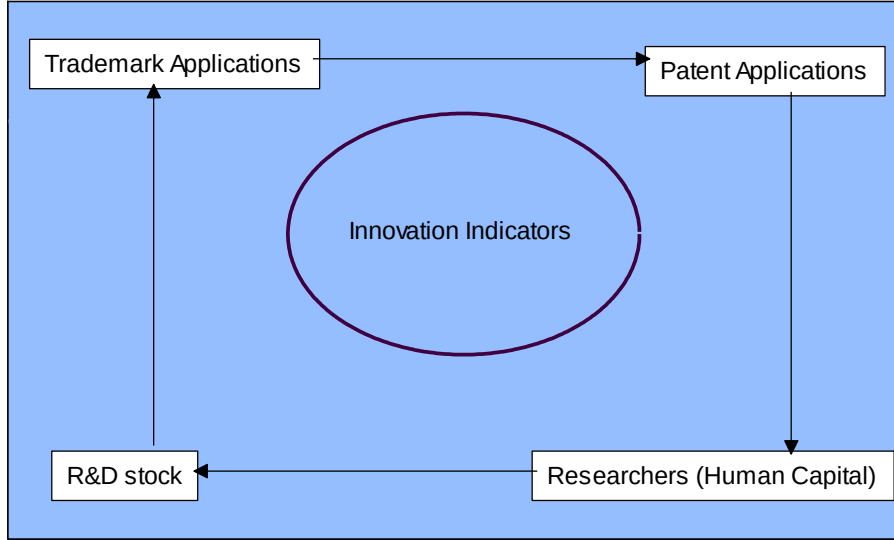


FIGURE 2.1: A SCHEMATIC MODEL OF INNOVATION INDICATORS

With patents, trademarks, researchers and R&D stock, the PCA uses weights for each innovation indicator arbitrarily in a manner which ensures that the ultimate component account for a maximum variance in the dataset. The study names the generated indices for each country PCI . The next question having generated these indices becomes: how is technology proxied by this index transmitted from South Korea, Japan and China to South Africa with an ultimate effect on TFP in manufacturing? Several channels have been proposed in the literature (for example FDI, trade and outsourcing) but the study (from chapter five to chapter eight) focuses on weights based on service imports. Following Lichtenberg and Pottelsberghe de la Potterie (1998) and more recently Belitz and Mölders (2016), the innovation spillover variable is measured as:

$$C_{it} = \sum_j \frac{S_IMP_{ijt}}{Y_{jt}} PCI_{jt}$$

$$K_{it} = \sum_j \frac{S_IMP_{ijt}}{Y_{jt}} PCI_{jt}$$

$$J_{it} = \sum_j \frac{S_IMP_{ijt}}{Y_{jt}} PCI_{jt}$$

where S_IMP denotes country i service imports coming from country j , where j is a vector comprising China, South Korea and Japan, Y_{jt} is output of the innovation transferring economy while PCI_{jt} is as defined before. Bilateral service imports are extracted from the Organisation of Economic, Cooperation and Development (OECD).

In theory, open economy endogenous growth models proposed by Aghion and Howitt (1990), Grossman and Helpman (1990), Grossman and Helpman (1991) and Coe and Helpman (1995), predict a positive transfer effect of technology on productivity of the technology lagging country. From an empirical standpoint however, it has been demonstrated the relationships can be significantly negative.

2.2 APPLICATION OF THE MODEL

The theoretical model outlined in this chapter is applied in subsequent chapters as follows; in chapter four and five which are the first and second analytical chapters respectively, the model is applied without modification on the outcome variable. In other words, total factor productivity is applied in both chapters measured using the Levinsohn and Petrin (2003) procedure and the Malmquist distance approach respectively. The main difference between chapter four and chapter five is that the latter measures innovation spillovers using a composite innovation index while the former applies the conventional research and development measure.

In chapter six and chapter eight, the model is modified without loss of generality by using labour productivity (which is a partial productivity measure) instead of total factor productivity. Chapter seven extends the main theoretical model to account for technical inefficiencies. In technical sense, chapter seven extends the production function based model into a stochastic frontier model in which deviations of actual output for each industry from the potential output represent technical inefficiencies.

2.3 CONCLUDING REMARKS

This chapter has provided a theoretical discussion on what governs the empirical interaction between innovation (both domestic and foreign) and productivity of the importing country. The model, in its current form, considers R&D stock as the innovation indicator. Also, the outcome variable here is chiefly total factor productivity. Without loss of generality, these features can be easily modified for example by changing the innovation indicator or the outcome variable. In other words, the basic theoretical idea remains the same even if one is to consider how foreign innovation interacts with technical efficiency of the importing industries. In what follows, the researcher provides a brief outline of how this theoretical model is applied in subsequent chapters.

CHAPTER 3

LITERATURE REVIEW

This chapter provides a review of theoretical and empirical literature on innovation, trade, productivity and efficiency. The title of the study embeds the word “trade” but it is important to highlight at this early stage that trade is in the sense of a mechanism that transfers innovation across borders. Therefore, relevant literature in this study relates to theories (i.e. open economy endogenous growth theories) and studies focusing on innovation spillovers through trade and not studies or theories focusing on the determinants of trade (i.e. gravity models, comparative advantage, absolute advantage etc.). In reviewing literature, the chapter comprises three subsections. Section one provides theoretical literature while section two covers empirical literature. Section three provides concluding remarks.

3.1 THEORETICAL LITERATURE

The effects of trade outcomes have been contentious since the advent of liberal trade policies in the mid-80s and early 90s which were mainly endorsed by the World Bank and the International Monetary Fund under the assumption that market-friendly policies were a recipe of economic success. Since then, there has been keen scholarly interest in examining how trade affects outcome variables such as productivity and efficiency of industries.

Trade theory is generally useful as a starting point of understanding productivity consequences of trade. Broadly speaking, theories of international trade can be grouped into three groups: 1) classical theory which include the absolute advantage proposed by Smith (1776) and the comparative advantage credited to Ricardo (1817); 2) neo-classical trade theory which encompass the factor proportions theory by Hecksher and Ohlin (1933) and 3) new trade theories pioneered by Krugman (1980).

Classical trade theory posits that trade facilitates consumption and production gains for both the exporting and the importing country if each country focuses in producing the good in which it is best at. New trade theories on the other hand focus on increasing returns to scale, the presence of imperfect competition and differentiated products as driving forces of international trade (Krugman, 1980). These theories are however not helpful in identifying the consequences of trade in terms of technological transfer on productivity because they assume a case where two countries exchanging goods and services have the same kind of technology.

Against this background, this study relies on open economy versions of endogenous growth theory by Grossman and Helpman (1991). Initially, the concept of innovation occasionally featured in different economic theories but the possibility of innovation moving across boundaries was largely marginalised. The theoretical foundation of innovation dates back to the 1950s and is linked with growth theories advocated by Schumpeter (1950). Proponents of classical economic theory disregarded the role of innovation as a determinant of productivity growth. Much emphasis had been placed on such factors as capital, land or labour in the production process. For Adam Smith, innovation was likely to result from specialisation which, in turn, stemmed from division of labour in the economy.

However, Smith viewed inventions as an outcome of human curiosity and instead placed much emphasis on the impact of planned activities. To him, inventions mainly machines, facilitated and enhanced work which improved efficiency and labour productivity (Smith, 1904). On the other hand, Ricardo (1973) focused on technological progress and emphasized its impact on productivity growth.

Later, proponents of classical economics were heavily criticised for placing too much emphasis on physical capital while neglecting the role of skills. This became the point of attraction for Schumpeter who contributed by linking growth, the business cycle and innovation. Schumpeter's argument was that growth momentum of an economy stemmed from key innovations that arise on a regular basis. His theoretical contribution gave birth to Schumpeter economics which largely maintained the view

that a healthy economy was not one that is constantly in equilibrium but rather one that is constantly disturbed by forces of technological innovation (Schumpeter, 1994).

The main intuition behind Schumpeterian economics is that the process of technological innovation is of dynamic nature and contributes significantly to the ups and downs of the business cycle. According to Schumpeter (1994), each and every business cycle is linked to completely different types of innovation. The recovery phase of a cycle begins with the new entrance of widespread innovation. Examples that were used during the time were those of textiles and iron markets during the eighteenth century, steam power and steel industries during the nineteenth century and internet and chemicals during the twentieth century.

Once the innovation reached its maturity stage and the positive externalities arising from its use begin to increase at a decreasing rate, then the recovery phase disappears. This was then followed by a recessionary phase after which a new wave of innovation began. This new wave of innovation completely destroyed the old structures replacing them by new and more efficient conditions for a new recovery cycle through a process termed “creative destruction”.

Constructive destruction essentially meant that the closure of some companies and the collapse of some industries did not necessarily exert dampening effects on the overall economy owing to the entrance of new and effective producers in place of the inefficient ones (Schumpeter, 1994). Given this feature, it is not surprising that Schumpeter’s theory has often been linked with the theory of competitiveness. As argued recently by Siudek and Zawojka (2014) within the auspices of the Schumpeterian economics, the firm’s ability generate new ideas is central for gaining a competitive advantage in the market.

Schumpeter’s theoretical proposition was not well recognised during the first half of the twentieth century the reason being that the link between scientific inventions and production activities was not easily discernible. The link was only appreciated later during the later stages the twentieth century (Fiedor, 1979). Motivated by

Schumpeter's views later in 1986, Romer published his influential paper on increasing returns and long-run economic growth which came to be known as the endogenous growth theory (Romer, 1986).

Romer's theory, which is a variant of Arrow's (1962) learning by doing theoretical model, holds the view that creation of new knowledge is associated with positive externalities owing to the fact that knowledge created is a public good and may not be completely patentable (Romer, 1986). Any producer uses technologies that are characterised by fixed revenues so that investments undertaken across the entire sector generates new knowledge that is subsequently disseminated through what are called spill-over effects. It is through this process that knowledge originating in one country ends up useful in other country. This brings the next question, how?

To answer the above posed question, Grossman and Helpman (1991) extended Romer's (1986) endogenous growth model to account for international knowledge spillovers that take place via cross border trade. In particular, Grossman and Helpman (1991) argued that developing countries which are technologically lagging can scale up and climb their productivity and efficiency escalators by simply adopting production technologies that have been invented elsewhere through intermediate imports. Developed and Newly Industrialised Countries (NICs) countries are generally frontiers in terms of technology discovery and adoption which means imports from these economies usually embody innovation that is often deficient in developing countries.

The contribution of intermediate imports from rich and advanced countries is usually embedded in the transmission of innovation. Accordingly, several indicators of technology show that technology is strongly concentrated in a handful of countries which means most countries (technology lagging economies) utilise innovation discovered elsewhere. Technical change and productivity growth in developing countries are therefore largely determined by international diffusion of technology. Along this line of reasoning, this study attempts to quantify the effects of innovation generated in selected Asian economies on productivity and efficiency of South Africa's manufacturing sector.

Standard proxies for innovation suggest that South Africa is a technologically lagging country when compared with China, South Korea and Japan. China currently spends more than 200 billion dollars (measured at 2010 constant USD purchasing power parity prices⁸) accounting for roughly 2 per cent of its output (World Bank, 2018). Japan's R&D expenditures are slightly over 100 billion dollars but accounts for about 3 per cent of its GDP while South Korea's R&D expenditures are quite high – over 4 per cent of GDP – with 14 of its 1000 employees being researchers (World Bank, 2018).

Judgements regarding the extent of innovation based on these indicators in isolation could be misleading but a crude assessment clearly suggests that South Africa could be technologically lagging in this group of economies. Perhaps substantiating this claim, estimates reported in the South African National Survey (SANS)⁹ of R&D statistical report 2011/12 indicate that gross domestic R&D expenditure accounted for only 0.76 per cent of GDP which is far below the World average of 1.77 per cent. One could rightly argue this 0.76 per cent estimate may not be comparable with the R&D to GDP ratios since it is measured in Rands but the basic message of South Africa being technologically lagging remains true even if one looks at statistics regarding the number of researchers per employment – only 1.4 per 1000 employees as compared to the 14 researchers per 1000 South Korean employees for example and 10 researchers per 1000 Japanese employees.

Given these low estimates for South Africa, this study attempts to analyse empirically the possibility of South Africa benefiting from South Korean, Chinese and Japanese research efforts as predicted by open economy endogenous growth models due to Grossman and Helpman (1991). According to Grossman and Helpman (1991), productivity growth rates tend to be higher and faster when innovation and technical knowledge flows across international boundaries as compared to a case where all technical knowledge must be locally generated.

⁸ Which implies they are comparable across countries

⁹ The National Survey of Research and Experimental Development (R&D) survey is conducted yearly to monitor South Africa's progress in R&D investment and it provides information regarding the profile, size and landscape of R&D.

Like Romer (1986), the logic behind their argument is that knowledge cannot be fully patented and is non-rival in nature implying that knowledge created in one country can spill over to another (i.e. knowledge externalities). This non-rival aspect of knowledge and innovation defines the logic behind Grossman and Helpman's (1991) growth models behind owners of innovation in one country cannot fully prevent imitators in other economies.

This argument is strongly supported by the OECD (2007) which posits that innovations generated in one sector, industry or country often builds on knowledge and ideas created by innovations and ideas in another industry, sector or country. The process of innovation spillover and diffusion is therefore central in explaining cross-country convergence (Howitt, 2000). As demonstrated by Howitt (2000), an industry, sector or country that starts off poor and far from the world technology leaders can grow faster and catch up with those that are already close to the technology frontiers. Gerschenkron (1962) described this as the advantage of backwardness as a poor industry, sector or country needs not to reduplicate research efforts by searching for innovation that has already been discovered elsewhere.

3.2 EMPIRICAL LITERATURE¹⁰

The theoretical reasoning proposed by Grossman and Helpman (1991) suggests that intermediate imports are a relevant mechanism through which technology can spread across regions, countries, industries and firms. Beginning with Schmookler (1966), Terleckyj (1974), Griliches and Lichtenberg (1984), Coe and Helpman (1995) and Keller (2002), researchers have analysed the possibility of innovation spillovers and their impact on total factor productivity and efficiency. Papers in this research area generally proxy innovation using either patents or R&D stock weighted by import shares. These studies paint different pictures of the causal effect of trade and R&D on productivity and it is not clear which approach, method and measure of innovation spillovers yields more reliable results.

¹⁰ Only a few leading papers are discussed in this section otherwise majority of studies are summarised in Table 3.1

Notwithstanding the inconclusiveness of empirical findings, it is fair, however, to suggest that most studies find innovation spillovers operating in the expected direction of raising total factor productivity of importing industries. This section turns to the empirical evidence on this subject and in doing so limits itself to the most recent, influential and leading views on this topic. The empirical evidence is grouped based on the level of aggregation. Studies are generally classified into four levels of analysis namely 1) country-level, 2) sector-level, 3) industry-level and 4) firm-level.

Country-level studies are interested in questions of the following sort; can South Africa improve its overall total factor productivity by importing technology from China, German or France? Can Ethiopia catch-up with advanced countries by adopting technology invented in the advanced parts of the world? These studies are mostly reliant on the predictions of conditional convergence neoclassical growth theory which posits the possibility of poor countries to catch-up with richer ones by simply adopting technology already existing in these advanced countries. This is often termed the advantage of backwardness as it prevents the re-duplication of research efforts.

A recent study that is similar to this one is that by Bloom *et al.*, (2016) which examines the impact of Chinese imports competition on TFP in the context of twelve European countries (panel data) between 1996 and 2007. The authors established that innovation is enhanced among the firms that are mostly impacted by imports from China on output markets. Endogeneity of trade variables in their study was corrected using instruments related to the removal of quotas after China's 2001 entry into the World Trade Organization.

Addressing endogeneity is imperative in trade, innovation and productivity since trade variables are also sensitive to productivity growth. Some empirical studies including Bloom *et al.*, (2017) capitalise on instrumental variable techniques while firm level literature (see Ahmed *et al.*, 2015) rely on the Olley and Pakes (1992) Control Function Approach (CFA) to circumvent the endogeneity problem that stems from unobservable productivity shocks. Using a variant of Cobb-Douglas functional form for Pakistan, Ahmed *et al.*, (2015) observe that trade promotes productivity growth but

their study failed to explicitly show and empirically test the channels through which trade influences productivity growth. In addition, their study was not bilateral and therefore could not ascertain the effect of import competition from particular trading partners. Lastly, the study used a Cobb Douglas which assumes homogeneity and therefore limits flexibility of the input-elasticity of substitution.

Literature that do not disregard the import source includes that by Dorn and Hanson (2015) who sought to analyse the relationship between trade and innovation on employment in the United States labour markets using data spanning the periods 1980 and 2007. Their study however is limited to the question how technological spillovers affect employment and does not explicitly address the effects of innovation spillovers on productivity and efficiency.

Alvarez (2001) on the other hand, tested the statistical significance of three transmission mechanisms of innovation namely exports, foreign direct investment and the acquisition of technical licenses from foreign countries. The results of his empirical test suggest that exports are important in technology adoption but causality is found to be bidirectional. Other channels of transmission are significant but less important when compared to exports. It is apparent that the approach followed by Alvarez (2001) is one which is close to the approach followed in this study except that it disregarded the effects of technological absorption on productivity and technical efficiency.

The same limitation is inherited by Damijan and Kostevc (2015) who explore the hypothesis that producers learn and imitate from international trade via the introduction of new products or production processes that are linked with foreign markets through trade. Their findings from micro-level data in Spain confirm that trade variables chiefly imports and exports are strongly correlated with innovation adoption. In addition to that, the results indicated that producers imitate mainly as a result of their import links, which essentially allow them to be innovative and dress up for exporting.

Kerr (2017) explores technology diffusion for immigrant communities in US and confirm presence of innovation spillovers. Santacreu (2015) on the other hand,

presents an innovation model that allows adoption of foreign innovation through the medium of international trade. After decomposing the sources of productivity growth, the empirical model indicates that adoption of innovation is responsible for about 65 per cent of “embodied” productivity growth in low income countries. The author argues that low income countries benefit in terms of productivity growth mainly through domestic innovation which accounts for 75 per cent of “embodied” growth.

The adoption of technology and the resultant increase in productivity of developing countries is interestingly one of the predictions put forth by the neoclassical conditional convergence growth theories. These theories, argue as benefits of starting off poor, that countries can be able to learn and utilise the knowledge that has been discovered by leaders. The approach therefore is to establish the productivity gap and link it to innovation proxies to identify if starting off poor increases the productivity growth along these lines. This is the approach used by Jung and Lee (2010) examined the factors affecting TFP catch-up for South Korean and Japanese firms.

In Jung and Lee (2010), TFP catch-up is proxied by the TFP gap between each firm in South Korea and the average TFP for each firm in Japan. Regression analysis is then applied to determine the nature and significance of the relationship. In particular, a linear model is estimated to establish the drivers of TFP catch-up for South Korean firms and these drivers were divided into two categories namely sectoral and firm-level factors. Their analysis found that South Korean firms’ TFP catch-up exists in industries where innovation is explicit and embodied in capital equipment imported.

Elu and Price (2010) consider whether trade relations between China and sub-Saharan countries result in technology transfers that enhance productivity growth in the sub-Saharan region mainly in manufacturing sectors. In their analysis, TFP is parameterized for sub-Saharan manufacturing producers as a function of foreign direct investment flows. Empirical results do not find a significant relationship between foreign direct investment, productivity growth and trade with China. In other words, the

authors concluded that China-Africa relations to do result in the adoption of technology from China.

Ramadani *et al.*, (2017) contributed to empirical literature by identifying spillover effects and innovation activities as explanatory variables that explain firm performance which is a novel way of estimating innovation activities by firms and knowledge spillovers. The authors confirmed that firm performance affected by innovation spillovers as well as innovation activities.

Leiva (2014) on the other hand sought to establish the impact of domestic and foreign R&D spillovers weighted by bilateral physical (not service) imports on productivity while taking into account the heterogeneous effect of unobserved common shocks. Based on a panel dataset comprising 50 economies between 1970 and 2011, Leiva (2014) observed a significant link between R&D and productivity but concluded that this link can be confounded by unobserved factors.

Unlike most studies, Le (2012) considered R&D spillovers transmitted through student flows across international borders. In particular, Le (2012) sought to establish the relevance of tertiary student flows in transferring technological knowhow from developed economies to African economies. Results from panel cointegrating estimation techniques were affirmative and supportive of the hypothesis that tertiary student flow is a significant innovation transmission mechanism. The weakness of the study however was that it did not control, in the model, domestic innovation.

In a bid to address endogeneity (which is crucial in literature) Nordin *et al.*, (2016) applied the dynamic ordinary least squares technique. The key objective was to determine the role of international R&D spillovers in the context of ASEAN countries between 1996 and 2012. Their results suggest that imports represent an important main channel for international R&D spillovers among the ASEAN countries.

While the majority of studies rely on parametric approaches, Gioldasis *et al.*, (2018) contributed to the body of knowledge by applying a non-parametric approach

to estimating the significance of international R&D spillovers. Controlling for domestic R&D, they found the impact of foreign R&D on TFP negligible. Also confirmed was that a country can only exploit the benefits of foreign R&D spillovers if both domestic R&D and human capital exceed a critical mass which is contrary to results observed in Coe et al. (2009).

Apart from endogeneity, cross sectional dependence is another estimation problem inherent in literature. Ertur and Musolesi (2017) apply the common correlated effects which is robust to cross sectional dependence in addressing the impact of international technology diffusion. Results indicate that developed economies benefit significantly from domestic and geographic R&D spillovers while developing economies are beneficiaries of technology spillovers emanating from trade.

On the other hand, in Kim and Park (2017), foreign direct investment (FDI) is tested as a channel through which technology spreads across countries among OECD economies. They find FDI as an important transmission mechanism of international R&D spillovers between OECD countries. Ogawa *et al.*, (2016) contribute by dividing R&D by the business sector, government sector and the education sectors. They confirm that R&D intensive economies marginally generate R&D spillovers.

Equally important studies are those that focus on trade liberalization and productivity. Wong (2009) sought to establish the impact of trade openness on Ecuador's manufacturing industries between 1997 and 2003 using micro-level data. The analysis confirms a positive and statistically significant effect of trade openness on the productivity of manufacturing industries in export-oriented manufacturing industries in the aftermath of trade reforms.

A positive and significant effect of trade openness on manufacturing growth is also confirmed by Chandran (2009) who examine the empirical link between trade openness and manufacturing growth while taking into account causality issues in the context of Malaysia between 1970 and 2003 using the bounds testing procedure developed by Pesaran *et al.*, (2001). In spite of contextual and methodological

differences, the two studies managed to confirm a similar result that trade openness enhances manufacturing productivity growth.

Siddharthan *et al.*, (2011) analyse the impact of trade liberalization (which is assumed to affect efficiency through technology transfer) on technical efficiency of Vietnamese manufacturing firms. Using a balanced panel data set on manufacturing firms from 2000 to 2003, when substantial trade liberalization took place, the study reveals that trade liberalization is conducive to better firm performance.

South Africa specific studies are very scant. The closest study is one by Edwards and Behar (2005) which, instead of trade innovation, focused on trade liberalisation and labour demand within South African manufacturing firms. They found empirical evidence in support of the hypothesis that trade opening and technological change have had an influence of the country's skill structure. In addition to that, they found that variables such as export orientation, imports of raw materials, training and development and computer investments are positive correlates of skill intensity in manufacturing production.

Sikwila and Ndoda (2014) on the other hand, addressed the question of whether openness to global trade has positively affected productivity growth in the case of South Africa. Using a time series regression approach based on quarterly data observed between 1994 and 2013, they found that trade openness has had a significant influence on productivity growth and development in South Africa. The study did not however address the effects of trade openness on productivity and efficiency of manufacturing industries as done in this present study.

A recent study that is close to the current analysis is that by Edwards and Jenkins (2015) which considers Chinese imports as a key source of slow growth in South Africa's output and employment in the manufacturing sector during the past decade. Relying on 44 manufacturing industries with data observed between 1992 and 2010, they observed a negative effect of increasing import penetration from China and domestic production. The present study is distinct in several respects. Firstly, it

focuses on productivity, technical and scale efficiency as opposed to growth, prices and employment. Secondly, this study not only considers import penetration from China but also the embodied knowledge spillovers from Japan and South Korea captured by foreign innovation weighted by bilateral import flows from these countries.

Putting the empirical evidence together leaves us with a conundrum of how trade and innovation spillovers affect productivity and efficiency of manufacturing industries. The results are evidently mixed and this necessitates further research that addresses the same question while addressing critical sources of results contradiction. Table 3.1 shows, briefly, previous studies and the conflicting findings.

There is a paucity of studies that are specific to South Africa addressing trade effects on productivity of industries at the 3-digit level. Also, most studies have been limited to productivity that comes from importing the new technology but less empirical effort has been devoted to analyse the efficiency with which the adopted technologies are utilised. Against this background, this study explores how South Africa's trade with China, Japan and South Korea influences productivity and efficiency growth of its manufacturing industries building from the work of Roberts (2000), Jonsson and Subramanian (2001), Edwards *et al.*, (2008) and Sikwila and Ndoda (2014) which are empirical studies that sought to establish the growth and productivity consequences of trade in the context of South Africa. This study departs from these previous studies in two ways. First it constructs a composite innovation index and second it considers service imports as the transmission mechanism.

TABLE 3.1: TRADE, TECHNOLOGICAL SPILLOVERS AND PRODUCTIVITY GROWTH

AUTHOR	COUNTRY	TRADE VARIABLE	IMPACT
Edwards and Jenkins	South Africa	Import competition proxy	Negative effect of import competition
Bloom <i>et al.</i> , (2017)	Panel of European countries	Import penetration	Positive effect of imports on innovation and productivity
Kerr (2017)	U.S.A	Knowledge spillovers and export intensity	Positive export-innovation link
Wang <i>et al.</i> , (2017)	China	Interregional technology spillovers	Negative interregional technology spillover effect that comes through FDI
Ramadani <i>et al.</i> , (2017)	11 Balkan countries	Innovation spillovers	Positive innovation and firm performance relationship
Santacreu (2015)	Cross country panel	Innovation (R&D) spillovers	Positive innovation-productivity link
Newman <i>et al.</i> , (2015)	Vietnam	FDI and imports of intermediate goods	Technology spillovers through FDI and access to intermediate inputs
Seyoum <i>et al.</i> , (2015)	China and Ethiopia	Outward FDI spillovers	Chinese firms' presence has different spillover on domestic firms.
Ha and Giroud (2015)	Korea	Knowledge spillovers	Presence of heterogeneous technological spillovers
Dorn and Hanson (2015)	U.S.A	Exports and innovation proxy	Robust relationship between exporting and innovation
Alvarez (2001)	Chile	Innovation and export intensity	Positive relationship
Damijan and Kostevc (2015)	Spain	Imports, exports and innovation spillovers	Positive relationship
Crescenzi <i>et al.</i> , (2015)	U.K	Multinational Enterprise innovation	Positive effect of knowledge spillovers
Goldberg (2010)	India	Imports of intermediate inputs	Positive productivity gains
Autant-Bernard and LeSage (2011)	France	R&D expenditure	Positive spillover effects
Elu and Price (2010)	China and SSA	FDI innovation spillovers	No relationship between Chinese technology spillovers and productivity of manufacturing industries in SSA

Source: Compiled from various studies as cited in the Table 3.1.

TABLE 3.1: TRADE, TECHNOLOGICAL SPILLOVERS AND PRODUCTIVITY GROWTH...continued

Gerschewski (2013)	Panel of developing countries	Knowledge spillovers through FDI	Negative intra-industry productivity spillover effects
Lee (2010)	Japan	Technology and exports	TFP catch up in sectors where technology is explicit
Alam and Morrison (2000)	Peru	ERP	Positive productivity effects
Chand and Sen (2002)	India	Price Wedge	Positive productivity effects
Wong (2009)	Ecuador	Tariffs, export intensity and import penetration	Positive productivity effects
Topalova and Khandelwal (2011)	Columbia	Tariffs	Positive
Biswas and Ghose (2012)	West Bengal	ERPs and import coverage	Positive
Hu and Liu (2012)	China	Output and input tariffs	Positive
Ahmed <i>et al.</i> , (2015)	Pakistan	ERP and excise duties	ERP has negative effects while excise duties have negative effects
Abegaz and Basu (2011)	Cross country	tariffs	Positive
Norouz (2001)	India	Export expansion and import substitution	No impact
Balakrishnan <i>et al.</i> , (2000)	India	Dummy variables	No impact
Sharma <i>et al.</i> , (2000)	Nepal	NRP	Statistically weak effect

Source: Compiled from various studies as cited in the Table 3.1.

3.3 CONCLUDING REMARKS

This chapter has provided a review of related literature on trade, productivity and innovation spillovers. What is apparent from this review is that focus has mainly been on trade openness and productivity growth. Very few studies have gone beyond that to look at the possibility of innovation spillovers across countries. Few studies that have done this appear to have relied chiefly on R&D and patents as the proxy variables for innovation using the flow of physical goods as weights. In other words, physical imports have mainly been considered as the mechanism through which technology

flows from one country to the other. This transfer of technology is generally observed to have a significant impact on total factor productivity growth as the outcome variable. There are several respects in which this study differs from existing literature including the use of a composite innovation spillover index, the consideration of service imports as the transmission mechanism and the focus on both productivity and technical efficiency.

CHAPTER 4

IMPACT OF CHINESE, KOREAN AND JAPANESE INNOVATION SPILLOVERS ON TOTAL FACTOR PRODUCTIVITY OF SOUTH AFRICA'S MANUFACTURING INDUSTRIES

This chapter deals with the effect of Chinese, South Korean and Japanese innovation spillovers embodied in physical intermediate imports on productivity growth of South Africa's manufacturing industries using a dynamic panel data approach. It addresses the first objective of the study which is to establish how Chinese, Japanese and South Korean innovation spillovers relate with total factor productivity of manufacturing industries in South Africa. The chapter comprises the following sections. Section one and section two provide a background and methodology respectively, section three and section four outline measurement of innovation spillovers and total factor productivity respectively, section five specifies the model while section six and section seven present data description and the results respectively. Section eight provides some concluding remarks.

4.1 BACKGROUND

The growing trade intensity between South Africa and Asian countries has sparked immense debate among policymakers. Pessimistic economists are generally fret about the obstacles and headwinds that South Africa will have to surmount in the short to medium term including the perishing of infant industries given the immense import competition. The gist of this argument is that the growing trade intensity between South Africa and the rising Asian region exposes South Africa's manufacturing sector to an onslaught of cheap manufacturing imports which makes it difficult for local industries to survive on their home turf.

On the other hand, optimistic economists go beyond these predictions of doom by pointing to the potential productivity gains that South Africa's manufacturing industries would get by adopting advanced technology that has been invented in the rising region of Asia; a mainstream proposition which is closely tied to the endogenous growth reasoning of Romer (1986) and its extended open economy version proposed by Grossman and Helpman (1990), Coe and Helpman (1995) and Coe *et al.*, (2009).

In extended open economy versions of endogenous growth theory, trade does enable the exchange of technical information across countries, which means that poor countries that invest less in R&D can adopt advanced technology that has already been invented in a technology frontier country (Apergis *et al.*, 2009). Trade between South Africa and most Asian economies has been one that has been in favour of the latter in terms of trade balance for the best part of the last two decades. However, in terms of the composition of imports, South Africa has also been a recipient of intermediate and capital goods from the same economies which in theory play an important role in spreading innovation.

World Bank statistics show that China spends close to 1.5 percent of GDP on R&D (which has generally been used as a proxy for innovation empirically), South Korea and Japan devote 2 percent or more GDP on R&D while the 2011/12 statistical report on South African national survey of research and experimental development shows that South Africa devoted around 0.76 per cent of GDP on R&D in 2012. Given that R&D is an essential input in the innovation creation process; the study finds it reasonable to consider South Africa as an innovation lagging economy relative to the selected Asian economies.

In the theory that forms the basis of this study's empirical analysis, knowledge generated in an innovation leading country or region transcends national boundaries and contributes to the productivity growth of other geographic areas. Grossman and Helpman (1991) posit that productivity growth will be faster when the technical knowledge that contributes to productivity in industrial research flows readily across

international borders as compared to a situation in which all such knowledge must be generated locally.

Notwithstanding the plausibility and existence of a well-established theory linking innovation spillovers and productivity growth, the empirical literature on this relationship remains inconclusive and largely debatable. The chain of evidence is mixed across studies for different countries which makes it difficult to generalise policy implications.

Studies that are supportive of open economy endogenous growth models are, but not limited to, Apergis *et al.*, (2009), Acharya and Keller (2009), Behera *et al.*, (2012), Nishioka and Ripoll (2012), Medda and Piga (2014), Piermartini and Rubínová (2014), Bloom *et al.*, (2016), Pradeep *et al.*, (2017) and Klein (2017). These studies confirm a positive and significant contribution of foreign innovation on productivity growth of local firms and industries that is transmitted through either imports or foreign direct investment.

On the contrary, there is another branch of studies that confirm a detrimental effect of innovation spillovers on productivity. Bruhn and Calegario (2014) for instance analyse the productivity spillovers of foreign direct investment in the Brazilian processing industry and find the effect negative in labour intensive industries. Higón (2007) on the impact of R&D spillovers on UK manufacturing using a cointegration approach conclude that foreign innovation does not significantly explain productivity and that it is domestic R&D that significantly drives productivity. Mehta (2013) and Elu and Price (2010) do not find technological spillovers to be a significant driver of productivity. The latter particularly conclude that trade between Africa and China does not bring productivity enhancing technology.

Within this empirical debate, there has been very little systematic analysis done so far to establish the possibility of innovation spillovers from innovation leading economies and its implication on productivity growth in the context of South Africa. Among these studies, Rodrik (2008) finds, among other factors, a significant impact of

import penetration on South Africa's manufacturing value added. Similarly, Edwards and Jenkins (2015) use a Chenery type decomposition and confirm a displacement effect of Chinese imports on domestic production. This study complements this empirical effort by evaluating the presence of innovation spillovers from China, South Korea and Japan on TFP growth of South Africa's 22 selected manufacturing industries between 2002 and 2014.

From a methodological viewpoint, the analysis contributes by measuring total factor productivity growth of South Africa's manufacturing industries using the Levinsohn and Petrin (2003) algorithm. This algorithm improves the Olley and Pakes (1996) approach by using the intermediate input as a proxy to control for the correlation between input levels and the unobserved productivity shock as opposed to the investment proxy that is costly to adjust and characterised by non-convex adjustment costs. The measure of TFP obtained as the residual in the Levinsohn and Petrin's functional relationship is then used to evaluate the impact of foreign innovation spillovers.

As is customary in literature, the operational definition for foreign innovation spillover is industry-specific R&D stock in each of the selected Asian economies weighted by industry-specific intermediate import shares. The analysis covers a 13-year period (2002 – 2014) hence the results can be regarded as representing medium to long term effects of embodied innovation on productivity growth. The analysis estimates separate regressions based on a standard reduced form model of productivity growth similar in structure to the one used in Medda and Piga (2014) using the Generalised Method of Moments (GMM) technique in a bid to address simultaneity and the endogeneity problem of R&D stock.

The baseline model is extended to establish the importance of South Africa's absorptive capacity. There are several factors that determine the importing country's ability to absorb foreign technology. Here two are considered, human capital accumulation and the quality of institutions. It is widely believed that long-term productivity gains that result from innovation embodied in imports are dependent on

the accumulation of these economy wide capabilities—from education (which determines the ability of the domestic industries to absorb foreign efficient production ideas) to improved regulatory frameworks and better governance (Acemoglu *et al.*, 2012 and Rodrik, 2014b).

To the best of our knowledge, this is the first empirical study that analyses the implications of Asian innovation spillovers on productivity growth of manufacturing industries in the context of South Africa.

4.2 METHODOLOGY

The aim of this chapter is to establish how innovation spillovers from China, Japan and South Korea relates with total factor productivity of manufacturing industries in South Africa. Therefore, the first methodological steps involve measurement of innovation spillovers and total factor productivity as shown in Figure 4.1. Once measured, these two variables are then included in the final model where total factor productivity of manufacturing industries will be the dependent variable and innovation spillover indices will be the independent variables.

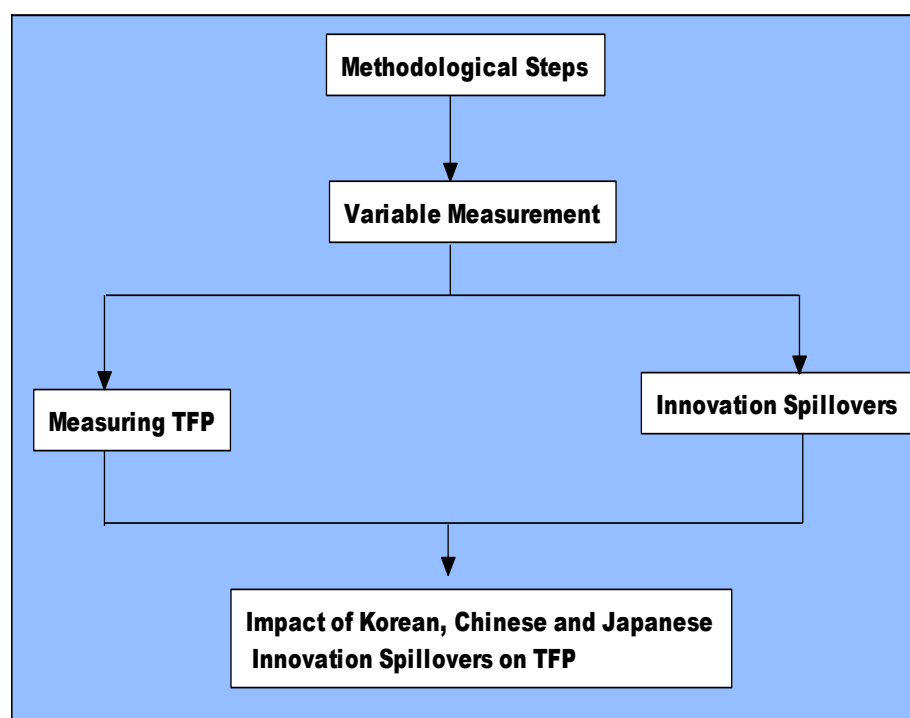


FIGURE 4.1: FLOW DIAGRAM OF METHODOLOGICAL STEPS

4.3 MEASURING INNOVATION SPILLOVERS

Innovation spillovers are computed in this first analytical chapter following the R&D stock measure weighted by bilateral imports between China, South Korea, Japan and South Africa as discussed fully in the theoretical framework (see chapter two). To save space, the same explanations are not repeated as they have been discussed in chapter two. Important to note is that this measure is only used in this first analytical chapter¹¹ so that the results can be comparable with all previous studies which applied the same measure.

R&D expenditure data are obtained from the OECD-ANBERD database measured in constant 2010-dollar Purchasing Power Parity (PPPs) prices (available at <http://www.oecd.org/science/inno/anberdanalyticalbusinessenterpriseanddevelopmentdatabase.htm> as indicated earlier on. Data on bilateral and industry-specific intermediate imports (used in the construction of R&D stock weights) are

¹¹ In subsequent chapters, a composite measure of innovation will be used instead of this common measure.

sourced from OECD-ANBERD ISIC revision 3. For years with missing data, linear interpolation has been used to obtain the missing numbers. Also, important to note is that for China, total R&D on business enterprise is used since industry-specific data is unavailable. However, China's measure of R&D eventually varies both over time and between industries since by construction the spillover term interacts the industry-invariant R&D variable with time-varying industry-specific import shares.

Domestic R&D expenditure data are extracted from South African National Survey of Research and Experimental Development statistical reports. These surveys are undertaken annually by South Africa's department of science and technology and they provide data on the size and shape of the R&D landscape. The analysis combined the 2011/12 and the 2014/15 statistical reports to gather a complete dataset on R&D expenditure in South Africa by standard industrial classification. These statistical reports are accessible online at <http://www.hsrc.ac.za/en/research-outputs/view/8614>. The study again used the Perpetual Inventory Method (PIM) to construct R&D stocks.

4.4 MEASURING TOTAL FACTOR PRODUCTIVITY¹²

One of the most contentious issues in literature relates to the measurement of total factor productivity and this is especially true for studies that rely on parametric approaches. The challenge is that total factor productivity is viewed as the unexplained residual in the Solow production function, yet the residual may contain unobserved factors that can be possibly correlated with the production inputs. Producers for instance generally respond to positive productivity shocks by expanding output which in turn requires them to employ more labour. The use of ordinary least squares in this case is criticised on grounds of generating biased and inconsistent output elasticities which ultimately compromises the measures of productivity.

An approach that has been commonly applied is one suggested by Olley and Pakes (1996) which uses the investment proxy derived from a structural model of an optimizing producer to control for the correlation between input levels and the

¹² The total factor productivity model applied in this chapter is based on Levinsohn and Petrin (2003).

unobserved productivity shock. Levinsohn and Petrin (2003) however show that investment might empirically fail as a proxy variable in this endogeneity correction procedure. The argument is that investment, as a control on a state variable, is costly to adjust and the non-convex adjustment costs may lead to kinks in the investment function that affect the responsiveness of investment to the transmitted shock even when investment is undertaken.

Levinsohn and Petrin (2003) then propose an estimator that uses intermediate inputs instead as proxies, arguing that intermediates may respond more smoothly to productivity shocks. The analysis therefore measures total factor productivity of the manufacturing industries following the approach proposed by Levinsohn and Petrin (2003a). In order to save space, the detailed procedure of this approach is explained in Appendix A.

4.5 THE MODEL

To ascertain the impact of domestic and Asian innovation on total factor productivity growth of South Africa's manufacturing industries, the analysis uses open economy endogenous growth models of Grossman and Helpman (1991) and Coe and Helpman (1995) as the theoretical framework. Empirically following Amann and Virmani (2015)¹³, the researcher specifies a parsimonious model in which total factor productivity growth is explained by domestic R&D stock and foreign R&D spillovers as follows:

$$\log TFP_{it} = \alpha_i + \beta_2 \log R\&D_{it}^D + \beta_3 \log R\&D_{it}^A + \varepsilon_{it} \quad (4.1)$$

$$i = 1, 2, 3, \dots, 22 \quad \& \quad t = 2002, \dots, 2014$$

where subscripts i & t represent industry and time period respectively, TFP_{it} is total factor productivity, $R\&D_{it}^D$ denotes domestic R&D stock¹⁴, $R\&D_{it}^A$ is a matrix of

¹³ Note that the Levinsohn and Petrin (2003) procedure was only used to measure TFP which is the dependent variable in equation 4.10 while Amann and Virmani (2015) are followed in specifying the empirical model, equation 4.10.

Studies such as Fu (2007) and Aghion *et al.*, (2007) have shown that foreign innovation spillovers can have a negative effect on domestic innovation effort. Given this argument, we control for domestic R&D as a proxy for domestic innovation effort.

innovation spillovers from China, South Korea, and Japan, β_3 is then a vector of the coefficients of interest which are expected to be positive in line with economic theory, α_i are unobservable time-invariant-industry specific factors and ε_{it} is a standard disturbance term.

The challenge with estimating equation (4.1) is that domestic R&D stock and import shares which represent the transmission mechanism of innovation could be endogenous which means that using the OLS procedure could result in biased and inconsistent estimates (Haskel *et al.*, 2007). A natural step in this case is to instrument the endogenous variable but the challenge is to find an appropriate instrument for R&D stocks and import shares.

Considering this challenge, Anderson and Hsiao (1981) proposed an approach in which one has to estimate the model in difference form and then use one lag of the level variable as an instrument. Arellano and Bond (1991) argue however that the Anderson and Hsiao (1981) approach although consistent fails to take all the potential conditions of orthogonality into account. Following Pradeep *et al.*, (2017), the analysis therefore relies on the Generalized Method of Moments (GMM) estimators proposed by Holtz-Eakin, Newey and Rosen (1988) and Arellano and Bond (1991).

Technically, the GMM estimators are based on differencing regressions and/ or instruments to account for unobserved effects and using lagged dependent and independent variables as instruments. In general, they are designed for panels with $T < N$. In the present case, $T = 13 < N = 22$ hence the GMM estimators are appropriate. From equation (4.1), the GMM approaches are based on a dynamic model of the following sort.

$$\log TFP_{it} = \alpha_i + \beta_1 \log TFP_{it-1} + \beta_2 \log R\&D_{it}^D + \beta_3 \log R\&D_{it}^A + \varepsilon_{it} \quad (4.1)$$

$$i = 1, 2, 3, \dots, 22 \quad \& \quad t = 2002, \dots, 2014$$

By incorporating the lagged term of the dependent variable, equation (4.1) can be viewed as a partial adjustment model where $\alpha - 1$ is the partial adjustment

mechanism. The use of industry-level data however brings to the forefront the issue of heterogeneity of industries which must be properly addressed even in a dynamic setting (Cameron and Trivedi, 2005). In the context of GMM estimators, this unobserved heterogeneity is removed by first differencing equation (4.1) as follows;

$$\Delta \log TFP_{it} = \beta_1 \Delta \log TFP_{it-1} + \beta_2 \Delta \log R\&D_{it}^D + \beta_3 \Delta \log R\&D_{it}^A + \Delta \varepsilon_{it} \quad (4.2)$$

where Δ denotes the first difference operator. This transformation wipes away industry-specific effects but requires instrumentation to control for endogeneity of the regressors and the correlation between the new error term ($\Delta \varepsilon_{it}$) and the lagged dependent variable ($\Delta \log TFP_{it-1}$). In a panel data setup, initial values of regressors as well as the lagged response variable are capitalized as instruments and this constitutes the difference GMM estimator.

Blundell and Bond (1998) show however that the difference GMM estimator is exposed to weak instruments in cases of high persistency. The presence of weak instruments further distorts both the small sample and asymptotic performance of the difference estimator. A solution to this problem of weak instruments is proposed by Arellano and Bover (1995) and Blundell and Bond (1998) and it requires using a system GMM which combines the first differenced equations with the equation in which the level regressors are instrumented by their first differenced terms.

Blundell and Bond (1998) through a Monte Carlo simulation conclude that the system GMM estimator is relatively more efficient as compared to the first difference estimator. For this reason, the Blundell and Bond system GMM (sysGMM) estimator is used. The sysGMM can be estimated using the one-step or two-step approach. In this case, the two-step sysGMM estimator is used since it is relatively more efficient as compared to the one-step estimator (Blundell and Bond, 1998).

Three diagnostic tests suggested by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) are conducted. The first is the Sargan/Hansen test of overidentifying restrictions which tests for overall validity of the

instruments. The null hypothesis is that all instruments are exogenous hence a higher probability value (above 0.1) is desired. The second test examines the null hypothesis that the error term of the differenced equation is not serially correlated particularly of second order (AR (2)). Again, a higher probability value is desired. The third is a test for cross sectional dependence. The GMM estimators maintain the assumption of cross sectional independence hence the Pesaran test for cross sectional independence was invoked. The null hypothesis of cross sectional independence is rejected if the probability value is above the 0.1 maximum significance level.

4.6 DATA DESCRIPTION

The study is based on a balanced panel data set which comprises 22 ISIC (3-digit level) manufacturing industries and data observed between 2002 and 2014. Although firm level data would be preferable as far as economic theory is concerned (Atkinson and Stiglitz, 1969), such data mostly comes from short period surveys which makes it unable to capture long-run dynamics in total factor productivity. This study therefore relies on 3-digit level industry data. Studies that have used such similar aggregation include Higón (2002), Fu and Gong (2009) and Mehta (2013). In line with these studies, the analysis holds an important assumption that each industry in the sample is essentially a representative firm as assumed in previous studies such as Higón (2002) and Mehta (2013).

Data on the selected industries are sourced from QUANTEC and OECD-Analytical Business Enterprise Research and Development (ANBERD). ANBERD is a database which comprises comprehensive annual data on industrial R&D expenditures. The reported data on ANBERD comply with the International Standard Industrial Classification and are expressed in Purchasing Power Parity (PPP) at constant prices which makes them comparable across countries. Selection of the sampling period is purely aided by data availability on research and development expenditure for the selected Asian economies. Focus is on China, Japan and South Korea which are technologically advanced economies in Asia relative to South Africa.

4.7 RESULTS AND DISCUSSION

Results pertaining the Levinsohn and Petrin (2003) productivity estimator which is implemented in STATA 14 via the “levpet” command are presented in Table 4.2. All variables are in natural log. Labour is treated as the only freely variable input and intermediate inputs are used to proxy for the unobservable productivity term. The dependent variable is real value added. Stationarity of variables was tested using a second generation panel unit root test proposed by Im, Pesaran and Shin (2003) in order to avoid spurious regression. Results from unit root tests, as Table 4.1 indicates, suggest that all variables used in the Levinsohn and Petrin (2003) productivity estimation procedure are generated by a non-stationary process in levels. Value added, and labour are integrated of order one while capital is integrated of order two.

Therefore, value added, and labour were differenced once and capital was differenced twice to avoid estimating spurious relationships. The study proceeds with results from the productivity measurement. From the results reported in Table 4.2, the dependent variable is the first difference of output, Δ and Δ^2 denote first and second difference operators respectively. The output elasticities in the Levinsohn and Petrin (2003) productivity estimator have the expected positive signs which are consistent with the neoclassical production theory. Although all the two variables inputs have the expected positive signs, it turns out that only capital enters significantly at the 5 per cent level.

According to Table 4.2, a percentage increase in capital stock raises output by 0.73 per cent on impact holding constant the labour input. The insignificance and low share of labour relative to capital on industrial output is consistent with the results in Kaseeram and Mahadea (2015) who observe a decline in labour share using long term data for South Africa. Rodrik (2006) and Banerjee *et al.*, (2008) observe a similar trend with the former attributing it to the relative decline in manufacturing employment. The argument raised by Rodrik (2006) is that manufacturing-led-labour-intensive growth is increasingly being replaced by technology that is turning a lot of manufacturing activities very much capital intensive.

Having measured total factor productivity as the residual term from the Levinsohn and Petrin (2003) productivity estimator, the study proceeds to estimate the impact of domestic R&D stocks and Asian innovation spillovers. A check on variable stationarity in Table 4.3 indicates that all the variables, including total factor productivity generated in Table 4.2, are stationary in levels which means there is no risk of estimating spurious regressions. Also, Table 4.4 suggest that the industries are cross sectionally independent which provides a greenlight with the system GMM.

TABLE 4.1: IM, PESARAN AND SHIN UNIT ROOT RESULTS

Variable	Levels t-bar	1 st Differencing t-bar	2 nd Differencing t-bar	Order of integration
logValue	-1.5208	-3.0194***		I(1)
Added	(-1.830)	(-1.830)		
LogLabour	-1.3986	-3.0017***		I(1)
	(-1.830)	(-1.830)		
logCapital	-0.7045	-1.5313	-2.5432***	1(2)
	(-1.830)	(-1.830)	(-1.830)	

Note: Three asterisks mean significance at 1 percent level. Figures in parentheses are Fixed-N exact t critical values at 5 percent. Panel means are included. Time trend is not included.

TABLE 4.2: LEVINSOHN AND PETRIN PRODUCTIVITY RESULTS

Variable	Coefficient	Standard error	z-statistic
$\Delta \log \text{labour}$	0.093	0.118	0.79
$\Delta^2 \log \text{capital}$	0.734**	0.302	2.43
Number of Observations	264		

Wald test of constant returns to scale: $\text{Chi}^2 = 0.37$ ($p=0.5444$)

TABLE 4.3: IM, PESARAN AND SHIN UNIT ROOT RESULTS

Variable	Levels	1 st Differencing	2 nd Differencing	Order of integration
	t-bar	t-bar	t-bar	
logTFP	-2.7224*** (-1.830)			I(0)
logR&D stock	-5.9380*** (-1.830)			I(0)
SA				
logR&D_China	-5.9551 (-1.830)			1(0)
logR&D_Korea	-2.6218*** (-1.830)			I(0)
logR&D_Japan	-2.7240*** (-1.830)			I(0)
Export intensity	-3.2156*** (-1.830)			I(0)

Note: Three asterisks denote significant at 1 percent level. Figures in parentheses are Fixed-N exact t critical values at 5 percent. Panel means are included. Time trend is not included.

TABLE 4.4: PESARAN CROSS SECTIONAL DEPENDENCE TEST

	Statistic	Probability value
Pesaran's test of cross sectional independence	-1.164	0.2444

Average absolute value of the off-diagonal elements = 0.294

Four regression variants are estimated in Table 4.5. The first variant controls for innovation from China and South Korea while variant (2) controls for innovation spillover from Japan. The four spillover regressors are not included in the same regression because of collinearity issues. Regression results in the first variant of Table 4.5 are strongly supportive of open economy versions of endogenous growth theory in that both Chinese and South Korean innovation spillovers enter with the expected positive and significant signs. A percentage increase in innovation from China and South Korea is estimated to raise total factor productivity growth of South Africa's selected manufacturing industries by 0.012 and 0.022 percent respectively holding domestic R&D stocks constant.

These elasticities are close to the 0.02 estimate reported in Aiello and Cardamone (2005) for Italian manufacturing industries and they lie within the 0.02 – 0.08 range reported in previous studies (Nishioka and Ripoll, 2012, Acharya and Keller, 2009) internationally. This result offers empirical support to the theoretical

argument raised by Grossman and Helpman (1991) and Aghion and Howitt (1990) that trade allows the exchange of technical information across countries which means that South Africa can possibly adopt technology that has already been invented in China and South Korea.

**TABLE 4.5: IMPACT OF CHINESE, KOREAN AND JAPANESE INNOVATION SPILLOVERS
ON TOTAL FACTOR PRODUCTIVITY – SYSTEM GMM ESTIMATES**

	(1)	(2)	(3)	(4)	(5)
Log TFP (-1)	-0.407*** (0.040)	0.086 (0.061)	-0.347*** (0.035)	-0.205** (0.102)	-0.427** (0.211)
Log Domestic R&D stock	0.083*** (0.013)	0.057*** (0.010)	0.431*** (0.073)	0.562*** (0.073)	0.054*** (0.017)
Log Chinese R&D Spillovers	0.012*** (0.004)		0.011* (0.005)	0.018 (0.015)	0.003*** (0.001)
Log Korean R&D Spillovers	0.022*** (0.004)		0.022*** (0.004)	0.005 (0.015)	0.014*** (0.003)
Log Japan R&D Spillovers		0.015*** (0.002)			
Log Real Effective Exchange Rate			0.372*** (0.105)	0.588*** (0.137)	
Log Terms of Trade			-1.887*** (0.361)	-2.392*** (0.440)	
Export Intensity				-0.002** (0.0007)	
Import penetration				0.0014* (0.0007)	
Human Capital Index					0.811*** (0.221)
Institutional Quality Index					0.036*** (0.002)
Human Capital Index*Log Japan R&D Spillovers					0.967*** (0.036)
Institutional Quality Index* Log Korean R&D Spillovers					0.356*** (0.013)
Constant	-0.898 (0.069)	-0.381 (0.102)	-0.378 (0.254)	0.287 (0.540)	-1.952 (0.662)
Obs	132	132	132	132	132
Sargan of over. Restrictions Prob> Chi2	0.156	0.243	0.305	0.878	0.135
AR (1) – 1 st differences = prob > z	0.000	0.000	0.092	0.083	0.024
AR (2) – 1 st differences = prob > z	0.198	0.155	0.493	0.141	0.118
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000

Note: One, two and three asterisks mean that the variable is statistically significant at 10 percent, 5 percent and 1 percent respectively. Figures in parentheses are robust standard errors. Time dummies were jointly insignificant hence they were excluded to avoid unnecessary model overfitting.

It is also clear that South Korean innovation has a more sizeable effect on productivity relative to Chinese innovation. The relatively small elasticity of Chinese innovation spillovers could be reflective of the fact that by construction, Chinese R&D expenditure (not stock) is invariant between industries as compared to South Korean

R&D expenditure which varies between the industries. Moving on to variant (2) in Table 4.5, the study finds that R&D spillovers from Japan do enter with a positive effect that is significant at 1 per cent level which again is confirmatory to open economy endogenous growth theories.

An important question that remains is “are these coefficients truly reflecting the partial effect of innovation from the selected Asian economies?” This is a relevant question considering that the baseline model is not controlling for imports from other countries as well as other macroeconomic fundamentals that may drive productivity. The omission of imports from other countries makes it difficult to convince the economist that the coefficients on the Asian innovation spillovers are reflecting their partial contributions and are not picking the effect of imports as well from other countries nested in the residual term. Because it is not reasonable to control for every country’s import share individually, the study rather includes an import penetration indicator which is measured by world imports less imports from the four Asian economies as a ratio of real output in each industry. Added to that, the study includes each industry’s export intensity as well denoted to capture the effect of specialization and economies of scale.

The analysis also, in Table 4.5 variants (3) and (4) controls for other macroeconomic fundamentals that may have an influence on productivity and selection of these variables is guided by empirical literature (see Rodrik, 2008). Controlling for these variables stems from an understanding that productivity of manufacturing industries is influenced by numerous factors other than technological upgrade. The analysis particularly controls for terms of trade, the real effective exchange rate (for external competitiveness), export intensity (for scale effects) and import penetration (for import competition).

All these fundamentals enter significantly as shown in Table 4.5, and the evidence suggests that an appreciation of the real effective exchange rate raises productivity perhaps through an importation of intermediate imports that can then be used in the production process. Export intensity enters with a surprisingly negative

and significant effect suggesting that increased export participation reduces productivity. A possible explanation for this puzzling result could be that South Africa's exports are mainly raw materials that do not have significant value addition. This explanation goes hand in hand with the result that improvements in terms of trade reduce productivity as confirmed in Table 4.5 across all the two variants.

What is important to note in Table 4.5 variant (3) and (4) is that once we control for real effective exchange rate, terms of trade, export intensity and import penetration, it turns out that the innovation spillover variables lose their statistical significance albeit with the expected positive signs. Noteworthy is that variant (4) particularly indicates that export intensity enters insignificantly while import intensity enters significantly. This result offers two possibilities. One is that the impact of innovation spillovers from China and South Korea is not significantly different from that of imports from the rest of the world. The second could be that innovation spillovers from China and South Korea does not have a direct effect on productivity.

Putting this evidence, one can suggest that Chinese and South Korean R&D spillovers have a significant effect on productivity that vanishes once the study controls for external conditions. This also suggests that previous parsimonious studies that excluded these macroeconomic fundamentals could have suffered an omitted variable bias as real effective exchange rate, terms of trade, export intensity and import penetration turn out to be relevant drivers of productivity in addition to foreign and domestic R&D stocks. The significance of all these other fundamentals is consistent with the result reported in Hausmann and Rodrik (2006). From variants (3) and (4), it is apparently clear that the introduction of these other fundamentals raises the size effect of domestic R&D stock significantly from 0.083 and 0.057 in variant (1) and (2) respectively to 0.431 and 0.562 in variants (3) and (4) respectively. This implies that the exclusion of these fundamentals is associated with a downward bias on the effect of domestic R&D stock on productivity.

Turning attention to domestic innovation in detail, the study finds two noteworthy results. The first relates to the positive effect of domestic R&D stocks on productivity

that is significant at 1 per cent level. In terms of size, it is interesting to note that the coefficient of domestic R&D stocks of 0.083 matches the 0.083 reported in Higón (2002) in the case of UK manufacturing industries and this corroborates the importance of domestic innovation creation as a fundamental driver of productivity growth. The second result to note is that domestic innovation has a larger impact on productivity growth than foreign innovation spillovers. This agrees with results reported in Acharya and Keller (2009), where domestic R&D stock is found to have a relatively greater impact on TFP of manufacturing industries than foreign innovation.

According to Piermartini and Rubínová (2014), this may be the case because foreign knowledge is less accessible relative to domestic knowledge. Piermartini and Rubínová (2014) notes that foreign knowledge may be difficult to absorb effectively because some of the knowledge is partially codified. The argument is that the non-codified part of innovation can be very essential for follow-up innovations, but such type of innovation is effectively transferred through face-to-face interactions. Yet these face to face communications between researchers in different countries (South Africa and the Asian countries in this case) are generally more difficult which consequently makes the transmission of non-codified innovation difficult (Piermartini and Rubínová, 2014).

One of the arguments raised in literature is that technology adoption depends on the skill capacity of the adopting country. To test this claim empirically, the study considers the importance of human capital accumulation and the quality of institutions in adopting the Asian innovation embodied in intermediated imports. In this direction, the study interacted in Table 4.5 the embodied innovation variable with the human capital index and an index that measures the overall quality of institutions, but the study only found this exercise to produce meaningful results when we interacted with spillovers from Japan and South Korea. For China, the interaction was statistically insignificant and was therefore dropped in a bid to avoid unnecessary model overfitting.

From Table 4.5, human capital is represented by HCAP while institutional quality index is denoted by INSQL. We extract the human capital index from PENN World Tables 9.0 and it is an index that is constructed based on years of schooling and returns to education. Note that human capital is constructed at country and not industry level due to the lack of internationally comparable human capital data measured at industry level. Unel (2006) suggests however that using human country level data seems appropriate given that education and the skill capacity of a country represent an externality within a country.

On the other hand, institutional quality index is measured as the overall score that aggregates different dimensions of institutional quality such as government integrity and investment freedom from the Freedom House Database. Note that these two variables are economy wide variables which means they vary over time and not across the industries.

Interestingly, as indicated in Table 4.5, both human capital and the institutional quality index enter with the expected positive and significant signs for both China and South Korea which corroborates the importance of institutions and human capital accumulation in driving productivity growth. The coefficients on the interactions show that innovation embodied in imports from Asia has a positive effect on TFP and this effect is intensified by institutional quality and South Africa's human capital endowment. The latter suggests that one way that human capital contributes to TFP is to serve as a facilitator for technology transfers embodied in imports. This empirical result is in tandem with Hassine (2008) who posits that superior technologies may not automatically affect the importing country's productivity and that the adaptability and local usability of foreign technologies depends on the skill content of the recipient country's workforce.

Apergis *et al.*, (2009) reveal an important role of human capital in influencing the trade-productivity relationship. Having good institutions is also crucial in setting the right economic environment for domestic R&D. If the importing country does not have

supportive rules and regulations, then local industries may not be able to adopt the new technologies even if they have quality human capital (Manca, 2009).

The empirical findings from the baseline specification (that excludes other drivers of productivity) do agree with most of earlier studies on international R&D spillovers such Griliches and Lichtenberg (1984), Coe and Helpman (1995) and Keller (2002). The result is also consistent with that reported in firm level studies (Melitz, 2003, Alexander *et al.*, 2006, Pradeep *et al.*, 2017, Medda and Piga, 2014 and Klein, 2017) which confirm the impact of technology spillovers on productivity.

The contribution is to show is that the presence of R&D spillovers is statistically weak once the study controls for external conditions (terms of trade), competitiveness (real effective exchange rate) and other economic fundamentals such as export intensity and import penetration. It turns out that once one controls for these other influences, then it is domestic R&D that stands as the significant driver of productivity.

But although the study could not find robust statistical evidence that R&D spillovers from China, South Korea and Japan raise productivity controlling for external conditions, we can use this result to reject alternative hypotheses such as those that suggest that Chinese and South Korean R&D embodying imports have been having a detrimental effect on productivity of South Africa's manufacturing industries.

There has been a general concern in South Africa over the years that the proliferation of imports from Asian economies, particularly China, has been having a detrimental effect on production of local industries. The argument has been that these imports create competition that results in the extinction of local industries. The evidence presented in this study is comforting in that the study finds existence of innovation spillovers from China, South Korea and Japan that correlates positively and significantly with productivity of domestic industries.

4.8 CONCLUDING REMARKS

This chapter has provided evidence of a positive impact of R&D spillovers on productivity of South Africa's manufacturing industries within the 0.02 – 0.08 per cent range which is intensified by institutional quality and human capital endowment. Importantly however, results indicate that domestic R&D stock has a stronger effect on TFP relative to embodied innovation from Asia. For the entire sample, a percentage increase in domestic R&D stocks is estimated to raise domestic TFP within the range of 0.08 – 0.56 per cent. Based on this result, the chapter argues that the ministry of trade and industry may need not to solely rely on foreign innovation as a driver of TFP. Instead, results imply that R&D embodied in imports from Asia has to be taken as a complement rather than a substitute for domestic R&D activities.

As part of the country's industrialization strategy, much attention needs to be devoted on generating more local knowledge as the study finds domestic R&D to have a more relevant and sizeable effect on TFP relative to imported innovation from Asia. Future work might possibly benefit from estimating the effect of foreign innovation on technical efficiency. This would allow a determination of whether foreign innovation results in outward shifts of the local production frontier or pushes local industries to move closer to the existing frontier.

CHAPTER 5

CHINESE, KOREAN AND JAPANESE INNOVATION SPILL OVER EFFECT ON TOTAL FACTOR PRODUCTIVITY OF SOUTH AFRICAN MANUFACTURING INDUSTRIES: A BAYESIAN ANALYSIS

This chapter analyses the impact of Chinese, South Korean and Japanese innovation spillovers on total factor productivity growth of South African manufacturing industries which, like the previous chapter, directly speaks with the first objective of the study. The first part of the chapter (section one) provides a brief background and more importantly how this chapter differs from the previous (chapter four). Thereafter, section two, section three and section four outline the background, literature review, methodology and measurement of TFP growth respectively. Section five, section six, section seven and section eight present measurement of innovation spillovers, link innovation and TFP growth, provide a description of the data and present the results respectively. Section nine and section ten provide diagnostic tests and concluding remarks respectively.

5.1 BACKGROUND

The relationship between innovation and productivity growth has received a great deal of attention since the ground breaking work of Romer (1990) in which innovation was considered a fundamental driver of long-term productivity growth. Grossman and Helpman (1990) and Grossman and Helpman (1991) extended these models to capture the possibility of innovation spilling over international boundaries the argument being that innovation created in one country can sustain productivity growth in another. This extension popularly known as open economy endogenous growth theories has yielded mixed findings at the empirical level (Wang and Wong, 2012, Elu and Price, 2010, Goldberg *et al.*, 2010). In joining this unsettled literature, this chapter differs from previous studies in many ways than one.

Firstly, it calculates total factor productivity indices in the importing country using a data envelopment analysis (DEA) Malmquist approach which is non-parametric and therefore not sensitive to distribution assumptions and functional form issues. Secondly, it measures innovation not only by a simple way of R&D expenditure but by a principal component analysis which allows one to accommodate other important indicators of innovation such as patent and trademark applications.

Thirdly, it establishes the relationship between foreign innovation spillovers on domestic productivity using a Bayesian analysis which circumvents the model uncertainty problem inherent in the frequentist approach. The analysis particularly considers the impact of Chinese, Japanese and South Korean innovation spillovers on total factor productivity of South Africa's 16 selected manufacturing industries between 2000 and 2015. The next section provides a brief literature review.

5.2 LITERATURE REVIEW

If there is one consensus in economics, it is that innovation is a fundamental driver of long-term productivity growth. This idea became well-accepted following the work of Romer (1990) who proposed a model in which diminishing marginal productivity of capital was eliminated by technological progress. In particular, Romer's (1990) endogenous growth model has become useful in explaining the continued lack of convergence between poor and rich countries as the latter continue to lead the race of inventing new ways of doing things than their developing counterparts.

What became interesting and perhaps controversial however was the idea raised by Grossman and Helpman (1991) which is that poor countries can benefit from adopting technology developed in rich countries. In essence, Grossman and Helpman (1991) developed a theoretical model which treats trade between countries as a central mechanism through which technology can cross international borders. This therefore, in the present case, means that manufacturing industries in South Africa

can sustain and augment their long-term productivity growth by adopting innovation from technology leading economies through trade.

Notwithstanding the plausibility of this argument, not all empirical studies have been kind to its prediction. A few of the studies do not find sufficient evidence to conclude that technology does migrate beyond borders. However, conclusions in most earlier studies on the creation, transfer and diffusion of innovation such as Eaton and Kortum (1996), Eaton and Kortum (1997), Eaton and Kortum (1999), Keller (2002), Keller (2004) and Peri (2004) are mostly affirmative. While this literature has grown rapidly over years, few empirical studies have analysed the role of service trade in transferring innovation across countries and impacting productivity growth in service importing countries.

Earlier, Francois (1990) partly addressed this aspect when he confirmed the possibility of experiencing increasing returns emanating from specialization combined with the growth of producer services. The argument raised by Francois (1990) was essentially that services bear an important role in coordinating, controlling and linking interdependent and specialised operations. Mun and Nadiri (2002) and Zhang and Lee (2007) later emphasized, from a cost function perspective, the relevance of information technology externalities in driving total factor productivity growth.

The point of divergence here with these previous studies is embedded in the way the present analysis views services as a mechanism through which technology generated in country A affects productivity growth in country B. Also, the analysis differs in the way it constructs innovation as will be fully explained in subsequent sections. The adopted approach to innovation measurement goes beyond the traditional way of using individual R&D and patent proxies. Although necessary, the researcher's view is that proxying innovation by such individual indicators may not be sufficient given the fact that each of these indicators is not without its own limitations.

Supporting this argument is a point raised by Evangelista (2000) which is that patents for example do not fully capture the extent of technology advancement. In this

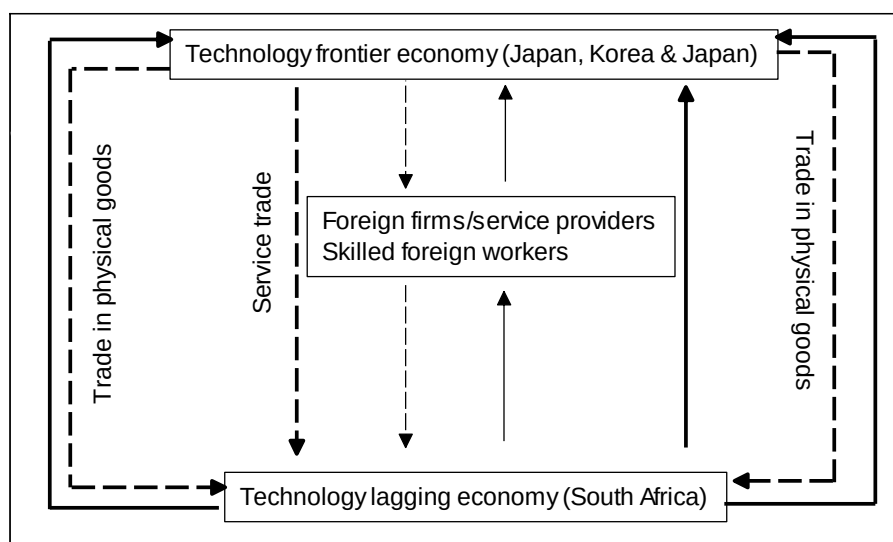
regard, a holistic approach which creates a composite index lumping relevant innovation indicators appears more desirable and this is the approach adopted in this study. With this composite measure of innovation coupled with the use of service imports as a transmission mechanism, the analysis contextualises the empirical test with Asia's technologically well-off countries – South Korea, China and Japan. This allows one to draw several policy implications for South Africa's industrial policy strategy as it strengthens its trade ties with Asia.

The structure of the proposed model is as follows. First, output growth is endogenously determined by labour and capital accumulation so that technological progress affects output growth through its effect on total factor productivity. Service imports in the model serve as a transmission mechanism which means that innovation existing in South Korea or Japan finds its way to South Africa through skilled South Korean or Japanese workers whose services are imported by South Africans.

Alternatively, this innovation can be transferred through South Korean or Japanese firms who may temporarily provide services in South Africa. Their presence in South Africa means that local producers can benefit from advanced techniques that they use during their stay. Note that in Grossman and Helpman (1991) and subsequent empirical literature, the main channel was considered to be chiefly physical goods so that technology would come embodied in capital or intermediate imports. As argued by Guerrieri (2005), the impact of business services as a catalyst of technology transfer is yet to receive significant attention in empirical literature.

Figure 5.1 displays the proposed channel of innovation transmission between Japan, South Korea, China and South Africa. The assumption is that Japan, China and South Korea are technology leading economies relative to South Africa. This assumption is followed by the argument that domestic and foreign producers interact through the trade mechanism proposed by Grossman and Helpman (1991) but that the interaction exists both in form of physical and service trade. The dashed arrow pointing downward through the middle demonstrate the fact that South Africa can import technologies from Japan, South Korea and China through service imports.

These service imports mainly take the form of foreign firms or skilled workers (technocrats) who provide services in the homeland.



**FIGURE 5.1: A SCHEMATIC MODEL OF TECHNOLOGY TRANSFER
THROUGH SERVICE TRADE**

The use of service imports as the technology transmission channel stems from an understanding that services themselves are generally characterised by enabling technologies (see Barras, 1986). As much as technology affects processes such as marketing and training, Tomlinson (2001) argues that most services are therefore more technology intensive than generally considered. Barras (1986) similarly attempted to explain the dynamics of the technology process and how they eventually influence industrial sectors through the reverse product cycle (RPC). In the initial stage of the RPC, services use for example information and communication technologies (ICT) to enhance, augment and improve back-office efficiency. As a result, learning subsequently leads to both product and process innovations. Finally, industries begin to take advantage of ICT as they expand into information-intensive activities.

5.3 METHODOLOGY

The methodology of this study proceed in steps. Firstly, the study measures total factor productivity and innovation spillover indices using the Data Envelopment Approach (DEA) and the Principal Component Analysis (PCA) respectively. The second step is to establish how these two variables relate and to achieve this, a Bayesian approach is used. These steps are displayed in Figure 5.2.

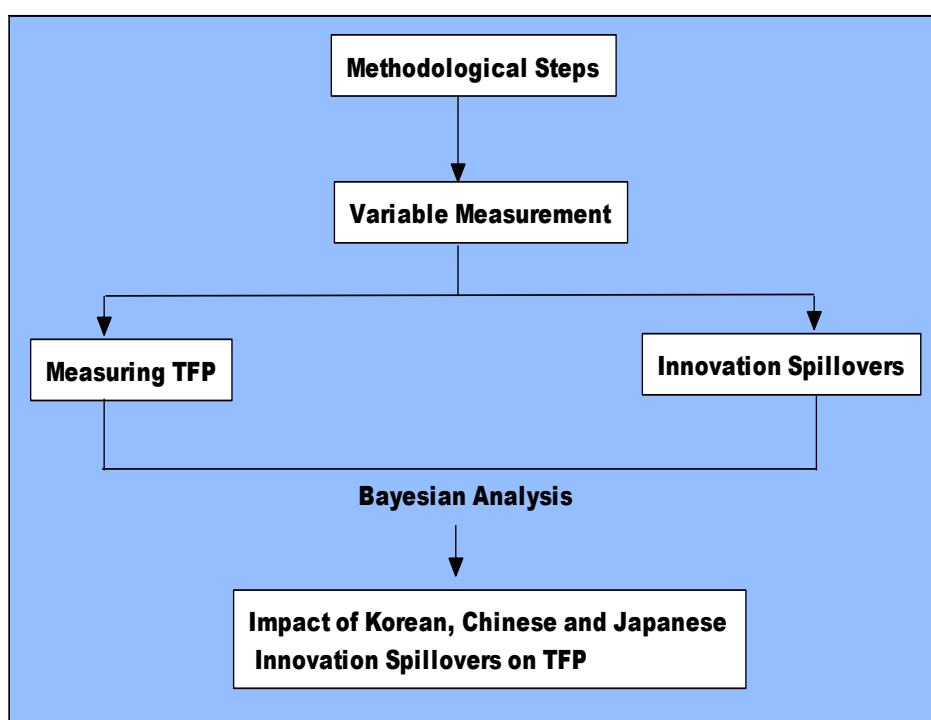


FIGURE 5.2: FLOW DIAGRAM OF METHODOLOGICAL STEPS

In the second step, TFP computed by the DEA will be the dependent variable while the innovation spillover indices will enter the regression model as one of the explanatory variables.

5.4 MEASURING TOTAL FACTOR PRODUCTIVITY

To measure multi-factor productivity which is the first step, the study relies on DEA Malmquist index approaches described in Fare *et al.*, (1994) and Coelli *et al.*, (1998). The Malmquist index approach strongly relies on the DEA which is a linear

programming methodology that constructs a piece-wise linear surface on input and output data quantities of a group of industries. For each industry in the sample, a solution of a sequence of linear programming problems is used to construct the frontier surface and the extent to which each industry deviates from the production frontier is generated as an end result of the frontier construction procedure.

One can compute an input-oriented or an output-oriented DEA. The input-oriented DEA is concerned with minimising input usage with output held fixed for each industry in the sample while the output-oriented DEA seeks to achieve the maximum possible output with inputs held constant. In the present case, the study is interested in output-oriented DEA as it is reasonable for manufacturing industries in South Africa to set, as an objective, raising output without necessarily having to employ more input resources. Details on measurement of TFP using the DEA approach are attached in Appendix B for brevity sake.

5.5 INNOVATION SPILLOVERS

As explained in the theoretical framework (see Chapter 2), the innovation spillovers index was computed using the Principal Component Index. Results of this PCA are attached in Appendix E for brevity sake. Overall, the show that the four innovation spillovers (trademark applications, R&D stock, R&D researchers and patent applications) are highly collinear as indicated by a Kaiser-Meyer-Olkin value above 0.7 for each of the three countries (China, South Korea and Japan). This provided further justification for proceeding with PCA as it uses this high degree of colinearity to compute a composite index.

5.6 INNOVATION AND TFP GROWTH

Unlike the vast majority of previous studies that relied on the frequentist approach characterised by model uncertainty, the study establishes the impact of innovation spillovers on productivity growth in a Bayesian framework. An advantage of this approach over the frequentist approach is that it estimates the probability of model parameters falling within some pre-specified interval. Also, the Bayesian framework

uses prior information and when combined with actual data observations, makes it more informative relative to the frequentist approach. Intuitively, the Bayesian approach makes the assumption that the model parameters are random while the actual data sample is fixed. For statistical inference, the posterior distribution of model parameters is then estimated based on actual data observations combined with the prior distribution of parameters that comes from the researcher or previous studies.

Noteworthy is that the posterior distribution in Bayesian modelling comprises two components namely the likelihood, which essentially includes information related to the model parameters based on observed data and a prior – which consists of prior information concerning model parameters. These two features – the prior model and the likelihood when combined together based on the Bayes rule produce the model's posterior distribution,

$$\text{Posterior} \propto \text{Likelihood} \times \text{Prior}$$

The posterior distribution of the Bayesian model cannot be derived in a closed form easily and researchers often overcome this difficulty by invoking simulations e.g. the Markov Chain Monte Carlo (MCMC) (a detailed illustration of the Bayesian framework is attached in Appendix D for brevity).

In essence, the Bayesian linear specification considered in this study comprises six parameters five of which are regression coefficients (China, South Korea, Japan, South Africa and the constant) while one of them is the variance of the data. The study firstly assumes in the first variant, a normal distribution for total factor productivity – the outcome – and invoke a non-informative Jeffreys prior for all the model parameters. With the Jeffreys prior technically, the variance and coefficients' joint prior distribution is essentially and directly proportional to an inverse of the data variance. One can specify this as,

$$\log TFP \sim N(F\lambda, \sigma^2) \tag{5.8}$$

$$(F\lambda, \sigma^2) \sim \frac{1}{\sigma^2}$$

where F represents the design matrix and λ is a vector of all regression coefficients i.e. $\lambda = (\lambda_0, \lambda_{\text{China}}, \lambda_{\text{Japan}}, \lambda_{\text{South Korea}}, \lambda_{\text{South Africa}})$. This non-informative prior is useful as a starting step but the study can improve the results by applying an informative prior. In other words, the strength of Bayesian analysis is that if we have reliable prior information concerning the distribution of the parameters, the study can have more informative results. In this regard, the study supplements the non-informative prior by separately invoking first an informative conjugate prior distribution with respect to the normal regression specification as follows,

$$(\lambda \mid \sigma^2) \sim \text{iid. } N(0, \sigma^2)$$

$$\sigma^2 \sim \text{InvGamma}(2.5, 2.5)$$

here, the analysis is making a plausible and common assumption that all regression coefficients are normally distributed with a zero and a variance, σ^2 which in turn follows an inverse gamma distribution. In another specification (variant 2 of the main results), the study arbitrarily includes a large variance of 1000 for robustness purposes.

Second, with informative priors, the analysis considered the commonly used Zellner's g-prior by Zellner (1986) for regression parameters in a normal linear regression set up (see Hoff, 2009). Mathematically, specification of the Zellner's g-priors takes the form,

$$(\lambda \mid \sigma^2) \sim \text{MVN}(0, g\sigma^2(X'X)^{-1})$$

$$\sigma^2 \sim \text{InvGamma}(v_0/2, v_0\sigma_0^2/2)$$

From these priors, g is the prior sample size (240 in this case) while v_0 and σ_0^2 represent the prior degrees of freedom (dof) and the prior variance of the inverse gamma distribution respectively. Following Hoff (2009), the study sets $v_0 = 1$ and $\sigma_0^2 = 8$. The dimension of the distribution is 5 in the present case which essentially represents the number of regression parameters.

5.7 DATA DESCRIPTION

The analysis is based on 16 three-digit level manufacturing industries with data observed between 2000 and 2015. These are the industries were selected by data availability at the time of writing. In terms of the sampling period, 2000 – 2015 essentially covers the period in which trade relations grew rapidly between South Africa and Asian countries particularly China. The list of industries included is as follows.

1. Food
2. Beverages
3. Textiles
4. Leather & leather products
5. Footwear
6. Wood & wood products
7. Paper and paper products
8. Coke & refined petroleum products
9. Basic Chemicals
10. Printing, publishing & recorded media
11. Plastic Products
12. Metal products excl. machinery
13. Rubber products
14. Machinery and equipment
15. Television, radio & communication equipment
16. Furniture & other manufacturing

For the DEA programming procedure which calculates the multifactor productivity indices, there is one output and two inputs labour and capital whose data is sourced from Quantec. Output is in real terms for each 3-digit level industry using 2010 as the base year. The base period has to be selected carefully because different results can be obtained by varying the base period.

In this analysis, the study finds it more appropriate to use 2010 as the base year in order to express the ratios in the latest year's prices. The variable labour

captures the labour input and is measured as the total number of formally and informally employed people (employees) in each industry.

Capital on the other hand is proxied by real fixed capital stock. The fixed capital stock is the sum of the value of the fixed capital goods in the industry at the end of the year shown and is computed based on the PIM. Mathematically, the productive stock K , at the end of period t is given by:

$$K_t = K_{t-1} + I_t - D_t \quad (5.9)$$

where K_t = capital stock at the end of period t , K_{t-1} = capital stock at the beginning of period t , I_t = gross domestic fixed investment in period t and D_t = provision for depreciation in period t . In the present case, fixed capital stock figures for the manufacturing industries were calculated by the Quantec, according to the same methodology.

5.8 RESULTS AND DISCUSSION

This section presents the empirical results on the assessment of how Chinese, South Korea and Japanese innovation relates on productivity and efficiency of South Africa's manufacturing industries. The chapter sets the stage by summarising DEA and TFP calculations before moving on to the main regression results.

TFP results in Table 5.1 indicate that annual TFP of the 16 industries grew by 1.6 per cent between 2000 and 2015. Also confirmed in Table 5.1 is that much of this growth emanated from technical progress as opposed to improvements in technical efficiency. Industries that recorded the highest TFP change are food, beverages and textiles while industries (0 – 7.5 per cent) that recorded the least technical progress are machinery and equipment television, radio and communication equipment, furniture and other manufacturing (0 – 0.5 per cent). Footwear, wood and wood products, paper and paper products experienced a decline in TFP by about 0.2 per cent.

The food industry recorded the highest average annual multi-factor productivity growth of 7.5 per cent in which 5.5 per cent of this growth was a direct result of technical changes and 1.9 per cent of it was a result of improvements in technical efficiency (Table 5.1). The second highest annual growth of multi-factor productivity growth came from the beverages industry, 5.5 per cent which, like the food industry, was mainly driven by technical changes, 4.2 per cent, while improvements in technical efficiency accounted for only 1.2 per cent of this growth (Table 5.1). Third and fourth were the textiles and the basic chemicals industry respectively.

The textiles industry posted an average annual growth of 3.6 per cent and 2.7 per cent of this multi-factor productivity growth emanated from technical changes while 0.9 per cent was due to gains in technical efficiency (Table 5.1). On the other hand, the basic chemicals industry recorded 2.7 per cent annual growth which when decomposed into technical changes and technical efficiency changes indicate that the industry grew by 2.8 per cent as a result of technical changes but eventually lost 0.1 per cent due to a decline in technical efficiency (Table 5.1).

TABLE 5.1: AVERAGE ANNUAL TFP GROWTH (2000-2015)

Industry	Efficiency Change %	Technical Change (%)	TFP Change (%)
Food,	1.019	1.055	1.075
Beverages,	1.012	1.042	1.055
Textiles,	1.009	1.027	1.036
Leather & leather products,	1.000	1.017	1.017
Footwear,	0.994	1.004	0.998
Wood & wood products,	0.985	0.999	0.984
Paper & paper products,	0.986	1.008	0.994
Printing, publishing & recorded media,	0.984	1.018	1.002
Coke & refined petroleum products,	0.995	1.024	1.019
Basic Chemicals,	0.998	1.028	1.027
Rubber products,	0.999	1.023	1.022
Plastic Products,	0.995	1.022	1.017
Metal products excl. machinery,	0.998	1.016	1.014
Machinery & equipment,	0.998	1.008	1.005
Television, radio and communication, equipment,	1.001	0.999	1.001
Furniture & other manufacturing	1.003	0.998	1.001

Source: Computation based on Malmquist DEA

It is clear from the results in Table 5.1 that 3 industries experienced a technical regression on average and these are wood and woods products, television, radio and

communication equipment and furniture and other manufacturing. The analysis also noted that 3 of the 16 industries in the sample experienced a decline in multi-factor productivity and these are footwear, wood and woods products and paper and paper products. On average for all industries, there was a decline in efficiency¹⁵ of 0.1 per cent and an increase in technical changes of 1.8 per cent.

This means that the chief source of multi-factor productivity growth of South Africa's 16 manufacturing industries in the sample was mainly technical progress. The question then is, was this technical progress domestically sourced (i.e. through R&D) or was it externally sourced through trade? The next part of this chapter addresses this question.

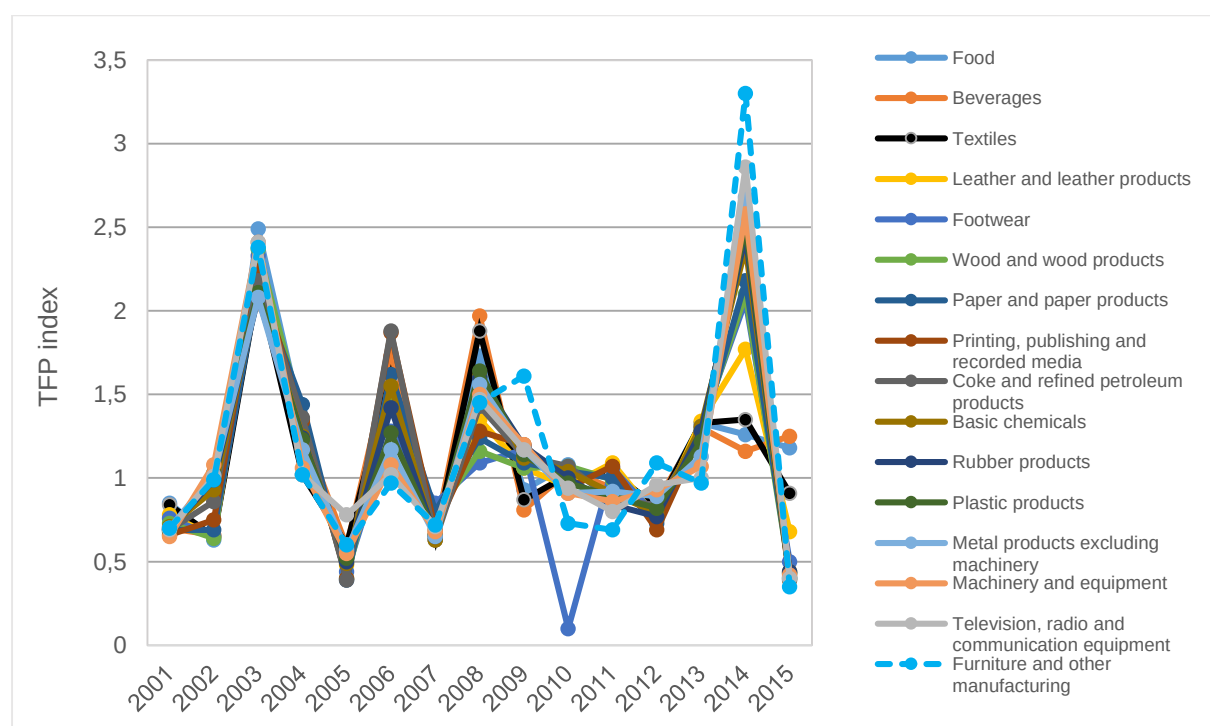


FIGURE 5.3: TFP INDICES FOR THE 16 INDUSTRIES (2000 – 2016)

¹⁵ These are calculated based on estimates from Table 5.1

Table 5.2 presents 4 regression variants and the logarithm of total factor productivity is the dependent variable in both cases. Each variant has three sub columns. The first column labelled mean represents the posterior mean estimates which are essentially the means of the corresponding marginal posterior distributions of the regression coefficients. The second column is the Markov Chain Monte Carlo (MCMC) standard errors which are simply standard errors from simulations. The third sub column labelled CI is for credible intervals which have a probabilistic interpretation unlike the conventional confidence intervals under the frequentist approach. With these labels, the results can be interpreted.

Firstly, the analysis observes positive posterior mean estimates for South Korea, Japan and domestic innovation variables and a negative mean estimate for China. The latter is interesting because it says that increasing trade with China negatively affects total factor productivity growth in South Africa; a result which emerges at a time where China's presence in Africa is heavily scrutinized from a development perspective.

The 95 per cent CI for China indicates a 95 per cent probability that its mean posterior estimate is between -0.336 and -0.026. Since this constructed 95 per cent interval does not contain a zero, the study can statistically conclude that China's innovation spillovers have a significant effect on total factor productivity of South Africa's manufacturing industries. Similarly, for South Korea and Japan, the 95 per cent credible intervals do not contain a zero suggesting a similar interpretation which is that the impact of innovation from these two countries is statistically significant.

The only point of divergence is that innovation from Japan and South Korea exerts a positive effect whereas that of China is negative. Put differently, only innovation from Japan and South Korea enter with signs that are consistent with open economy endogenous growth theories by Grossman and Helpman (1991), Coe and Helpman (1995) and Coe *et al.*, (2009) which view trade albeit in terms of physical goods, as an important vehicle through which productivity enhancing technology can be transmitted across international boundaries.

TABLE 5.2: IMPACT OF CHINESE, JAPANESE AND SOUTH KOREAN INNOVATION SPILLOVERS ON TOTAL FACTOR PRODUCTIVITY: BAYESIAN RESULTS, RANDOM-WALK METROPOLIS-HASTINGS

	Variant (1): Priors ~ 1(Flat) var ~ Jeffrey's				Variant (2): Priors ~ N(0,1000) var ~ igamma(2.5, 2.5)			
	Mean	MCSE	95% CI		Mean	MCSE	95% CI	
China	-0.176***	0.002	-0.292	-0.055	-0.176***	0.002	-0.336	-0.026
Korea	0.061***	0.004	0.010	0.226	0.044***	0.004	0.032	0.272
Japan	0.141***	0.001	0.099	0.182	0.132***	0.001	0.076	0.189
S.A	0.033	0.059	-0.509	0.398	0.318***	0.041	-0.539	2.181
Constant	0.101	0.246	-1.679	2.062	-1.355	0.168	-5.219	1.254
Var	0.036	0.0001	0.035	0.029	0.056***	0.001	0.046	0.067
Acceptance rate	0.18				0.35			
MCMC	12500				12500			
Burn-in	2500				2500			
MCMC sample size	10000				10 000			
Obs.	240				240			
Log ML	47.945				-19.167			
Efficiency average	0.143				0.210			

	Variant (3): Priors ~ N(0,var) var ~ igamma(2.5, 2.5)				Variant (4): Zellner Priors: ~ zellnersg (5,240,0, {var}) {var} ~ igamma(0.5,4)			
	Mean	MCSE	95% CI		Mean	MCSE	95% CI	
China	-0.150***	0.003	-0.282	-0.023	-0.172***	0.004	-0.344	-0.007
Korea	0.023***	0.004	0.010	0.188	0.035***	0.005	0.013	0.281
Japan	0.142***	0.001	0.094	0.205	0.134***	0.001	0.074	0.197
S.A	0.021	0.055	0.332	0.508	0.303***	0.022	-0.621	1.248
Constant	-0.022	0.012	-0.501	0.431	-1.298	0.093	-5.193	2.531
Var	0.055	0.0001	0.045	0.065	0.068***	0.0003	0.057	0.080
Acceptance rate	0.23				0.18			
MCMC	12500				12500			
Burn-in	2500				2500			
MCMC sample size	10000				10 000			
Obs.	240				240			
Log ML	2.301				-32.608			
Efficiency average	0.031				0.053			

TABLE 5.3: ESS SUMMARIES A

	Model (1)			Model(2)		
	ESS	Corr. time	Efficiency	ESS	Corr. time	Efficiency
China	418.25	23.91	0.041	486.24	20.57	0.045
Korea	377.51	26.49	0.037	526.49	18.99	0.050
Japan	284.65	35.13	0.028	450.76	22.18	0.045
S.A	15.59	641.41	0.002	214.12	46.70	0.021
Constant	15.60	640.90	0.002	208.52	47.96	0.021
var	411.39	24.31	0.162	1981	5.05	0.198

TABLE 5.4: ESS SUMMARIES B

	Model (3)			Model(4)		
	ESS	Corr. time	Efficiency	ESS	Corr. time	Efficiency
China	431.33	23.18	0.043	462.44	21.62	0.046
Korea	423.82	72.64	0.013	539.21	18.55	0.053
Japan	137.67	23.60	0.042	526.08	19.01	0.052
S.A	409.32	24.43	0.040	441.38	22.66	0.044
Constant	348.56	28.69	0.035	440.84	22.68	0.044
var	152.31	65.65	0.015	396.05	25.25	0.039

Although the baseline measure of innovation is quite different from previous both in terms of being composite and using trade in services as the transmission channel (weights), the results for Japan and South Korea are very much in agreement with most of these previous studies which include Apergis *et al.*, (2009), Acharya and Keller (2009), Behera *et al.*, (2012), Nishioka and Ripoll (2012), Medda and Piga (2014), Piermartini and Rubínová (2014), Bloom *et al.*, (2016) and Pradeep *et al.*, (2017). For China, the story is different and could be unique for different reasons suggested in recent literature.

One possible reason explaining this surprising result could be the alleged exploitation of resources by China in countries where they provide services. Another reason could be the second allegation that when China provides services, they hardly employ workers from the host country. Yet the study is making a theoretical case that workers in the host countries have to be employed in order to learn and adopt the technology that comes with China's service providers. When the foreign service provider does not employ workers from the host country, the technology learning process might be undermined. In other words, the foreign service provider will eventually leave the host country without imparting the innovation in the local industry and local labour force.

What is reassuring here is that in spite of these different specifications from variant (1) – (4), all the models confirm a similar result which is that China's innovation spillover negatively affects total factor productivity of manufacturing industries in South Africa. Only Japan and South Korea's innovation spillovers appear to positively affect total factor productivity. The study tried several experiments to check the sensitivity of

results and improve our estimates. Such experiments included the control of time and industry fixed effects particularly for the Bayesian specification with flat priors but the results on posterior means did not significantly change.

The Zellner specification could not accommodate time and industry fixed effects as it is constrained by the maximum dimension of the distribution. What only changed with this robustness check were the efficiency levels that dropped significantly implying a loss of precision. Another experiment aimed at improving efficiency of the algorithm was that of blocking of parameters. In the present case, the analysis blocked the variance parameter which improved efficiency levels significantly but the posterior distributions of regression parameters were not significantly altered which was reassuring as far as the main result is concerned.

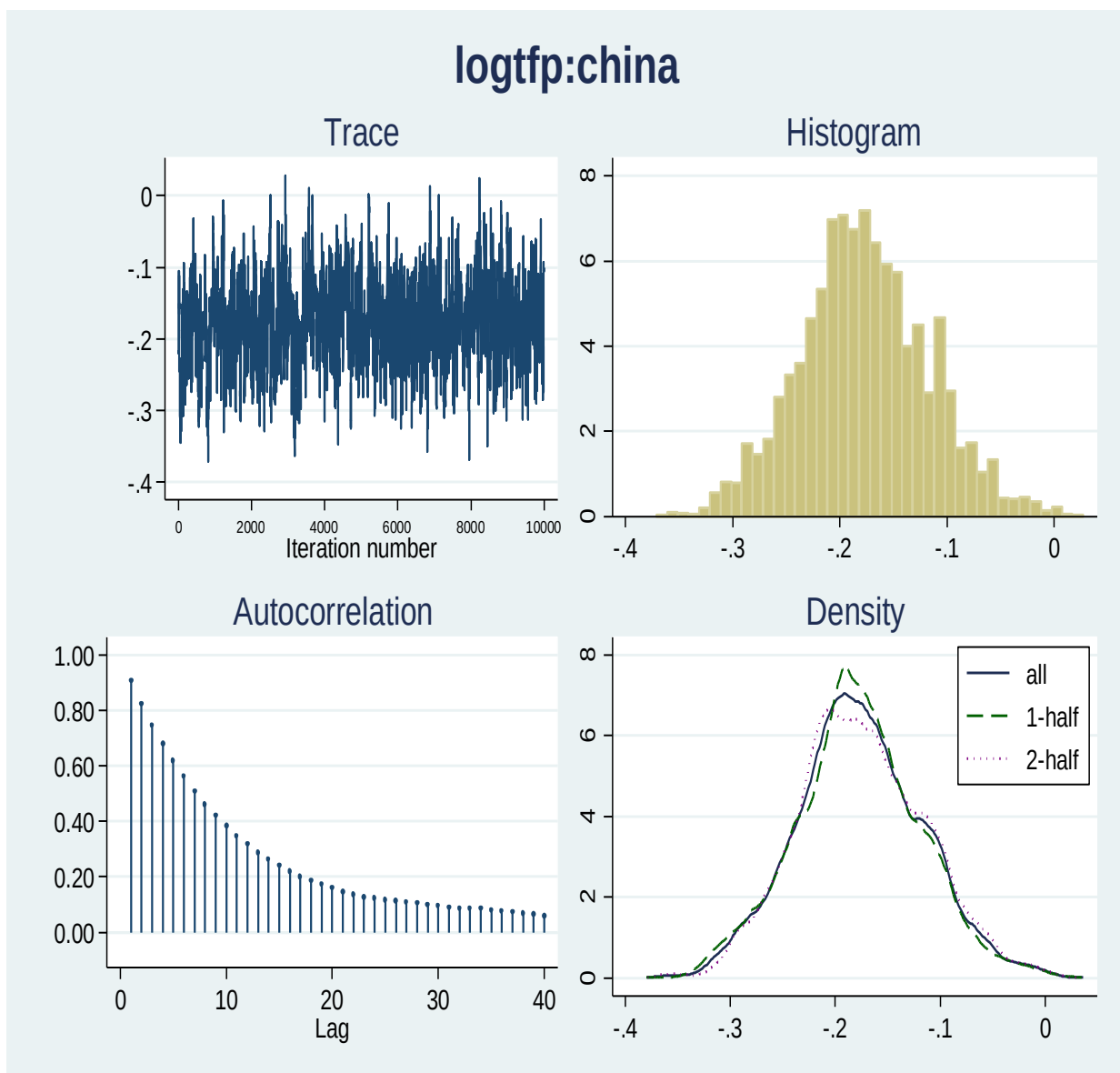
5.9 DIAGNOSTIC TESTS

Variants (1) and (2) have acceptance rates of 0.18 and 0.35 respectively. This means that 18 per cent and 35 per cent out of 10 000 proposal parameter values for variants (1) and (2) respectively were accepted by the employed algorithm. Similarly, for variants (3) and (4), the acceptance rates are 0.23 and 0.18 respectively implying that 23 per cent and 18 per cent out of 10 000 proposal parameter values for variants (3) and (4) are accepted by the Metropolis-Hastings algorithm. For this algorithm, the acceptance rate rarely exceeds 50 per cent and usually falls below 30 per cent.

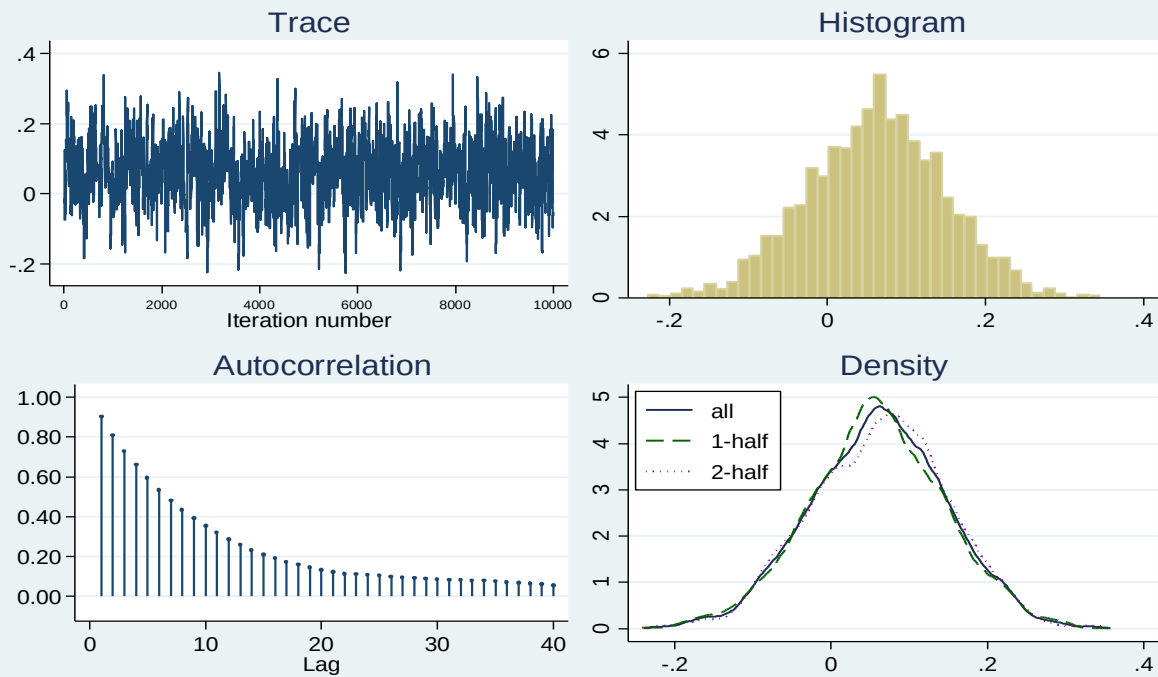
By implication, a low acceptance rate typically below 10 per cent signals convergence problems. In the present case, the acceptance rate for variant (2) is higher than that of variant (1) which is not surprising since the former is based on flat priors. With regard to efficiency by rough rule of thumb, efficiencies above 10 per cent are generally considered good. Here, only the efficiency of variants (1) and (2) are higher than 10 per cent suggesting again that variants (1) and (2) are better models than variant (3) and (4).

Figure 5.4 displays diagnostic checks for variants (1) and (2) with relatively high efficiency levels. The kernel density estimate for each variable has densities estimated based on the first, second and all the halves of the Markov Chain Monte Carlo sample. Observed are fairly normally distributed posterior estimates with autocorrelation that taps off fairly quickly. This rule out the possibility of convergence problems in the estimation and simulations.

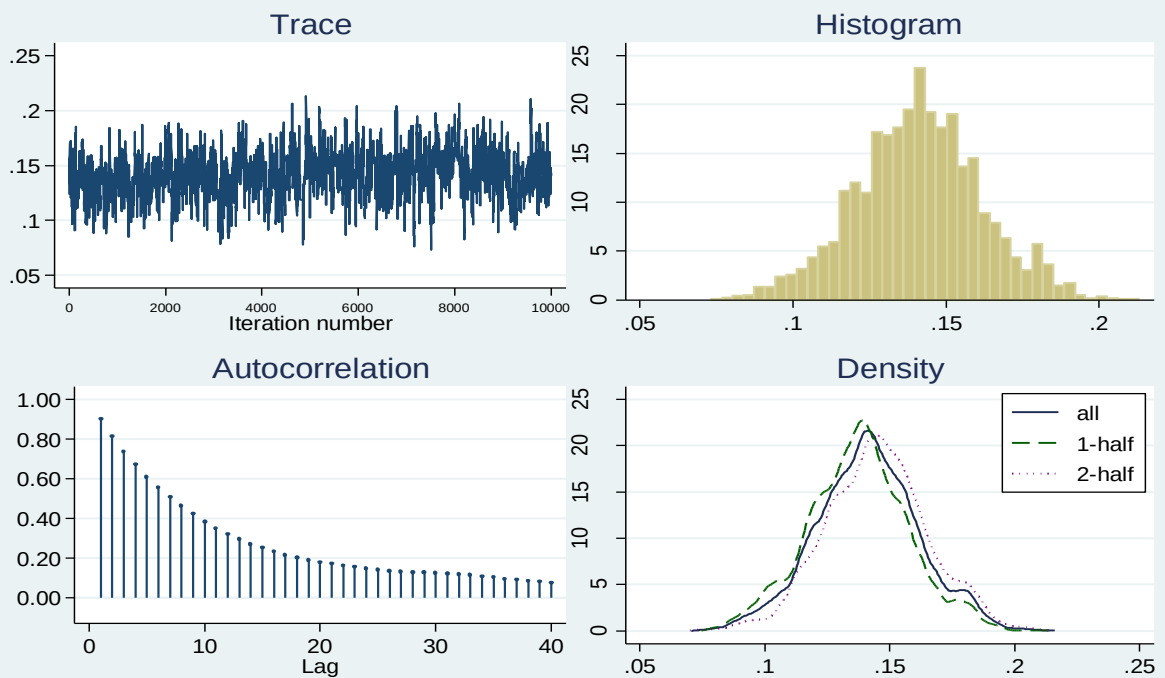
Variant (1)



logtfp:korea

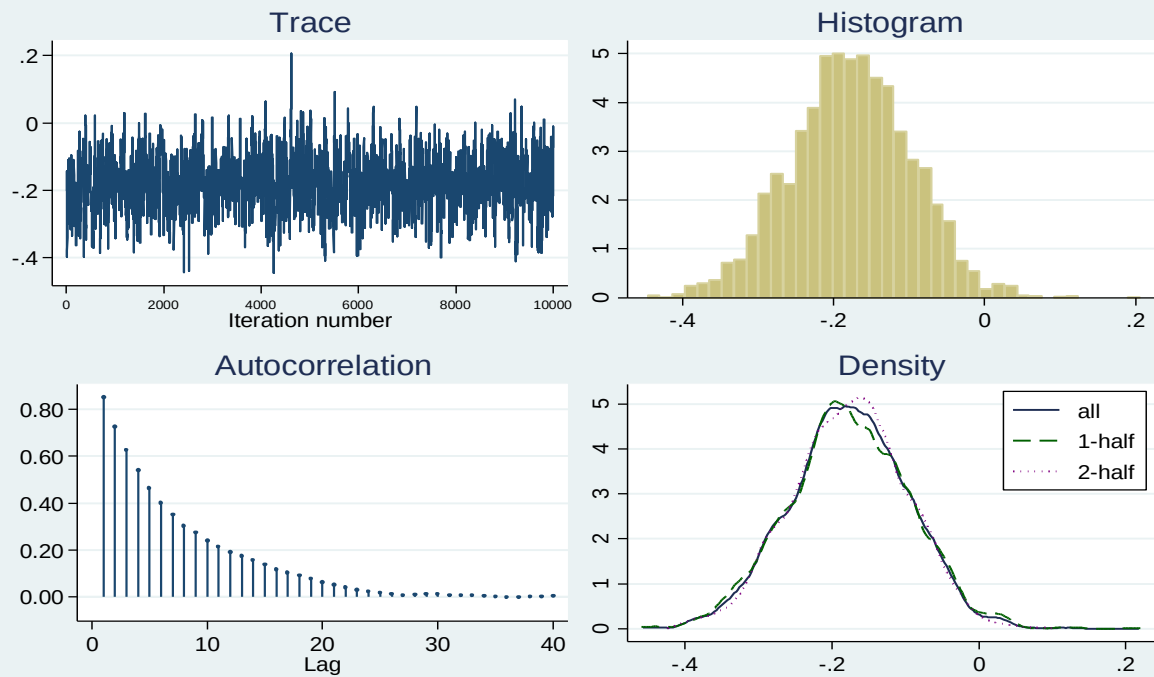


logtfp:japan

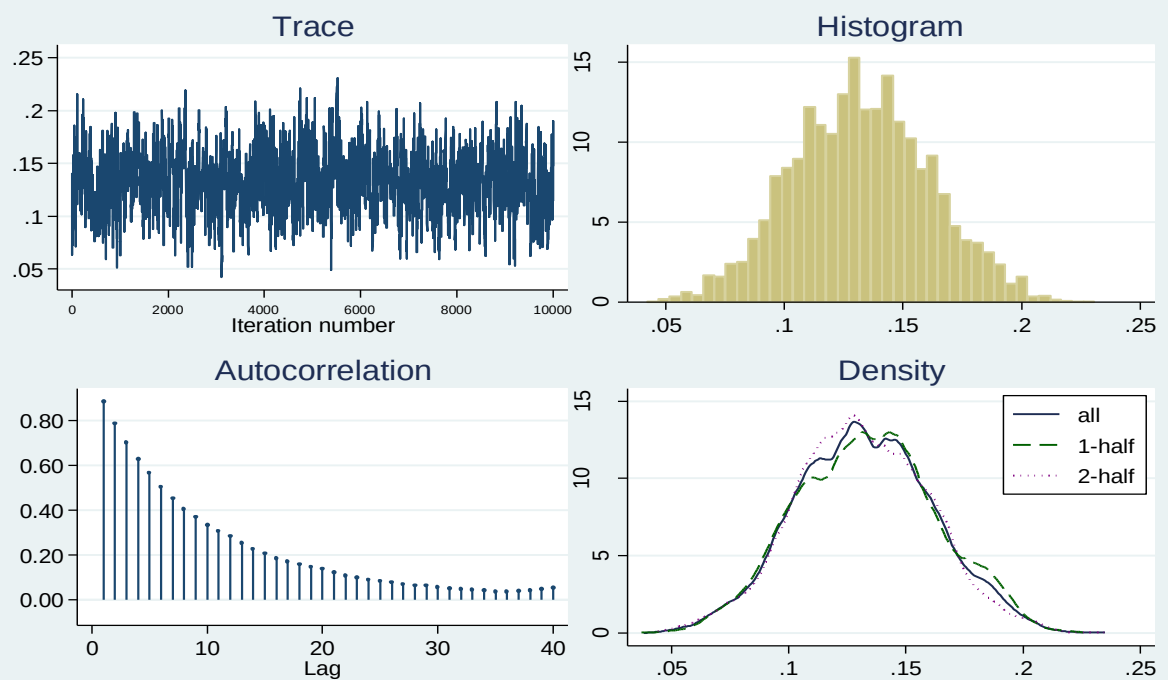


Variant (2)

logtfp:china



logtfp:japan



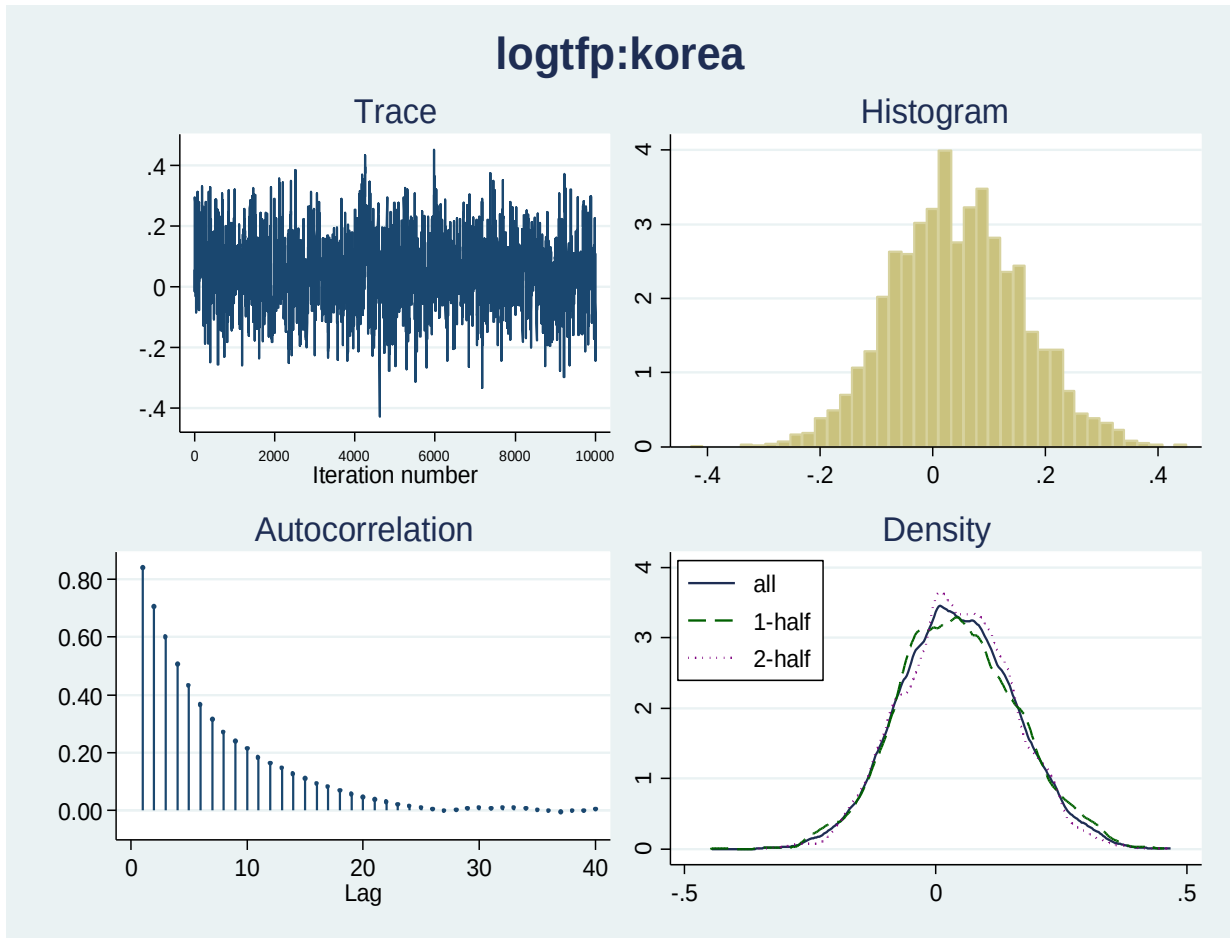


FIGURE 5.4: BAYESIAN DIAGNOSTICS

5.10 CONCLUDING REMARKS

This chapter has provided evidence that Chinese, South Korean and Japanese innovation spillovers significantly influence total factor productivity growth of South Africa's manufacturing industries between 2000 and 2015. Unlike the majority of previous studies, this chapter contributed to existing body of knowledge in four important ways. First, it applied a Bayesian analysis which circumvents the model uncertainty problem inherent in the frequentist approach. Second, it computed a composite index of innovation which comprises both inputs and outputs of research and development. Third, it pays particular attention to trade in services as the key channel through technology from China, South Korea and Japan impacts total factor productivity growth of South Africa's manufacturing industries.

Fourth, it measures total factor productivity using a non-parametric approach which is not susceptible to model functional form issues. Results from both flat and informative priors point to a positive spillover effect of Japanese and Chinese technology but a negative effect of Chinese innovation spillovers. The former result is consistent with open economy endogenous growth models which view technological spillovers as a way through which technology lagging economies can catch-up with their technology frontier counterparts.

The effect is found to be significant and sizeable particularly for Japan (0.14 per cent) which perhaps is the most industrialised economy with highly advanced technology relative to South Korea (0.06 per cent). The negative effect for China (-0.17 per cent) is contrary to a priori theoretical expectations but somewhat complementing to recent literature that raise concerns over China's predatory presence in Africa as a whole citing resource exploitation as the area of concern. If this concern is indeed true, then the negative technology spillover effect would imply that the resource exploitation effect is dominating the technology effect otherwise more work is required to deeply explore the negative effect of China's technology spillover effect.

CHAPTER 6

THE IMPACT OF CHINESE, KOREAN AND JAPANESE INNOVATION SPILLOVERS ON MANUFACTURING LABOUR PRODUCTIVITY IN SOUTH AFRICA

The objective of this chapter is to estimate the impact of Chinese, South Korean and Japanese innovation spillovers on labour productivity growth in South Africa's manufacturing sector which is an attempt to answer the second objective of the study. In essence, the two previous chapters (chapter four and five) dealt with total factor productivity and the present chapter focuses on labour productivity. The entry point of the chapter gives a background (section one) which is then followed by a review of related literature in section two. Section three and section four specify the model and describe the data respectively. The estimation procedure is outlined in section five. Section six and section seven present and discuss the empirical results and robustness checks respectively while section eight provides concluding remarks.

6.1 BACKGROUND

Open economy endogenous growth theories by Aghion and Howitt (1990) Grossman and Helpman (1991), and Coe and Helpman (1995) provide the standard theoretical foundation upon which empirical literature on innovation spillovers is grounded. These models predict that technology transcends international boundaries through trade in intermediate imports. Consequently, the benefits of innovation created in technology frontier economies can be enjoyed by their technology lagging counterparts.

While literature on this theoretical discourse is well established, a closer look to the existing evidence reveals a number of gaps and shortcomings. First, few studies have considered trade in services as the transmission mechanism. Francois (1990), Mun and Nadiri (2002) and Guerrieri *et al.*, (2005) have shown that services play an important role in explaining productivity through the linkage and coordination of technology transfers. Empirically, trade in services has gained more prominence in

recent decades than trade in physical goods (Balchin *et al.*, 2016). Despite the negligible role given to services as a determinant of long-run productivity growth in traditional growth models, there is little debate that trade in services has become fundamental in transferring skills, knowledge and technology across countries through, for example, service contracts where companies offer technical services abroad.

Second, a substantial literature on technology spillovers (Apergis *et al.*, 2008, Behera *et al.*, 2012, Nishioka and Ripoll, 2013, Medda and Piga, 2014, Bloom *et al.*, 2016 and Pradeep *et al.*, 2017) has commonly proxied innovation by research and development (R&D) stock which is essentially an input in the innovation creation process. According to OECD (2010) however, indicator and related econometric research must move forward from innovation inputs and activities to include the outputs. Motivated by this recommendation, the study proposes and constructs, using the principal component analysis (PCA), a novel composite innovation index that comprises both innovation inputs (R&D stock and human capital in R&D) and outputs (patent and trademark applications).

An autoregressive distributed lag model (ARDL) due to Pesaran and Smith (1998) and Pesaran *et al.*, (2001) is estimated through the bounds testing procedure to establish the relation between productivity and foreign innovation. This procedure utilizes lags which makes it capable of adequately capturing the underlying data generating process. For robustness purposes, the study employs alternative cointegrating estimators that remedy, in part, some of the problems inherent in the innovation-productivity relation. These include the dynamic ordinary least squares (DOLS); the fully modified ordinary least squares (FMOLS) and the canonical cointegrating regression (CCR) techniques.

South Africa enjoys strong trade and diplomatic ties with China, Japan and South Korea. According to South Africa's Industrial Development Cooperation (IDC) (2009), the majority of South Africa's imports from Asia originate from China, Japan, South Korea and Saudi Arabia with a combined 53.5 per cent share of total imports

from the Asian region. In theory, one would expect technology to flow from technology frontier economies to technology lagging ones. Japan, South Korea and China have higher per capita incomes relative to South Africa which makes it reasonable to consider the former three as technology leading economies. Also, Japan and South Korea are service driven economies hence the study expects them to transmit innovative and high quality services to innovation lagging economies like South Africa.

6.2 LITERATURE REVIEW

In theory, trade spurs innovation by enhancing industrial learning through the exchange of technical information across countries. It is through this process that an innovation lagging country can simply adopt a superior technology that has already been invented in a technology frontier country (Apergis *et al.*, 2008). This is termed “the advantage of backwardness” as it prevents duplication of research efforts. The superior technology that is traditionally embodied in intermediate goods traded across countries constitutes an important mechanism for innovation diffusion in the endogenous growth models pioneered by Romer (1989) and their extended open economy versions of Grossman and Helpman (1991) and Aghion and Howitt (1990). According to these theoretical models, the use of domestic and foreign-sourced intermediate and capital goods is fundamental in raising and sustaining productivity growth through superior technologies.

Empirically, the idea that imports embody superior technology and their use raises productivity growth of the importing country was pioneered by Schmookler (1966) and subsequently examined by Terleckyj (1974), Griliches and Lichtenberg (1984), Coe and Helpman (1995) and Keller (2002). Recent literature uses firm, industry and sectoral level data to analyse the connection and mechanism linking imports and productivity. Influential firm-level studies such as Melitz (2003), Pradeep *et al.*, (2017) and Medda and Piga (2014) confirm the presence of technology spillovers on productivity.

The present study is closely related to industry and sectoral level literature which includes Badinger and Egger (2016), Mehta (2013), Nishioka and Ripoll (2012), Raouf Abdel Fattah (2015), Apergis *et al.*, (2008) and Behera *et al.*, (2012). These studies generally exploit data on manufacturing industries over time and use panel data techniques to explain the empirical link between technological spillovers and productivity. The chain of evidence is mixed across most of these studies. For example, Behera *et al.*, (2012) confirm that technology spillovers are significant drivers of productivity and that the effect is stronger in industries like food products, textiles, chemicals, drugs and pharmaceuticals and non-metallic mineral products. On the contrary, Mehta (2013) and Elu and Price (2010) do not find technological spillovers to be a significant driver of productivity. The latter particularly conclude that trade between Africa and China does not bring productivity enhancing technology.

Although the source of results contradiction may not be determined *a priori* with virtual certainty, it is likely that the source of controversy lies in different estimation approaches employed by different studies. An important shortcoming of earlier studies is that of disregarding issues of non-stationarity as noted by Apergis *et al.*, (2008). The problems of ignoring data stationarity property are well known; statistical inference in the conventional ordinary least squares method will be spurious. It is against this background that the study performs unit root and cointegration tests which would then allow us so to employ an estimation technique that is less susceptible to spurious inferences.

There is however a fair amount of studies that conduct unit root and cointegration tests and these include Apergis *et al.*, (2008), Lee (2006) and Guellec and Van Pottelsberghe de la Potterie (2004). These studies generally find productivity and technology spillovers to be cointegrated and hence proceed with cointegrating estimation techniques. To our knowledge however, none of these studies adequately addresses the issue of simultaneity.

The correction of simultaneity is critical in this kind of literature as trade variables may also react to changes in productivity growth. Some of the studies including Bloom

et al., (2016) rely on instruments while firm level studies such as one by Ahmed *et al.*, (2015) capitalise on the Olley and Pakes (1992) Control Function Approach (CFA) to deal with the endogeneity that arises from unobserved productivity shocks. Using a variant of Cobb-Douglas production function Ahmed *et al.*, (2015) conclude, in the context of Pakistan, that policies that promote trade encourages productivity growth. Their study did not however focus on the channels through which trade can foster productivity growth.

Other studies focus on the channels through which innovation spreads across countries apart from imports. Alvarez (2005) for the Chilean manufacturing industry focus on three main channels of technological absorption: exports, direct foreign investment and purchase of foreign technical licenses. The author shows that exports significantly increase technological innovation. For Egypt, Fattah (2015) finds innovation spillovers from 16 countries on Egypt's domestic productivity through imports, exports, inward FDI and outward FDI. On the contrary, Goldberg *et al.*, (2010) reach the conclusion that innovation is transferred through access to new imported inputs. This is similarly confirmed by Kasahara and Rodrigue (2008).

Different from these studies, this study focuses on trade in services as the transmission mechanism. It is interested in services of two forms: 1) Commercial presence - which is essentially the provision of a service by a service provider of a country by establishing a commercial presence in another country. This can take the establishment of a branch, subsidiary or any other type of business establishment and 2) Movement of natural persons which involves the provision of services via the temporary presence of a company or a person of one country in another country. This category can include the temporary movement of independent professionals such as electricians, auto-mechanics and tailors in a foreign country.

The ultimate objective is to assess the relevance of service imports in transferring innovation across international boundaries and the eventual effect on labour productivity in the importing country. The analysis is conducted at sectoral level which necessitates the use of a time series approach.

One might question the suitability of a sectoral level approach i.e. aggregation issues. Related empirical work in this area – trade in services - tends to rely on aggregated data¹⁶ often of cross-section in nature. Mattoo *et al.*, (2006) demonstrate for example using a cross sectional data set that countries with liberalized financial and telecommunication sectors exhibit high productivity growth rate. Similarly, Eschenbach and Hoekman (2006) report that liberalization combined with the adoption of good practices in the regulation of telecommunications, financial and energy and transport services are relevant determinants of economic performance. This chapter differs from these studies in that it considers trade in services as a mechanism through which innovation in one country affects productivity in the other.

Close to this kind of analysis are studies that consider foreign direct investment as a productivity driver in the host country (Arnold *et al.*, 2011a, Fernandes and Paunov, 2012 for Chile; and Arnold *et al.*, 2016 for India). Indeed, FDI is a key mechanism for the international provision of enabling services and the transfer of knowledge and the know-how as well as a relevant channel through which high-quality; low-cost services can improve total factor productivity (TFP) of manufacturing producers in the host country. However, this analysis aggregates a broad range of services other than FDI which makes it capable of providing a complete picture of how trade in services influences productivity of the importing country as an innovation transmission mechanism.

¹⁶ Also one of the pioneering works by Coe and Helpman (1995) was even more aggregated as it was conducted at country level.

6.3 MODEL SPECIFICATION

To ascertain the impact of innovation embodied in service imports from China, Korea and Japan, the analysis specifies a multivariate model of the following form¹⁷:

$$\log LP_t = \beta_0 + \beta_1 \log S_t + \beta_2 \log C_t + \beta_3 \log K_t + \beta_4 \log J_t + \varepsilon_t \quad (6.1)$$

$$t = 1995Q1, \dots, 2017Q4$$

where $\log$ denotes logarithm, $\beta_0 - \beta_4$ are unknown parameters to be estimated, t signifies time period, ε_t is the white noise error term, LP is labour productivity defined as real output per worker in manufacturing. By focusing on productivity at sectoral level, the chapter makes an assumption that manufacturing productivity draws from a common pool of technology. Variable S represents South Africa's composite innovation index, C , K and J are composite innovation indices for China, South Korea and Japan respectively so that their corresponding slope parameters represent spillover effects as explained in the theoretical framework.

6.4 DATA DESCRIPTION

The sampling period is 1995 – 2017 guided by data availability. Despite the issue of data considerations, this period coincidentally represents the era in which trade between South Africa, China, South Korea and Japan grew remarkably. In order to increase the sample size, the annual data are converted into quarterly intervals using the quadratic interpolation method. With this transformation, the analysis ends up with a sample size of 92 observations. Data are sourced from QUANTEC data providers and South African Reserve Bank (SARB), OECD and World Development Indicators (WDI).

¹⁷ This model theoretically builds from open economy versions of endogenous growth models by Grossman and Helpman (1991). It is similar to that applied in Apergis *et al.*, (2009) and Behera *et al.*, (2012), Nishioka and Ripoll (2012), Badinger *et al.*, (2013), Mehta (2013), Raouf Abdel Fattah (2015). The difference is that we focus on innovation transferred via service imports rather than R&D embodied in physical imports.

6.5 ESTIMATION PROCEDURE

This section outlines and explains the steps taken by the study in estimating the specified regression model. These steps include pre-estimation tests such as unit root and long-run (the bounds testing procedure) as well as post-estimation diagnostic tests.

6.5.1 UNIT ROOT TESTING

With time series, it is important to first check the data generating process so as to avoid making spurious inferences which occur when the study estimates a seemingly strong relationship which does not exist. To achieve this, the chapter applies the Breakpoint unit root test, the Augmented-Dickey-Fuller (ADF), Phillip-Perron (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for robustness purposes.

6.5.2 ARDL MODEL SPECIFICATION

Having checked the data generating process, the chapter applies the linear Autoregressive Distributed Lag (ARDL) bounds testing procedure proposed by Pesaran and Smith (1998) and Pesaran *et al.*, (2001) which has the main advantage of being applicable even in the presence of I (0) and 1 (1) regressors. With the ARDL bounds testing procedure, equation (6.1) becomes.

$$\begin{aligned}\Delta \log LP_t = & \theta_0 + \theta_1 \log LP_{t-1} + \theta_2 \log C_{t-1} + \theta_3 \log J_{t-1} + \theta_4 \log K_{t-1} + \theta_5 \log S_{t-1} \\ & + \sum_{i=1}^n \beta_i \Delta \log LP_{t-i} + \sum_{i=1}^n \varphi_i \Delta \log C_{t-i} + \sum_{i=1}^n \alpha_i \Delta \log J_{t-i} + \sum_{i=1}^n w_i \Delta \log K_{t-i} \\ & + \sum_{i=1}^n a_i \Delta \log S_{t-i} + \varepsilon_t\end{aligned}\tag{6.2}$$
$$t = 1995Q1, \dots, 2017Q4$$

where Δ denotes the first difference operator. The optimum lag order for each regressor is automatically selected by the Akaike Information Criterion (AIC) which, according to Lütkepohl (2006), performs better than other alternatives. In performing the bounds testing procedure, the chapter first estimates equation (6.2) by the OLS

method and test for joint significance of lagged level variable parameters using an F-test.

The corresponding F-statistic in the bounds testing procedure has a non-standard distribution which is dependent upon four key factors namely (i) the number of observations (n), i.e. sample size (ii) number of regressors (k-1) in the ARDL model, (iii) whether the model contains an intercept and or a trend and (iv) whether variables are I(0) or I(1). In this study, n=92, k-1=4, case three is assumed i.e. unrestricted intercept and no trend and the variables are all I(1) as will be shown in the subsequent section. Two sets of critical values are tabulated in Pesaran *et al.*, (2001) for the lower and the upper bound. An F-statistic above (below) the upper (lower) bound signals presence (absence) of a long-run relationship while the test is inconclusive if the F-statistic lies in between the upper and the lower bound.

The null hypothesis of no long-run relationship among the variables is given by, $H_0: \theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = \theta_6 = 0$ against the alternative hypothesis $H_A: \theta_1 \neq \theta_2 \neq \theta_3 \neq \theta_4 \neq \theta_5 \neq \theta_6 \neq 0$. This can be denoted by $F_P (\ln LP \mid C, K, J, S)$. It is possible to estimate several equations where variables take turns to be dependent variables. According to Narayan and Smyth (2004), this enables one to identify the number of cointegrating relationships among the variables in the system.

If a long-run relationship is confirmed in the equation that is normalised with labour productivity, then equation (6.2) can be re-specified into an error correction representation of the following form:

$$\begin{aligned} \Delta \log LP_t = & c + \sum_{i=1}^n \beta_i \Delta \log LP_{t-i} + \sum_{i=1}^n \varphi_i \Delta \log C_{t-i} + \sum_{i=1}^n \alpha_i \Delta \log K_{t-i} + \sum_{i=1}^n w_{iP} \Delta \log J_{t-i} \\ & + \sum_{i=1}^n \eta_{iP} \Delta \log S_{t-i} + \delta ECT_{t-1} + \varepsilon_{1t} \end{aligned} \quad (6.3)$$

Adding to the variables already defined; ECT_{t-1} represents a year lagged error correction term that reconciles long-run information with short-run dynamics. As a

robustness check, the results of the baseline ARDL are compared with those from alternative estimators – the Dynamic Ordinary Least Squares (DOLS), the Fully Modified Ordinary Least Squares (FMOLS) and the Canonical Cointegrating Regression (CCR) techniques.

The DOLS technique proposed by Stock and Watson (1993) essentially solves the problem of endogeneity through inclusion of leads and lags of differenced endogenous regressors such that the new cointegrating equation error term is orthogonal to the entire history of the stochastic regressor innovations (Stock and Watson, 1993, Belke and Czudaj, 2010).

The Fully Modified Least Squares (FMOLS) regression technique is due to Phillips and Hansen (1990). Similar to the DOLS approach, this estimation technique provides optimal parameter estimates of cointegrating regressions while taking into account the possibility of serial correlation in the residuals and endogeneity of right hand side variables. The Canonical Cointegration Regression (CCR) developed by Park (1992) is similar to the FMOLS technique except that it employs stationary transformations of the data to obtain least squares estimates in a bid to remove the long run dependence between the cointegrating equation and stochastic regressor innovations. Results are presented in the subsequent section.

6.6 RESULTS AND DISCUSSION

Principal components results are attached in Appendix E for brevity sake¹⁸. Out of four factors; the first two components explain 79 per cent variation of the overall index for Japan and 98.8 per cent variation for South Korea and China. In all cases, the Kaiser-Meyer-Olkin¹⁹ is above the 0.6 threshold which provides justification for using the principal component analysis. Interesting is that in all cases i.e. for Japan, China and South Korea, all the four indicators load highly in the first factor. It is also the first factor

¹⁸ Note that chapter five to chapter eight virtually use the same innovation spillovers measure which means all these chapters (chapter five to chapter eight) rely on the same PCA results.

¹⁹ A Kaiser-Meyer-Olkin value above 0.6 generally provides a greenlight to proceed with the PCA. It is a sign that the factors are highly correlated and can therefore be used to formulate a composite index.

(R&D stock) that is retained as its Eigen values²⁰ are more than 1 in all cases, 2.3 for Japan, 3.9 for South Korea and 3.7 for China.

Figure 6.1 displays the computed innovation spillovers for China, South Korea and Japan at quarterly intervals between 2000 and 2015. The way in which China has overtaken Japan as South Africa's source of technology absorption is dramatic. Recall that the transmission mechanism of technology here is service imports which rules out the well-known story of Chinese physical goods imported by South Africa. What this tells us is that China has also gained heights in exporting services.

South Korea has also followed China's direction as far as exporting service embodying technology exports to South Africa is concerned. There is also a high likelihood that South Korea might overtake Japan in a few years' time in this respect given the declining trend of Japan's service embodying exports to South Africa and the rising trend of South Korea's.

²⁰ In a PCA, Eigen values are essentially used to determine the number of factors retained in the computation of the composite index. In particular, the PCA retains all factors, as a rough rule of thumb, whose Eigen values are above one.

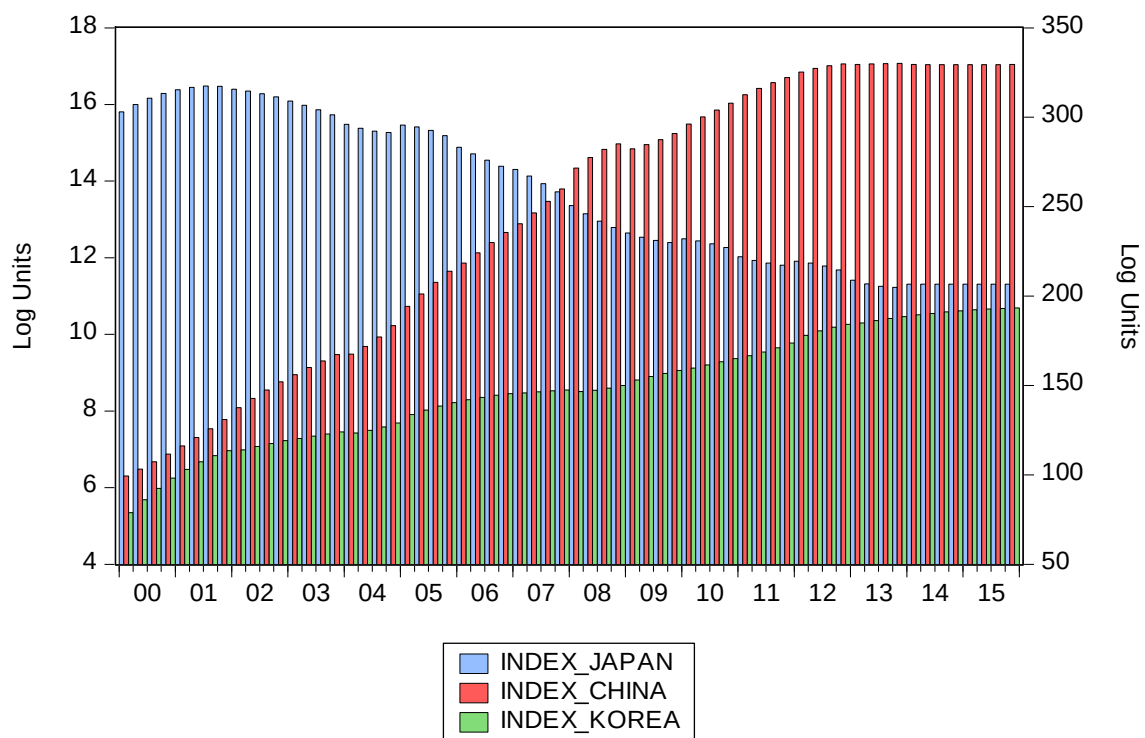


FIGURE 6.1: COMPOSITE INNOVATION SPILLOVERS FOR CHINA, SOUTH KOREA AND JAPAN

To verify the applicability of the ARDL bounds testing procedure, the study evaluated the integration properties of the data using four tests for unit roots namely the Breakpoint, ADF, PP and KPSS. With the Breakpoint, ADF and PP tests, the null hypothesis is of a unit root i.e. a non-stationary process. The opposite is true for the KPSS test. Three out of four tests in Table 6.1 confirm that the variables are I (1) and that none of them is I(2) which gives us the green light to apply the ARDL technique (Pesaran *et al.*, 2001).

The calculated F-statistics are presented in Table 6.2 and the outcome points to a presence of one cointegrating vector in which $\log LP$ is the dependent variable. This is the equation in which the calculated F-statistic is above the 5 per cent critical upper bound. According to Pesaran *et al.*, (2001) a long-run relationship exists if the calculated F-statistic is above the 5 per cent upper bound critical value. For equations normalised with other regressors in Table 6.2, the test either confirms absence of a long-run relationship or is rather inconclusive.

TABLE 6.1: UNIT ROOT RESULTS

Variable		Break-Point	ADF	PP	KPSS	Order of integration
lnLP	Levels	2.423	1.253	2.840*	1.219***	I(1)
	Δ	6.852***	2.940**	-----	0.438	
lnS	Levels	3.686	1.641	0.846	0.998***	I(1)
	Δ	4.237*	^{TI} 5.926***	3.357**	0.082	
lnC	Levels	1.729	0.782	3.087**	1.177***	I(1)
	Δ	4.976***	3.956***	-----	0.439	
lnJ	Levels	1.255	^{TI} 1.896	0.708	0.715**	I(1)
	Δ	17.255***	2.361**	3.136***	0.346	
lnK	Levels	1.389	1.787	15.741***	1.142***	I(1)
	Δ	9.749***	6.892***	-----	0.194	

Note: One, two and three asterisks mean that the variable is statistically significant at 10 percent, 5 percent and 1 percent respectively.

. ^{TI} Signifies specification with trend and intercept. Figures in tables are test statistics for the Break-Point, ADF and PP tests. For the KPSS, the values represent the LM-statistic. ADF = Augmented Dickey Fuller, PP=Phillips-Perron, KSS=Kwiatkowski-Phillips-Schmidt-Shin.

TABLE 6.2: BOUNDS F-TESTS FOR A LONG-RUN RELATIONSHIP

F-statistics	5% critical value bounds		10% critical value bounds		Conclusion
	I(0)	I(1)	I(0)	I(1)	
$F_{LP}(\ln C, \ln K, \ln J, \ln S) = 6.68$	2.86	4.01	2.45	3.52	Cointegrated
$F_S(\ln LP, \ln C, \ln K, \ln J) = 2.37$	2.86	4.01	2.45	3.52	Not Cointegrated
$F_K(\ln LP, \ln C, \ln S, \ln J) = 1.38$	2.86	4.01	2.45	3.52	Not Cointegrated
$F_J(\ln LP, \ln C, \ln K, \ln S) = 3.00$	2.86	4.01	2.45	3.52	Inconclusive
$F_C(\ln LP, \ln K, \ln S, \ln J) = 2.13$	2.86	4.01	2.45	3.52	Not Cointegrated

The main specification that is normalized with labour productivity (*LP*) is based on an ARDL (10, 5, 9, 10, 5) automatically selected by the AIC²¹ (see Figure 6.2).

²¹ The AIC is a model selection criterion which essentially considers the best model as that which has the lowest AIC value. In Figure 4.2, for example, the best model is an ARDL (10,5,9,10,5) as it is the one with the lowest AIC value.

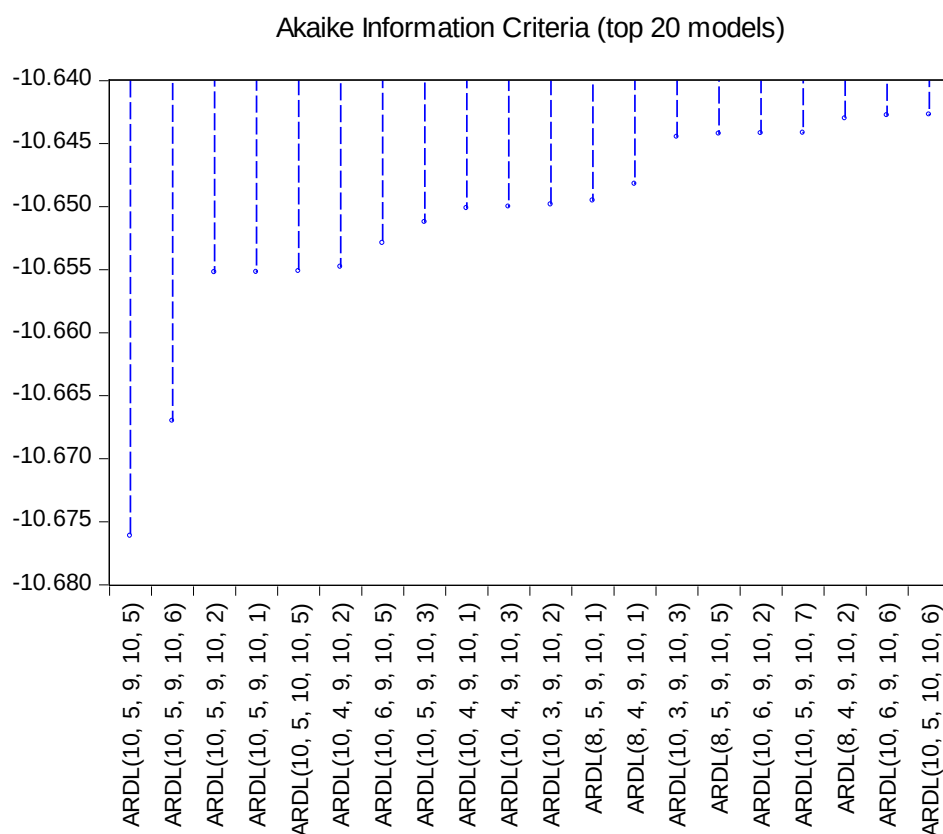


FIGURE 6.2: AKAIKE INFORMATION CRITERION MODEL SELECTION

Since open economy endogenous growth theories are long-run models, the study therefore reports only long-run parameters with Newey-West standard errors in Table 6.3. Three results are noteworthy. Firstly, innovation spillovers transmitted through service imports from China enters with a significantly negative effect on labour productivity which supports Freschi (2010), Renard (2011) and Diaw and Lessoua (2013). A 10 per cent increase in innovation from China reduces South Africa's labour productivity in manufacturing by 0.1 per cent on impact holding constant other regressors (see Table 6.3 in the ARDL column). This is not a surprising result in literature. According to Koumou *et al.*, (2016), many authors (Akomolafe 2008, Asche and Schüller 2008., Kamwanga and Koyi 2009., Fantu and Cyril 2010., Freschi 2010., Renard 2011., Diaw and Lessoua 2013) claim that Chinese investments in Africa bring more harm than good to the economy. They go even far to claiming that Chinese are predators of the African raw materials, and most authors remain very cautious when it

comes to listing the positive effects of these investments (technology transfer) on labour productivity of African economies (Koumou *et al.*, 2016).

TABLE 6.3: IMPACT OF INNOVATION SPILLOVERS ON LABOUR PRODUCTIVITY

Dependent variable: lnLP

Regressors	ARDL	DOLS	FMOLS	CCR
ln South Africa (lnS)	0.210*** (0.042)	0.125** (0.062)	0.124** (0.055)	0.124** (0.055)
ln Korea (lnK)	0.024*** (0.005)	0.059* (0.009)	0.053*** (0.007)	0.053*** (0.007)
ln Japan (lnJ)	0.013*** (0.004)	0.010** (0.004)	0.011*** (0.003)	0.011*** (0.003)
ln China (lnC)	-0.010*** (0.003)	-0.042*** (0.007)	-0.036*** (0.006)	-0.036*** (0.006)
c	4.647 (0.167)	4.999 (0.185)	4.999 (0.227)	4.999 (0.227)
Adj. R-squared	0.903	0.956	0.961	0.953
Hansen Prob.		>0.2	>0.2	>0.2
No of Obs.	82	85	91	91

Note: One, two and three asterisks mean that the variable is statistically significant at 10 percent, 5 percent and 1 percent respectively. Figures in parentheses are Newey-West standard errors. The DOLS is estimated with 3 leads and 3 lags.

Secondly, innovation from South Korea and Japan enter with the expected positive and significant effects predicted by Grossman and Helpman (1991) open economy endogenous growth theory. According to the results in Table 6.3 ARDL column, a 10 per cent increase in innovation spillovers from South Korea (lnK) and Japan (lnJ) raises South Africa's labour productivity in manufacturing by 0.24 per cent and 0.13 per cent on impact respectively holding domestic innovation (lnS) and innovation from China (lnC) constant. This is empirically consistent with studies such as Nishioka and Ripoll (2012) and Acharya and Keller (2009) which all confirmed a positive effect of spillover effects on manufacturing productivity of the importing country.

Thirdly, domestic innovation has a larger effect on labour productivity as compared to innovation from Japan and South Korea. A 10 per cent increase in

domestic innovation is estimated to raise labour productivity by 2.1 per cent holding constant foreign innovation spillovers (see Table 6.3 ARDL column). This is in agreement with results reported in Acharya and Keller (2009), where domestic R&D stock is found to have a relatively greater impact on manufacturing productivity of the importing country. According to Piermartini and Rubínová (2014) and Eaton and Kortum (1996), this may be the case because foreign knowledge is less accessible relative to domestic knowledge owing to barriers related to such things as language and cultural differences.

For robustness check, the long-run parameters were estimated by the Dynamic Ordinary Least Squares (DOLS), Fully Modified Ordinary Least Squares (FMOLS) and Canonical Cointegrating Regression (CCR) techniques with Newey-West standard errors. The DOLS is estimated with 3 leads and 3 lags selected by the Akaike Information Criteria (AIC). Coefficients of leads and lags are not reported for brevity sake. Results are reported in Table 6.3 and they are confirmatory in that; i) Chinese innovation spillovers have a negative effect on labour productivity, ii) South Korean and Japanese innovation spillovers have a positive effect and that iii) domestic innovation has a relatively larger effect on labour productivity. The evidence suggest however that the ARDL appears to over-estimate (upwards bias) the effect of domestic innovation owing to its insufficient ability to adequately address the simultaneity problem.

The adjusted R-squared is over 90 per cent across all the variants of Table 6.3, which makes the estimated model capable of explaining variations in labour productivity. All specifications were subjected to a battery of diagnostic tests. These include residual normality using the Jarque-Bera test (see Figure 6.4), autocorrelation using the Breusch-Godfrey Serial Correlation LM test, heteroscedasticity using the Breusch-Pagan-Godfrey test, model specification using the Ramsey RESET test and parameter stability using the CUSUM test (see Figure 6.3) for parameter stability. Results suggested that the models passed the normality test, Ramsey RESET test and parameter stability but failed the autocorrelation and heteroscedasticity tests (see

Table 6.4). In order to correct for these two problems (autocorrelation and heteroscedasticity) the model was re-estimated with Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors.

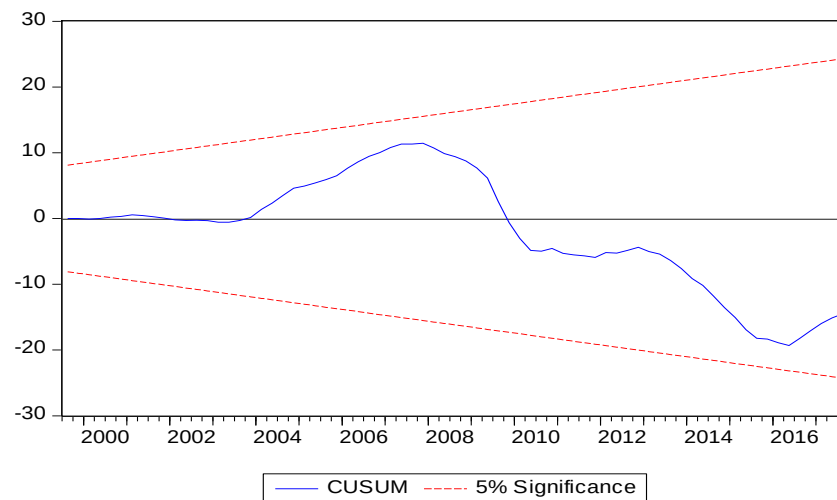


FIGURE 6.3: CUSUM TEST FOR PARAMETER STABILITY

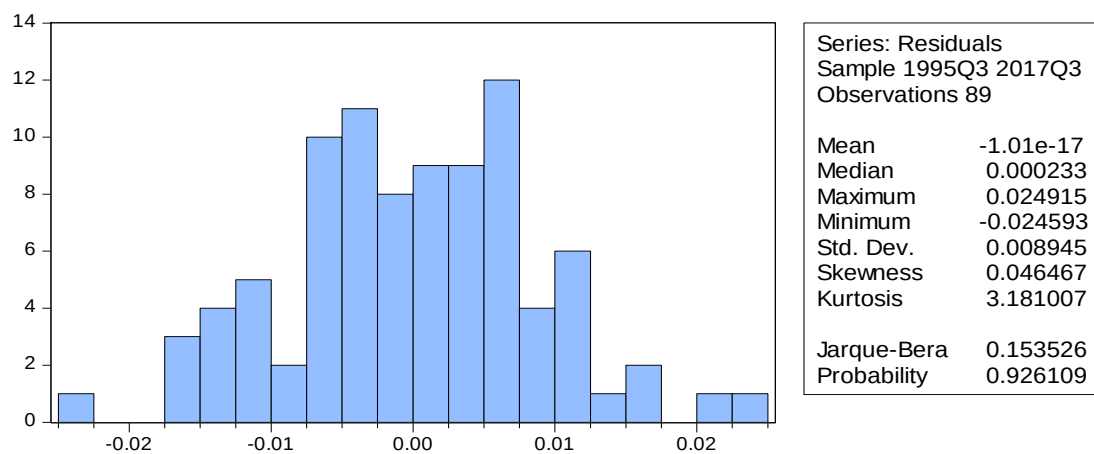


FIGURE 6.4: JARQUE BERA TEST FOR RESIDUAL NORMALITY

TABLE 6.4: ARDL DIAGNOSTIC TESTS

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	41.94458	Prob. F(2,74)	0.0000
Obs*R-squared	47.28719	Prob. Chi-Square(2)	0.0000
Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	2.010427	Prob. F(12,76)	0.0345
Obs*R-squared	21.44452	Prob. Chi-Square(12)	0.0442
Scaled explained SS	17.05260	Prob. Chi-Square(12)	0.1476
Ramsey RESET Test			
	Value	df	Probability
t-statistic	0.555857	75	0.5800
F-statistic	0.308977	(1, 75)	0.5800
Likelihood ratio	0.365900	1	0.5452

The Hansen probability value tests the null of no cointegration post estimation of the DOLS, FMOLS and the CCR. In all cases, the probability values exceed 20 per cent which indicates insufficient statistical evidence to reject the null (results are not presented here for brevity sake since they are only associated with estimation techniques used for robustness checks). This outcome points to a cointegrating relationship substantiating the bounds testing results reported earlier in Table 6.2.

6.7 FURTHER ROBUSTNESS CHECKS

How robust are these results? Firstly, the chapter decomposes the total sample into two sets 1995Q1 – 2008Q4 and 2009Q1 – 2017Q4. This decomposition allows us to establish whether or not the relationship between foreign innovation spillovers has changed over time particularly pre and post the 2009 global financial crisis. The results in Table 6.5 variant (1) represent the 1995Q1 – 2008Q4 sub sample and they are based on an ARDL (1, 4, 4, 4, 3) automatically selected by the AIC with Newey-West

standard errors. Because the sample has 56 quarterly observations after adjusting for degrees of freedom, the study relies on critical values re-formulated by Narayan (2005). These critical values are suitable for small sample sizes ranging from 30 to 80 observations.

The computed F-statistic²² was 18.99 which is above the 3.813 5 per cent upper critical bound given $n=56$, $k=4$ with an intercept and no trend. This provided the green light to estimate the long-run estimates. Similarly, for variant (2), the F statistic is 4.693 which is above the 4.062 5 per cent upper critical bound given $n=36$ and $k=4$. As shown in Table 6.5, the sample decomposition does not bring significant alterations to the main results i.e. Chinese innovation correlate negatively with productivity, South Korea and Japanese innovation spillovers correlate positively but domestic innovation stock has a larger effect.

TABLE 6.5: IMPACT OF INNOVATION SPILLOVERS ON LABOUR PRODUCTIVITY

Dependent variable: logLP

Regressors	Variant (1) 1995Q1 – 2008Q4	Variant (2) 2009Q1 – 2017Q4
log South Africa (logS)	0.288** (0.107)	0.255*** (0.054)
log Korea (logK)	0.091*** (0.013)	0.043*** (0.009)
log Japan (logJ)	0.014*** (0.002)	0.004** (0.002)
log China (logC)	-0.103*** (0.029)	-0.050*** (0.007)
C	4.309 (0.453)	6.610 (0.224)
Adj. sample size	54	33

Note: One, two and three asterisks mean that the variable is statistically significant at 10 percent, 5 percent and 1 percent respectively. Figures in parentheses are Newey-West standard errors.

Secondly, the chapter changes the interpolation method from quadratic to linear interpolation when converting initial annual data to quarterly data. The results in Table

²² These results are not reported here but can be provided upon request.

6.6 are based on an ARDL (2, 0, 2, 2, 2) again automatically selected by the AIC. Following the same stages, i.e. the bounds testing procedure for the entire sample, the results in Table 6.6 corroborate the central result that Chinese innovation is harmful to labour productivity in South Africa's manufacturing sector, Japanese and South Korean innovation spillovers have the opposite effect but domestic innovation has a larger effect.

TABLE 6.6: IMPACT OF INNOVATION SPILLOVERS ON LABOUR PRODUCTIVITY

Dependent variable: logLP

Regressors	Coefficient	Std. Error	t-Statistic	Prob.
log South Africa (logS)	0.295	0.095	3.09	0.0028
log Korea (logK)	0.035	0.012	2.92	0.0045
log Japan (logJ)	0.008	0.001	8.00	0.0000
log China (logC)	-0.021	0.009	-2.24	0.0279
C	4.289	0.396	10.823	0.0000

6.8 CONCLUDING REMARKS

This chapter has constructed a composite innovation index that comprises R&D stock, R&D researchers, patents and trademarks using the principal component analysis. Different from previous studies, service imports are used as the transmission mechanism. Two results are noteworthy. Firstly, service imports have a fundamental role in transferring innovation across international boundaries and this is true for Japan and South Korea in which domestic labour productivity is raised within the 0.01 per cent – 0.06 per cent range. Secondly, although innovation from South Korea and Japan correlates significantly with labour productivity, it is domestic innovation that has a relatively larger effect on productivity.

Based on the evidence, a number of concluding remarks can be made. Firstly, the results imply that domestic policy that affects trade in services with South Korea and Japan such as restrictive rules and regulations can deny South Africa an opportunity to raise labour productivity through absorption of foreign innovation that comes along with their services. The second implication of the results is that labour

productivity is more sensitive to domestic innovation which means that foreign innovation that might be transferred through service imports has to be treated as a complement rather than a substitute for domestic innovation efforts.

CHAPTER 7

THE IMPACT OF CHINESE, KOREAN AND JAPANESE INNOVATION SPILLOVERS ON TECHNICAL EFFICIENCY OF MANUFACTURING INDUSTRIES IN SOUTH AFRICA

This chapter estimates the impact of Chinese, South Korean and Japanese innovation spillovers on technical efficiency of manufacturing industries in South Africa. It primarily answers the third objective of the study which essentially seeks to establish how innovation influences the movement of industries towards the production possibility frontier. Section one of this chapter provides a brief background of the study which is then followed by a brief review of literature in section two. An outline of the stochastic frontier model is then provided in section three before the empirical specification in section four. Section five and section six provide data description and present the empirical results respectively while concluding remarks are provided in section seven.

7.1 BACKGROUND

An important economic question is whether industries in developing countries improve their level of technical efficiency by importing technology or outsourcing inputs from technology frontier economies. We want to know, for instance, whether footwear, textile, clothing and rubber industries in technology lagging economies like South Africa, Mozambique, Kenya or Zimbabwe will move closer to their productivity frontier by outsourcing innovation-embodied intermediate inputs from middle to high income countries such as China, South Korea and Japan.

Although open economy versions of endogenous growth theories of Coe and Helpman (1995) and Coe, Helpman, and Hoffmaister (2009) predict a positive relationship, the empirical evidence has been a subject of debate (Shchetynin, 2015).

This chapter examines the impact of technology-embodied service imports from China, South Korea and Japan on technical efficiency²³ of South Africa's 28 manufacturing industries. Technical efficiency is defined by the gap between observed output and potential output. It can be input oriented or output oriented. In the former case, the objective is to optimise inputs with fixed output. In the latter case, the objective is to raise output with fixed inputs. In this chapter, focus is on output oriented technical efficiency.

Edwards and Jenkins (2015) provide evidence that South Africa's imports from China have a negative effect on manufacturing sector that goes through displacement of domestic production. What is the implication of such findings? In general, unions have taken empirical evidence of imports displacing local production to be supportive of their call for government protection.

In theory however, any policy that reduces the volume of imports consequently minimises the contact of domestic firms and foreign business partners which ultimately denies the host country an opportunity to raise knowledge stock through adoption of foreign innovation. Grossman and Helpman (1990), Grossman and Helpman (1991), Coe and Helpman (1995), Aghion and Howitt (1990) raise these arguments in their open economy versions of endogenous growth models pioneered by Romer (1986). They consider imports as a channel through which innovation may be transferred from technology frontier countries to technology lagging economies.

Previous studies testing Grossman and Helpman's (1991) theory have shown that the relationship can either be negative or positive (Andersson and Stone, 2017., Keller, 2010., Van den Berg and Van Marrewijk, 2017., Lööf and Andersson, 2010). An important weakness of these studies however is that they relied on the Battese and Coelli (1995) time-varying decay model which, according to Greene (2005a and

²³ Productivity growth comprises two components, technical efficiency and technical changes. Technical changes are frontier shifts while technical efficiency represents movement towards the production frontier

2005b) does not distinguish between time-invariant heterogeneity from time-varying inefficiency. This has an implication of generating biased technical efficiency scores of industries by treating unobserved heterogeneity as inefficiency.

Differently from these studies, this chapter controls for heterogeneity of industries when estimating the levels of technical efficiency. It does so by applying the true-fixed effects (TFE) stochastic frontier model proposed by Greene (2005b). The TFE technique improves early time-varying decay models by separating time-invariant heterogeneity from time-varying technical inefficiency; an issue which is relevant in the present case where time-invariant industry-specific effects are likely to be correlated with production inputs, labour and capital. As recommended by Wang and Ho (2010), the chapter estimates the true-fixed effects through the within estimator to circumvent the incidental parameters problem associated with likelihood dummy variable approach of estimating the true-fixed effects model.

7.2 LITERATURE REVIEW

In economic theory, trade influences innovation by promoting industrial learning through the international exchange of knowledge across countries. It is essentially through this important channel that a country lagging in technology can adopt and imitate technology that has already been invented in a technology frontier country (Apergis *et al.*, 2009). This is termed “the advantage of backwardness” as it prevents duplication of research efforts.

Empirically, several studies have sought to empirically test the impact of intermediate imports and technological spillovers on technical efficiency of the importing country. One can broadly decompose these studies into three categories namely i) firm-level, ii) industry-level and iii) country-level. Examples of firm level studies are Keshari (2013), Kalayci and Pamukçu (2014), Pamukçu and Erdil (2015), Shchetynin (2015), Cetin and Kalayci (2016), Andersson and Stone (2017) which apply the stochastic frontier technique mostly based on survey data and confirm a positive connection between importing and the level of technical efficiency.

In the context of Spain, Jorge and Suárez (2011) sought to establish how innovation measured by subsidies allocated towards R&D relate with efficiency of manufacturing firms. Based on survey data with 5349 observations observed between 1993 and 2002, results from a stochastic frontier analysis finds beneficiaries of R&D subsidies less efficient. The limitation of their study is that they focused on R&D subsidies and did not explicitly address the effects of R&D stock on technical efficiency.

Unlike Jorge and Suárez (2011), Barasa *et al.*, (2019) explicitly addresses the effect of R&D on technical efficiency of manufacturing firms but in the context of developing countries. Close to the present analysis, their study was interested in comparing the effect of domestic and foreign innovation on technical efficiency in manufacturing. Using cross sectional data from the World Bank Enterprise survey and a stochastic frontier analysis, the authors find a negative relationship between domestic (internal) innovation and technical efficiency. On the other hand, no significant link is confirmed between adoption of foreign innovation and efficiency.

Deraniyagala (2001) empirically attempt to determine how adaptive technology strategies relate with technical efficiency in the agriculture machinery industry in Sri Lanka. Using survey data observed between 1987 and 1992 analysed through a stochastic frontier analysis, adaptive technology strategies are found to have a significantly positive effect on technical efficiency. In other words, the results support the hypothesis that innovation enhances technical efficiency although this is not explicit in the empirical specification.

Díaz-Mayans and Sánchez-Pérez (2014) address the link between innovation, exports and technical efficiency of 2247 manufacturing firms in Spain between 2004 and 2009. Results from a translog stochastic frontier model indicate that exporting manufacturing firms are relatively more efficient than non-exporting ones perhaps. This result can be taken to suggest that exporting firms are more efficient because

they are able to adopt new innovation on the global market which makes them better able to produce closer to their production possibility frontier.

Berghäll (2016), considers the relationship between innovation, competition and technical efficiency based on an unbalanced panel dataset spanning the periods 1990 and 2003 in Finnish ICT manufacturing. The contribution made by Berghäll (2016) was chiefly the use of several innovation measures ranging from measures of technical efficiency, R&D intensity, technical change, Lerner index to foreign ownership. The weakness was however embedded in the use of the Battese and Coelli (1995) stochastic frontier model which does not distinguish between time-invariant heterogeneity from time-varying technical inefficiency.

Munisamy and Wong (2015) analyse the empirical link between innovation and technical efficiency in Malaysian manufacturing industries. Unlike most studies, the authors measured technical efficiency scores using the Data Envelopment Approach (DEA) which is non-parametric. There are two limitations associated with their study. The first is that the measured technical efficiency using the DEA which does not take into account noise (Battese and Broca, 1997). Secondly, they literally used technical efficiency scores as measures of innovation. One would have expected common proxies of innovation (such as R&D stock and patent applications) as part of the regressors in their Tobit regression.

On the other hand, an industry level by Kim and Lee (2004) confirms that innovation spillovers proxied generally by R&D stock of the exporting country raises efficiency levels of industries in the importing countries. This chapter is closely related to this strand of literature as it relies on an industry level dataset.

Country level studies generally assume an aggregate production frontier in which national output is regressed on labour and capital inputs so that deviations from the ideal frontier can be explained by exogenous factors. Keller (2010) and Wang and Wong (2012) are examples of such studies and their conclusion is generally that

technical efficiency increases with the share of intermediate imports and technology spillovers from technology leading economies.

Within technical efficiency literature, a number of caveats should be noted. First, technical efficiency is broadly measured using either parametric or non-parametric methods. Parametric methods encompass the stochastic frontier analysis (SFA) applied in Wang and Wong (2012) and Andersson and Stone (2017). This technique was developed by Aigner *et al.*, (1977) and Meeusen and Broeck (1977).

Non-parametric methods on the other hand rely on linear programming techniques particularly the data envelopment analysis (DEA). The DEA is a deterministic linear programming technique which makes it inherently difficult to purge the effect of the decision-making unit (DMU) from those outside the control of the DMU when measuring efficiency. In contrast, the SFA considers measurement errors and other exogenous effects that are beyond the control of the DMU. This chapter relies on secondary manufacturing data which is muddled by measurement error as well as production noise which necessitates the use of a stochastic frontier model.

7.3 THE STOCHASTIC FRONTIER ANALYSIS

The SFA due to Aigner *et al.*, (1977) is an approach to measuring technical efficiency that relies on the standard production function methodology. This technique technically recognises explicitly that a production function is a maximum attainable level of output for a given level of input. Common ordinary least squares (OLS) method only fit a function based on an unrealistic assumption that all producers or decision making units are fully efficient. Deterministic production frontiers on the other hand fit a frontier function over the data and assumes absence of noise in data. SFA production frontiers represent a mix of these two approaches.

Following Aigner *et al.*, (1977), a primal stochastic frontier approach assumes that output is a function of conventional factors of production labour and capital in industry i at time period t .

$$\text{Output}_{it} = f(\text{Labour}_{it}, \text{Capital}_{it}) \quad (7.1)$$

Assumed is that observed output can be less than potential output, meaning that equation (7.2) exhibits technical inefficiency. This assumption allows one to specify a stochastic frontier model of the following form:

$$\text{Output}_{it} = f(\text{Labour}_{it}, \text{Capital}_{it}, T, \beta) \cdot TE_{it} e^{v_{it}} \quad (7.2)$$

where T represents a time trend that controls for technical changes, β is a vector of unknown parameters to be estimated, TE measures technical efficiency which is given by the exponential of parameter $-u_{it}$ where u_{it} quantifies the shortfall of observed output from the potential output and v_{it} captures random noise. Introducing logarithms on equation (7.2) gives:

$$\log \text{Output}_{it} = \log f(\text{Labour}_{it}, \text{Capital}_{it}, T, \beta) + \log TE_{it} + v_{it} \quad (7.3)$$

Replacing TE with $\exp(-u_{it})$, one can re-write equation (7.3) as:

$$\log \text{Output}_{it} = \log f(\text{Labour}_{it}, \text{Capital}_{it}, T, \beta) + (v_{it} - u_{it}) \quad (7.4)$$

Equation (7.4) says that output in industry i year t is influenced by labour, capital, technical changes, technical inefficiency and random noise.

There are several contentious issues in the stochastic frontier literature. The first issue relates to whether the analysis should be conducted using a one-step or two-step procedure (Wang and Schmidt, 2002). In the two-step approach as applied in Hasan *et al.*, (2012) and Masunda and Chiweshe (2015), one must first estimate the production frontier by regressing output on factor inputs usually labour and capital omitting variables that affect technical efficiency (Wang and Schmidt, 2002). In the second step, the generated technical efficiency scores are regressed on explanatory variables that are believed to be relevant sources of technical efficiency of the Decision Making Unit (DMU) using, in most cases, truncated regressions.

The problem with the two-step approach is that it lacks consistency in the way it treats the distribution of the inefficiency component (Wang and Schmidt, 2002). In the first stage when estimating the frontier regression, the technical inefficiency component is assumed to be identical and independently distributed. However, in the second stage, the same inefficiency component is assumed to depend on other explanatory variables. Wang and Schmidt (2002) show that this two-step procedure is, as a result, biased and recommend the use of a one-step procedure where determinants of technical efficiency are incorporated directly in the maximum likelihood estimation. This is the approach used in this study.

Another contentious issue in the stochastic frontier literature relates to the choice of the functional form (Greene, 2008). In empirical literature, the commonly assumed functional forms are the Cobb-Douglas and the Translog specifications. Each of these functional forms is not without its own limitations. The advantage of the former is that it is characterised by universally convex isoquants. Nonetheless, its demand elasticities are constant by assumption for given input prices (Greene, 2008). The criticisms that the Cobb-Douglas specification is too restrictive have generally motivated most empirical applications to assume a more flexible functional form which is the Translog.

Notwithstanding the flexibility of the Translog specification, the price to be paid for its flexibility is that it is not globally convex (Greene, 2008). Also, it is generally challenging to impose an appropriate curvature on a Translog model. Despite these criticisms, the Translog and the Cobb-Douglas specifications continue to be widely used in the stochastic frontier literature and a common practice in literature is to estimate both specifications and then conduct relevant statistical tests to determine the form which best suits the data.

Overall, the empirical analysis proceeds as illustrated in Figure 7.1. There is need for measuring both technical efficiency scores and innovation indices. These two variables will then be used in the model in which the aim is to regress innovation spillovers on technical efficiency which is the overall objective of this chapter.

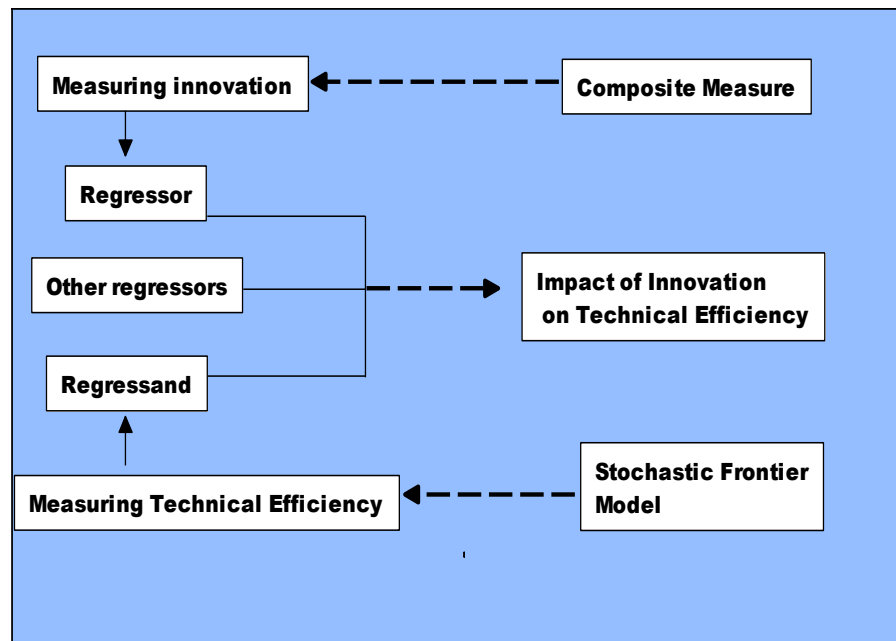


FIGURE 7.1: FLOW DIAGRAM OF THE EMPIRICAL ANALYSIS

From Figure 7.1, the composite measure is essentially the index computed by the Principal Component Analysis (PCA). The solid arrow pointing to the regressor indicates that this variable is included in the model as an independent variable. Other regressors in this study are export intensity and import penetration (justification is given in the subsequent section). On the other hand, the stochastic frontier model will be used to measure technical efficiency as indicated by the dashed arrow pointing leftwards towards “measuring technical efficiency.” These technical efficiency scores will enter the main model as the dependent variable so that their response to changes in innovation indices can be established.

7.4 MODEL SPECIFICATION

To ascertain the impact of Chinese, South Korean and Japanese service imports on technical efficiency of South Africa's manufacturing industries; a stochastic frontier model by Aigner *et al.*, (1977) is adopted due to its advantage over the data envelopment analysis of separating noise from technical inefficiencies. Within the stochastic frontier framework, the translog specification is preferred over the Cobb-Douglas production function due to its flexibility. The estimated stochastic frontier model takes the following form:

$$\begin{aligned} \log(\text{Output})_{it} = & \delta_i + \beta_1 \log(\text{Labour})_{it} + \beta_2 \log(\text{Capital})_{it} + \beta_3 \text{Year} \\ & + \beta_4 [0.5 * \log(\text{Labour})_{it}^2] + \beta_5 [0.5 * \log(\text{Capital})_{it}^2] \\ & + \beta_6 [\log(\text{Capital})_{it} * \log(\text{Labour})_{it}] + \beta_7 [\log(\text{Capital})_{it} * \text{Year}] \\ & + \beta_8 [\log(\text{Labour})_{it} * \text{Year}] + \beta_9 [0.5 * \text{Year}^2] \\ & + \varepsilon_{it} \end{aligned} \quad (7.5)$$

$$\varepsilon_{it} = v_{it} - u_{it}$$

$$v_{it} \sim \text{IID } N(0, \psi^2)$$

$$u_{it} \sim \text{IID } F_u(\sigma)$$

$$i = 1, \dots, 28 \text{ \& } t = 1995, \dots, 2016$$

where the two components of the composite error term; v_{it} and u_{it} are independently distributed. The technical inefficiency component represented by u_{it} is distributed according to F_u which is defined as $\mathbb{R}^+$ with parameter σ . In the specification, Year is a trend variable included to capture the possibility of frontier shifts i.e. technical changes and its squared term accommodates non-monotonic technical changes. Interaction terms of the trend variable and input factors are included to capture Hicks non-neutral technical change (Wang and Wong, 2012). If the following null hypothesis cannot be rejected;

$$\beta_4 = \dots = \beta_9 = 0$$

then equation (7.5) reduces to a Cobb-Douglas specification of the form;

$$\log(\text{Output})_{it} = \delta_i + \beta_1 \log(\text{Labour})_{it} + \beta_2 \log(\text{Capital})_{it} + \beta_3 \text{Year} + \varepsilon_{it} \quad (7.6)$$

$$\varepsilon_{it} = v_{it} - u_{it}$$

$$v_{it} \sim \text{IID } N(0, \psi^2)$$

$$u_{it} \sim \text{IID } F_u(\sigma)$$

$$i = 1, \dots, 28 \text{ \& } t = 1995, \dots, 2016$$

Equations (7.5) and (7.6) are estimated via the within transformation so that the final specifications are without δ_i . This transformation is proposed by Wang and Ho (2010) and it circumvents the incidental parameters problem that may arise if estimation is done via the use of industry-specific dummy variables. For equation (7.6) for instance, the within estimator results in:

$$\hat{\delta}_i = \frac{1}{T} \sum_{t=1}^T (\log(\text{Output})_{it} - \hat{\beta}_1 \log(\text{Labour})_{it} - \hat{\beta}_2 \log(\text{Capital})_{it} + \hat{c}_{it})$$

$$i = 1, \dots, 28$$

where parameters $\hat{\beta}$ & $\hat{c} = E(u_{it} | \hat{\beta}, \hat{c})$ are now consistently estimated using the maximum likelihood (ML) technique. Since the objective is to establish the impact of foreign innovation spillovers on technical (in) efficiency²⁴, the technical inefficiency model is then specified as:

$$u_{it} = \alpha_1 \log S_{t-1} + \alpha_2 \log K_{t-1} + \alpha_3 \log C_{t-1} + \alpha_4 \log J_{t-1} + \alpha_5 \log EX_{it-1} + \alpha_6 \log IM_{it-1} + w_{it} \quad (7.7)$$

$$i = 1, \dots, 28 \text{ \& } t = 1995, \dots, 2016$$

where positive signs on regressors in equation (7.7) imply a negative effect on technical efficiency and vice versa, S is domestic R&D stock, K, C and J capture

²⁴ (In) efficiency scores can be computed from the mean of the conditional distribution of u_{it} given ε_{it} .

innovation spillovers from South Korea, China and Japan respectively. EX and IM represent export intensity and import penetration included to capture economies of scale and the possibility of technological upgrades from other countries respectively.

The regressors in equation (7.7) are lagged once to circumvent the endogeneity problem (Wang and Wong, 2012). Note that the composite innovation indicators do not have subscript i since they vary over time but not across industries. The assumption here is that manufacturing industries draw from a pool of common technology.

It is important to test the suitability of the stochastic frontier analysis over the general production function with normal errors. To achieve this, the study computes the likelihood ratio test statistic as recommended by Kumbhakar, Wang and Horncastle (2015). The Likelihood Ratio test statistic is computed from the formula,

$$-2[L(H_0) - L(H_1)]$$

where $L(H_0)$ and $L(H_1)$ represent the log-likelihood values computed from restricted ordinary least squares (OLS) model²⁵ and the unrestricted stochastic frontier model respectively with one degree of freedom representing the imposed restriction. Critical values for the mixed distribution are obtained from Kodde and Palm (1986). Technical efficiency scores were then computed via Jondrow *et al.*, (1982).

$$TE_{it} = \exp(-U_{it})$$

The next subsection provides a description of variables used in this empirical analysis. Most importantly, it describes the measurement of the variable of interest – innovation index.

²⁵ In STATA, this is achieved through the generalized linear model

7.5 DATA DESCRIPTION

Annual time series data observed between 1995 and 2016 are applied. Selection of this sampling period is guided by data availability. The main data source of the empirical analysis was the South African Standardised Industrial (SASI) database which provides input, output, price and trade variables for 45 industries and 28 of these 45 industries are manufacturing. Here, the chapter relies on the 28 3-digit level manufacturing industries classified according to the International Standard Industrial Classification (ISIC), Rev.2.

Focus is on manufacturing industries as they are largely tradable and sensitive to trade changes. An ideal situation was to use firm level data which adequately captures firm optimization behaviour. However, such data are not available for long horizons hence the chapter relied on industry level data that are based on the assumption that all firms in a given industry behave homogenously. The same assumption is assumed in Ocampo (2002), Kumar (2006), Jenkins (1995) and Liu and Wang (2003). The industries included in the analysis are listed below.

- 1) Non-Ferrous Metals
- 2) Basic Iron and Steel
- 3) Machinery
- 4) Professional and Scientific Equipment
- 5) Leather and Leather Products
- 6) Other Manufacturing
- 7) Other Transport Equipment
- 8) Basic Chemicals
- 9) Paper and Paper Products
- 10) Rubber
- 11) TV, Radio and Communication Equipment
- 12) Furniture
- 13) Transport Equipment
- 14) Other Chemicals
- 15) Textiles
- 16) Metal Products
- 17) Wood
- 18) Food

- 19) Glass
- 20) Clothing
- 21) Electrical Machinery
- 22) Tobacco
- 23) Non-Metallic Minerals
- 24) Beverages
- 25) Coke and Petroleum Products
- 26) Plastics
- 27) Footwear
- 28) Printing and Publishing

In the model (equation (7.7)), variable S represents South Africa's composite innovation index, C , K and J are composite innovation indices for China, South Korea and Japan respectively so that their corresponding slope parameters represent spillover effects. The composite innovation indices are computed using the principal component analysis (PCA) as explained in the theoretical framework.

7.6 RESULTS AND DISCUSSION

Principal components results are reported in Appendix E. Out of four factors; the first two components explain 79 per cent variation of the overall index for Japan and 98.8 per cent variation for South Korea and China. In all cases, the Kaiser-Meyer-Olkin is above the 0.6 threshold which provides justification for using the principal component analysis. Interesting is that in all cases i.e. for Japan, China and South Korea, all the four indicators load highly in the first factor. It is also the first factor that is retained as its Eigen values are more than 1 in all cases, 2.3 for Japan, 3.9 for South Korea and 3.7 for China.

In Table 7.1, stochastic frontier results are reported using a one-step estimation procedure with robust standard errors to ameliorate the problem of potential heteroscedasticity. To test the suitability of the stochastic frontier model, the study defines the total variance as; $\sigma^2 = \sigma_u^2 + \sigma_v^2$ so that $\gamma = \sigma_u^2 / \sigma^2$ approximates the

proportion of variance in σ^2 attributed to technical inefficiencies. A likelihood ratio test can also be used to test the null hypothesis $u = 0$.

The conventional ordinary least squares technique generates inconsistent estimates in the presence of technical inefficiencies. However, if the null hypothesis cannot be rejected, then the stochastic frontier model collapses to an ordinary production function and the ordinary least squares method suffices. From Table 7.1, $\gamma = 0.746$ which indicates that 75 per cent variation in σ^2 can be attributed to technical inefficiencies. The likelihood ratio test also suggests rejection of the null hypothesis implying that a stochastic frontier model is appropriate.

The test for functional form supports the use of translog specification over the Cobb-Douglas production function. The null hypothesis that the slope coefficients of squared terms and interactions are jointly zero is strongly rejected implying that a Cobb-Douglas specification would inadequately represent the data. Secondly, the interaction term between capital and the trend variable is significantly positive as observed in Wang and Wong (2012). In microeconomic theory, this signifies that technology has been capital saving among these industries during the sampling period.

On the other hand, the interaction between labour and the trend variable is significantly negative indicating that technology has been labour using. According to Coelli *et al.*, (2005) for cases where technical changes are labour using and capital saving as suggested in Table 7.1, the isoquants will be shifting inwards faster in the capital-intensive portion of the production input set.

The lower part of Table 7.1 reports the main results in which the connection between Chinese, South Korean and Japanese innovation spillovers and technical inefficiency is examined. Note that technical inefficiency is the dependent variable in this model so that a variable with a positive sign would have a negative effect on technical efficiency and a positive effect on technical inefficiency.

TABLE 7.1: IMPACT OF INNOVATION SPILLOVERS ON TECHNICAL EFFICIENCY

	Coefficient	Standard Error	Z-Statistic
Frontier Model			
logLabour	1.402***	0.351	3.98
logCapital	1.033***	0.292	3.53
0.5*logLabour squared	0.194***	0.045	4.29
0.5*logCapital squared	-0.112***	0.029	-3.82
logLabour*logCapital	0.060***	0.019	3.16
Year*logLabour	-0.008***	0.001	-4.47
Year*logCapital	0.005***	0.001	3.52
Year	0.0001	0.005	0.02
0.5*Year squared	0.00002	0.00005	0.43
Technical Inefficiency			
L.Log South Africa	-0.505***	0.148	-3.40
L.Log Korea	-0.310***	0.117	-2.66
L.Log Japan	-0.129***	0.044	-2.93
L.Log China	0.197**	0.100	1.97
L.Log Export Intensity	-0.089***	0.019	-4.63
L.Log Import Penetration	0.056***	0.020	2.77

Note: One, two and three asterisks mean that the variable is statistically significant at 10 percent, 5 percent and 1 percent respectively.

According to the results, domestic innovation represented by L.log South Africa has a negative and significant effect on technical inefficiency which supports Romer's (1986) endogenous growth theory which emphasizes the importance of knowledge investment as a driver of productivity and efficiency. A 10 per cent contemporaneous increase in domestic innovation stock is estimated to raise technical efficiency by a magnitude of 5.05 per cent in the subsequent period ceteris paribus (Table 7.1).

With regards to foreign innovation spillovers, two results are noteworthy. Firstly, Chinese innovation spillovers enter with a seemingly surprising result which points to

a positive effect of Chinese innovation on technical inefficiency of South Africa's manufacturing industries. This result offers empirical support to Koumou and Manyi (2016), Akomolafe (2008), Asche and Schüller (2008), Kamwanga and Koyi (2009); Fantu and Cyril (2010), Freschi (2010); Renard (2011), Diaw and Lessoua (2013) who claim that Chinese services in Africa can potentially bring more harm than good to the economy. They go even far to claiming that Chinese are predators of the African raw materials, and most authors remain very cautious when it comes to listing the positive effects of these investments (technology transfer) on African manufacturing sector. The negative effect of Chinese innovation spillovers reported in Table 7.1 also supports Edwards and Jenkins (2015) who confirmed a detrimental effect of Chinese imports on South Africa's manufacturing sector.

Secondly and for South Korea and Japan, the slope coefficients are significantly negative as predicted by open economy endogenous growth theories of Grossman and Helpman (1991) suggesting that innovation embodied in South Korean and Japanese services improves technical efficiency or reduces technical inefficiency of manufacturing industries in South Africa. This is empirically consistent with findings reported in Wang and Wong (2012), Henry, *et al.*, (2009) and Mastromarco and Ghosh (2009). They confirm that foreign services (FDI for Wang and Wong, 2012) represent an important mechanism through which innovation from one country raises technical efficiency of the other country.

A 10 per cent contemporaneous increase in innovation embodied in South Korean services raises technical inefficiency of South Africa's manufacturing industries on impact by 3.1 per cent in the subsequent period *ceteris paribus* (Table 7.1). For Japan, technical efficiency rises by 1.3 per cent in the subsequent period in response to every 10 per cent, contemporaneous increase in Japanese innovation spillovers (Table 7.1). This empirical result corroborates the view that trade in services facilitates the transfer of skills, knowledge and innovation across international borders which consequently allows technology lagging countries to improve their levels of technical efficiency by learning and adopting innovation created in other technology better-off countries.

It is also observed in Table 7.1 that the positive impact of South Korean (0.310) and Japanese (0.129) innovation spillovers on technical efficiency of South Africa's manufacturing industries is relatively lower than the positive impact of domestic innovation stock (0.505). This is in agreement with results reported in Acharya and Keller (2009), where domestic R&D stock is found to have a relatively larger impact on manufacturing productivity of the importing country than foreign innovation. An explanation given by Piermartini and Rubínová (2014) and Eaton and Kortum (1996) for this kind of a result is that foreign knowledge is less accessible to domestic producers as compared to domestic knowledge owing to barriers related to such things as language and cultural differences.

With regards to other control variables, export intensity enters with an expected negative effect on technical inefficiency reflecting productivity gains that arise from specialization. A 10 per cent contemporaneous increase in export intensity reduces technical inefficiency by 0.89 per cent in the subsequent period (Table 7.1). This is consistent with economic theory predicting a positive impact of export intensity on technical efficiency of manufacturing industries.

On the other hand, technical inefficiency rises by 0.56 per cent in the subsequent period following a 10 per cent contemporaneous increase in import intensity (Table 7.1). This result is not surprising for two reasons. The first reason is that the import penetration variable by construction does not capture technical efficiency enhancing aspects such as foreign innovation stock as does other regressors. Second, the negative impact on technical inefficiency might reflect that the displacement effect of domestic production by imports outweighs the import discipline that is expected to arise through import competition effect. This positive impact of import penetration (which is normally used as a proxy for trade openness) is consistent with the empirical conclusions reached by Rodriguez and Rodrik (1999) and more recently Wang and Wong (2012).

Descriptive statistics concerning technical efficiency are reported in Table 7.2. They confirm a mean technical efficiency level of 0.84 indicating that a typical manufacturing industry operated 16 per cent below its maximum possible output. Put differently, a typical manufacturing industry could have possibly increased output by 16 per cent with the inputs it had and the technology that prevailed during the sampling period.

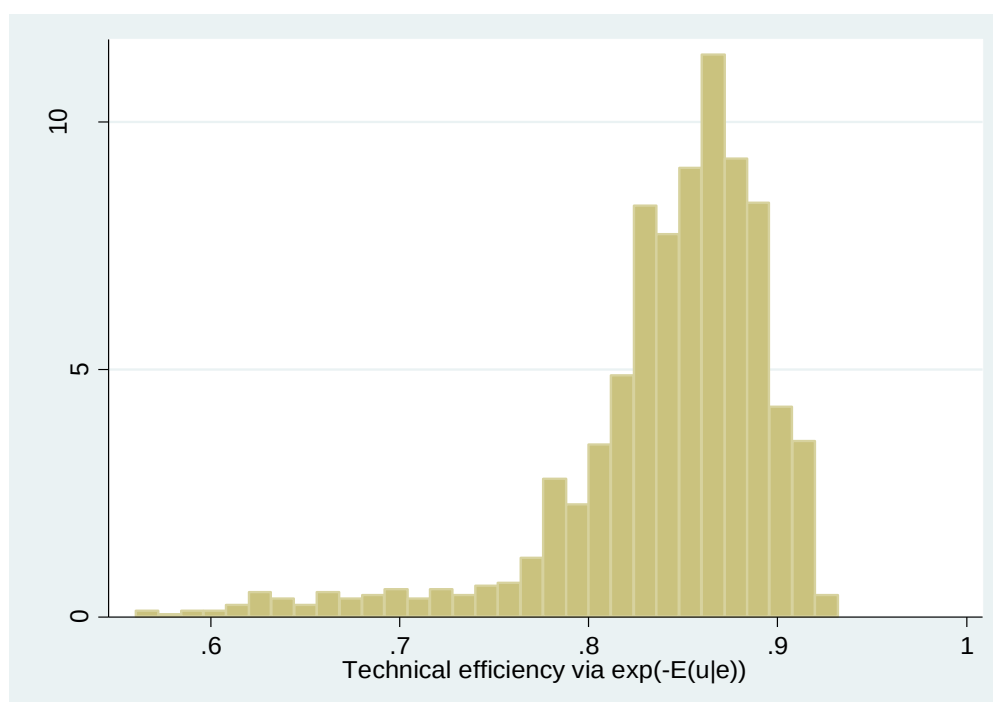


FIGURE 7.2: TFE TECHNICAL EFFICIENCY OF MANUFACTURING INDUSTRIES

TABLE 7.2: SUMMARY STATISTICS ON TECHNICAL EFFICIENCY

	Mean	Standard deviation	Minimum	Maximum
TE	0.841	0.057	0.560	0.931

7.7 CONCLUDING REMARKS

The evidence presented in this chapter based on the true-fixed effects stochastic frontier analysis shows that South Africa's 28 3-digit level manufacturing industries exhibited technical inefficiencies between 1995 and 2016 and that innovation spillovers from China, South Korea and Japan had a relevant effect on these

inefficiencies. In particular, evidence supports two key conclusions. Firstly, Chinese innovation spillovers correlates negatively with technical efficiency of manufacturing industries of manufacturing industries in South Africa. Secondly, the chapter finds that innovation spillovers from Japan and South Korea is one which correlates positively with technical efficiency of manufacturing industries which is in line with open economy endogenous growth theories. The policy implication arising from this empirical inquiry is that policies that allow trade in services with Japan and South Korea can allow skill transfer which allows industries in South Africa to improve their level of technical efficiency. On the other hand, the results raise scepticism over China's increasing presence in South Africa as her innovation embodying services are found to correlate negatively with manufacturing industries in South Africa.

CHAPTER 8

THE IMPACT OF CHINESE, KOREAN AND JAPANESE INNOVATION SHOCKS ON MANUFACTURING LABOUR PRODUCTIVITY IN SOUTH AFRICA USING THE LOCAL PROJECTIONS METHOD

In this chapter, focus is on how labour productivity in South African manufacturing industries responds to innovation spillover shocks from China, Japan and South Korea which is essentially the fourth objective of the study. The analysis is essentially complementary to that in chapter six in the sense that labour productivity is the endogenous variable. The chapter comprises six sections. Section one provides a brief background which is followed by a review of related literature and research methods in section two and section three respectively. Thereafter, section four specifies the local projections method which is the main analytical tool. Section five provides data description while section six and section seven present the empirical results from impulse response functions and concluding remarks respectively.

8.1 BACKGROUND

The role of trade in fostering productivity has been topical in recent years but literature on this subject (Topalova and Khandelwal, 2011, Yu, 2015, Lileeva, 2008, Bai *et al.*, 2017, Njikam and Cockburn, 2011, Bas and Ledezma, 2010, Edwards and Jenkins, 2015, Edwards *et al.*, 2008) remains unsettled. Most time series and panel studies (Zahonogo, 2017, Sarkar, 2008) confirm a positive link between trade and productivity growth while cross sectional studies (Eriş and Ulaşan, 2013) do not find any robust link. Although theoretical ambiguities are partly responsible, it is also fair to consider the inconclusiveness of results as a hybrid of methodological and conceptual shortfalls.

Methodologically most studies concerned with the innovation-trade-productivity linkage have been plagued by problems of endogeneity (see for instance Badinger and Breuss, 2008, Economidou and Murshid, 2008 and Aghion and Jaravel, 2015). This endogeneity comes mainly in two forms namely the feedback effect i.e. productivity having a reverse effect on innovation decisions and the omitted variable bias. In the present case for instance, innovation spillovers from China, Japan and South Korea (which are mainly transmitted through trade) can be correlated with macroeconomic variables in South Africa such as foreign direct investment or the exchange rate. Irrespective of the source, endogeneity is important to address in the estimation procedure as its presence results in estimates that are both biased and inconsistent (Abdallah *et al.*, 2015).

In trying to address the above cited endogeneity problem, the majority of previous studies in literature have mainly relied on a single equation framework (usually production functions proposed by Griliches (1980)) by using either cointegrating estimators such the panel dynamic ordinary least squares approach, the fully modified ordinary least squares and the pooled mean group estimator that are immune to endogeneity (see for instance Edmond, 2001, Gutierrez, and Gutierrez, 2003, Higon, 2007 and Ang, and Madsen, 2013) while others have relied on instruments (Fu, 2005).

In this chapter, the study takes a novel approach to analysing the innovation spillover-productivity link by invoking impulse response functions from the Local Projection Method developed by Jordà (2005) which is immune to endogeneity issues. This approach is similar to that applied in García and Montero (2009). The difference is that García and Montero (2009) particularly used a structural vector autoregression (SVAR) approach as opposed to the Local Projections Method. The advantages of the LPM over the SVAR approach are that its impulse response functions (IRFs) are based on local projections which bypass estimation of the unknown true-multivariate dynamic system itself and that they are robust to model misspecification (Jordà, 2005).

Unlike SVAR, local projections are derived from sequential regressions of the endogenous variable(s) shifted a number of steps ahead which means they comprise several points of commonality allowing multi-step forecasting. Their impulse responses allow one to analyse empirical regularities, if any, that can help explain in the present case Grossman and Helpman's (1991) theoretical model in which innovation spillovers are expected to have a permanent effect on productivity.

8.2 LITERATURE REVIEW

In theory, the study is based on endogenous growth models described comprehensively in Aghion *et al.*, (2009) and Acemoglu (2010). Product variety models advocated by Romer (1990) and Grossman and Helpman (1991) essentially describe productivity growth as a function of innovative intermediate products. Importantly, innovative intermediate products can represent a transmission mechanism of innovation between firms, industries or sectors in different countries. Herein, the study relies on this assumption but defines innovation slightly different in the sense of computing a composite index made of several innovation indicators.

At the empirical quantitative level, studies on innovation can be broadly decomposed into two categories i.e. those that focus on endogenous growth theories such as Goulder and Schneider (1999), Popp (2004, 2006), Edenhofer *et al.*, (2005), Kemfert (2005), Otto *et al.*, (2007, 2008) and Loschel and Otto (2009) and those that directly test international innovation spillovers (open economy endogenous growth theories) such as Diao *et al.*, (2005), Leimbach and Baumstark (2010), Hübler (2011) and Parrado and De Cian (2014). In line with the latter, this study tests the significance of Chinese, South Korean and Japanese innovation shocks on labour productivity in South Africa.

Within the extensive literature on innovation and productivity, studies conducted in a system of equations framework are very scant. Most studies such as Aghion and Jaravel (2015), Ang and Madsen (2013), Apergis, Economidou and Filippidis (2009) have been conducted in a single equation framework and the

common result observed in these studies is that both domestic and foreign innovation have a significant effect on productivity.

Griffith *et al.*, (2003) provide a comprehensive review of literature related to innovation spillovers and productivity. The majority of studies in the review define proxy innovation by R&D expenditures. Examples of leading studies relying on the R&D measure are Griliches and Lichtenberg (1984) who observe estimates in the range of 0.21 – 0.76, Schankerman (1981) who reports 0.24 – 0.73 and Scherer (1982) who finds 0.29 – 0.43. Overall, this literature supports the view that R&D exerts a positive impact on productivity growth. In this study, focus is on innovation and productivity but the methodological approach is heavily related to studies that compute impulse responses from a system of equations.

Among the few studies that have been conducted in a system of equations framework is a paper by Hiebert and Vansteenkiste (2010) which empirically estimates the response of labour market variables in the context of US manufacturing to innovation shocks in a Global Vector Autoregression methodology (GVAR) framework based on 12 manufacturing industries between 1977 and 2003. The GVAR framework in Hiebert and Vansteenkiste (2010) included several labour market variables such as real compensation, productivity, employment and capital stock. Results from generalized impulse responses confirmed that technology shocks significantly induce positively effects on compensation and employment. However, the study did not extend to analyse the response of labour productivity to foreign innovation shocks.

Chu and Yeh (2007) on the other hand proposed a novel approach to measuring international R&D spillovers through R&D expenditure in the context of developed countries. The authors relied on a methodology that is robust to endogeneity and multi-collinearity which are two problems that normally feature in this analysis. Results from a system of dynamic vector autoregressive (VAR) model for the G7 countries between 1981 and 2004 suggested that the overall proposed spillover

index is higher for long term horizon forecasts while bilateral cross spillover effects may decrease or increase depending on the country in question.

Pouraghaei (2016) focused on the causal impact of R&D on growth in the context of 11 OECD countries with data observed between 1980 and 2014. Based on a system of equations calibrated in form of a dynamic stochastic general equilibrium (DSGE) model, Pouraghaei (2016) conclude that R&D spending which is an indicator of innovation, has a significant influence on growth and productivity in the long-run for small open economy supporting open economy endogenous growth theories.

Endersa and Müllera (2009) on the other hand apply a vector auto-regression (VAR) on U.S. time series combined with an aggregate of selected industrialized countries. Calibrating a Business Cycle Model (BCM) with both complete and incomplete financial markets, the authors confirm significant wealth effects of innovation shocks. Endersa and Müllera (2009) did not however answer the question of whether innovation spillover shocks have an influence on productivity in the manufacturing sector which is important given the increasing interdependence among countries through trade.

This chapter contributes to the body of knowledge by conducting impulse response from local projections in an effort to determine how Chinese, Japanese and South Korean innovation shocks impact labour productivity in South Africa's manufacturing sector. An advantage of analysing the innovation spillover impact this way is that it enables one to trace the path taken by domestic labour productivity from short, medium to long-term horizons following a shock in foreign innovation. As alluded to earlier, impulse response functions from local projections are immune to model misspecification and are appropriate in cases where serial correlation can be problematic as in the present case given the conversion of annual data to quarterly observations which is one of the main causes of autocorrelation.

8.3 RESEARCH METHODS

An important caveat when analysing the interactions between trade-related innovation shocks and labour productivity growth is that there is no guarantee regarding the direction of causation. It can run either way which makes it difficult to make statistical inference on endogeneity grounds. If the direction of causality is two-way, then we have the “simultaneity problem” whose consequence is endogeneity that biases the response of productivity growth to technology shocks. Circumventing this bias requires either instrumental variables techniques or resorting to a system of equation modelling technique where the variables take turns to be endogenous.

The challenge with the former solution is that its effectiveness rests in finding an appropriate instrument for foreign innovation. In practice, it is empirically and generally difficult to find an appropriate instrument and having a weak instrument can result in consequences that are worse than ignoring the endogeneity problem in the first place. This therefore leads us to the later solution.

A standard system of equation technique is known as the vector autoregression (VAR) which is essentially used to analyse interactions among two or more variables and making statistical inferences concerning the historical evolution of the entire system. When analysing the interactions, however, interpretation of the system coefficients is generally both challenging and less useful due to the complicated system dynamics. In this regard, Stock and Watson (2001) recommends the use of impulse responses instead as a more useful and informative statistic post estimation of the VAR.

The impulse response function technically measures the response or reaction of the system to an innovation or a shock of a particular variable. Unfortunately, as argued by Jordà (2005), impulse response functions can be biased and statistically misleading when the underlying data generating process of the system cannot be well approximated by a VAR(p) process. Jordà (2005), as a solution, introduced an alternative approach for computing impulse response functions based on the local

projections method that do not require a pre-specification and pre-estimation of the unknown true multivariate dynamic system itself. This is the approach used in this study.

8.4 THE LOCAL PROJECTIONS METHOD

To ascertain the response of labour productivity to shocks in Chinese, South Korea and Japanese technology spillovers, the study applies the local projections method proposed and developed by Jordà (2005). Local linear projections are based on sequential regressions of the endogenous variable using a number of steps ahead and it has been chosen for this particular exercise due to the advantages that it possesses over the traditional vector autoregression (VAR) approach (see Jordà, 2009). The estimated model takes the following form:

$$\begin{aligned} \log LP_{t+h} - \log LP_{t+h-1} = & c^{(h)} + \sum_{j=1}^J \varphi_j (\log LP_{t-j} - \log LP_{t-j-1}) + \sum_{i=1}^I \tau_i^{(h)} (e_{t-i}^S) + \\ & \sum_{i=1}^I \omega_i^{(h)} (e_{t-i}^C) + \sum_{i=1}^I \pi_i^{(h)} (e_{t-i}^J) + \sum_{i=1}^I \theta_i^{(h)} (e_{t-i}^K) + error_{t+h} \quad (8.1) \end{aligned}$$

$$h = 0, \dots, H$$

where subscript t denotes year, $\log LP_t$ is the logarithm of labour productivity, S represents the composite index for domestic innovation, C , K , and J are composite indices for Chinese, South Korean and Japanese innovation spillovers respectively. The number of horizons (h) is set at 24, $J=2$ and $I=24$. The system of equations is jointly estimated across the entire horizon which essentially allows us to test the null hypothesis that the response of $\log LP_t$ to aid is equal to zero for all horizons. The study applies conditional error bands to remove the variability caused by serial correlation. Conditional error bands are consistent with the joint null of significance and give a better sense about the significance of individual responses.

The chapter estimates and computes local projections method using the E-views 9 “localirfs” add-in. In each case when building the VAR, the optimum lag is selected using the common criterions namely the Akaike information criterion (AIC), Schwarz information criterion (SIC) and the Hannan-Quinn information criterion (HQIC). Dynamic stability of each VAR is evaluated by observing if the inverse roots lie within the unit circle.

A contentious issue when building this VAR before execution of the local projections method is whether the VAR should be estimated in levels or first difference. A considerable literature shows that estimation of a VAR in levels is still desirable even if the variables have unit roots (Basher *et al.*, 2012). Stock and Watson (1990) on the other hand demonstrate that the VAR coefficients are consistent and their asymptotic distribution remains standard in the presence of non-stationary variables that form a cointegrating relationship. Despite this argument however, this study disregards the possibility of a cointegrating relationship and specify a level relationship basing on Basher *et al.*, (2012) who argue that impulse response functions from a VAR in levels are consistent in the short-to medium run. The composite innovation indices are computed using the principal component analysis (PCA).

8.5 DATA DESCRIPTION

The analysis is spanning the periods 1995Q1 and 2017Q4. The chapter essentially applies a dataset that is identical to that applied in chapter six in which the analysis sought to establish the impact of innovation spillovers on labour productivity. In this regard, the same data transformation applied in chapter six (i.e. conversion of annual into quarterly observations) apply in this chapter. Data are sourced from QUANTEC data providers and South African Reserve Bank (SARB), OECD and World Development Indicators (WDI).

8.6 RESULTS AND DISCUSSION

This section presents the empirical findings of the study. The usual presentation of impulse response functions is through the visualization of the dynamic propagation

mechanism that is accompanied by error bands. In addition to marginal error bands, Jordà (2009) improved the interpretation of impulse response functions by proposing error bands that allow us to examine the individual and cumulative significance of coefficients in a given trajectory.

Figure 8.1 reports impulse responses from the local projections method. In each figure, the response of interest is shaded in grey which is the response of productivity to a shock in innovation. The results are technically responses to Cholesky one standard deviation shock with 95 per cent conditional confidence bands. Note that each impulse response includes p-values of two null hypotheses, joint and cumulative. Joint refers to the null hypothesis that all the response coefficients are jointly zero while cumulative refers to the null hypothesis that the accumulated impulse response after 24 periods is statistically zero.

As Figure 8.1 indicates, the response of labour productivity to a positive shock in domestic innovation is positive for the entire 24 period horizon. Important to note is that the positive response of labour productivity is small in the short to medium term but rises sizeably in the long term horizon (i.e. above 10 quarters). In other words, evidence here suggests that a shock in domestic technology has permanent effects on labour productivity. This is consistent with endogenous growth theories which view technology as a key driver of long-term productivity growth.

The positive labour productivity response to domestic innovation shocks is empirically in agreement with Hiebert and Vansteenkiste (2007) in the case of US manufacturing albeit proxying technology by R&D expenditure. Both the joint and cumulative probability values are less than 10 per cent indicating that domestic technology shocks significantly affect productivity both in the short and long-term horizon.

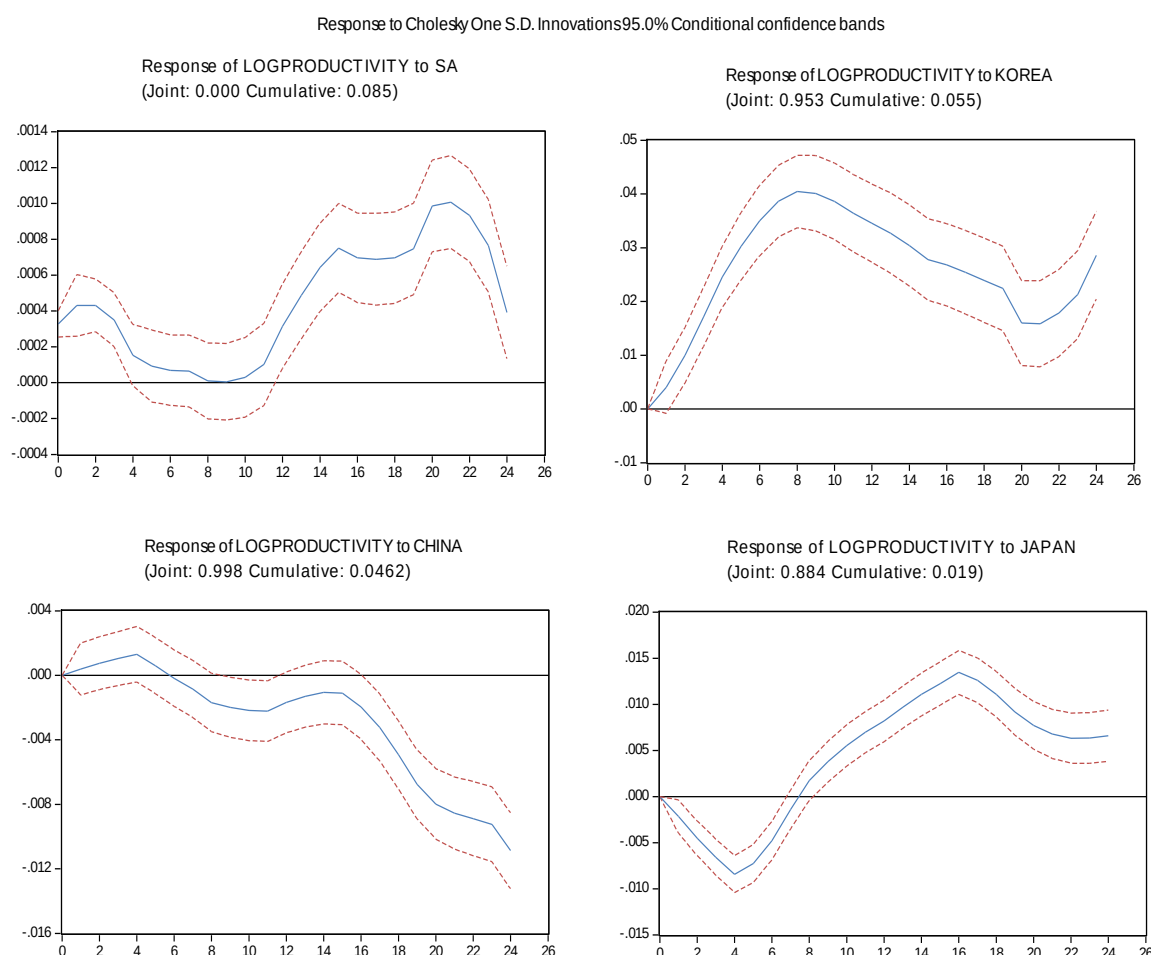
For South Korea, the response of South Africa's labour productivity is sizeable and positive throughout the entire horizon but peaks after approximately 8 quarters. Beyond 8 quarters, the positive response of labour productivity declines steadily but remains positive before picking up again from year 20. The joint probability value is statistically insignificant while the cumulative probability value is significant at 10 per cent level. This means that shocks in South Korean technology do not have a significant spillover effect on South Africa's manufacturing labour productivity in the short term horizon. Their effect is only relevant in explaining labour productivity responses in the long term (i.e. permanent effects).

For Japan, the response of South Africa's labour productivity declines sharply in the first period and begins rising after 4 quarters. The negative labour productivity response turns positive after 6 quarters and peaks after approximately 16 quarters before declining steadily until 22nd quarter where it remains constant in the positive region. Similar to South Korean technology shocks, Japanese shocks do not have transitory effects but have permanent effects on South Africa's labour productivity given the significance of only the cumulative probability value.

Turning to China, the effect of Chinese technology shocks is positive but quite negligible during the first 6 quarters. During these first 6 quarters which could be crudely interpreted as the short-medium term horizon, the actual rise in labour productivity lasts up to the 4th quarter and declines thereafter turning negative after the 6th quarter. There appears to be a slight productivity recovery after roughly 10 quarters but the rise is quite small and lasts until the 16th quarter where it persistently declines in the negative region. Also noteworthy is that shocks in China's technology have permanent negative effects on labour productivity in South Africa.

Looking at results from all shocks, the study observes that shocks in domestic technology are the only ones that significantly influence both transitory and permanent labour productivity responses in South Africa. Shocks on Chinese, South Korean and Japanese do not significantly influence transitory labour productivity responses but

influence permanent responses. This might be explained by the fact that domestic technology is local and therefore easy to adopt and absorb unlike foreign technology which might take time for domestic labour to adopt and learn before it takes full effect on productivity.



**FIGURE 8.1: LOCAL PROJECTIONS IMPULSE RESPONSE FUNCTIONS WITH
CONDITIONAL BANDS²⁶**

Table 8.1 presents variance decomposition which helps in quantifying the importance of each shock in the system on labour productivity. Results show that domestic innovation shocks represented by SA are more important as it accounts for 35 percent variation in labour productivity followed by South Korean innovation shocks which

²⁶ The graphs do not show impulse response functions for own shocks for brevity sake

account for 25 percent variation. Japanese innovation shocks explain 18 percent variation in labour productivity while Chinese innovation shocks from Table 8.1 are the least in terms of importance (explaining only 3 percent variation in labour productivity).

TABLE 8.1: VARIANCE DECOMPOSITION FOR LABOUR PRODUCTIVITY

Period	S.E.	LOGPRODUCTIVITY	CHINA	KOREA	JAPAN	SA
1	0.002910	9.672965	1.892929	2.885242	18.65828	66.89058
2	0.005478	8.142016	1.082833	2.356812	18.54550	69.87283
3	0.007969	7.339634	0.622593	2.596084	18.64110	70.80058
4	0.010297	6.825478	0.356683	3.145623	18.70798	70.96423
5	0.012511	7.715588	0.236894	3.163376	21.57677	67.30737
6	0.014932	8.741221	0.171847	3.510424	24.15293	63.42358
7	0.017556	9.620248	0.130581	4.152951	26.21697	59.87925
8	0.020303	10.39663	0.104497	5.061171	27.76006	56.67765
9	0.022116	10.56626	0.087174	7.134584	27.41219	54.79979
10	0.023547	10.71996	0.086692	9.394637	26.48113	53.31757
11	0.024591	10.93965	0.114944	11.74219	25.26629	51.93692
12	0.025298	11.23033	0.194190	14.11187	23.93735	50.52626
13	0.025977	11.69876	0.265703	15.93213	23.11263	48.99078
14	0.026579	12.19992	0.349203	17.74251	22.41797	47.29039
15	0.027168	12.76015	0.456755	19.41877	21.83942	45.52490
16	0.027802	13.38328	0.595931	20.89754	21.37357	43.74967
17	0.028372	14.18915	0.820396	22.10865	20.78014	42.10167
18	0.028957	15.05366	1.132579	22.98792	20.23683	40.58902
19	0.029563	15.89426	1.511960	23.61365	19.74203	39.23809
20	0.030172	16.66029	1.928848	24.01830	19.29001	38.10256
21	0.030805	17.15679	2.366485	24.46710	18.94431	37.06532
22	0.031410	17.55222	2.766127	24.78564	18.64006	36.25596
23	0.031952	17.86141	3.127696	24.98943	18.36834	35.65313
24	0.032424	18.09856	3.444895	25.10115	18.12645	35.22895

Overall, the results for domestic innovation, South Korean and Japanese innovation spillovers corroborate those observed in Hiebert and Vansteenkiste (2010), Doraszelski and Jaumandreu (2013) and Leiva (2014) in which technology (innovation) shocks are found to have a positive and significant impact on productivity. On the other hand, the result for China is surprising but consistent with previous studies such as Engelbrecht (1997), Aitken and Harrison (1999), Damijan *et al.*, (2001), Djankov and Hoekman (2000), and Konings (2001) which all confirmed a negative impact of international R&D spillovers on domestic productivity.

8.7 CONCLUDING REMARKS

This chapter sought to establish the response of South Africa's manufacturing labour productivity to exogenous Chinese, Japanese and South Korean technology spillover shocks using quarterly data spanning the period 1995Q – 2017Q4. The adopted empirical strategy was the computation of IRFs based on the local projections method which allows us to estimate the labour response to exogenous shocks without having to estimate the unknown true-multivariate dynamic system itself. Chinese, South Korean and Japanese technology spillover indices were computed based on the PCA which, unlike the majority of previous studies, enabled us to compute a composite technology proxy that comprises several key indicators of technological progress such as R&D stock, researchers in the R&D sector, trademark and patent applications.

Having computed these composite technology indices, service imports were then used as weights and a relevant channel through which foreign innovation impacts domestic labour productivity. Empirical results confirmed that domestic technology shocks seem to have a more robust transitory and permanent impact on labour productivity which is consistent with endogenous growth theories. Support for open economy endogenous growth proponents is confirmed in the case of South Korean and Japanese technology spillover shocks. In particular, evidence suggests that South Korean and Japanese technology shocks do have permanent effects of labour productivity in South Africa's manufacturing sector. China's technology shock impacts South Africa's labour productivity negatively in the long-term.

CHAPTER 9

SUMMARY, CONCLUSION AND POLICY RECOMMENDATIONS

9.1 SUMMARY

This study has provided empirical evidence on innovation spillovers from a selected number of Asian economies (China, Japan and South Korea) on total factor productivity, labour productivity and technical efficiency of South Africa's manufacturing sector using a combination of time series and panel data techniques. This is an important area whose importance is largely reflected in the burgeoning but largely inconclusive empirical literature. In an effort to achieve the overarching objective of the study which was to establish the significance of technology spillovers mainly from China, South Korea and Japan on productivity and efficiency of South Africa's manufacturing industries), the study specifically sought to determine:

- 1) the impact of Chinese, South Korean and Japanese innovation spillovers on total factor productivity of South Africa's manufacturing industries;
- 2) the impact of Chinese, South Korean and Japanese innovation spillovers on labour productivity of South Africa's manufacturing sector;
- 3) the impact of Chinese, South Korean and Japanese innovation spillovers on technical efficiency of South Africa's manufacturing industries; and
- 4) the response of labour productivity to exogenous technology spillover shocks from China, South Korea and Japan;

TABLE 9.1: SUMMARY OF THE STUDY

OBJECTIVE	METHODOLOGY	CHAPTER
Establishing the impact of Chinese, South Korean and Japanese innovation spillovers on total factor productivity of South Africa's manufacturing industries	System Generalised Method of Moments (sysGMM), Bayesian Techniques , Panel data	Four and Five
Establishing the impact of Chinese, South Korean and Japanese innovation spillovers on labour productivity of South Africa's manufacturing sector	Autoregressive Distributed Lag Model (ARDL), Time series data	Six
Determining the impact of Chinese, South Korean and Japanese innovation spillovers on technical efficiency of South Africa's manufacturing industries	True-Fixed effects Stochastic Frontier Analysis, Panel data	Seven
Determining the response of labour productivity to exogenous technology spillover shocks from China, South Korea and Japan	Local Projections Method (LPM), Time series data	Eight

In a bid to help settle the on-going debate, the study has sought to make several contributions. Firstly, unlike the majority of previous studies, the study has computed a composite innovation proxy that comprises both input and output indicators of innovation. This contribution stems from the inadequacy of one indicator as a proxy variable for innovation.

Secondly, the study has provided a theoretical modification of Grossman and Helpman's (1990, 1991) theory by accommodating trade in services as the transmission channel rather than the traditional channel of physical intermediate imports. Thirdly, and for the first time in literature, the study analysed the response of labour productivity from both domestic and foreign innovation shocks for a 24 period horizon using the local projections method.

These contributions have been spread across five analytical chapters. In the first analytical chapter which is chapter four, the impact of foreign innovation spillovers proxied by R&D spillovers from China, Japan and South Korea on total factor productivity of 22 selected manufacturing industries in South Africa has been examined using the system Generalised Method of Moments (sysGMM) technique. In particular, chapter four measured innovation spillovers using the common R&D stock measure weighted by physical intermediate imports.

Chapter five sought to establish the impact of Chinese, South Korean and Japanese innovation spillovers on total factor productivity of manufacturing industries in South Africa and it differed with chapter four in three key respects. Firstly, analysis in chapter five was based on Bayesian techniques. Secondly, chapter five measured innovation spillovers not using the common R&D stock measure but rather using a composite innovation index computed by the Principal Component Index. Thirdly, the innovation transmission mechanism in chapter five was service imports as opposed to intermediate physical imports.

Chapter six focused on the impact of Chinese, South Korean and Japanese innovation spillovers on labour productivity in a time series context. It applied the same innovation spillover index used in chapter five but was converted into quarterly intervals to increase the sample size. In addition to that, chapter six focused mainly on labour productivity in manufacturing at sector level and the model was estimated by the autoregressive distributed lag model.

The subsequent chapter, which is chapter seven addressed the effect of innovation spillovers on technical efficiency rather than labour productivity at industry level. The innovation spillover index applied in chapter seven is identical to that applied in chapter five. The central aim of chapter seven was to establish how Chinese, South Korean and Japanese innovation spillovers influence the movement of industries

towards the production possibility frontier. Analysis in this chapter was based on a true-fixed effects stochastic frontier technique.

The last analytical chapter – chapter eight – dealt with the response of labour productivity growth to shocks in foreign innovation using the local projects method. The chapter essentially applied the labour productivity measure which is identical to that applied in chapter six. Data was then analysed in form of impulse response functions which were able to show the response of labour productivity over time to a shock in each of the innovation spillovers included in the system.

9.2 RESULTS AND DISCUSSION OF FINDINGS

For the first specific objective which was aimed at establishing the impact of Chinese, South Korean and Japanese spillovers on total factor productivity of manufacturing industries in South Africa, the results of the study indicated that Japanese and South Korean innovation spillovers correlate positively with total factor productivity but Chinese innovation spillovers correlate negatively and significantly (this is particularly true when the study applied the composite innovation spillover index). This finding was arrived at while holding constant domestic innovation.

With respect to the second specific objective which sought to determine the impact of Chinese, South Korean and Japanese innovation spillovers on labour productivity, the results indicated that labour productivity in South Africa's manufacturing sector is affected negatively and significantly by Chinese innovation spillovers but affected positively and significantly by innovation spillovers from Japan and South Korea while holding domestic innovation constant. These results were robust to alternative estimation techniques, the decomposition of the total sample into pre and post 2009 Global Financial Crisis and the use of different interpolation assumptions when converting annual observations into quarterly intervals.

For the third specific objective which was aimed at determining the influence of Chinese, South Korean and Japanese innovation spillovers on technical efficiency of manufacturing industries in South Africa, it was observed that technical efficiency of manufacturing industries is significantly impacted by innovation spillovers. In particular, the study found that technical efficiency of manufacturing industries in South Africa increases with innovation spillovers from Japan and South Korea but decreases with innovation spillovers in China. In other words, innovation spillovers from Japan and South Korea were found to have a positive impact on technical efficiency of manufacturing industries while innovation spillovers from China were found to have a negative impact.

Turning to the last specific objective which sought to establish the responses of labour productivity to shocks in Chinese, South Korean and Japanese innovation spillovers, impulse response functions indicated that labour productivity is, over long term horizons, influenced negatively by Chinese innovation spillover shocks but positively by Japanese and South Korean innovation spillover shocks (although the impact of Japanese innovation spillovers is negative within the first 7 quarters of the shock).

From these chapters collectively, empirical results confirmed for South Africa the findings of Griliches and Lichtenberg (1984), Coe and Helpman (1995) and Keller (2002), Melitz (2003), Pradeep *et al.*, (2017), Medda and Piga (2014) and Klein (2017) that foreign innovation spillovers are important drivers of productivity in the importing country but domestic innovation has the larger effect. In particular, the conclusion is that raising technology embodying imports from Japan and South Korea by 1 per cent increases productivity in South Africa's manufacturing sector in the 0.01 per cent – 0.06 per cent range. The effect of domestic innovation stock was found to be larger in all cases ranging from 0.25 per cent to 0.56 per cent.

Furthermore, the empirical results (in chapter four) confirmed the conclusions of Hassine (2008), Apergis *et al.*, (2009) and Manca (2009) that foreign innovation may not automatically affect the importing country's productivity and that the adaptability and local usability of foreign technologies depends on the skill content of the recipient country's workforce. Apergis *et al.*, (2009) in particular find an important role of human capital in influencing the trade-productivity relationship. Having good institutions is also crucial in setting the right economic environment for domestic research and development. If the importing country does not have supportive rules and regulations according to Manca (2009), then local industries may not be able to adopt the new technologies even if they have quality human capital.

Secondly, China's presence in Africa has been heavily scrutinized among both academic and policymaking realms. The major criticism levelled against China's presence revolves around the extraction and looting of African resources whose negative effect on productivity may outweigh the positive technology transfer effect.

Last but not least, chapter seven sought to establish the impact of innovation spillovers on technical efficiency of South Africa's manufacturing industries using a true-fixed effects stochastic frontier technique which separates industrial heterogeneity from time invariant factors. The conclusion made from this chapter is that the effect of foreign innovation spillovers transferred through service imports can be significantly positive on technical efficiency. In practice, this conclusion implies that foreign innovation (from Japan and South Korea) not only leads to technology upgrades represented particularly by a shift in the domestic technology frontier. It also allows domestic industries to improve their utilisation of existing technology and resources by moving them closer to the maximum production possibility frontier.

There are two new findings observed in this study. The first is that trade in services significantly matters as a channel through which technology spreads across countries and that the transferred effect does have a significant impact on both productivity and efficiency of manufacturing industries in the importing country. What

is historically well known and appreciated in open economy endogenous growth theories by Grossman and Helpman (1991) is that the channel is mostly physical intermediate goods that are used directly in the production process. The study shows however that the movement of services across international boundaries can also explain why technology developed in one country can influence productivity in another country that imports services.

The second important novel finding confirmed in this study is that relying on the R&D stock alone measure can be misleading. Indeed, when the study applied this indicator in the first analytical chapter (chapter four), it managed to replicate the results observed in previous studies such as Pradeep *et al.*, (2017), Medda and Piga, (2014) and Klein (2017) that innovation spillovers from China, Japan and South Korea correlate positively with the performance of manufacturing industries in South Africa.

However, when the study computed a composite measure of innovation which includes trademark applications, patents, R&D stock and researchers in R&D using the principal component analysis, it reached a different and insightful conclusion particularly for China suggesting that trade in goods and trade in services as transmission channels of technology might have distinct ultimate impacts on productivity and efficiency of the importing countries. For countries in which the effect remains positive, the study finds that the effect is more sizeable (0.010 per cent-0.059 per cent) when compared with the positive effect reported by the R&D stock measure alone (0.003 per cent-0.022 per cent). In other words, the R&D stock measure alone appears to underestimate the impact of technology spillovers on productivity and efficiency.

This may not be surprising given that physical intermediate goods may fail to transmit non-codified knowledge which can only be effectively conveyed through human interactions as observed by Piermartini and Rubínová (2014). Trade in services overcomes this major challenge. Services mean that explanation on technology use in the foreign country can be made which is relatively impossible in the

case of physical goods. The result substantiates the OECD's claim that R&D alone is a necessary but not sufficient measure of technology advancement and that new composite measures need to be developed.

Overall, the results reported in this study particularly those of a positive innovation spillover effect on total factor productivity, labour productivity and technical efficiency clearly show that arguments and concerns that have been raised in South Africa of Asian imports negatively affecting the manufacturing sector do not provide a complete picture. The effect of these imports can be positive. In other words, based on the evidence, scholars and policymakers ought to move beyond the historical predictions of doom and consider imports as a relevant channel through which South Africa can make technology upgrades that will consequently raise productivity and resource use efficiency of local manufacturing industries.

This conclusion is quite informative and complementary to South Africa's Integrated Manufacturing Strategy (IMS) launched in 2002 as a collective position aimed at improving competitiveness in the industrial sector. The strategy stresses integration with the international economy through increased trade, particularly through increased knowledge intensity in production. The IMS was set to build on the efforts of the decade (1994-2003), where South Africa's trade policy was driven by the need to weaken the effects of factors that discriminated against productivity growth and export development in the form of taxation and protectionism.

9.3 POLICY IMPLICATIONS AND RECOMMENDATIONS

Based on the empirical evidence presented in this study, four policy implications can be made. Firstly, the study has observed a significant positive impact of technology spillovers from Japan and South Korea on productivity and efficiency of manufacturing industries in South Africa during the sampling period. This means that Grossman and Helpman's (1991) theory holds for South Korea and Japan and therefore policy effort might be required by the South African government to strengthen trade ties with these

two particular Asian countries. More importantly, the result validates the role played by trade in services in transferring technology.

Secondly, the study has observed that domestic innovation has a larger effect on productivity and efficiency relative to South Korean and Japanese innovation spillovers. The implication of this result is that Japanese and South Korean innovation, important as it is, needs to be taken as a complement and not a substitute for domestic innovation effort. Local policy effort is required in increasing research and development expenditure and researchers so that South Korean and Japanese innovation can only serve to strengthen these local efforts. South Africa generally lacks adequate human skill which is necessary in pushing the technology frontier upwards. Enhancement of human skill might therefore take the form of increasing the number and amount of scholarships and research grants in critical scientific research areas at universities.

Thirdly, Chinese innovation effect on productivity and efficiency of South Africa's manufacturing industries is found to be significantly negative. The policy implication of this result is that the South African government needs to be cautious when it comes to doing business with China particularly in the context of trade in services. Two possible reasons why China's innovation effect is negative are that Chinese companies hardly employ labour that is local in countries that they provide services. In most cases, they travel with their own Chinese workforce which bypasses the need for domestic labour. Given this circumstance, the South African government may need to simply have negotiations with China so that their companies employ a certain percentage of local labour. This will allow local labour to retain the technology and knowhow of Chinese innovation when the contract of Chinese services in South Africa expires.

Another possible reason explaining the negative effect relates to the resource looting effect outweighing the innovation effect. China has been regularly accused of

syphoning resources from Africa. This only requires the South African government to be more cautious with its resources especially when it comes to mega deals with the Chinese government.

Fourthly, it is observed that trade in services is an important mechanism through which innovation from South Korea and Japan affects productivity and efficiency of South Africa's manufacturing industries. This result calls for policy effort in reducing the restrictiveness of trade in services particularly for these two economies from which the result is based. Currently, South Africa applies some labour market tests for all natural professionals, persons and companies seeking to offer and provide temporary and contractual services in the economy. These are essential but can be made more welcoming particularly for trading partners from which technological upgrades are likely to emanate.

9.4 LIMITATIONS AND AREAS FOR FURTHER STUDY

The study has managed to come up with revealing results but like any empirical work, it has its own weaknesses. Firstly, it was conducted at industry and sector level under the assumption that all firms behave homogenously in each industry which is plausible in economics. Ideally however, one would want to conduct this kind of analysis at firm level. Given this limitation one would hope that future studies conduct innovation spillover analyses using firm level data that can be obtained through surveys.

Secondly, the study addressed the influence of innovation spillovers on total factor productivity, labour productivity and technical efficiency but was silent on scale efficiency. It would be interesting to have an analysis which considers the effects of these innovation spillovers on scale efficiency. The reasoning behind this is that trade (as the innovation transmission mechanism) in general is theoretically predicted to influence scale efficiency of industries in the importing economy through exploitation of economies of scale and adoption of new technology.

Thirdly, technical efficiency scores have been computed in chapter seven using a stochastic frontier analysis which is sensitive to functional form. Future studies might consider other alternative methods of computing technical efficiency scores such as the Data Envelopment Analysis (DEA). This would allow a comparison of results for robustness purposes.

Fourthly, the study has relied on a few selected Asian countries namely Japan, South Korea and China on the basis of their economic progress characterised by technological advancement. However, future work might include countries from other regions that have equally progressed in the past two or three decades.

REFERENCES

- ABDALLAH, W., GOERGEN, M. & O'SULLIVAN, N., 2015. Endogeneity: How Failure to Correct for it can Cause Wrong Inferences and Some Remedies. *British Journal of Management*, 26(4): 791-804.
- ABEGAZ, B. & BASU, A.K., 2011. The Elusive Productivity Effect Of Trade Liberalization in the Manufacturing Industries of Emerging Economies. *Emerging Markets Finance and Trade*, 47(1): 5-27.
- ABEL-KOCH, J., 2013. Who Uses Intermediaries in International Trade? Evidence from Firm-level Survey Data. *The World Economy*, 36(8): 1041-1064.
- ACEMOGLU, D., 2010. When does Labor Scarcity Encourage Innovation?. *Journal of Political Economy*, 118(6): 1037-1078.
- ACEMOGLU, D., 2012. What Does Human Capital do? A Review of Goldin and Katz's The Race Between Education and Technology. *Journal of Economic Literature*, 50(2): 426-63.
- ACEMOGLU, D. & ROBINSON, J.A., 2013. Economics versus Politics: Pitfalls of Policy Advice. *Journal of Economic Perspectives*, 27(2): 173-92.
- ACHARYA, R.C. & KELLER, W., 2009. Technology Transfer Through Imports. *Canadian Journal of Economics/Revue canadienne d'économique*, 42(4): 1411-1448.
- ADLER, G., DUVAL, M.R.A., FURCERI, D., SINEM, K., KOLOSKOVA, K. & POPLAWSKI-RIBEIRO, M., 2017. *Gone with the Headwinds: Global Productivity*. IMF Staff Discussion Note, International Monetary Fund, Washington, DC.
- AGHION, P. & HOWITT, P., 1990. A Model of Growth Through Creative Destruction, *Econometrica*, 60 (2): 323–351.

- AGHION, P., BRAUN, M. & FEDDERKE, J., 2008. Competition and Productivity Growth in South Africa. *Economics of Transition*, 16(4): 741-768.
- AGHION, P., BLUNDELL, R., GRIFFITH, R., HOWITT, P. & PRANTL, S., 2009. The Effects of Entry on Incumbent Innovation and Productivity. *The Review of Economics and Statistics*, 91(1): 20-32.
- AGHION, P. & JARAVEL, X., 2015. Knowledge Spillovers, Innovation and Growth. *The Economic Journal*, 125(583): 533-573.
- AHMED, G., KHAN, M.A., MAHMOOD, T. & AFZAL, M., 2015. Trade Liberalisation and Industrial Productivity: Evidence from Manufacturing Industries in Pakistan. *Pakistan Development Review*, 56(4): 319-348.
- AHN, J., KHANDELWAL, A.K. & WEI, S.J., 2011. The Role of Intermediaries in Facilitating Trade. *Journal of International Economics*, 84(1): 73-85.
- AIELLO, F. & CARDAMONE, P., 2005. R&D Spillovers and Productivity Growth: Evidence from Italian Manufacturing Microdata. *Applied Economics Letters*, 12(10): 625-631.
- AIGNER, D., LOVELL, C.K. & SCHMIDT, P., 1977. Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics*, 6(1): 21-37.
- AITKEN, B. J. & HARRISON, A. E., 1990. Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela, *American Economic Review*, 89(3): 605-618.
- AKOMOLAFE, F., 2008. No one is Laughing at the Asians Anymore: On the Lessons Africa can Learn from China: Stop Listening to the West and China, in ADO, A. & SU, Z., 2016. China in Africa: A Critical Literature Review. *Critical Perspectives On International Business*, 12(1): 40-60.

- ALAM, I.M.S. & MORRISON, A.R., 2000. Trade Reform Dynamics and Technical Efficiency: The Peruvian Experience. *The World Bank Economic Review*, 14(2): 309-330.
- ALVAREZ, R. & LOPEZ, R.A., 2005. Exporting and Performance: Evidence From Chilean Plants. *Canadian Journal of Economics/Revue canadienne d'économique*, 38(4): 1384-1400.
- ALVAREZ, R., 2001. External Sources Of Technological Innovation In Chilean Manufacturing Industry. *Estudios de economía*, 28(1): 53-68.
- ANDERSON, T.W. & HSIAO, C., 1981. Estimation of Dynamic Models with Error Components. *Journal of the American statistical Association*, 76(375): 598-606.
- ANDERSSON, M. & STONE, T.A., 2017. Global Sourcing and Technical Efficiency—A Firm-Level Study on the ICT Industry in Sweden. *Journal of Business Economics and Management*, 18(5): 877-896.
- ANG, J.B. & MADSEN, J.B., 2013. International R&D Spillovers and Productivity Trends in the Asian Miracle Economies. *Economic Inquiry*, 51(2): 1523-1541.
- APERGIS, N., ECONOMIDOU, C. & FILIPPIDIS, I., 2009. International Technology Spillovers, Human Capital and Productivity Linkages: Evidence from the Industrial Sector. *Empirica*, 36(4): 365.
- ARELLANO, M. & BOND, S., 1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The review of economic studies*, 58(2): 277-297.
- ARELLANO, M. & BOVER, O., 1995. Another Look at the Instrumental Variable Estimation of Error-Components Models. *Journal of econometrics*, 68(1): 29-51.

- ARNOLD, J., NICOLETTI, G. & SCARPETTA, S., 2011. Regulation, Resource Reallocation and Productivity Growth. *Nordic Economic Policy Review*, 2(1): 61-94.
- ARNOLD, J.M., JAVORCIK, B., LIPSCOMB, M. & MATTOO, A., 2016. Services Reform and Manufacturing Performance: Evidence from India. *The Economic Journal*, 126(590): 1-39.
- ARROW, K.J., 1962. The Economic Implications of Learning by Doing. *The Review of Economic Studies*, 29(3): 155-173.
- ASCHE, H. & SCHULLER, M., 2008. China's Engagement in Africa. Chances and Risks for Development, in ASONGU, S.A. & AMINKENG, G.A., 2013. The Economic Consequences of China–Africa Relations: Debunking Myths in the Debate. *Journal of Chinese Economic and Business Studies*, 11(4): 261-277.
- ASONGU, S.A. & AMINKENG, G.A., 2013. The economic consequences of China–Africa relations: debunking myths in the debate. *Journal of Chinese Economic and Business Studies*, 11(4): 261-277.
- AUTANT-BERNARD, C. & LESAGE, J.P., 2011. Quantifying Knowledge Spillovers Using Spatial Econometric Models. *Journal of Regional Science*, 51(3): 471-496.
- BADINGER, H. & BREUSS, F., 2008. Trade and Productivity: An Industry Perspective. *Empirica*, 35(2): 213-231.
- BADINGER, H. & EGGER, P., 2016. Productivity Spillovers Across Countries and Industries: New Evidence From OECD Countries. *Oxford Bulletin of Economics and Statistics*, 78(4): 501-521.
- BAI, J. & NG, S., 2004. A Panic Attack on Unit Roots and Cointegration. *Econometrica*, 72(4): 1127-1177.
- BAI, X., KRISHNA, K. & MA, H. 2017. How you Export Matters: Export Mode, Learning and Productivity In China. *Journal of International Economics*, 104(1): 122-137.

- BALAKRISHNAN, P., PUSHPANGADAN, K. & BABU, M. S. 2000. Trade Liberalisation and Productivity Growth in Manufacturing: Evidence from firm-level panel data. *Economic and Political weekly*, 33(12): 3679 - 3682.
- BALCHIN, N., HOEKMAN, B.M., MARTIN, H., MENDEZ-PARRA, M., PAPADAVID, P. & TE VELDE, D.W., 2016. *Trade in services and economic transformation*, in HOEKMAN, B. & SHEPHERD, B., 2017. Services Productivity, Trade Policy and Manufacturing Exports. *The World Economy*, 40(3): 499-516.
- BALTAGI, B. 2008. *Econometric Analysis of Panel Data*, 4th Edition, John Wiley & Sons, United States of America.
- BARRAS, R., 1986. Towards a Theory of Innovation in Services. *Research policy*, 15(4): 161-173.
- BARASA, L., VERMEULEN, P., KNOBEN, J., KINYANJUI, B. & KIMUYU, P., 2019. Innovation Inputs and Efficiency: Manufacturing Firms in Sub-Saharan Africa. *European Journal of Innovation Management*, 22(1): 59-83.
- BAS, M. & LEDEZMA, I., 2010. Trade Integration and within-plant Productivity Evolution in Chile. *Review of World Economics*, 146(1): 113-146.
- BASCAVUSOGLU, E., 2004. Patterns of Technology Transfer to the Developing Countries: Differentiating between Embodied and Disembodied Knowledge. *European Trade Study Group*, 4(2): 112-121.
- BASHER, S.A., HAUG, A.A. & SADORSKY, P., 2012. Oil Prices, Exchange Rates and Emerging Stock Markets. *Energy Economics*, 34(1): 227-240.
- BATTESE, G.E. & COELLI, T.J., 1995. A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical economics*, 20(2): 325-332.
- BATTESE, G.E. & BROCA, S.S., 1997. Functional Forms of Stochastic Frontier Production Functions and Models for Technical Inefficiency Effects: A

- Comparative Study for Wheat Farmers In Pakistan. *Journal of productivity analysis*, 8(4): 395-414.
- BEHERA, S.R., DUA, P. & GOLDAR, B., 2012. Foreign Direct Investment and Technology Spillover: Evidence Across Indian Manufacturing Industries. *The Singapore Economic Review*, 57(02): 125-141.
- BELITZ, H. & MÖLDERS, F., 2016. International Knowledge Spillovers Through High-Tech Imports and R&D of Foreign-Owned Firms. *The Journal of International Trade Economic Development*, 25(4): 590-613.
- BERGHÄLL, E., 2016. Innovation, Competition and Technical Efficiency. *Cogent Business & Management*, 3(1): 1199 -2012.
- BERNARD, A.B., JENSEN, J.B. & SCHOTT, P.K., 2006. Trade Costs, Firms and Productivity. *Journal of Monetary Economics*, 53(5): 917-937.
- BERNARD, A.B., JENSEN, J.B., REDDING, S.J. & SCHOTT, P.K., 2012. The Empirics of Firm Heterogeneity and International Trade. *Annu. Rev. Econ.*, 4(1): 283-313.
- BISWAS, P.R. & GHOSE, A., 2012. Role of Trade-related Factors in Determining Technical Efficiency of West Bengal's Industries: Evidence from a Stochastic Frontier Approach. *Trade and Development Review*, 5(1): 178-187.
- BLOOM, N., DRACA, M. & VAN REENEN, J., 2016. Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. *The Review of Economic Studies*, 83(1): 87-117.
- BLUNDELL, R. & BOND, S., 1998. Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of econometrics*, 87(1): 115-143.
- BRAHMBHATT, M. & HU, A. 2009. Ideas and Innovation in East Asia. *The World Bank Research Observer*, in SANIDAS, E., 2014. Emerging Economies of East and South East Asia: Some Salient Points about Technology's Role in Economic Development. *Journal of Emerging Economies and Islamic Research*, 2(3):1-4.

- BRINK, A., CANT, M. & LIGTHELM, A., 2003, September. Problems Experienced by Small Businesses in South Africa. In *16th Annual Conference of Small Enterprise Association of Australia and New Zealand*, 28(1): 1-20.
- BRUHN, N.C.P. & CALEGARIO, C.L.L., 2014. Productivity Spillovers from Foreign Direct Investment in The Brazilian Processing Industry. *BAR-Brazilian Administration Review*, 11(1): 22-46.
- CAVES, D.W., CHRISTENSEN, L.R. & DIEWERT, W.E., 1982. The Economic Theory Of Index Numbers and the Measurement of Input, Output, and Productivity. *Econometrica: Journal of the Econometric Society*, 456(23): 1393-1414.
- CETIN, D. & KALAYCI, E., 2016. Spatial Econometric Analysis of R&D Spillovers in Turkey. *Journal of Applied Economics & Business Research*, 6(3): 400-418.
- CHAND, S. & SEN, K. 2002. Trade Liberalization and Productivity Growth: Evidence from Indian Manufacturing. *Review of Development Economics*, 6(1): 120-132.
- CHANDRAN, V. 2009. Trade Openness and Manufacturing Growth in Malaysia. *Journal of Policy Modeling*, 31(3): 637-647.
- CHAUDHURI, D. D. 2016. Impact of Economic Liberalization on Technical Efficiency of Firms: Evidence from India's Electronics Industry. *Theoretical Economics Letters*, 6(3): 549-562.
- CHEN, B., MCCOSKEY, S.K. & KAO, C., 1999. Estimation and Inference of a Cointegrated Regression in Panel Data: A Monte Carlo Study. *American Journal of Mathematical and Management Sciences*, 19(1-2): 75-114.
- CHOI, I. 2001. Unit Root tests for Panel Data. *Journal of International Money and Finance*, 20(2): 249-272.
- CHU, S.Y. & YEH, J.H., 2007. International R&D Spillovers—A New Dynamic Perspective. Conference Paper, Accessed at https://editorialexpress.com/cgi-bin/conference/download.cgi?db_name=FEMES11&paper_id=771

- CHUDIK, A. & PESARAN, M. H. 2015. Common Correlated Effects Estimation of Heterogeneous Dynamic Panel Data Models With Weakly Exogenous Regressors. *Journal of Econometrics*, 188(23): 393-420.
- COE, D.T. & HELPMAN, E., 1995. International R&D Spillovers. *European Economic Review*, 39(5): 859-887.
- COE, D.T., HELPMAN, E. & HOFFMAISTER, A.W., 2009. International R&D Spillovers and Institutions. *European Economic Review*, 53(7): 723-741.
- COELLI, T., 1998. A Multi-Stage Methodology for the Solution of Orientated DEA Models. *Operations Research Letters*, 23(3-5): 143-149.
- COELLI, T.J. & RAO, D.P., 2005. Total Factor Productivity Growth in Agriculture: A Malmquist Index Analysis of 93 countries, 1980–2000. *Agricultural Economics*, 32(1): 115-134.
- COELLI, T.J., PRASADA-RAO, D.S., O'DONNELL, C.J. & BATTESE, G.E. (2005) An Introduction to Efficiency and Productivity Analysis. 2nd Edition, Springer, Berlin.
- CRESCENZI, R., GAGLIARDI, L. & IAMMARINO, S. 2015. Foreign Multinationals and Domestic Innovation: Intra-Industry Effects and Firm Heterogeneity. *Research Policy*, 44(8): 596-609.
- DAMIJAN, J.P., KNELL, M., MAJCEN, B. & ROJEC, M., 2003. The Role of FDI, R&D Accumulation and Trade in Transferring Technology to Transition Countries: Evidence from Firm Panel Data for Eight Transition Countries. *Economic systems*, 27(2): 189-204.
- DAS, D. K. 2001. Liberalization Efforts in China and Accession to the World Trade Organization. *J. World Investment*, 2(5): 700-761.
- DE JORGE, J. & SUÁREZ, C., 2011. Influence of R&D Subsidies on Efficiency: The Case of Spanish Manufacturing Firms. *Cuadernos de Economía y Dirección de la Empresa*, 14(3): 185-193.

- DE LOECKER, J. 2011. Product Differentiation, Multiproduct Firms, and Estimating The Impact of Trade Liberalization on Productivity. *Econometrica*, 79(1): 1407-1451.
- DERANIYAGALA, S., 2001. The Impact of Technology Accumulation on Technical Efficiency: An Analysis of the Sri Lankan Clothing and Agricultural Machinery Industries. *Oxford Development Studies*, 29(1): 101-114.
- DESSUS, S.C., GODDARD, J.G. & HANUSCH, M., 2017. South Africa economic update: Innovation for productivity and inclusiveness. World Bank Report No. 119695. *Washington, DC*.
- DIAO, X., RATTSSØ, J. & STOKKE, H.E., 2005. International Spillovers, Productivity Growth and Openness in Thailand: An Intertemporal General Equilibrium Analysis. *Journal of Development Economics*, 76(2): 429-450.
- DIOW, D. & LESSOUA, A., 2013. Natural Resources Exports, Diversification and Economic Growth of CEMAC Countries: On the Impact of Trade with China. *African Development Review*, 25(2): 189-202.
- DÍAZ-MAYANS, M.Á. & SÁNCHEZ-PÉREZ, R., 2014. Innovation, Exports and Technical Efficiency in Spain. *Design a Pattern of Sustainable Growth*, 6(3): 20-38.
- DJANKOV, S. & B. HOEKMAN (2000), Foreign Investment and Productivity Growth in Czech Enterprises, *World Bank Economic Review*, 14(1): 49-64.
- DORASZELSKI, U. & JAUMANDREU, J., 2013. R&D and Productivity: Estimating Endogenous Productivity. *Review of Economic Studies*, 80(4): 1338-1383.
- DORN, D. & HANSON, G. H. 2015. Untangling Trade and Technology: Evidence From Local Labour Markets. *Economic Journal*, 125(584): 621-646.
- EATON, J. & KORTUM, S., 1997. Engines of Growth: Domestic and Foreign Sources Of Innovation. *Japan and the World Economy*, 9(2): 235-259.

- EATON, J. & KORTUM, S., 1999. International Technology Diffusion: Theory and measurement. *International Economic Review*, 40(3): 537-570.
- ECONOMIDOU, C. & MURSHID, A.P., 2008. Testing the Linkages Between Trade and Productivity Growth. *Review of Development Economics*, 12(4): 845-860.
- EDENHOFER, O., BAUER, N. & KRIEGLER, E., 2005. The Impact of Technological Change on Climate Protection and Welfare: Insights from the Model MIND. *Ecological Economics*, 54(2): 277-292.
- EDMOND, C., 2001. Some Panel Cointegration Models of International R&D Spillovers. *Journal of Macroeconomics*, 23(2): 241-260.
- EDWARDS, L., 2004. A Firm Level Analysis of Trade, Technology and Employment in South Africa. *Journal of International Development*, 16(1): 45-61.
- EDWARDS, L. & BEHAR, A., 2005. Trade Liberalisation and Labour Demand Within South African Manufacturing Firms. *Studies in Economics and Econometrics*, 30(2): 127-146.
- EDWARDS, L. & JENKINS, R., 2015. The Impact of Chinese Import Penetration on the South African Manufacturing Sector. *The Journal of Development Studies*, 51(4): 447-463.
- EDWARDS, L., RANKIN, N. & SCHOER, V., 2008. South African Exporting firms: What do we know and what should we know?. *Journal of Development Perspectives*, 4(1): 67-92.
- EDWARDS, S. 1998. Openness, Productivity and Growth: What do we Really Know? *The Economic Journal*, 108(447): 383-398.
- ELU, J. U. & PRICE, G. N. 2010. Does China Transfer Productivity Enhancing Technology to Sub-Saharan Africa? Evidence from Manufacturing Firms. *African Development Review*, 22(1): 587-598.

- ENDERS, Z. & MÜLLER, G.J., 2009. On the International Transmission of Technology Shocks. *Journal of International Economics*, 78(1): 45-59.
- ENGELBRECHT, H. J. 1997. International R&D Spillovers Among OECD Economics, *Applied Economics Letters*, 4(5): 315-319.
- ERİŞ, M. N. & ULAŞAN, B. 2013. Trade Openness and Economic Growth: Bayesian model averaging estimate of cross-country growth regressions. *Economic Modelling*, 33(1): 867-883.
- ERTUR, C. & MUSOLESI, A., 2017. Weak and Strong Cross-Sectional Dependence: A Panel Data Analysis of International Technology Diffusion. *Journal of Applied Econometrics*, 32(3): 477-503.
- ESCHENBACH, F. & HOEKMAN, B., 2006. Services Policies in Transition Economies: on the EU and WTO as Commitment Mechanisms. *World Trade Review*, 5(3): 415-443.
- EVANGELISTA, R., 2000. Sectoral Patterns of Technological Change in Services. *Economics of Innovation and New Technology*, 9(3): 183-222.
- EVERAERT, G. & DE GROOTE, T. 2016. Common Correlated Effects Estimation of Dynamic Panels With Cross-Sectional Dependence. *Econometric Reviews*, 35(1): 428-463.
- FANTU, C. & CYRIL, O., 2010. The rise of China & India in Africa, in AYABEI, C., 2017. The rise of China and conflicts in Africa: The case of Sudan. *African Journal of Political Science and International Relations*, 11(2): 29-35.
- FÄRE, R., GROSSKOPF, S., LINDGREN, B. & ROOS, P., 1994. Productivity Developments In Swedish Hospitals: A Malmquist Output Index Approach. In *Data Envelopment Analysis: Theory, Methodology, and Applications*, Springer, 457(3): 253-272.
- FELDMAN, M. P. & KOGLER, D. F. 2010. Stylized Facts in the Geography of Innovation. *Handbook of the Economics of Innovation*, 1(1): 381-410.

- FERNANDES, A.M. & PAUNOV, C., 2012. Foreign Direct Investment in Services and Manufacturing Productivity: Evidence for Chile. *Journal of Development Economics*, 97(2): 305-321.
- FILIPPETTI, A., FRENZ, M. & IETTO-GILLIES, G. 2017. The Impact of Internationalization on Innovation at Countries' Level: The Role Of Absorptive Capacity. *Cambridge Journal of Economics*, 41(2): 413-439.
- FOSTER-MCGREGOR, N., ISAKSSON, A. & KAULICH, F. 2016. Importing, Productivity and Absorptive Capacity in Sub-Saharan African Manufacturing and Services Firms. *Open Economies Review*, 27(1): 87-117.
- FRANCOIS, J.F., 1990. Trade in producer services and returns due to specialization under monopolistic competition. *Canadian Journal of Economics*, 6(1): 109-124.
- FRESCHI, L., 2010. China in Africa Myths and Realities. *AIDWATCH*. Accessed August, 16, p.2012, in ASONGU, S.A. & AMINKENG, G.A., 2013. The economic consequences of China–Africa relations: debunking myths in the debate. *Journal of Chinese Economic and Business Studies*, 11(4): 261-277.
- FU, X., 2005. Exports, Technical Progress and Productivity Growth in a Transition Economy: A Non-parametric Approach for China. *Applied Economics*, 37(7): 725-739.
- GARCÍA, A.E. & MONTERO, J.M., 2009. R&D Investment and Endogenous Growth: A SVAR Approach. *Documentos de trabajo del Banco de España*, (25): 9-38.
- GERSCHEWSKI, S., 2013. Do Local Firms Benefit From Foreign Direct Investment? An Analysis of Spillover Effects in Developing Countries. *Asian Social Science*, 9(4): 67-76.
- GIOLDASIS, G., MUSOLESI, A. & SIMIONI, M., 2018. *Nonparametric estimation of international R&D spillovers*. Working Paper No. 0318. SEEDS, Sustainability Environmental Economics and Dynamics Studies.

- GOLDBERG, P. K., KHANDELWAL, A. K., PAVCNIK, N. & TOPALOVA, P. 2010. Imported Intermediate Inputs and Domestic Product Growth: Evidence from India. *The Quarterly Journal of Economics*, 125(4): 1727-1767.
- GOULDER, L.H. & SCHNEIDER, S.H., 1999. Induced Technological Change and the Attractiveness of CO₂ Abatement Policies. *Resource and Energy Economics*, 21(3-4): 211-253.
- GRAZZI, M. 2012. Export and Firm Performance: Evidence on Productivity and Profitability of Italian Companies. *Journal of Industry, Competition and Trade*, 12(4): 413-444.
- GREENE, W. 2004. The Behaviour of The Maximum Likelihood Estimator of Limited Dependent Variable Models in the Presence of Fixed Effects. *The Econometrics Journal*, 7(1): 98-119.
- GREENE, W., 2005a. Fixed and Random Effects in Stochastic Frontier Models. *Journal of Productivity Analysis*, 23(1): 7-32.
- GREENE, W., 2005b. Reconsidering Heterogeneity in Panel Data Estimators of The Stochastic Frontier Model. *Journal of Econometrics*, 126(2): 269-303.
- GREENE, W. H. 2003. *Econometric Analysis*, 1st Edition, Pearson Education, India.
- GREENE, W.H., 2008. The Econometric Approach to Efficiency Analysis. *The Measurement of Productive Efficiency and Productivity Growth*, 1(1): 92-250.
- GRIFFITH, R., REDDING, S. & VAN REENEN, J., 2003. R&D and Absorptive Capacity: Theory and Empirical Evidence. *Scandinavian Journal of Economics*, 105(1): 99-118.
- GRIFELL-TATJÉ, E. & LOVELL, C.K., 1997. The Sources of Productivity Change in Spanish Banking. *European Journal of Operational Research*, 98(2): 364-380.

- GRILICHES, Z. 1979. Issues in Assessing the Contribution of Research and Development to Productivity Growth. *The Bell Journal of Economics*, 10(1), pp.92-116.
- GRILICHES, Z. & LICHTENBERG, F. 1984. Interindustry Technology Flows and Productivity Growth: A Reexamination. *The Review of Economics and Statistics*, 10(3), pp. 324-329.
- GROSSMAN, G. M. & HELPMAN, E. 1990. Trade, Innovation, and Growth. *The American Economic Review*, 80(1): 86-91.
- GROSSMAN, G. M. & HELPMAN, E. 1991. Trade, Knowledge Spillovers, and Growth. *European Economic Review*, 35(1): 517-526.
- GUELLEC, D. & VAN POTTELSBERGHE DE LA POTTERIE, B., 2004. From R&D to Productivity Growth: Do the Institutional Settings and the Source of Funds of R&D matter?. *Oxford Bulletin of Economics and Statistics*, 66(3): 353-378.
- GUERRIERI, P., 2005. *Technology Diffusion, Services, and Endogenous Growth in Europe. Is the Lisbon Strategy Useful?* International Monetary Fund, 5(1): 234-256.
- GUO, K. & N'DIAYE, M.P., 2009. Is China's Export-Oriented Growth Sustainable? Working Paper No. 9-172. International Monetary Fund.
- GUTIERREZ, L. & GUTIERREZ, M.M., 2003. International R&D Spillovers and Productivity Growth in the Agricultural Sector. A Panel Cointegration Approach. *European Review of Agricultural Economics*, 30(3): 281-303.
- HA, Y. J. & GIROUD, A. 2015. Competence-creating Subsidiaries and FDI Technology Spillovers. *International Business Review*, 24(1): 605-614.
- HADRI, K. 2000. Testing for Stationarity in Heterogeneous Panel Data. *The Econometrics Journal*, 3(1): 148-161.

- HALL, B.H. & ROSENBERG, N., 2010. Economics of Innovation. *Handbooks in Economics, Amsterdam, Elsevier-North Holland*.
- HARRIS, R. D. & TZAVALLIS, E. 1999. Inference for unit roots in Dynamic Panels where the Time Dimension is Fixed. *Journal of econometrics*, 91(2): 201-226.
- HASKEL, J.E., PEREIRA, S.C. & SLAUGHTER, M.J., 2007. Does Inward Foreign Direct Investment Boost the Productivity of Domestic Firms? *The review of economics and statistics*, 89(3): 482-496.
- HASAN, M.Z., KAMIL, A.A., MUSTAFA, A. & BATEN, M.A., 2012. A Cobb Douglas Stochastic Frontier Model on Measuring Domestic Bank Efficiency in Malaysia. *PLOS one*, 7(8): 422-239.
- HASSINE, N. B. 2008. Trade, Human Capital, and Technology Diffusion in the Mediterranean Agricultural Sector. *Economie Internationale*, 1(1): 115-142.
- HAUSMANN, R., RODRIK, D. & SABEL, C., 2008. Reconfiguring industrial policy: a framework with an application to South Africa. Centre for International Development, in WEISS, J., 2013. Industrial policy in the twenty-first century: challenges for the future. *Pathways to Industrialization in the Twenty-First Century: New Challenges and Emerging Paradigms*, 45(1): 393-412.
- HECKSHER, E. & OHLIN, B. 1933. Interregional and International Trade. Harvard University Press, Cambridge, MA.
- HENRY, M., KNELLER, R. & MILNER, C. 2009. Trade, Technology Transfer And National Efficiency In Developing Countries. *European Economic Review*, 53(2): 237-254.
- HIEBERT, P. & VANSTEENKISTE, I., 2010. International Trade, Technological Shocks and Spillovers in the Labour Market: A GVAR Analysis of the US Manufacturing Sector. *Applied Economics*, 42(24): 3045-3066.
- HIGÓN, D.A., 2007. The Impact of R&D Spillovers on UK manufacturing TFP: A Dynamic Panel Approach. *Research Policy*, 36(7): 964-979.

- HOFF, P.D., 2009. *A First Course in Bayesian Statistical Methods*. Springer Science & Business Media. Germany.
- HOLTZ-EAKIN, D., NEWHEY, W. & ROSEN, H.S., 1988. Estimating Vector Autoregressions with Panel Data. *Econometrica: Journal of the Econometric Society*, 1(1): 1371-1395.
- HU, A. G. & LIU, Z. 2014. Trade Liberalization and Firm Productivity: Evidence from Chinese Manufacturing Industries. *Review of International Economics*, 22(3), 488-512.
- HÜBLER, M., 2011. Technology Diffusion Under Contraction and Convergence: A CGE Analysis Of China. *Energy Economics*, 33(1): 131-142.
- HÜBLER, M. & POTHEN, F. 2017. Trade-induced Productivity Gains Reduce Incentives to Impose Strategic Tariffs. *Economic Modelling*, 61(1): 420-431.
- IM, K. S., PESARAN, M. H. & SHIN, Y. 2003. Testing for Unit Roots in Heterogeneous Panels. *Journal of Econometrics*, 115(1): 53-74.
- INDUSTRIAL DEVELOPMENT COOPERATION., 2009. Trends in South African manufacturing Production, Employment and Trade, Department of Research and Information, Fourth Quarter.
- JENKINS, R., 1995. Does Trade Liberalization Lead to Productivity Increases? A case Study of Bolivian Manufacturing. *Journal of International Development*, 7(4): 577-597.
- JONDROW, J., LOVELL, C.K., MATEROV, I.S. & SCHMIDT, P., 1982. On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model. *Journal of econometrics*, 19(2-3): 233-238.
- JONSSON, G. & SUBRAMANIAN, A. 2001. Dynamic gains from Trade: Evidence from South Africa. *IMF Staff Papers*, 48(1): 197-224.

- JORDÀ, Ò., 2005. Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review*, 95(1): 161-182.
- JORDÀ, Ò., 2009. Simultaneous Confidence Regions for Impulse responses. *The Review of Economics and Statistics*, 91(3): 629-647.
- JUNG, M. & LEE, K., 2010. Sectoral Systems of Innovation and Productivity Catch-Up: Determinants of the Productivity Gap Between Korean and Japanese firms. *Industrial and Corporate Change*, 19(4): 1037-1069.
- KALAYCI, E. & PAMUKÇU, T., 2014. Assessing the Drivers of R&D Activities of Firms in Developing Countries: Evidence from Turkey. *The European Journal of Development Research*, 26(5): 853-869.
- KAMWANGA, J. & KOYI, G., 2009. Impact of China-Africa Investment Relations: The Case of Zambia. *Submitted to the African Economic Research Consortium*.
- KASAHARA, H. & RODRIGUE, J. 2008. Does the use of imported intermediates increase productivity? Plant-level evidence. *Journal of development economics*, 87(1): 106-118.
- KASEERAM, I. & MAHADEA, D., 2015. Declining Labour Share of Income in South Africa: the Kalman Filter Approach. *Journal of Economic and Financial Sciences*, 8(2): 372-391.
- KEMFERT, C., 2005. Induced Technological Change in a Multi-Regional, Multi-Sectoral, Integrated Assessment Model (WIAGEM): Impact Assessment of Climate Policy Strategies. *Ecological Economics*, 54(2-3): 293-305.
- KELLER, W., 2002. Trade and the Transmission of Technology. *Journal of Economic growth*, 7(1): 5-24.
- KELLER, W., 2004. International technology diffusion. *Journal of economic literature*, 42(3): 752-782.

- KELLER, W. 2010. International trade, Foreign Direct Investment, and Technology Spillovers. *Handbook of the Economics of Innovation*, 2(1): 793-829.
- KERR, W. R. 2017. Heterogeneous Technology Diffusion and Ricardian Trade Patterns. Policy Research working paper; no. WPS 8027. Washington, D.C. : World Bank Group.
- KESHARI, P.K., 2013. Efficiency spillovers from FDI in the Indian machinery industry: a firm-level study using panel data models, in: TRIPATHY, T., BHATTACHARAYA, P., ARUNA, M. (EDS), A Compendium of Essays in Applied Econometrics, IBS, Hyderabad, 23(1): 24-55.
- KIM, J.W. & LEE, H.K., 2004. Embodied and Disembodied International Spillovers of R&D in OECD Manufacturing Industries. *Technovation*, 24(4): 359-368.
- KIM, S. & PARK, J., 2017. Foreign Direct Investment and International R&D Spillovers in OECD Countries Revisited. *Journal of Institutional and Theoretical Economics JITE*, 173(3): 431-453.
- KLEIN, M. A. 2017. Technological Catch-Up and Productivity Spillovers From FDI: Evidence from Indian Manufacturing. Preliminary Draft., Unpublished.
- KODDE, D.A. & PALM, F.C., 1986. Wald Criteria for Jointly Testing Equality and Inequality Restrictions. *Econometrica: journal of the Econometric Society*, 33(1): 1243-1248.
- KONINGS, J. 2001. The Effects of Foreign Direct Investment on Domestic Firms: evidence from Firm level Panel Data in Emerging Economies, *Economics of Transition*, 9(3): 619-633.
- KOPP, R. J. & SMITH, V. K. 1980. Frontier Production Function Estimates for Steam electric generation: A comparative analysis. *Southern Economic Journal*, 33(2): 1049-1059.
- KOWALSKI ET AL, P. L., R. BOTTINI, N. 2009. South Africa's Trade and Growth. *OECD Working Paper No. 91*, 82.

- KOUMOU, R. F. M., & MANYI, W., 2016. Effects of Chinese Foreign Direct Investment in Africa. *Journal of Finance and Accounting*, 4(3): 131-139.
- KRISHNA, P. & MITRA, D. 1998. Trade Liberalization, Market Discipline And Productivity Growth: New Evidence From India. *Journal of development Economics*, 56(1): 447-462.
- KRUGMAN, P. R. 1980. Scale Economies, Product Differentiation, and the Pattern of Trade. *The American Economic Review*, 70(5): 950-959.
- KUMAR, T.S., 2006. Productivity in Indian Chemical Sector: An Intra-sectoral Analysis. *Economic and Political Weekly*, 8(1): 4148-4152.
- KUMBHAKAR, S.C., WANG, H. & HORNCastle, A.P., 2015. *A Practitioner's Guide to Stochastic Frontier Analysis Using Stata*. Cambridge University Press.
- LANCASTER, T. 2000. The Incidental Parameter Problem Since 1948. *Journal of Econometrics*, 95: 391-413.
- LAWRENCE, R. Z. & WEINSTEIN, D. E. 2001. Trade and Growth: import-led or export-led? Evidence from Japan and Korea. *Rethinking the East Asian Miracle*, 45(2): 379-408.
- LE, T., 2012. R&D Spillovers through Student Flows, Institutions, and Economic Growth: What can we Learn from African Countries?. *Scottish Journal of Political Economy*, 59(1): 115-130.
- LEE, G., 2006. The Effectiveness of International Knowledge Spillover Channels. *European Economic Review*, 50(8): 2075-2088.
- LEIMBACH, M. & BAUMSTARK, L., 2010. The Impact of Capital Trade and Technological Spillovers on Climate Policies. *Ecological Economics*, 69(12): 2341-2355.

- LEIVA, D.I.R., 2014. International R&D Spillovers and Unobserved Common Shocks. *Documentos de Trabajo (IAES, Instituto Universitario de Análisis Económico y Social)*, (8): 1-74.
- LEVIN, A. & LIN, C.-F. 1993. Unit Root Tests in Panel Data: New Results. *University of California at San Diego, Economics Working Paper Series No. 34*.
- LEVINE, R., 1997. Financial development and economic growth: views and agenda. *Journal of economic literature*, 35(2): 688-726.
- LEVINSOHN, J. & PETRIN, A., 2003. Estimating Production Functions Using Inputs to Control for Unobservables. *The Review of Economic Studies*, 70(2): 317-341.
- LICHTENBERG, F. R. & DE LA POTTERIE, B. V. P. 1998. International R&D spillovers: a comment. *European Economic Review*, 42(1): 1483-1491.
- LILEEVA, A. 2008. Trade liberalization and productivity dynamics: evidence from Canada. *Canadian Journal of Economics/Revue canadienne d'économique*, 41(1): 360-390.
- LIPSEY, R. G., COURANT, P.N., & RAGAN C.T.S. 1999. Economics, Twelfth Edition. *Addison-Wesley Publishing Company* Reading, Massachusetts.
- LIU, X. & WANG, C., 2003. Does foreign direct investment facilitate technological progress? Evidence from Chinese industries. *Research policy*, 32(6): 945-953.
- LÖÖF, H. & ANDERSSON, M., 2010. Imports, Productivity and Origin Markets: The Role of Knowledge-intensive Economies. *World Economy*, 33(3): 458-481.
- LÖSCHEL, A. & OTTO, V.M., 2009. Technological Uncertainty and Cost Effectiveness of CO2 Emission Reduction. *Energy Economics*, 31: 4-17.
- MANCA, F. 2009. Appropriate IPRs, Human Capital Composition and Economic Growth. *IREA–Working Papers, 2009, IR09/014*.

- MADDALA, G. S. & WU, S. 1999. A comparative Study of Unit Root Tests With Panel Data And A New Simple Test. *Oxford Bulletin of Economics and statistics*, 61(1): 631-652.
- MANKIW, N. G., ROMER, D. & WEIL, D. N. 1992. A Contribution to the Empirics of Economic Growth. *The Quarterly Journal of Economics*, 107(1): 407-437.
- MASTROMARCO, C. & GHOSH, S., 2009. Foreign Capital, Human Capital, and Efficiency: A Stochastic Frontier Analysis for Developing Countries. *World Development*, 37(2): 489-502.
- MASUNDA, S. & CHIWESHE, A.R., 2015. A Stochastic Frontier Analysis on Farm Level Technical Efficiency in Zimbabwe: A case of Marirangwe Smallholder Dairy Farmers. *Journal of Development and Agricultural Economics*, 7(6): 237-242.
- MATTOO, A., RATHINDRAN, R. & SUBRAMANIAN, A., 2006. Measuring services trade liberalization and its impact on economic growth: An illustration. *Journal of Economic Integration*, 18(1): 64-98.
- MEDDA, G. & PIGA, C. A. 2014. Technological Spillovers and Productivity in Italian Manufacturing Firms. *Journal of Productivity Analysis*, 41(1): 419-434.
- MEEUSEN, W. & VAN DEN BROECK, J., 1977. Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review*, 53(1): 435-444.
- MELITZ, M.J., 2003. The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity. *Econometrica*, 71(6): 1695-1725.
- MCMILLAN, M. S. & RODRIK, D. 2011. *Globalization, Structural Change and Productivity Growth*. Working Paper No. w1426. National Bureau of Economic Research.
- MEHTA, S. 2013. Technology Spillovers and Productivity: Analysis of the Indian Manufacturing Sector. *Innovation and Development*, 3(1): 55-69

- MUN, S.B. & NADIRI, M.I., 2002. *Information Technology Externalities: Empirical Evidence From 42 US Industries*, Working Paper No. w9272. National Bureau of Economic Research.
- MUNISAMY, S., FON, C.Z. & WONG, E.S., 2015. Innovation and Technical Efficiency In Malaysian Family Manufacturing Industries. *Journal of Economic & Financial Studies*, 3(04): 50-67.
- NEWMAN, C., RAND, J., TALBOT, T. & TARP, F. 2015. Technology Transfers, Foreign Investment and Productivity Spillovers. *European Economic Review*, 76(1): 168-187.
- NEYMAN, J. & SCOTT, E. L. 1948. Consistent estimates based on partially consistent observations. *Econometrica: Journal of the Econometric Society*, 42(3): 1-32.
- NISHIOKA, S. & RIPOLL, M. 2012. Productivity, Trade and the R&D Content of Intermediate Inputs. *European Economic Review*, 56(1): 1573-1592.
- NJIKAM, O. & COCKBURN, J. 2011. Trade liberalization and Productivity Growth: Firm-level evidence from Cameroon. *The Journal of Developing Areas*, 64(2): 279-302.
- NORDIN, N., ISMAIL, N.W. & NORDIN, N., 2016. International R&D Spillovers and Productivity Growth in the Asean Countries. *Journal of Global Business and Social Entrepreneurship (GBSE)*, 3(5): 75-85.
- OCAMPO, J.A., 2002. Trade Policy and Industrialization in Colombia, 1967–91. In Trade Policy and Industrialization in Turbulent Times. *Routledge*, 5(1): 150-187.
- OGAWA, K., STERKEN, E. & TOKUTSU, I., 2016. International R&D Spillovers and Marginal Social Returns on R&D. Working Paper 6255. CESifo.
- OLLEY, G. S. & PAKES, A. 1992. *The Dynamics of Productivity in the Telecommunications Equipment Industry*. Working Paper No. w617. National Bureau of Economic Research.

- OTTO, V.M., LÖSCHEL, A. & DELLINK, R., 2007. Energy Biased Technical Change: A CGE Analysis. *Resource and Energy Economics*, 29(2): 137-158.
- OTTO, V.M. & REILLY, J., 2008. Directed Technical Change and the Adoption of CO₂ Abatement Technology: The Case Of CO₂ Capture and Storage. *Energy Economics*, 30(6): 2879-2898.
- PAGAN, A. & VELLA, F. 1989. Diagnostic tests for models based on individual data: a survey. *Journal of Applied Econometrics*, 4(1): 662-674.
- PAGE, J. M. 1994. The East Asian Miracle: An Introduction. *World Development*, 22(1): 615-625.
- PAMUKÇU, M.T. & ERDIL, E., 2015. Analysing R&D Activities of Foreign Enterprises in Emerging Economies: Lessons from Turkey. *In World Scientific Reference On Globalisation In Eurasia and the Pacific Rim: 1(1): 185-232.*
- PARRADO, R. & DE CIAN, E., 2014. Technology Spillovers Embodied in International Trade: Intertemporal, Regional and Sectoral Effects an a Global CGE Framework. *Energy Economics*, 41(1): 76-89.
- PARK, J.Y., 1992. Canonical cointegrating regressions. *Econometrica: Journal of the Econometric Society*, 54(3): 119-143.
- PESARAN, M. H. 2007. A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22(1): 265-312.
- PESARAN, M. H. 2015. Testing Weak Cross-Sectional Dependence in Large Panels. *Econometric Reviews*, 34(1): 1089-1117.
- PESARAN, M. H., SHIN, Y. & SMITH, R. J. 2001. Bounds testing Approaches to the Analysis of Level Relationships. *Journal of applied econometrics*, 16(1): 289-326.
- PESARAN, M.H. & SMITH, R.P., 1998. Structural Analysis of Cointegrating VARs. *Journal of Economic Surveys*, 12(5): 471-505.

- PESARAN, M. H., SHIN, Y. & SMITH, R. P. 1999. Pooled Mean Group Estimation of Dynamic Heterogeneous Panels. *Journal of the American Statistical Association*, 94(1): 621-634.
- PHILLIPS, P.C. & HANSEN, B.E., 1990. Statistical Inference in Instrumental Variables Regression with I (1) processes. *The Review of Economic Studies*, 57(1): 99-125.
- PIERMARTINI, R. & RUBÍNOVÁ, S., 2014. Knowledge Spillovers Through International Supply Chains. Working Paper No. ERSD-2014-11. World Trade Organisation.
- PINTO, A., PERI, D., CAMPANA, E.F. & INSEAN, 2004. Global Optimization Algorithms in Naval Hydrodynamics. *Ship Technology Research*, 51(3): 123-133.
- POPP, D., 2004. ENTICE: Endogenous Technological Change in the DICE Model Of Global Warming. *Journal of Environmental Economics and Management*, 48(1): 742-768.
- POPP, D., 2006. International Innovation and Diffusion of Air Pollution Control Technologies: The Effects of NOX and SO2 Regulation in the US, Japan, and Germany. *Journal of Environmental Economics and Management*, 51(1): 46-71.
- POTTERIE, B.V.P.D.L. & LICHTENBERG, F., 2001. Does Foreign Direct Investment Transfer Technology across Borders?. *Review of Economics and Statistics*, 83(3): 490-497.
- POURAGHAEI, N., 2016. *Testing a DSGE Endogenous Growth Model Of R&D Via Indirect Inference: Productivity Growth in a Panel of OECD* (Doctoral Dissertation, Cardiff University).
- POWELL, J. L. 1986. Symmetrically Trimmed Least Squares Estimation for Tobit Models. *Econometrica: Journal of the Econometric Society*, 50(2): 1435-1460.

- PRADEEP, V., BHATTACHARYA, M. & CHEN, J. R. 2017. Spillover Effects of Research and Development, Exports and Foreign Investment on Productivity: Empirical Evidence from Indian Manufacturing. *Journal of South Asian Development*, 12(1): 18-41.
- PRITCHETT, L. 2000. Understanding Patterns of Economic Growth: Searching for Hills Among Plateaus, Mountains, and Plains. *World Bank Economic Review*, 14(1): 221-250.
- RAMADANI, V., ABAZI-ALILI, H., DANA, L.-P., REXHEPI, G. & IBRAIMI, S. 2017. The Impact of Knowledge Spillovers and Innovation on Firm-Performance: Findings from the Balkans Countries. *International Entrepreneurship and Management Journal*, 13(1): 299-325.
- RAOUF ABDEL FATTAH, E., 2015. Total Factor Productivity and Technology Spillovers in Egypt. *Middle East Development Journal*, 7(2): 149-159.
- RENARD, M.F., 2011. China's Trade and FDI in Africa. *China and Africa: An emerging Partnership For Development*, 25(1): 558-469.
- RICARDO, D., 1973. *The Works and Correspondence of David Ricardo: Volume 10, Biographical Miscellany*. Cambridge University Press. United Kingdom.
- ROBERTS, S. 2000. Understanding the Effects of Trade Policy Reform: The Case of South Africa. *South African Journal of Economics*, 68(1): 270-281.
- RODRIGUEZ, F. & RODRIK, D., 2000. Trade Policy and Economic Growth: A Skeptic's Guide to the Cross-National Evidence. *NBER macroeconomics annual*, 15(1): 261-325.
- RODRIK, D., 1993. *Trade and Industrial Policy Reform in Developing Countries: A Review of Recent Theory and Evidence*. Working Paper No. w4417. National Bureau of Economic Research.
- RODRIK, R., 1995. Trade and Industrial Policy Reform. *Handbook of Development Economics*, 3(1): 2925-2982.

- RODRIK, D. 2008. Understanding South Africa's economic puzzles. *Economics of Transition*, 16(1): 769-797.
- RODRIK, D. 2014a. Has Sustained Growth Decoupled from Industrialization? *How Economies Grow*, 12(3): 55-63.
- RODRIK, D. 2014b. The Past, Present, and Future of Economic Growth. *Challenge*, 57(1): 5-39.
- ROMER, P. M. 1986. Increasing Returns and Long-Run Growth. *Journal of political economy*, 94(1): 1002-1037.
- ROMER, P.M., 1989. *Increasing Returns and New Developments in the Theory of Growth*. Working Paper No. w3098. National Bureau of Economic Research.
- ROMER, P.M., 1990. Endogenous Technological Change. *Journal of Political Economy*, 98(5): 71-102.
- SANTACREU, A. M. 2015. Innovation, Diffusion, and Trade: Theory and measurement. *Journal of Monetary Economics*, 75(1): 1-20.
- SARI, D. W., KHALIFAH, N. A. & SUYANTO, S. 2016. The Spillover Effects of Foreign Direct Investment on the Firms' Productivity Performances. *Journal of Productivity Analysis*, 46(1): 199-233.
- SARKAR, P. 2008. Trade Openness and Growth: is there any Link? *Journal of Economic Issues*, 42(1): 763-785.
- SCHMOOKLER, J., 1966, *Invention and Economic Growth*, Cambridge, MA; Harvard University Press. United Kingdom.
- SCHUMPETER, J. A. 1951. Essays: On Entrepreneurs, Innovations, Business Cycles, and the Evolution Of Capitalism, *Transaction Publishers*. 78(3): 345-360.

- SEYOUM, M., WU, R. & YANG, L. 2015. Technology Spillovers from Chinese Outward Direct Investment: The Case of Ethiopia. *China Economic Review*, 33(1): 35-49.
- SHARMA, K., JAYASURIYA, S. & OCZKOWSKI, E. 2000. Liberalization and Productivity Growth: The Case of Manufacturing Industry in Nepal. *Oxford Development Studies*, 28(1): 205-222.
- SHCHETYNNIN, Y, 2015., Effects of Imports on Technical Efficiency in Russian food Industry," *Applied Econometrics*, Publishing House "SINERGIA PRESS", 37(1): 27-42.
- SCHANKERMAN, M., 1981. The Effects of Double-Counting and Expensing on the Measured Returns to R&D. *The Review of Economics and Statistics*, 23(1): 454-458.
- SCHERER, F.M., 1982. Inter-Industry Technology Flows and Productivity Growth. *The Review of Economics and Statistics*, 1(2): 627-634.
- SIDDHARTHAN, N., HASHIM, S., CHU, S. N. & KALIRAJAN, K. 2011. Impact of Trade Liberalisation on Technical Efficiency of Vietnamese Manufacturing Firms. *Science, Technology and Society*, 16(1): 265-284.
- SIKWILA, N. & NDODA, G. R. T. J. M. 2014. Trade Openness and GDP Growth Nexus in South Africa. *Global Journal of Management and Business Research*, 14(1): 154-168.
- SIMAR, L. & WILSON, P. W. 2015. Statistical Approaches for Non-Parametric Frontier Models: A Guided Tour. *International Statistical Review*, 83(1): 77-110.
- SMITH, A. 1776. An Inquiry into the Nature and Causes of the Wealth of Nations. *George Routledge and Sons*. 189(2): 1671-2110.
- STIGLITZ, J. E. 1996. Some lessons from the East Asian miracle. *The world Bank research observer*, 11(1): 151-177.

- STOCK, J. H. & WATSON, M. W. 1993. A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems. *Econometrica: Journal of the Econometric Society*, 1(1): 783-820.
- SUN, H., HONE, P. & DOUCOULIAGO, H., 1999. Economic Openness and Technical Efficiency: A Case Study of Chinese Manufacturing Industries. *Economics of Transition*, 7(3): 615-636.
- TERLECKYJ, H., 1974 , Effects of R&D on the Productivity Growth of Industries: An Exploratory National Planning Association, Washington, D.C. 84(1): 456-470.
- TEWELDEMEDHIN, M. Y. & VAN SCHALKWYK, H. D. 2010. The Impact of Trade Liberalisation on South African Agricultural Productivity. *African Journal of Agricultural Research*, 5(1): 1380-1387.
- TOMLINSON, M. & LUNDVALL, B.Å., 2001. Policy Learning through Benchmarking National Systems of Competence Building and Innovation–Learning by Comparing. *Report for the Advanced Benchmarking Concepts (ABC) Project, Strasbourg*: European Council.
- TOPALOVA, P. & KHANDELWAL, A. 2011. Trade liberalization and Firm Productivity: The case of India. *Review of Economics and Statistics*, 93(1): 995-1009.
- TYBOUT, J., DE MELO, J. & CORBO, V. 1991. The effects of Trade Reforms on Scale and Technical Efficiency: New Evidence From Chile. *Journal of International Economics*, 31(1): 231-250.
- UNEL, M.B. & ZEBREGS, M.H., 2006. *The Dynamics of Provincial Growth in China: A Nonparametric Approach*. Working Paper No. 6-55. International Monetary Fund.
- VAN BIESEBROECK, J. 2007. Robustness of Productivity Estimates. *The Journal of Industrial Economics*, 55(1): 529-569.

- VAN DEN BERG, M. & VAN MARREWIJK, C., 2017. Imports and Productivity: The Impact of Geography and Factor Intensity. *The Journal of International Trade & Economic Development*, 26(4): 425-450.
- WACZIARG, R. & WELCH, K. H. 2008. Trade Liberalization and Growth: New Evidence. *The World Bank Economic Review*, 22(1): 187-231.
- WAGNER, J. 2012. International Trade and Firm Performance: A Survey of Empirical Studies since 2006. *Review of World Economics*, 148(1): 235-267.
- WANG, J.H., 2007. From Technological Catch-Up To Innovation-Based Economic Growth: South Korea and Taiwan compared. *The Journal of Development Studies*, 43(6): 1084-1104.
- WANG, H.J. & HO, C.W., 2010. Estimating Fixed-Effect Panel Stochastic Frontier Models by Model Transformation. *Journal of Econometrics*, 157(2): 286-296.
- WANG, H.-J. & SCHMIDT, P. 2002. One-Step and Two-Step Estimation of the Effects of Exogenous Variables on Technical Efficiency Levels. *Journal of Productivity Analysis*, 18(1): 129-144.
- WANG, L., MEIJERS, H. & SZIRMAI, A. 2017. Technological Spillovers and Industrial Growth in Chinese Regions. *Industrial and Corporate Change*, 26(1): 233-257.
- WANG, M. & WONG, M.S., 2012. International R&D Transfer and Technical Efficiency: Evidence from Panel Study using Stochastic Frontier Analysis. *World Development*, 40(10): 1982-1998.
- WONG, S. A. 2009. Productivity and Trade Openness In Ecuador's Manufacturing Industries. *Journal of Business Research*, 62(1): 868-875.
- XU, H., LAI, M. & QI, P., 2008. Openness, Human Capital and Total Factor Productivity: Evidence From China. *Journal of Chinese Economic and Business Studies*, 6(3): 279-289.

- YU, M. 2015. Processing Trade, Tariff Reductions and Firm Productivity: Evidence from Chinese Firms. *The Economic Journal*, 125(1): 943-988.
- ZAHONOGO, P. 2017. Trade and Economic Growth in Developing Countries: Evidence from sub-Saharan Africa. *Journal of African Trade*.16(1): 2214-8515.
- ZELLNER, A., 1986. On Assessing Prior Distributions and Bayesian Regression Analysis with g-prior distributions. *Bayesian inference and Decision Techniques*, in GHOSH, J. & GHATTAS, A.E., 2015. Bayesian variable selection under collinearity. *The American Statistician*, 69(3): 165-173.
- ZHANG, J.J. & LEE, S.Y.T., 2007. A Time Series Analysis of International ICT Spillover. *Journal of Global Information Management (JGIM)*, 15(4): 64-78.

APPENDIX A

MEASUREMENT OF TFP USING LEVINSOHN AND PETRIN (2003a)

As a starting point, the by Levinsohn and Petrin (2003a) approach assumes that production of output (y) is described by a Cobb-Douglas representation.

$$\log Y_{it} = \beta_0 + \beta_L \log L_{it} + \beta_K \log K_{it} + \beta_M \log M_{it} + \omega_{it} + \mu_{it} \quad (1)$$

where Y_{it} is the output variable which is essentially real value added for industry i , period t , L_{it} and M_{it} are freely variable input factors namely labour and the intermediate input while K_{it} represents capital which is considered to be a state variable. The study measures capital as gross fixed capital stock and labour as employment in each industry. The intermediate input is computed by subtracting real value added from real output.

From equation (4.1), the disturbance term is composite and consists of two components namely the transmitted productivity component denoted by ω_{it} and the white noise error term μ_{it} that is orthogonal to input choices. The difference between these two components is that the transmitted productivity component is a state variable which means it impacts the industry's production decision rules. It is unobservable to the econometrician and impacts the choices of input variables, a situation which creates a simultaneity problem in the production function estimation. The demand for the intermediates is assumed to be dependent on the producer's state variables capital and the transmitted productivity component.

$$m_{it} = m_{it}(k_{it}, \omega_{it}) \quad 4.2$$

Following Levinsohn and Petrin (2003), the analysis assumes that the specified demand function is monotonically increasing in the transmitted productivity component, ω_{it} . This assumption allows the inversion of the intermediate demand function so that one can re-write ω_{it} as a function of capital and intermediate inputs:

$$\omega_{it} = \omega_{it}(k_{it}, m_{it}) \quad 4.3$$

The unobservable productivity component ω_{it} is now expressed uniquely as a function of the two observed inputs. Finally, the Levinsohn and Petrin (2003) procedure assumes that ω_{it} follows a first-order Markov process which is an identification restriction borrowed from Olley and Pakes (1996).

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}] + \xi_{it} \quad 4.4$$

where symbol ξ_{it} signifies a shock to productivity that is orthogonal to the capital input but not necessarily to labour. One can re-write the production function as:

$$\log Y_{it} = \beta_L \log L_{it} + \varphi(\log K_{it}, \log M_{it}) + u_{it} \quad 4.5$$

where

$$\varphi(\log K_{it}, \log M_{it}) = \beta_0 + \beta_K \log K_{it} + \omega_{it}(\log K_{it}, \log M_{it})$$

By substituting a third-order polynomial approximation in capital and the intermediate input in place of $\varphi(\log K_{it}, \log M_{it})$, it is possible to consistently estimate the parameters of our value-added specification using the ordinary least squares method as:

$$\log Y_{it} = \delta_0 + \beta_L \log L_{it} + \sum_{i=0}^3 \sum_{j=0}^{3-i} \delta_{ij} \log K_{it}^i \log M_{it}^j + u_{it} \quad 4.6$$

where the intercept δ_0 is not identified separately from the constant term of $\varphi_{it}(\log K_{it}, \log M_{it})$. This specification defines the first stage estimation proposed by Levinsohn and Petrin (2003) from which β_L and φ_{it} can be computed. The second stage estimation then identifies the coefficient β_K and it begins by generating the predicted values of φ_{it} from;

$$\begin{aligned} \hat{\varphi}_{it} &= \log Y_{it} - \widehat{\beta_L} \log L_{it} \quad 4.7 \\ &= \hat{\delta}_0 + \sum_{i=0}^3 \sum_{j=0}^{3-i} \widehat{\delta_{ij}} \log K_{it}^i \log M_{it}^j - \hat{\beta_L} \log L_{it} \end{aligned}$$

One can compute, for any candidate value of β_K^* , prediction values for ω_{it} using;

$$\widehat{\omega}_{it} = \widehat{\phi}_{it} - \beta_K^* \log L_{it}$$

Using these estimated values, it is then possible to derive a consistent approximation to $E[\omega_{it}|\omega_{it-1}]$ from the predicted values from the following regression.

$$\widehat{\omega}_{it} = \gamma_0 + \gamma_1 \omega_{it-1} + \gamma_2 \omega_{it-1}^2 + \gamma_3 \omega_{it-1}^3 + \epsilon_{it} \quad 4.8$$

Levinsohn and Petrin (2003) define these predicted values as: $E[\omega_{it}|\widehat{\omega}_{it-1}]$ and given $\widehat{\beta}_L$, β_K^* and $E[\omega_{it}|\widehat{\omega}_{it-1}]$, we can write the sample residual of the estimated production function as;

$$u_{it} + \xi_{it} = \log Y_{it} - \widehat{\beta}_L \log L_{it} - \beta_K^* \log K_{it} - E[\omega_{it}|\widehat{\omega}_{it-1}] \quad 4.9$$

The study applies bootstrapping to construct standard errors for the estimated parameters. The generated measure of total factor productivity (TFP) from this procedure is then used as a dependent variable in a model where domestic R&D stocks and foreign innovation spillovers are the explanatory variables of interest. Having outlined our procedure of measuring TFP, the next section is devoted on estimating its response to changes in innovation spillovers

APPENDIX B

MEASUREMENT OF TFP USING DEA

Procedurally if we have N industries in a particular year, the linear programming problem solved for the i^{th} industry assuming an output-orientation efficiency measurement, the model for DEA appears as follows:

$$\begin{aligned} & \max_{\phi, \lambda} \phi, \\ \text{st} \quad & -\phi y_i + Y \lambda \geq 0, \\ & x_i - X \lambda \geq 0, \\ & \lambda \geq 0 \quad (5.1) \end{aligned}$$

where:

- y_i represents $M \times 1$ output vector for the i^{th} industry
- x_i denotes $K \times 1$ input vector for the i^{th} industry
- Y signifies $N \times M$ matrix of output quantities for all N
- X is represents $N \times K$ matrix of input quantities for all N
- λ symbolises $N \times 1$ vector of weights and,
- ϕ is a scalar

In the DEA procedure, scalar ϕ takes a value that is equal to or greater than one and also $\phi - 1$ represents a proportional output increase that an industry can achieve holding constant input quantities. It is important to note that technical efficiency is defined by $1/\phi$ which ranges between zero and one. The linear programming specified in (5.1) is solved N times once for each industry in our sample where each linear programming generates scalar ϕ and a λ vector. Importantly, scalar ϕ contains information regarding the technical efficiency score for the i^{th} industry while λ captures information on peers of the inefficient i^{th} industry. Industry i^{th} peers are essentially efficient industries that define the frontier from which the inefficient i^{th} industry is derived.

The Malmquist productivity index was developed by Caves, Christensen and Dietwert (1982) who defined multi-factor productivity using Malmquist distance functions. The distance in this case enables one to describe both a multi-input and multi-output production technology without necessarily having to specify the decision making unit's (DMU, hereafter) behavioural objective such as profit maximisation or cost minimisation. It also allows one to focus on output and input distance functions though our analysis is only interested in analysing the former. The output distance function which we focus on specifically seeks to attain the maximum proportional increase in the output vector with the input vector held fixed.

One can define a production technology using the output set $P(x)$ which is essentially a set of all output vectors (y) produced by input vector (x) as:

$$P(x) = \{y: x \text{ can produce } y\} \quad 5.2$$

We make the assumption that the production technology satisfies all the axioms outlined in Coelli *et al.* (1998) and proceed to define the output distance function on $P(x)$ as:

$$d_0(x, y) = \min \left\{ \delta : \left(\frac{y}{\delta} \right) \in P(x) \right\} \quad 5.3$$

From this definition, the output distance $d_0(x, y)$ will have a value of one or equal to one if element y lies in the feasible production set given by $P(x)$. Also, $d_0(x, y)$ will take the value greater than one if the output vector lies outside the feasible production set and takes the value of unity if it lies on the outer boundary of $P(x)$. In this study, we rely on DEA based methods to compute our output distance functions.

The Malmquist multi-factor productivity index measures the change in multi-factor productivity between two data points such as those of a particular industry in two adjacent periods. In particular, the index calculates the ratio of distances for each data point in relation to a common production technology. Following Färe *et al.* (1994), the output-oriented Malmquist MFP change index between the base period (s) and period (t) is given by:

$$m_0 = (y_s, x_s, y_t, x_t) = \left[\frac{d_0^s(y_t, x_t)}{d_0^s(y_s, x_s)} \cdot \frac{d_0^t(y_t, x_t)}{d_0^t(y_s, x_s)} \right]^{1/2} \quad 5.4$$

where $d_0^s(y_t, x_t)$ is the distance from year t observation to year s technology, a value of m_0 above one would imply a positive multi-factor productivity growth from the base year, s , to year, t . on the other hand, a value of m_0 less than one would be indicative of multi-factor productivity decline.

Important to note is that specification (5.4) is in actual fact a geometric mean of two multi-factor productivity indices where the first is computed with respect to technology existing in the base period, s and the second one is evaluated with respect to technology existing in year t . Another equivalent way of writing equation (5.4) is:

$$m_0 = (y_s, x_s, y_t, x_t) = \frac{d_0^t(y_t, x_t)}{d_0^s(y_s, x_s)} \left[\frac{d_0^s(y_t, x_t)}{d_0^t(y_t, x_t)} \cdot \frac{d_0^s(y_s, x_s)}{d_0^t(y_s, x_s)} \right]^{1/2} \quad 5.5$$

From equation (5.5), the ratio outside square brackets represent the change in Farrell's output-oriented technical efficiency between period s and period t while the remaining part of measures technical change. This is essentially the geometric average of a shift in the technology period s and t that is evaluated at x_t and at x_s .

In line with Färe *et al.*, (1994), we can compute the required distances for the Malmquist multifactor-productivity index given an appropriate panel dataset using a DEA linear programming technique. We must compute, for the i^{th} industry, four output distance functions in order to measure the change in multifactor productivity between the period s and period t and this necessitates solving four linear programming problems. Assuming constant returns to scale for the given technology as in Färe *et al.*, (1994) (a justification for this assumption will be given later in this section), the necessary linear programming problems are:

$$[d_0^t(y_t, x_t)]^{-1} = \max_{\phi, \lambda} \phi,$$

$$\text{st} \quad -\phi y_{it} + Y_t \lambda \geq 0,$$

$$x_{it} - X_t \lambda \geq 0,$$

$$\lambda \geq 0 \quad 5.6$$

$$[d_0^s(y_s, x_s)]^{-1} = \max_{\phi, \lambda} \phi,$$

$$\text{st} \quad -\phi y_{is} + Y_s \lambda \geq 0,$$

$$x_{is} - X_s \lambda \geq 0,$$

$$\lambda \geq 0 \quad 5.7$$

$$[d_0^t(y_s, x_s)]^{-1} = \max_{\phi, \lambda} \phi,$$

$$\text{st} \quad -\phi y_{is} + Y_t \lambda \geq 0,$$

$$x_{is} - X_t \lambda \geq 0,$$

$$\lambda \geq 0 \quad 5.8$$

$$[d_0^s(y_t, x_t)]^{-1} = \max_{\phi, \lambda} \phi,$$

$$\text{st} \quad -\phi y_{it} + Y_s \lambda \geq 0,$$

$$x_{it} - X_s \lambda \geq 0,$$

$$\lambda \geq 0 \quad 5.9$$

Noteworthy is that in linear programming problems (5.8) and (5.9), production data points are being evaluated based on technologies from two different time periods hence the condition that parameter ϕ be greater than or equal to 1 ($\phi \geq 1$) need not be satisfied as in the case of calculating output oriented measures of technical efficiencies. The reason is that a data point may possibly lie above a production frontier and this situation is more likely to occur in linear programming problem (5.8) where a production data point from time period t is compared to period s technology. If as in most cases, technical progress occurs, between these two periods, then it is possible

to observe $\phi < 1$. The same could happen to linear programming (5.9) when a technical regression has occurred although this is less likely to occur in the real world.

Returns to scale properties are very important in this procedure (Coelli and Rao, 2005). We can use either the constant returns to scale or the variable returns to scale. A result in Grifell and Tatjé and Lovell (1995) shows that the Malmquist productivity index may incorrectly measure multifactor-productivity changes when the variable returns to scale property is assumed. Hence it is important to impose the constant returns to scale assumption when computing changes in the multifactor productivity index. In addition to this argument, Coelli and Rao (2005) assert that the variable returns to scale assumption is mostly appropriate when one is dealing with firm-level data.

The study is relying on industry-level data which makes the variable returns to scale assumption less appropriate. Against the background of these two arguments, we assume in this paper the constant returns to scale property in measuring changes in the Malmquist productivity index as recommended by Coelli and Rao (2005) when one is dealing with aggregated data.

APPENDIX C

SFA FURTHER TECHNICAL DETAILS

To address the incidental parameters problem, Wang and Ho (2010) propose the use of a first difference estimator or the within estimator. This study applies the former. To illustrate how this works, the study first defines the following first difference notation:

$$\Delta a_{it} = a_{it} - a_{it-1}$$

and the stacked vector of Δa_{it} for industry i and,

$$t = 2, 3, 4, \dots, T$$

is given by,

$$\widetilde{\Delta a}_i = (\Delta a_{i2}, \Delta a_{i3}, \Delta a_{i4}, \dots, \Delta a_{iT})$$

With a non-constant scaling property²⁷ h_{it} , first differencing equation (1) gives us;

$$\ln(\widetilde{\text{output}}_{it}) = \beta_1 \Delta \ln(\widetilde{\text{Labour}}_i) + \beta_2 \Delta \ln(\widetilde{\text{Capital}}_i) + \beta_t t + \widetilde{\Delta \varepsilon}_i \quad (2)$$

$$\widetilde{\varepsilon}_i = \widetilde{v}_i - \widetilde{u}_i \quad (3)$$

$$\widetilde{v}_i = MN\left(0, \sum\right) \quad (4)$$

$$\widetilde{u}_i = \widetilde{\Delta h}_i u_i^*, \quad (5)$$

$$u_i^* \sim N^+(\mu, \sigma_u^2), \quad (6)$$

$$i = 1, 2, 3, \dots, 22$$

This transformation yields an estimator that is consistent either as $N \rightarrow \infty$ or $T \rightarrow \infty$. Importantly, $u_i^* \sim N^+(\mu, \sigma_u^2)$ is not affected by the first difference transformation which is a key aspect that ensures a tractable likelihood function of the following sort;

²⁷ Note that; $\varepsilon_{it} = v_{it} - u_{it}$, $v_{it} \sim N(0, \sigma_v^2)$, $u_{it} = h_{it} \cdot u_i^*$, $h_{it} = f(z_{it}\delta)$, $u_i^* \sim N^+(\mu, \sigma_u^2)$

$$\begin{aligned}
\ln L_i^D = & -1/2 (T-1) \ln(2\pi) \\
& -1/2 \ln(T) \\
& -1/2 (T-1) \ln(\sigma_v^2) \\
& -1/2 \Delta \tilde{\varepsilon}_i' \sum^{-1} \Delta \tilde{\varepsilon}_i + 1/2 \left(\frac{\mu_*^2}{\sigma_*^2} - \frac{\mu^2}{\sigma_u^2} \right) \\
& + \ln \left(\sigma_* \Phi \left(\frac{\mu_*}{\sigma_*} \right) \right) - \ln \left(\sigma_u \Phi \left(\frac{\mu}{\sigma_u} \right) \right) \quad (7)
\end{aligned}$$

where; Φ represents a cumulative density function of the standard normal distribution and,

$$\mu_* = \frac{\mu / \sigma_u^2 - \Delta \tilde{\varepsilon}_i' \sum^{-1} \Delta \tilde{h}_i}{\Delta \tilde{h}_i' \sum^{-1} \Delta \tilde{h}_i + 1 / \sigma_u^2} \quad (8)$$

$$\sigma_*^2 = \frac{1}{\Delta \tilde{h}_i' \sum^{-1} \Delta \tilde{h}_i + 1 / \sigma_u^2} \quad (9)$$

$$\widetilde{\Delta \varepsilon}_i = \widetilde{\Delta \ln(Y_i)} - \beta_1 \Delta \ln(\widetilde{\text{Labour}_i}) - \beta_2 \Delta \ln(\widetilde{\text{Capital}_i}) - \beta_t t \quad (10)$$

The marginal log-likelihood function of the differenced stochastic frontier model is given by the summation of the above function for all industries, i.e. $i = 1, 2, 3, \dots, 22$ while the unknown parameters are obtained by maximising this marginal log-likelihood function. The technical inefficiency definition of Jondrow et al. (1982), $\exp \{-E(u|\varepsilon)\}$ is slightly modified to represent inefficiency conditioned on the transformed error term from the differenced specification, $E(u_{it} | \widetilde{\Delta \varepsilon}_i)$.

APPENDIX D

BAYESIAN ANALYSIS

To illustrate the formulation of Bayesian statistics principles, consider a simple case of two random variables, which can be illustratively called A and B for simplicity. Let $p(\cdot)$ denote a density function since this analysis is based on continuous data. The conditional probability rule.

$$p(A | B) = \frac{p(A, B)}{p(B)} \quad (5.1)$$

is applied in order to derive the Bayes' theorem;

$$p(B | A) = \frac{p(A | B)p(B)}{p(A)} \quad (5.2)$$

A typical statistical case assumes data vector y which, by assumption, is a sample drawn from a probability model with parameter vector θ which is unknown. The model is represented by the likelihood of the following sort,

$$L(\theta; y) = f(y; \theta) = \prod_{i=1}^n f(y_i | \theta) \quad (5.3)$$

in which, $f(y_i | \theta)$

is y_i 's probability density function given the random vector θ . The intuition behind the Bayesian approach is to make statistical inference on θ given observed data on y . The prior distribution is assumed to take the form;

$$p(\theta) = \pi(\theta) \quad (5.4)$$

Since y and θ are random vectors, one can derive their posterior distribution using the Bayes' theorem.

$$p(\theta | y) = \frac{p(y | \theta)p(\theta)}{p(y)} = \frac{f(y; \theta)\pi(\theta)}{m(y)} \quad (5.5)$$

Here, $m(y) \equiv p(y)$ is the y 's marginal distribution and it is computed from,

$$m(y) = \int f(y; \theta)\pi(\theta)d\theta \quad (5.6)$$

which is independent of θ . This means one can reduce equation (5.6) to,

$$p(\theta | y) \propto L(\theta; y)\pi(\theta) \quad (5.7)$$

This says that the posterior distribution of the model parameters is directly proportional to their prior probability distributions combined with the corresponding likelihood. The gist of Bayesian analysis is embedded in finding the optimal balance between the researcher's belief or prior information and the empirical evidence from the data at hand. Striking the right balance is however challenging. In essence, there is need for avoiding a situation where the prior information overwhelms the evidence in data particularly when we have a reasonably large sample size²⁸. However, for relatively small sample sizes, strong priors are a necessity in order to augment the weak evidence derived from an insufficient sample.

Given these arguments, the analysis invokes two approaches in the Bayesian analysis. Firstly, the study performs a series of robustness checks for different priors to check the sensitivity of the results. Normally, priors are derived from previous studies but the challenge is that the analysis is pioneering the use of a novel composite innovation index hence there is a lack of previous studies to base prior belief on as far as selecting the prior distribution of coefficients is concerned. Comforting nonetheless is that the study is based on a panel dataset which gives a reasonably large sample size so that the posterior distribution is not heavily distorted by the priors. Secondly, the study performs the Bayesian analysis both using non-informative (flat) and informative priors.

²⁸ Noteworthy is the Bernstein–von Mises theorem which posits the posterior distribution is not dependent on the prior distribution in large samples hence the Bayesian and likelihood-based inferences will produce essentially the same results.

APPENDIX E

PRINCIPAL COMPONENT ANALYSIS RESULTS

TABLE 1: JAPAN EIGENVALUES AND FACTOR LOADINGS

	F1	F2	F3	F4
Eigenvalue,	2.248	0.903	0.708	0.140
Variability (%),	56.211	22.585	17.700	3.504
Cumulative (%),	56.211	78.796	96.496	100.000
Japan Factor loadings	F1	F2	F3	F4
R&D stock	0.945	0.128	0.104	0.282
Patents	0.684	0.691	0.148	0.181
R&D Researchers	0.724	0.414	0.528	0.160
Trademarks	0.603	0.488	0.630	0.045
Kaiser-Meyer-Olkin	0.788			

TABLE 2: KOREA EIGENVALUES AND FACTOR LOADINGS

	F1	F2	F3	F4
Eigenvalue	3.867	0.086	0.044	0.003
Variability (%)	96.678	2.145	1.099	0.078
Cumulative (%)	96.678	98.823	99.922	100.000
Japan Factor loadings	F1	F2	F3	F4
R&D stock	0.987	-0.127	-0.092	-0.034
Patents	0.993	-0.108	-0.026	0.043
R&D Researchers	0.984	-0.002	0.177	-0.011
Trademarks	0.969	0.241	-0.059	0.001
Kaiser-Meyer-Olkin	0.752			

TABLE 3: CHINA EIGENVALUES AND FACTOR LOADINGS

	F1	F2	F3	F4
Eigenvalue	3.686	0.270	0.036	0.009
Variability (%)	92.139	6.745	0.892	0.224
Cumulative %	92.139	98.884	99.776	100.000
	F1	F2	F3	F4
R&D stock	0.993	-0.054	-0.076	0.071
Patents	0.896	0.442	0.043	-0.008
R&D Researchers	0.960	-0.245	0.137	-0.002
Trademarks	0.988	-0.107	-0.096	-0.063
Kaiser-Meyer-Olkin	0.794			