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Innovation in Middle–income Economies

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ATTESTATION OF AUTHORSHIP

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person except that which appears in the citations and acknowledgements. Nor does it contain material which to a substantial extent I have submitted for the qualification for any other degree of another university or other institution of higher learning.

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ACRONYMS AND ABBREVIATIONS

ADB	Asian Development Bank
AFR	Africa
CUI	Catch–Up Index
DTHM	Discrete–time Hazard Model
ECA	Eastern Europe and Central Asia
EAP	East Asia and the Pacific
EU	European Union
FDI	Foreign Direct Investment
FEM	Fixed effect model
GDP	Gross Domestic Product
GNI	Gross National Income
HIC	High–income Country
ICT	Information and communication technology
ILO	International Labor Organization
IMF	International Monetary Fund
IPR	Intellectual Property Rights
ISIC	International Standard Industrial Classification of All Economics Activities
LAC	Latin America and Caribbean

LMIC	Lower Middle–income Country
LR	Likelihood ratio
MIE	Middle–income economy
MIT	Middle–income trap
MNA	Middle East and North Africa
MSME	Micros, Small, and Medium–sized Enterprise
NIS	National Innovation System
Pooled OLS	Pooled Ordinary Least Squares
OECD	Organization for Economic Cooperation and Development
R&D	Research and development
REM	Random effect model
SAR	South Asia
SME	Small and Medium–sized Enterprise
TFP	Total Factor Productivity
UH	Unobserved heterogeneity
UMIC	Upper Middle–income Country
UN	The United Nations
UN Comtrade	The United Nations Commodity Trade Statistics Database
UNCTAD	The United Nations Conference on Trade and Development

UNESCO	The United Nations Educational, Scientific and Cultural Organization
USA	The United States of America
USD	United States Dollar
WB	The World Bank
WBES	World Bank Enterprise Surveys
WDI	World Development Indicators
WIPO	World Intellectual Property Organization

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ABSTRACT

Innovation is presumed to be an important driver of economic growth when countries move away from the low-income category to the middle-income rank (Solow 1956; Romer 1990). This thesis aims to analyze the role of innovation in the development of the middle–income economies (MIEs) and related factors impacting innovation in these MIEs. This study makes the following contributions to the existing literature. First, the study examines the three important issues but are limitedly analyzed, i.e., whether indigenous or foreign innovation efforts matter more to support MIEs in transitioning to the next income category; the innovation–enhancing effect of the human capital composition of unskilled, skilled, and high–skilled levels; and the impact of informal competition on innovation outputs of formal manufacturing firms in MIEs. Second, the thesis extends the empirical findings on MIEs by studying numerous economies at both aggregate and firm levels. Given the more prevalent firm–level data in current studies on innovation in MIEs, the inclusion of both aggregate national–level data (in the first and second research issues) and firm–level data (in the third research issue) might bring comprehensive insights. Third, the use of more innovation measures such as various innovation effort indicators of domestic R&D, import– and FDI–embodied foreign R&D, and resident and nonresident patents (in the first research issue) and the composition of human capital variables (in the second research issue) also bring improvements on previous studies. Forth, based on empirical findings, policy implications are made focusing on MIEs. In the first and second research issues, implications are made separately for the sub–groups of lower middle–income countries (LMICs) and upper middle–income countries (UMICs), while implications for the whole group of MIEs are made in the third issue.

In the first research issue, the role of indigenous vs. foreign innovation efforts in contributing to the transition of MIEs to the next income category is investigated. With limited resources, MIEs need to prioritize whether to invest in innovation domestically or adopt foreign innovation. The origins of innovation that matter to MIEs have not been widely studied. To quantify the impact of innovation efforts on the probability of attaining the next income rank for MIEs, the cloglog link discrete–time hazard model (DTHM) of duration analysis is employed. This is the first attempt to estimate the impact of innovation efforts on the probability of MIEs' moving up the income ladder using DTHM, a useful tool that is often forgotten in innovation studies. Data of 61 countries between 1980 and 2018 is used. Estimation results show that foreign sources of innovation measured by nonresident patents and international R&D spillovers through

the FDI channel are more important for the LMI group to move up the income ladder. For the UMICs, the domestic source of innovation measured by R&D capital stock is the most important, followed by foreign innovation diffused through the import channel.

In the second research issue, the innovation–enhancing effect of the human capital composition of unskilled, skilled, and high–skilled levels in MIEs is examined. Human capital has a dual role in affecting the output growth of an economy. It serves as labor input in the production function and is also utilized to foster the innovation output of the economy. The understanding of how human capital composition enhances innovation, especially in MIEs remains limited. Panel data regressions of fixed effect models are applied on the data of 65 countries in LMI, UMI, and high–income (HI) categories from 1985 to 2019. Unobserved country–specific effects and time–invariant effects are controlled for in the regression models. Results of this study suggest that for LMICs, the skilled human capital of the tertiary education completion workforce is the most important one in fostering their innovation outputs while the R&D personnel of the high–skilled human capital is yet to be important. FDI–embodied foreign innovation supplements the skilled human capital to build up innovation capacity for LMICs. In UMICs and HICs, results of estimations show the innovation output-enhancing effects of high-skilled human capital for these groups. High-skilled human capital is supported by foreign innovation diffusion through imports and R&D capital stock in UMICs. In HICs, findings highlight that the vital role of R&D personnel is supported by R&D capital stock, FDI embodied foreign innovation and institutional quality. The unskilled human capital of primary and secondary education completion population is confirmed not to play any role in innovation development in MIEs and above.

In the third research issue, the impact of informal competition caused by unregistered firms on innovation in formal manufacturing firms in MIEs is examined. Probit regression is employed on the World Bank's Enterprise Survey dataset of 68,568 firms from 92 MIEs between 2006–2019. Estimation results prove that informal competition induces innovation activities of formal manufacturing firms in MIEs. It confirms the escape-competition effect in which competition incentivizes formal firms in MIEs to innovate by introducing new products and processes that are also new to the main market of the firms. R&D investment positively affects the innovation outputs of formal manufacturing firms as vastly concluded in the existing literature. While a firm's age, size, being affiliated to a larger company, and share of foreign ownership are found to not affect the innovation activities of formal firms, export and access to finance are important to foster innovation activities of formal manufacturing firms. The length of the manager's experience, on the contrary, might negatively affect innovation activities of firms covered in this study.

These findings have implications for policymakers that the LMI group should focus more on foreign innovation diffused through foreign patents and FDI. Policies to attract foreign investment should be the focus. For UMICs aiming to attain high-income status, the foremost policy priority should be strengthening indigenous innovation capabilities through investing in R&D. Regarding human capital for innovation, study results imply that policymakers in UMICs and above should concentrate on fostering and enlarging the pool of high-skilled R&D personnel to elevate the level of innovation outputs. LMICs should continue to invest in raising the number of learners completing tertiary education. In terms of informal economy competition and its impact on innovation of formal manufacturing firms, findings of this study imply that efforts by policymakers in MIEs to formalize the informal sector should be carefully considered when the targets are to elevate the innovation activities of formal manufacturing firms. It also suggests policymakers review the on-going efforts to eradicate the informal firms and consider them as one component of the national innovation system.

Chapter 1 Introduction

1.1 Research background and scope of the thesis

In 2022, there are 108 out of 217 countries, or 50% of the world economies being classified by the World Bank as middle-income economies (MIEs) by GNI per capita (illustrated in Figure 1.1). In terms of population, 75% of the world population live in the middle-income countries (World Bank 2022). Many of these MIEs experience a similar growth pattern of rapid development to exit the low-income group and then achieve the middle-income rank. However, trespassing the low-income threshold and attaining the middle-income status do not guarantee economic convergence toward the high-income level.

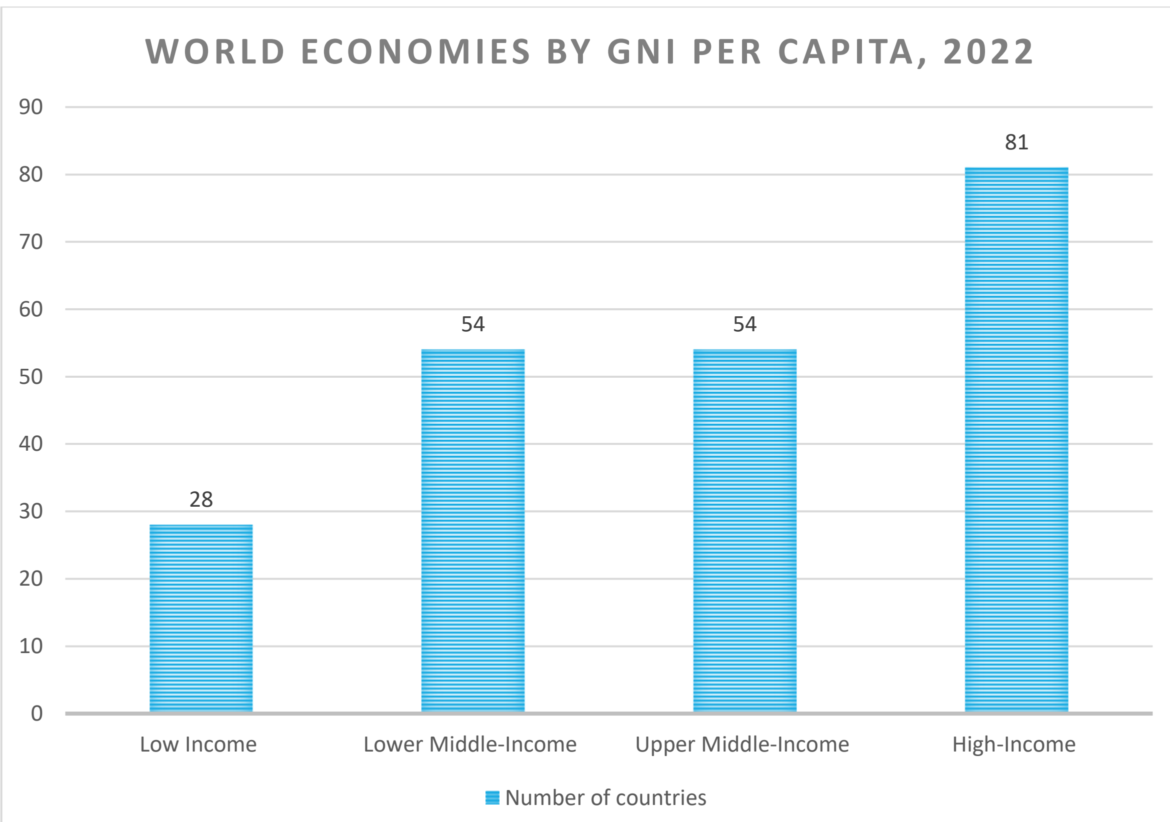

Figure 1.1 Overview of the World Economies by GNI per capita

Source: Own creation based on the World Development Indicators (2022)

It observes that only several MIEs successfully completed the transition, while the majority got stuck in this group. From over 100 countries classified as MIEs in the 1960s, only 13 countries managed to attain a high-income level in 2008, i.e., Equatorial Guinea, Greece, Hong Kong, Ireland, Israel, Japan, Mauritius, Portugal, Puerto Rico, Singapore, Republic of Korea, Spain, and Taiwan (P. Agénor 2017). Even though MIEs aspire to join the rank of high-income within the next several decades, numerous countries are trapped in the middle-income status. In Asia, countries like India, Indonesia, Malaysia, Philippines, Thailand, and Vietnam are typical examples of this phenomenon. Only five economies of Taiwan, Hongkong, Japan, the Republic of Korea, and Singapore successfully leaped to the high-income rank.

The share of MIEs in the global economy value has accelerated. At the beginning of the 20th century, MIEs accounted for 17% of the global economy size. However, by 2017, their GDP share doubled to 35%. High-income economies, on the other hand, have their GDP share in the global economy decreased from 83% in 1997 to 64% in 2017. The total GDP share of low-income countries valued at only 0.5% of the global GDP in 2017. Hence, the important role of MIEs in the global economy is worth emphasizing. Figure 1.2 illustrates the trend of rising share of MIEs in the world economy during the past decades.

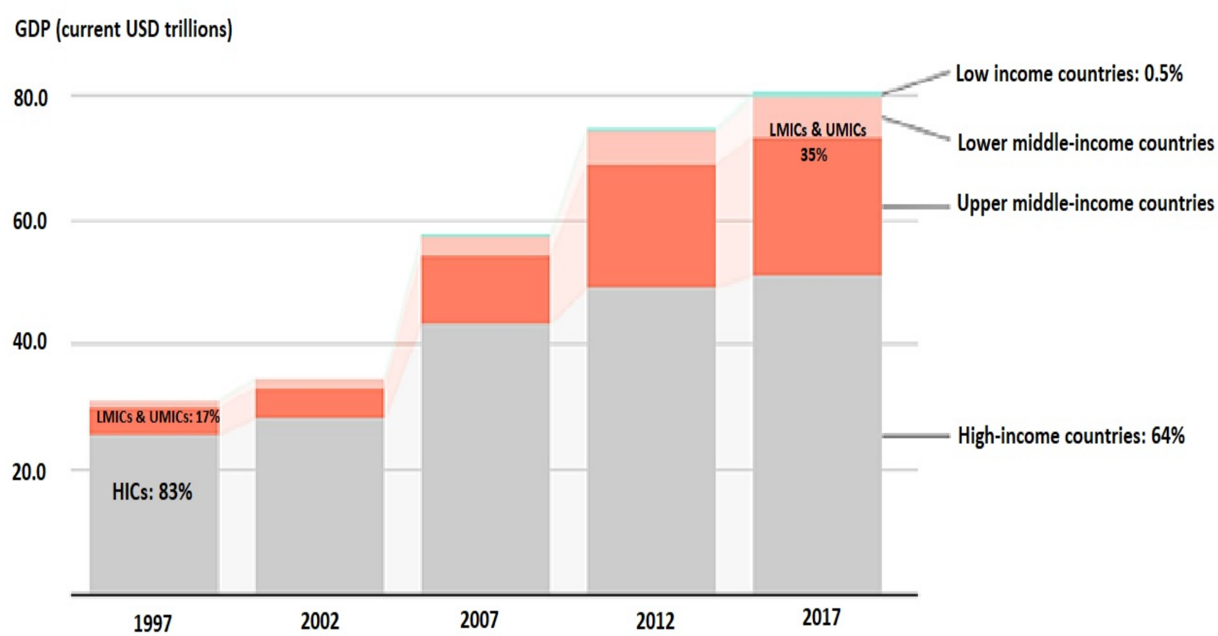

Figure 1.2 Trend of Increasing Share of MIEs in the Global GDP

Source: World Bank (2019)

The MIEs face difficulties in sustaining their high grow rate and in evolving to the high-income status. The development challenges faced in the transition from the middle-income to high-income are not similar to those encountered by the low-income countries aiming to evolve to the middle-income rank. They might be trapped in the situation of being unable to compete with either low-income economies with low-wage advantage or with innovative high-income economies (Kharas and Kohli 2011). It's because when the income per capita reaches the middle level, wages also increase and the MIEs lose the advantage of cheap labor that they used to have at the low-income stage. These MIEs no longer remain competitive in terms of low-cost production due to the rising wage for labor. They also face competition from high-income countries with more advanced technology, the high-skilled labor force, strong manufacturing, and high institutional quality in terms of regulations on intellectual property rights and industrial standards. The bottleneck for many MIEs is the difficulty to move up the value chain and break into the knowledge and innovation-based product and services market. Therefore, MIEs might require new growth models to avoid the situation of being squeezed between the low-wage poor country competitors that dominate in mature industries, and the high-income country innovators that dominate in rapid technological advancing industries (Kharas and Gill 2007).

A situation of a country getting stuck in the middle-income rank might also be viewed as an economy is experiencing a bad or low-growth equilibrium (Acemoglu 2009). In such condition, moving away from the low-growth equilibrium toward a high-growth equilibrium requires a significant shock. The economy gravitates unless major intervention such as policies that are bold enough taking place to shift the economy to a path leading to high-growth equilibrium (P. Agénor 2017). Besides, the lack of innovation capacity might be one root cause that prevents those countries from escaping a low-growth equilibrium.

The slowdown of the development pace after the period of intense growth might lead MIEs to face severe challenges. They include not only economic setbacks such as the rising production cost that undercuts the competitiveness of a country (OECD 2014), but also protracted growth that might imply less potential to raise the living standards of citizens, and less potential to reduce poverty level while increasing the prosperity gap in the society. While improving the living standard and reducing the poverty level would contribute greatly to enhancing a country's economic and social stability, the opposite situation faced by these MIEs might be challenging (P. Agénor 2017). It is, therefore, critical for the MIEs to increase the level of income per capita, exit the middle-income level to obtain a higher income rank, and avoid being stuck in the middle-income rank or the so-called middle-income trap.

There has been rising attention of scholars and policymakers in searching for causes of the ongoing growth slowdown of MIEs, delay in transitioning to the next income level, and measures for MIEs to address these multidimensional challenges. Fostering innovation and technological advances has been considered critical for MIEs to avoid the deferment of economic development and to avoid falling into the middle-income trap (Asian Development Bank 2017). In the development trajectories of high-income countries like the OECD, innovation is the top contributor to economic growth. Innovation is reasoned to become an important source of economic growth when the economy approaches the technological frontier or moves from intensive resource usage to the more efficient use of resources. The need of shifting to areas like advanced manufacturing is obvious. Additionally, capital accumulation, which is the key to attaining middle-income rank, is assumed to be less relevant at this stage and new drivers of growth are required. In the neoclassical growth model and new growth theory, economists such as Solow (1956) and Romer (1990) postulate that technological progress is at the heart of long-run economic growth when the marginal productivity of capital and labor diminishes. Innovation and technological advancement are emphasized as necessary ingredients to catch up with high-income countries, especially for economies that have attained middle-income status for a long time (Kharas and Gill 2007). Sufficient development of domestic innovation capabilities, scaling up technological capabilities, fostering innovation and enhancing high value-added economics activities have been argued to pave the way for those MIE to advance to the higher income rank, ultimately to graduate from middle-income status and reach the high-income rank (Paus 2017).

A better understanding of the development phase of MIEs and its challenges might generate some implications to improve the quality of life of 75% world population and the future low-income countries' transition. On the global scale, the issue of MIEs' economic growth hindrance is pivotal because these MIEs account for most of the global demand growth in recent years given that emerging markets of MIEs have expanded much faster than the advanced high-income economies (Kim and Park 2018). Recognizing the importance of innovation for growth and the critical role of MIEs' development, this thesis aims to analyze innovation in the MIEs and related issues that are important for MIEs' innovation but have not been widely analyzed: (1) the comparison on the importance of domestic vs. foreign source of innovation for MIEs transition to the next income rank; (2) the role of human-capital composition in enhancing innovation outputs of MIEs; and (3) the impact of informal competition on the innovation of formal firms in MIEs. In the next section, the overall research objectives, research questions and their hypotheses based on the gaps under each research issue are detailed.

1.2 Gaps in literature, research objectives, questions, and hypotheses

There is an extensive range of factors that affect economic growth slowdown and innovation that need to be addressed in MIEs such as inefficient resource allocation, diminishing returns to physical capital, insufficient quality of human capital, misallocation of talent, lack of access to advanced infrastructure, and lack of access to finance for firms' innovation (Kim and Park 2018). In this thesis, focusing on the role of innovation in MIEs, I aim to examine several critical issues related to innovation in MIEs that have not been widely analyzed. First, while acknowledging the role of innovation in enabling MIEs to exit the current income category and evolve to the next income rank after successfully trespassing the low-income category, this thesis investigates whether indigenous or foreign innovation efforts matter more to support MIEs in transitioning to the next income category. The second research issue is the innovation-enhancing effect of the human capital composition of unskilled, skilled, and high-skilled levels. Third, looking into the innovation of firms in MIEs, I analyze the impact of competition caused by unregistered firms on the innovation outputs of formal firms. The rationale for the selection of these research issues based on the gaps in existing literature, and the formulation of research questions and hypotheses are explained in the next section.

1.2.1 Indigenous and foreign innovation efforts for MIE growth

In the growth path of the current high-income countries, the application and diffusion of innovation often brought about industrial revolutions, resulting in increased total factor productivity (TFP), positive changes in societal aspects, and improvement in the living standard of citizens and welfare of nations (Fu, Pietrobelli and Soete 2011). The economic growth of MIEs might not be different from this trajectory, in which innovation plays an important role. New technologies and the advancement of knowledge bring an impact on the economy when innovation is diffused and adopted by numerous firms and individuals. Both the adoption of technologies developed abroad, and the development of indigenous innovation capacity are highlighted by Fagerberg, Sroholec and Verspagen (2010) as two critical factors in the economic growth of innovation. The origins of innovation, whether being developed abroad or domestically, that matter to MIEs have not been widely studied while it is critical to strategize the resource allocation. With limited resources, MIEs need to prioritize whether to invest in innovation domestically or adopt foreign innovation. Against this background, in the first research issue, the role of indigenous vs. foreign innovation efforts in contributing to the transition of MIEs to the next income category is investigated. In low-income and lower middle-income countries (LMICs), adopting and deploying new technologies from developed countries are postulated to be more relevant than developing cutting-edge innovation. On the other hand, insufficient development of domestic innovation capabilities might be one reason for countries to be trapped in the middle-income group, especially for those that are closer to the high-income rank. Upper middle-income countries (UMICs) that have moved closer to the technological frontier and aim for more ground-breaking innovation might need to build up their indigenous capabilities. Based on these observations, to quantify the impact of innovation efforts on the probability of attaining the next income rank for MIEs, the first research question and its hypotheses are made as follows.

Research question 1: *How are indigenous and foreign innovation efforts different in contributing to the transition of MIEs to the next income category?*

Hypothesis 1.1: *LMICs depend more on foreign innovation diffusion to attain UMI status.*

Hypothesis 1.2: *UMICs depend more on indigenous innovation effort to attain the high-income rank.*

1.2.2 Human capital for innovation of MIEs

To foster innovation for economic growth in MIEs, there are severe challenges. Developing new technologies and enhancing innovation capacities in these MIEs are more than just R&D investment. One possible factor causing countries to standstill in middle-income rank and lack innovation capacity is poor quality of human capital, a component of production inputs (P. Agénor 2017). Adequate human capital plays a vital role in the success of domestic innovation development. Besides, the foreign technology diffused and adopted by MIEs might depend on factors supporting the process (Keller 2004). MIEs as countries receiving technologies might have to face constraints in both financial resources to acquire these technologies and developing appropriate absorptive capacity to adopt and then reproduce those technologies. The successful adoption and implementation of foreign technology are viewed to rely on both sufficient financial resources and the absorptive capacity of local human capital (Fu, Pietrobelli and Soete 2011).

Human capital has a dual role in affecting the output growth of an economy. It serves as labor input in the production function and fosters the innovation output of the economy. However, the understanding of how human capital enhances innovation, especially in MIEs, remains scarce. Moreover, at each development stage, or with different distances from the technological frontier, a country might find the contribution of each human capital component of unskilled, skilled, and high-skilled differently significant. There are limited numbers of studies analyzing the human capital composition effect on the growth of countries at different income levels (Ang, Madsen and Islam 2011). To contribute to closing this gap, the focus of the second research issue of this thesis is on human capital for innovation in MIEs. The innovation-enhancing effect of the human capital composition of unskilled, skilled, and high-skilled levels in MIEs is examined in detail. The second research question and its hypotheses are detailed as follows.

Research question 2: *How does human capital affect the innovation outputs of MIEs?*

Hypothesis 2.1: *Skilled human capital is more important than unskilled and high-skilled human capital for the innovation outputs of LMICs.*

Hypothesis 2.2: *High-skilled human capital contributes more than unskilled and skilled human capital to the innovation outputs of UMICs.*

Hypothesis 2.3*: Unskilled human capital is not important for innovation outputs of MIEs.*

1.2.3 Informality and innovation of formal firms in MIEs

Throughout the innovation diffusion and adoption process, firms play a critical role. The firm-level innovation activities and strategies contribute significantly to the aggregate economic and innovation performance of a country (Fu, Pietrobelli and Soete 2011). Therefore, it is important to look at firm-level innovation activities while studying innovation in MIEs. From the perspective of innovation activities, firm growth is a process in which firms that are able to create and adopt new technologies and accumulate knowledge would grow, while the non-innovative ones might not be able to survive. In most MIEs, the existence of the informal economy which employs a large share of workers poses a remarkable challenge to firms' innovation and performance. Therefore, the impact on innovation activities of formal firms caused by informal firms is worth studying. Besides, the impact that informal firms brought to the innovation of formal firms might shape the aggregate innovation level of a country. In other words, the phenomenon of informality might affect the aggregate level of firms' innovation (Kraemer-Mbula and Wunsch-Vincent 2016). There has been a limited amount of analysis in existing literature that focuses on impact of informal competition to innovation of formal firms. Besides, existing studies cover several countries, or a specific region, or are limited by the type of firms like only SMEs. There has been no cross-country study focusing on firms of middle-income countries on a large scale. Given this background, in the third research issue, the impact of informal competition on the innovation activities of formal firms in manufacturing sectors, the driving innovative sector of MIEs, is examined. Taking into account the characteristic of innovation in MIEs of being technological laggards and aiming to catch up with leading-edge technologies (Aghion, Harris, et al. 2001), the innovation-inducing effect of the informal competition is presumed. The research question and its hypothesis are presented as follows.

Research question 3: *How does the competition caused by informal firms affect the innovation of formal manufacturing sector firms in MIEs?*

Hypothesis 3.1: *The competition caused by informal firms induce innovation of formal manufacturing firms in MIEs.*

Finding the answers to the research questions and the hypotheses raised above would contribute to enlarging the empirical evidence for innovation activities in MIEs, as well as generating implications for innovation-related policies, and fill in some gaps in the existing literature. In the next section, the methodology and sources of data used in this thesis are summarized.

1.3 Data sources and research methodology

In this thesis, both country-level and firm-level data are utilized. The country-level data published by renowned scholars and international organizations are used in Chapter 3 and Chapter 4. More specifically, R&D data is based on the UNESCO Institute of Statistics. Patent data is sourced from the World Intellectual Property Organization (WIPO). FDI and trade data are from the database of the UNCTAD and the UN Comtrade. Human capital data is sourced from Barro and Lee (2013) with its online database updated until September 2021. Institutional quality data is extracted from the Economic Freedom of the World by the Fraser Institute. These data sources are supplemented by other datasets of the World Development Indicators (WDI) by the World Bank.

The firm-level data from the World Bank Enterprise Survey (WBES) is used in Chapter 5 of this thesis. This dataset is relevant to study the impact of informal competition caused by unregistered firms on the innovation of formal manufacturing firms in MIEs. It is because the WBES dataset is the only available one that contains information on the informal competition and other relevant firms' data comparable across countries. The WBES collects data from a large number of firms in more than 100 countries, mainly developing ones, for a long period. The WBES is the nationally representative survey of the targeted private economy. Even though the data are collected at different intervals for different countries, its wide coverage in terms of countries and long period are advantageous to study in-depth the impact of informal competition on innovation activities at firm-level.

Three estimation methodologies are applied for empirical analysis in the three main chapters of this thesis. In Chapter 3, the cloglog link discrete-time hazard model of survival analysis is employed to quantify the impact of innovation efforts on the probability of attaining the next income rank for MIEs. In Chapter 4, panel data regression of fixed effects models is utilized to study the impact of the human capital composition of unskilled, skilled, and high-skilled levels on the innovation output of MIEs. In Chapter 5, probit regression model is applied to estimate the impact of informal competition on the innovation activities of formal manufacturing firms. The logit regression model is used for robustness check in this chapter.

In the following section, the contributions of this thesis based on the analyses of the three research issues above are presented.

1.4 Contribution of the thesis

In this thesis, I attempt to analyze in-depth the critical but limitedly examined topics of whether the indigenous or foreign innovation efforts matter more to support MIEs in transitioning to the next income category; how the human capital composition of unskilled, skilled, and high-skilled levels affect innovation of MIEs at the aggregate level; and how the competition caused by informal firms impact the innovation of formal manufacturing firms in MIEs. The first contribution of this thesis is that it extends the empirical findings on MIEs by studying more than 90 economies from 1980 to 2019 leveraging both national country–level and firm–level data. Given the scarcity of empirical works that focus solely on middle–income level countries, this thesis aims to contribute to fulfilling this gap.

Another contribution this thesis makes to the literature is the empirical results based on the approach to innovation from both important measures. In the first form, innovation is measured by patents and ground–breaking discoveries, which are the results of costly and lengthy processes that require intense knowledge and capital investment. The empirical studies in Chapters 3 and 4 are built on this measure of innovation. In the second form, an innovation measure of the implementation of new or significantly improved products or processes which is more adaptable to MIEs is utilized. The study in Chapter 5 is based on this measure of innovation. The use of both innovation measures enables the comparison across countries. It also mitigates the shortcomings of the R&D investment and patent data by supplementing with innovation measures that go beyond the high–tech picture and are relevant to the context of innovation in MIEs.

Third, the empirical results based on the use of more foreign innovation spillover variables and human capital variables in this thesis make another contribution to the literature. Foreign innovation efforts measured through various import– and FDI–embodied foreign R&D in the first research issue complement the foreign innovation measure of nonresident patents. The composition of human capital variables in the second research issue also brings improvements compared with previous studies.

Fourth, another contribution of this thesis is that policy implications with a focus on MIEs are made based on the empirical findings. It contributes to appropriate and sound policymaking in MIEs regarding innovation–related issues. Details on the contribution of each empirical paper in this thesis to closing those research gaps are as follows.

In Chapter 3, with the focus on MIEs with technological catch–up processes underway, while acknowledging that fostering innovation from both the diffusion process within a country and knowledge spillovers from foreign partners might support MIEs to graduate from middle–income status, the study determines whether indigenous or foreign innovation efforts matter more for economic growth. In this chapter, innovation efforts at the aggregate level are measured by various indicators of domestic R&D, import– and FDI–embodied foreign R&D, and resident and nonresident patents. The inclusion of more innovation variables is one improvement on previous studies that either estimate within limited innovation measures or review the literature theoretically. Second, this is the first attempt to estimate the impact of innovation efforts on the probability of MIEs' moving up the income ladder using DTHM, a useful tool that is often forgotten in innovation studies according to Triguero, Corcoles and Cuerva (2014). Third, policy implications made separately for two middle–income sub–groups of lower middle–income countries (LMICs) and upper middle–income countries (UMICs) is another contribution of this thesis. The findings have implications for policymakers that the LMI group should focus more on foreign innovation diffused through foreign patents and FDI. Policies to attract foreign investment should be the focus. For UMICs aiming to attain high–income status, the foremost policy priority should be strengthening indigenous innovation capabilities through investing in R&D. The content of this chapter is revised from the academic article entitled "Do indigenous or foreign innovation efforts matter for the middle–income economies transition to the higher–income rank? An empirical evidence" published on the *Innovation and Development* in August 2022.

The analysis of Chapter 4, to the best of my knowledge, is the first attempt to examine the impact of unskilled, skilled, and high–skilled human capital composition on innovation at the aggregate level. Utilizing the national level data is one contribution I have made given the more prevalent firm–level innovation data in current studies. It contributes to extending the literature on the role of human capital in innovation at the aggregate level. Second, it expands empirical results on the innovation–enhancing effect of the human capital composition. The inclusion of high–skilled human capital variable in addition to the educational outcome variables of unskilled and skilled human capital is the uniqueness of this study. Third, the analysis of this research issue extends the empirical findings on MIEs by including 44 middle–income countries in the sample of 65 countries.

In Chapter 5, with the focus on the prevalent phenomenon of the informal economy which accounts for a large share compared with the GDP size especially in MIEs, and the recognized obstacles caused by unregistered firms to innovation activities of formal firms, the study makes the following contributions. First, it extends the empirical results in literature by studying a large scale of 68,568 manufacturing firms in 92 MIEs and bringing more insights into the inconclusive debate of whether the informal economy and the competition caused by informal firms are beneficial or detrimental to formal firms' innovation activities. While a lesser number of empirical evidence has been found on this topic, it is critical to study in–depth the impact of informal competition on innovation of formal firms. Second, the study might provide useful inputs based on empirical evidence for policymakers in MIEs to deal with the phenomenon of informal competition while aiming to enhance innovation of a country. In the next section, the structure of the thesis is summarized.

1.5 Structure of the thesis

With the aim of understanding multiple facets of innovation in MIEs, this thesis is divided into six chapters. This first chapter introduces the background of the innovation in middle–income countries research topic selection, objectives of the study, research questions and the hypotheses, as well as the gaps in existing studies, and the research contribution to the existing literature (Chapter 1). The second chapter presents key concepts used in this study. The definition and measures of innovation, role of innovation in economic growth, and its diffusion process are zoomed in. Regarding MIEs, the income classification approaches and issues faced by MIEs are included. Some characteristics of innovation in MIEs are highlighted (Chapter 2). Subsequently, the three chapters serving as the main body of this research are formulated. These chapters form three empirical studies on different issues relating to innovation in MIEs (Chapters 3, 4, and 5). The final chapter provides a summary of key results and findings, implications for policymaking, limitations of this study, and suggestions for future research. The structure of this thesis can be summarized in Figure 1.3.

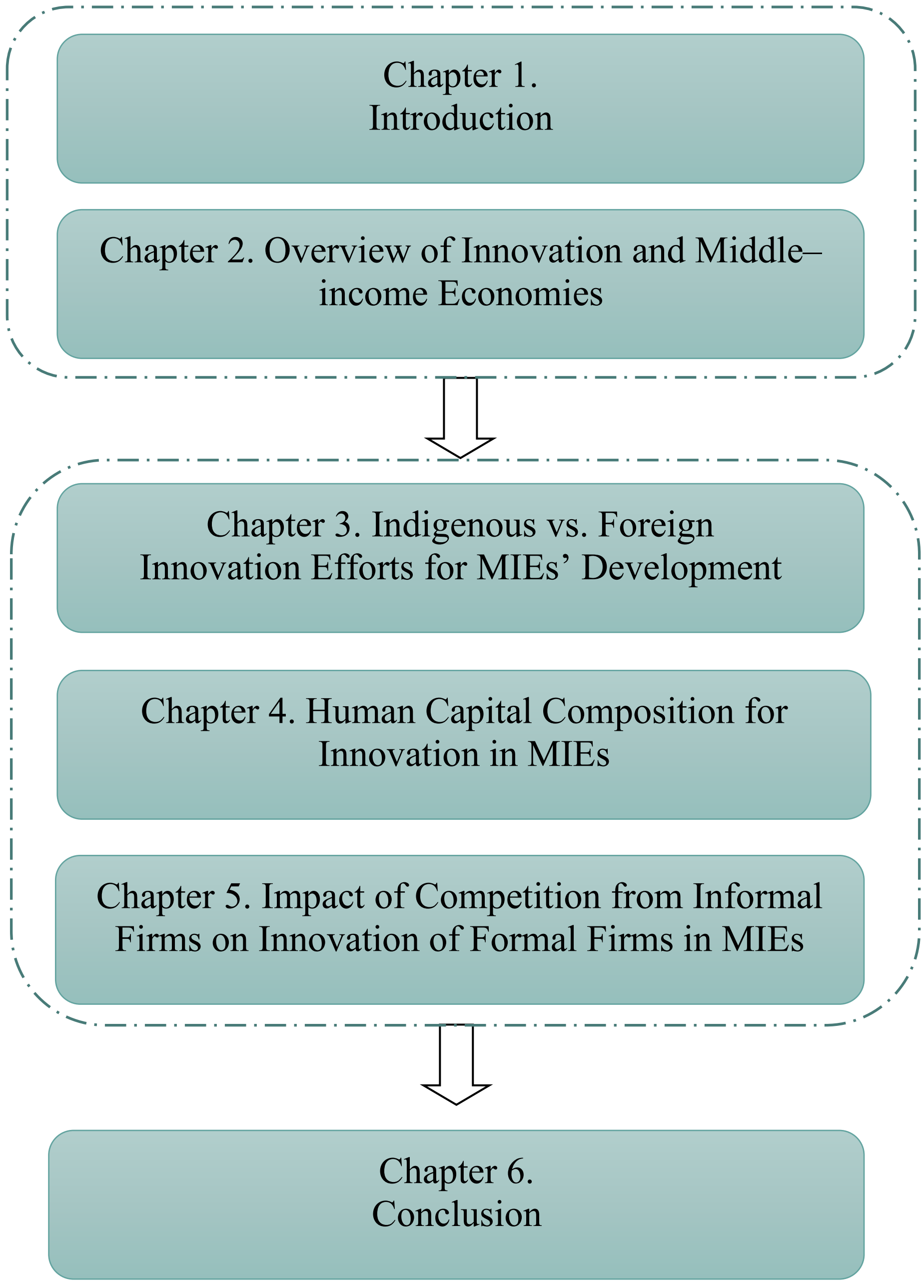

Figure 1.3 Structure of the Thesis

Chapter 2 Overview of Innovation and Middle–income Economies

In this chapter, the two concepts that play an important role in this thesis are elaborated. Different approaches to these concepts are presented to provide an overall background for the subsequent analysis of different issues of innovation in middle–income economies in the next three chapters.

2.1 Innovation

2.1.1 Definition and measure of innovation

The innovation concept might be traced back to the work of Joseph Schumpeter (1934), one influential innovation economist in the 20th century, in which innovation is described as "*the setting up of new production function*". He refers to the term "*new combination*" to distinguish innovation from other concepts such as technological change, or invention (Schumpeter 1942). He explains that innovation is a source of economic change, a fundamental impulse that keeps the capitalist engine in motions coming from new consumers' goods, new methods of production or transportation, new markets, and new forms of industrial organizations (Schumpeter 1934). He defines the innovation process as "*a process of creative destruction incessantly revolutionizes the economic structure from within, incessantly destroying the old one and incessantly creating a new one*" (Schumpeter 1942). The economic growth literature has used this approach to investigate drivers of long–term growth (OECD/Eurostat 2018).

Another common definition of innovation is articulated in the series of Oslo Manuals by the OECD/ Eurostat. The Oslo Manual series was first published in 1992. Similar to the approach of Schumpeter, innovation is defined as the implementation of new or significantly improved products (goods and services), processes, new marketing methods, or new organizational methods in business practice, workplace organization, or external relations (OECD/Eurostat 2005). This definition of innovation is widely used in studies on innovation at the firm level.

- Product innovation refers to the market introduction of a new or significantly improved good or service concerning its characteristics or intended use. This includes significant improvement in specifications, components, and material, functional characteristics.

- Process innovation is the implementation of a new or significantly improved production process, distribution method, or support activity for goods or services. In the service sector, it relates to significant improvement in how services are being produced.
- Marketing innovation is the implementation of a new marketing method that includes substantial alterations in product design, and packaging.
- Organizational innovation is the implementation of a new organizational method in a firm's business, or external relations.

Among these four types of innovation, product and process innovation are the most common. The other two innovation types of marketing and organizational innovation are not popular due to the measurement problems (OECD/Eurostat 2005).

In the latest Oslo Manual (2018), innovation is considered as a process and as an outcome. Innovation is viewed as a dynamic and pervasive activity that occurs in all sectors of an economy. Innovation requires the implementation which might involve activities such as training, acquisition of patents, and other technical know–how. These activities might lead to tangible innovation outcomes. In other words, the diffusion of innovation brings economic and social impacts. The Oslo Manual (2018) definition of innovation highlights two important features. First, innovation can take a multitude of forms as described above. Second, regarding the novelty level defined in innovation, it can be a new or significantly improved products introduced to the world, or to the market, or introduced within the enterprise.

Scholars hardly reach a consensus in the measurement of innovation as the innovation process is frequently considered a black box. Most scholars use research and development (R&D) and patents as innovation measures as R&D might be reasoned to represent part of innovation inputs, while patents reflect part of innovation outputs. R&D investment, either expenditure or stock, as a proxy for innovation input, measures part of the resources that are used for developing new products or processes and increasing the stock of knowledge. Patents are considered as the outcome of prior R&D investments and patent statistics are often used as proxies for innovation outputs (Grossman and Helpman 1991a). Patent data is heavily affected by the characteristics of national systems at different times, however, they contain rich details on inventors and technical areas and are archived systematically. Even though these indicators do not encompass all the innovation efforts, given their advantages of data availability for cross–country comparison, they are used frequently.

At the firm level, innovation can also be measured as (1) new to the firm, (2) new to the market, or (3) new to the world as detailed in the Oslo Manual (OECD/Eurostat 2018). In the third case, when a firm is the first to introduce a new product, or process, or new marketing method, organization method that are also new to all domestic and international markets, this type of innovation contains the highest level of novelty. It involves the development of brand–new, advanced and sophisticated solutions, and breakthrough technologies through the exploitation of recent advances in knowledge. Innovation from this perspective is often carried out by highly educated labor in R&D and typically belongs to the developed countries (Fagerberg, Sroholec and Verspagen 2010).

In this thesis, the measurement of innovation and innovation activities are based on both approaches of R&D and patent data at country level in Chapters 3 and 4; and innovation at the firm level measured by the introduction of new products/services that are also new to the main market of the firm (Chapter 5). This combination of innovation measurement leverages the advantages of long–time series R&D and patent data that are available for a wide range of countries. It enables the obtaining of a robust understanding of innovation and to compare across countries. Besides, the utilization of innovation measures at firm level which refers to the attempt to try out new or improved products, processes, or ways of doing things at the firm and its main market, brings a broader perspective that goes beyond the high–tech picture of innovation (Fagerberg, Sroholec and Verspagen 2010). It also provides additional analysis to supplement the shortcomings of the national aggregate level data of patent in the context of innovation in MIEs.

In the next section, the role of innovation underlined by scholars in economic growth theories and the innovation diffusion process which contributes to driving growth are elaborated.

2.1.2 Innovation role in economic growth

Innovation in growth theories

The question of how innovation influences economic development has drawn the attention of economists for a long time (Fagerberg, Sroholec and Verspagen 2010) such as since the time of Schumpeter. Schumpeter (1934) elaborates that economic growth is a creative destruction process that is generated by innovation. In this process, entrepreneurs are the ones diffusing technological improvements to the market. The successful commercialization of innovation adds values to the economy and enables economic growth. The Schumpeterian growth paradigm (Schumpeter 1942) places the notion of creative destruction at the epicenter of economic growth. Innovation replaces old technologies and induce growth in long run.

In the 1950s, Solow and Swan introduce the endogenous growth model or neoclassical growth model. Solow (1956) bases on assumptions of a closed economy with no externalities, perfect competition, maximizing behavior, and absence of scale economies. He postulates in the neoclassical growth theory that the aggregate output of an economy is produced through a production function consisting of labor and capital. The continuous rise in capital leads to growth in per capita income in the short term. Economic growth results from increases in the amount of capital per worker. Capital accumulation is the main source of growth or output expansion. However, as capital per worker increases, the marginal productivity of capital declines (Fagerberg, Sroholec and Verspagen 2010). It reflects diminishing marginal productivity of capital and labor, in which additional capital inputs will not contribute to economic growth. Ultimately, the capital–labor ratio approaches a constant, an economy will reach the steady state equilibrium. In this steady state, GDP per capita and capital per capita are no longer changing. Therefore, in the long term, there is no growth. To explain the growth in GDP per capita in the long run, Solow (1956) refers to technological progress as an exogenous factor of the model. Technological progress serves as the key driver of growth in this model and generates growth in GDP per capita. It means growth in neoclassical model is determined exogenously by the rate of technical progress. The important conclusion of the Solow–Swan model is that with the diminishing marginal returns to capital, the steady–state rate of growth of income per capita and capital in the long term is driven by the rate of technological progress, an exogenous factor of the model. However, one drawback of the Solow–Swan neoclassical growth model is that the components and determinants of technological progress are left unexplained.

During the late 1980s and early 1990s, interest in the possible role of technology in growth and development increased with the emergence of the new growth theory, or so-called endogenous growth theory (Fagerberg, Sroholec and Verspagen 2010). A growing amount of economics literature was devoted to explaining the non–convergence of the world economy, or the difference in GDP growth rate and GDP per capita among countries. The new growth theory extends the Solow–Swan neoclassical model by treating the driver of the steady–state equilibrium of growth as endogenous, i.e., the growth rate is determined within the model. Endogenous growth model replaced Solow's assumption of diminishing returns to capital by constant or increasing return to capital broadly defined, and the rate of technological progress was endogenously determined. Romer (1986) and (1990) emphasizes that innovation is a major engine of technological progress and a primary driving force stimulating economic growth, along with physical and human capital. The technological progress change depends on population growth and capital accumulation. Technical progress results from the rate of investment, the size of the capital stock, and the stock of human capital. It's contrary to the assumption in the neoclassical growth theory of Solow–Swan that technological change or innovation is not part of the economic growth model. Romer (1986) and (1990) postulates that technological progress stems from investment decisions made by profit–maximizing agents in response to market incentives. In this way, technological change is endogenous. Technological progress is considered the real force behind the perpetually rising standard of living (Grossman and Helpman 1991a).

Another approach to explain economic growth is with the growth accounting framework, in which the growth of GDP was decomposed into its constituents, i.e., factor inputs and technological change. The growth rate of output is not explained by the share–weighted growth rate of the inputs as residual (Fagerberg, Sroholec and Verspagen 2010). The residual was termed total factor productivity (TFP). Even though residual is linked to an underlying production function, TFP is an index number, not a function. The questions of where technological change originates and how it spreads across countries are still not clearly understood.

In these economic growth theories and models, the role of innovation or technological progress is underlined. Innovation is emphasized as a driver of growth. Based on this highlighted role of innovation, this thesis dives into topic of innovation in MIEs. However, a main challenge in those economic growth models is that the definition and determinants of innovation or technological progress variables are not explicitly explained (Ozturk 2016). The approach to explain innovation driving growth through its diffusion process will be elaborated in the next section.

Innovation diffusion process to drive economic growth

In this section, some ideas from economic development theories explaining the diffusion process of innovation to drive growth are presented. In the market, the process of spreading new technology is referred to as the diffusion of innovation. Innovation diffusion is the process by which the market for a new technology change over time (Stoneman and Batisti 2010).

In 1942, Schumpeter explained that innovation is diffused by entrepreneurs. The successful diffusion of innovation results in the economy growth (Schumpeter 1942). In the neoclassical and endogenous growth theories, scholars reasoned that innovation drives growth through the knowledge accumulation and diffusion process. Innovation is considered public goods and freely available (Fagerberg, Sroholec and Verspagen 2010). The freely–to access previous knowledge is the main input to produce new knowledge and invention. However, innovation diffusion is not clearly explained in terms of its mechanisms of domestic diffusion and across countries. In endogenous growth models, it's explained that previous knowledge is used as one of the main inputs for new knowledge and can be accessed at no additional cost for producing new designs of intermediate capital goods (Romer 1990). These models assume that the knowledge created by R&D investment can be used freely by others. Grossman and Helpman (1991a) emphasize that the knowledge spillover process multiplies the benefit from original inventors to other firms and individuals. Knowledge spillovers help to improve the efficiency of production or the R&D process of the receiving firms as they obtain useful knowledge, usually for free (Keller 2004).

Innovation might be diffused domestically and internationally (Keller 2004). International technological diffusion, or international knowledge spillovers may create benefits to other firms and individuals aside from original inventor by adding to their knowledge base as the public return. Keller (2004) also explains that technology can be diffused between firms, regions, and countries internationally through various transmission mechanisms including international trade; foreign direct investment (FDI); migration; foreign education of students and workers; the international research collaboration; the diffusion of disembodied knowledge through media and internet. Fu, Pietrobelli, and Soete (2011) add the transfer of foreign technology within the supply chain as one channel of innovation diffusion.

The innovation diffusion process plays an important role in building up assumptions of this thesis on domestic and foreign innovation efforts in Chapters 3 and 4.

2.2 Middle–income economies

2.2.1 Income classifications

Different approaches are introduced to define the income categories of the world economies. The most common approach is the one published by the World Bank. According to this classification, there are three groups of high–income, middle–income, and low–income countries. Under the middle–income category, there are two sub–categories of upper middle–income (UMI) and lower middle–income (LMI). The low–income countries are those with a gross national income (GNI) per capita of lower than USD1,035; lower middle–income countries (LMICs) are those with a GNI per capita of USD1,036–USD4,045; upper middle–income countries (UMICs) are those with a GNI per capita of USD4,046–USD12,535; high–income countries are the ones with a GNI per capita of greater than USD12,536 (World Bank 2020). The classification is revised annually based on inflation and exchange rate changes (P. Agénor 2017).

Other scholars also classify income of countries while focusing on defining the middle–income trap. Felipe (2012) divides income categories into four groups of lower than USD2,000 as low income; between USD2,000 – USD7,250 as lower middle–income; between USD 7,250 – USD11,750 as upper middle–income; and greater than USD11,750 as high–income. Another approach is to define income categories based on a relative measure of domestic per capita income compared to the United States, or a group of developed countries. This relative approach is based on the neoclassical model, which focus on the catch–up of poorer economies with the richer economies. GDP per capita in the percentage of the US level of GDP per capita was proposed in Catch–Up Index (CUI). A high–income country has a CUI higher than 55%. A CUI between 20% and 55% defines middle–income countries. Lower than 20% in CUI would qualify a country as low–income category (P. Agénor 2017).

In this study, given its updated and widely available data, the income categories of the World Bank (2020) based on the absolute level of GNI per capita (Atlas method, in current prices of 2020) is used. These income classifications are summarized in Figure 2.1.

Figure 2.1. Country Income Classification Used in this Study.

Source: Own creation based on World Bank (2020)

2.2.2 Issues faced by MIEs

While aspiring to join the high–income rank economies, after a period of accelerating growth, MIEs might face obstacles to maintaining continuous progress and ultimately converging with their high–income peers. However economic convergence seems a more complicated and lengthy process than the optimistic views tend to suggest (Zanello, et al. 2016). The challenges might contain both social and economic setbacks.

Losing competitiveness, sluggish growth, and the risk of falling into middle–income trap

With the transition to the middle–income, the rise of wages might undercut the country's competitiveness in labor–intensive sector and prevent the economy evolution into new higher value activities (OECD 2014). Middle–income countries are in the sandwich situation in which they lose competitiveness in terms of labor cost to low–income countries while yet to be able to compete with high–income countries possessing high technology, advances in science and technology, and high-skilled labor (Paus 2017). In a similar vein, Gill and Kharas (2007) explain that those countries are being squeezed between the low–wage poor country competitors that dominate the mature industries and the rich–country innovators that dominate industries under–going rapid technological change.

These MIEs are also likely to experience a sharp slowdown in its growth rate, based on the observation over the past half century as claimed by Lee (2020). The stagnant economic growth that MIEs face is elaborated by Spence (2011) by using the term “middle–income transition”. He specifies that when a country’s GNI per capita gets into the range of USD5,000–USD10,000, the sluggish growth occurs. Agénor, Canuto, and Jelenic (2012) observe that economic growth is likely to slow down substantively when a country’s income reaches around USD15,000–USD16,000 and is often attributed to a middle–income trap (MIT) characterized by a sharp deceleration in growth. Similarly, Eichengreen et al. (2012) study the cases of growth slowdown in fast–growing economies and suggest that fast–growing economies slowed down sharply when the income per capita reach around USD17,000 (in 2005 constant prices). Extending this study, they then analyze the prevalence of growth stagnation in middle–income countries. They conclude that many countries experience growth slowdowns in the middle–income level twice: first time when the income per capita is in the range of USD10,000–USD11,000; second time when income per capita is in the range of USD15,000–USD16,000.

The stagnating economic growth once a country enters a category of middle income is also referred as MIT situation. The MIT phenomenon has been discussed extensively in the last decade. The MIT term was first introduced by Garrett (2004) when referring to the stagnation of growth rate of MIEs since the 1980s. The concept was then defined by Kharas and Gill (2007). In the past decades, two main topics surrounding the theme of MIT are to figure out if the MIT exists (quantitative term), or what can MIE do to accelerate to high–income state and what reforms is necessary for the continuous economic growth and attain the next income category (qualitative term). Scholars have made efforts to find the trap threshold either in absolute income per capita terms, or relative to the frontier. There have been mixed analyses in proving the existence of the trap. There are two main approaches in studying the existence of the MIT. The first approach in defining middle–income trap bases on the absolute level of Gross National Income (GNI) per capita by Felipe (2012), Aiyar et al. (2013), Eichengreen et al. (2012). In this approach, the trap is considered as the existence of stagnating growth in absolute income per capita level. The commonalities among these studies are to apply econometrics analysis to define significant breaks or turning point in the time–series data on level of growth and growth rate in GNI per capita across countries (P. Agénor 2017). The second approach in defining MIT is based on relative measure. It considers MIT as unsatisfactory relative convergence of income per capita level on those of rich economies. MIE is defined by the assessment of growth slowdown relatively to other economies such as the US. Both approaches either on absolute threshold level of GNI per capita, or relative measure to other economies have the limitation that they rely on assumptions of defining threshold. In recent literature the former approach is used more prevalent due to data availability (P. Agénor 2017). Even though the definition of the MIT is rather controversial among scholars, the situation of a country getting stuck for a long duration in the middle–income status is not favorable to reaching the target of economic convergence with advanced economies.

Another perspective to analyze the situation of these middle–income countries staying too long in this income category is that these MIEs might experience a bad or low–growth equilibrium but stable and persistent state (Acemoglu 2009). The models by Acemoglu explain the differences in economic performance across countries and suggest that an economy might have different types of equilibrium, some reach equilibrium at higher levels of income, while other equilibria involve lower income levels and stagnation. Once a specific state of equilibrium is reached, it might not be easy and perhaps might be impossible to transition to the other steady–state equilibrium (P. Agénor 2017). A typical disadvantage of sluggish growth in MIEs is that it might result in the inability of MIEs to induce a shift in their industrial and export structure and a failure in meeting the needs of fast–evolving product markets where the emphasis is on innovation and product differentiation (P. Agénor 2017). In this way, these MIEs cannot enhance its competitiveness compared with the low–income countries and high–income economies. Therefore, determining causes, impetus to accelerate growth, measures to addressing the duration and magnitude of growth slowdowns are critical for MIEs.

Lowering future living standard, growing poverty, widening income inequality

The protracted growth would impact future living standards. Economic growth remains the most important determinant of rising societal living standards. MIEs ultimately aim to increasing wealth and welfare and accelerate process of catching up (Fu, X. , Mohnen, P. and Zanello 2018). The slowdown of growth might result in less potential to raise living standards of citizens aside from the inability to move up and resume rapid growth.

MIEs face a significant number of populations below the poverty line. Elevating a country's income per capita might also reduce the poverty level in MIEs that are home to more than three–quarters of the world's poor who live on less than USD2 a day. For example, in MIEs, the ADB (2017) estimates the total population living below its national poverty line might reach 39.9% for Papua New Guinea, 31.5% for Bangladesh, 25.2% for the Philippines, 21.9% for India. In another estimate, referring to the benchmark for extreme poverty of less than USD1.25 a day in purchasing–power–parity terms, the poverty incidence might reach 43.3% in Bangladesh, 23.6% in India, and 19% in the Philippines. This part of the population lacks access to social protection, inadequate safety net, and rising income inequality. An increase in living standards and a reduction in poverty level would contribute greatly to stability and quality of life. When a middle–income country experience protracted growth, they face an overriding challenge in sustaining development progress. The target of continuing to raise living standards and eliminating poverty might be affected.

In addition to the above, there is a risk that the inequality has risen higher and endure longer in today's MIEs than in the earlier industrializers. The current MIEs have passed the level of GDP per capita when the inequality level started reducing in the OECD countries at the beginning of 20th century (Doner and Schneider 2016). MIEs also face big income disparities in terms of Gini coefficients. The ADB (2017) finds that among a group of MIEs in Asia, the Gini coefficients is 40% or more and is projected to increase. It shows the huge and increasing disparities in these MIEs. Ensuring the fair distribution of wealth and equal access to opportunities to all segments of society remains challenging in these MIEs. It is, therefore, critical for these countries to increase the level of income per capita and obtain a higher income rank and focus on the social advancement agenda.

2.2.3 Innovation in MIEs

Until a decade ago, innovation in MIEs was a focus of only a handful of studies (Zanello, et al. 2016) and was often associated with patents, ground–breaking discoveries, which are the results of costly, risky and lengthy processes that require intense knowledge and capital investment (Fu, Pietrobelli and Soete 2011). Innovation in MIEs is more incremental, which involves the extension or modification of existing products and does not require significant changes, bringing simple adjustments or refinement of current technology (Keller 2004). Therefore, MIEs might depend on high–income countries for ground–breaking innovation. Based on R&D and patent statistics, innovation highly concentrates in a small group of developed, high–income, and highly industrialized economies according to Grossman & Helpman (1991b). Eaton & Kortum (1999) and Fu, Pietrobelli and Soete (2011) claim that most innovation activities concentrate in the USA, Japan, and a few European countries. 80% of world innovation activity are performed in the G7, with the US accounting for 40% of world R&D expenditures, followed by Japan, the second largest R&D investing country accounting for 18% of the world R&D expenditure, and EU members account for 30% (Crispolti and Marconi 2005). Groundbreaking innovation is costly and may only be pursued with high research capacity and well–connected national innovation systems. Low– and middle–income countries are technology followers whose technical progress eventually relies upon the ability to adopt and appropriate innovation produced by high–income countries (Coe, Helpman and Hoffmaister 1997; Zanello et al. 2016; Fagerberg, Sroholec and Verspagen 2010). Therefore, the spillover from high–income to MIEs is the focus of this thesis.

The characteristic of a low level of novelty in innovation compared with the high–income technological frontier, and the direction of innovation spillover assumption are important in studying the innovation in MIEs. In the subsequent chapters, the three key issues related to innvovation that pose major challenges for MIEs to evolve to the next income category will be analyzed. These analyses take into account the above additional characteristic of innovation in MIEs, i.e. the assumption on the direction of innovation spillover, together with the importance of R&D efforts emphasized in the innovation–driven endogenous growth models.

Chapter 3 Does Indigenous or Foreign Innovation Efforts Matter for the MIEs' Transition to the Higher Income Rank?[1]

3.1 Introduction

Growth of a country has been a central issue of study in economics. Economic growth theories identify factors that are important to explain the faster growth of some countries than the others. Enhanced capital, labor and technological progress are the three principal sources of economic growth for a country. In the neoclassical growth model and new growth theory, economists such as Solow (1956) and Romer (1990) postulate that technological progress is at the heart of long–run economic growth when the marginal productivity of capital and labor diminishes. Fostering innovation from both the diffusion process within a country and knowledge spillovers from foreign partners might support MIEs to graduate from middle–income status. However, with limited resources, MIEs need to prioritize whether to invest in indigenous innovative capacity or adopt foreign innovation.

The choice of investing in innovation through R&D is costly, risky, and path dependent (Fu, Pietrobelli and Soete 2011). It might provide a rationale for poor countries to rely on foreign technology acquisition for technological development (Keller 2004). However, it is not that simple to decide. The question of whether a country should rely solely on foreign technology, or completely depend on indigenous innovation since foreign technologies do not fit the local social and technical context, or pursue both strategies with different emphasis is a big question posed by Fu, Pietrobelli and Soete (2011). It is important for a country to plan and allocate its resources and strategize accordingly.

Against that background, the study aims to investigate the comparison of whether indigenous or foreign innovation efforts matter more for economic growth of MIEs. This topic has not been widely studied and even fewer analyses have focused on MIEs with technological catch–up processes underway. Empirical studies by Coe, Helpman and Hoffmaister (1997), Xu &

[1] This chapter has been reproduced from the preprint version of a paper published in Innovation and Development on 9 August 2022 by Taylor & Francis, available at: https://www.tandfonline.com/doi/full/10.1080/2157930X.2022.2110663 (Ngo, T. H., 2022)

Wang (2001), Pottelsberghe & Lichtenberg (2001), etc. that include both domestic and international innovation diffusion mainly target identifying channels and measures of international R&D spillovers, and estimating their impact on total factor productivity (TFP) in developed countries. This paper attempts to address this research gap by comparing the importance of domestic vs. foreign innovation efforts in supporting MIEs in transition to the next income category. Discrete–time hazard models (DTHMs) of duration analysis are applied. The research question is formulated as: ***"How are indigenous and foreign innovation efforts different in contributing to the transition of MIEs to the next income category?"***

The main contribution of this study is twofold. First, innovation efforts at the aggregate level are measured through various indicators of domestic R&D, import– and FDI–embodied foreign R&D, resident and nonresident patents. The inclusion of more innovation measures is one improvement on previous studies by Kang, Nabeshima, and Cheng (2015) who estimate within limited innovation measures, and Fu, Pietrobelli and Soete (2011) who review the literature theoretically. Second, to the best of the author's knowledge, this is the first attempt to estimate the impact of innovation efforts on the probability of MIEs' moving up the income ladder using DTHM, a useful tool that is often forgotten in innovation studies according to Triguero, Corcoles and Cuerva (2014). Using DTHM, the study aims to mitigate the shortcomings of continuous–time hazard model in previous research.

Sixty–one countries in the group of MIEs were studied (Appendices 1 and 2) between 1980 and 2018. One finding is that lower middle–income countries (LMICs) depend on foreign innovation spillovers more than domestic sources to move to the next income group. Foreign innovations diffused through the patent channel, followed by foreign R&D spillovers through the FDI channel, are highly significant for these countries. On the contrary, upper middle–income countries (UMICs) are found to rely more on indigenous innovation efforts than on foreign sources to attain high–income status. Investing in domestic R&D is the most crucial, followed by adopting foreign innovation diffusion through the import of technologies to reach the high–income level. Institutional quality is also confirmed to be significant for these UMICs.

The paper is structured as follows. Section 3.2 reviews the literature on innovation and the domestic and foreign sources that lay the foundation for the design of the empirical analysis. Section 3.3 details the data and construction of variables to study the impact of innovation on the probability of MIEs exiting their current income categories. The econometric estimation method of discrete–time hazard models of duration analysis is also presented in this section. Section 3.4 describes the results together with the robustness checks. The conclusion is made in section 3.5.

3.2 Literature review

This study relies mainly on three strands of research. First, the role of innovation in economic growth theories for MIEs is examined. Indigenous and foreign sources of innovation in the diffusion process are discussed. The second strand of literature on quantifying indigenous innovation efforts is then reviewed. The third strand of research on international R&D spillovers and their channels are synthesized as the basis to estimate foreign innovation efforts.

3.2.1 Innovation–led MIE growth

Innovation is assumed to be an important driver of economic growth when moving away from the low–income category with intensive resource usage. The neoclassical growth model by Solow–Swan postulates that the expansion of aggregate output results from capital accumulation. In the long run, when the growth rate of capital deepening reaches a plateau, a steady–equilibrium economy must rely on the exogenous factor of technological progress as a source of growth (Solow 1956). The endogenous growth theory that emerged in the late 1980s also emphasizes that technological progress is a major engine stimulating economic development, along with physical and human capital. Economists such as Romer (1990) and Aghion & Howitt (1992) differentiate their assumptions from the neoclassical model stating that technological progress is determined within the model based on the rate of investment, size of capital, human capital stock, etc. They suggest that innovation drives growth through its diffusion process. In the model by Romer (1990), accumulated knowledge is main inputs of new knowledge production. He considers cumulative knowledge as public goods and be accessed at no additional costs. Grossman & Helpman (1991a) emphasize that free access to previous knowledge and the spillover effect multiply the benefit from original inventors to other firms and individuals. Researchers, individual inventors, and firms can draw on knowledge stock as a source of reference during the innovation process. In both the neoclassical model and new growth theory, the role of innovation in fueling long–term economic growth is highlighted. However, the components, diffusion process, and sources of innovation are left unexplained.

The origins of innovation that matter to MIEs have not been widely studied while it is critical to strategize the resource allocation. Even though Rivera–Batiz & Romer (1991) demonstrate that both domestic technology of R&D and innovation diffusion through foreign goods are sources of growth, the idea that technological change has both domestic and foreign sources is less common in the literature as concluded by Gong & Keller (2003). Eaton & Kortum (1997) also raise the controversy of whether domestic– or foreign–origin source of innovation serves the primary role. This study examines this research gap.

Blyde (2003) claims that international R&D spillovers are a relatively more important source of productivity gains for developing than for developed countries. Fagerberg & Verspagen (2002) and Santacreu (2015) argue that countries in early stages of development grow by adopting foreign technologies. Countries in later stages of development and relatively close to the technological frontier grow by developing new technologies. It can be further hypothesized that sources of innovation which play the more important role in boosting growth are not identical for LMICs and UMICs.

Sources of innovation for LMICs

In low–income and LMICs, adopting and deploying new technologies from developed countries are postulated to be more relevant than developing cutting–edge innovation. Zanello et al. (2016) observe that in these countries, innovation is imitative and incremental, which can be assumed due to the high cost and relatively low level of human capital. Eaton & Kortum (1999) shows that major sources of technical change for the productivity growth of LMICs lie abroad. Keller (2004) claims that 90% of productivity growth for those weak in technology and R&D can be attributed to foreign technologies. Santacreu (2015) finds that 65% of embodied growth in emerging economies can be explained by innovations from OECD countries. From these findings, the first hypothesis is formulated as follows.

Hypothesis 1.1*: LMICs depend more on foreign innovation diffusion to attain UMI status.*

Sources of innovation for UMICs

Insufficient development of domestic innovation capabilities might be one reason for countries to be trapped in the middle–income group, especially for those that are closer to the high–income rank. UMICs that have moved closer to the technological frontier and aim for more ground–

breaking innovation might need to build up their indigenous capabilities. Santacreu (2015) concludes that domestic innovation accounts for 75% of their "embodied" growth of developed countries. Zanello et al. (2016) claim that foreign innovation diffusion might not be realized when advanced technology transferred from developed countries cannot find the matching local absorptive capacity. Keller (2010) observes that once the level of technological complexity increases, difficulties in adopting foreign technologies might arise owing to the nontransferability or noncodifiability of highly complex technological know–how. Fu, Pietrobelli and Soete (2011) and Eaton & Kortum (1997) argue that the transfer and adoption of advanced technologies from foreign countries might not be easy. Otherwise, late developers could have caught up and even leapfrogged. Based on those arguments, the second hypothesis is formulated below.

Hypothesis 1.2*: UMICs depend more on indigenous innovation effort to attain the high–income rank.*

In the following subsections, components and measures of domestic and foreign innovation are investigated in more detail.

3.2.2 Measuring domestic innovation efforts

Given the importance of innovation in economic growth, while noting the unexplained components, sources, and the diffusion process of innovation in the existing literature, the review is focused on measures of innovation within a country. Despite numerous attempts, it is difficult to find commonly agreed upon measures of innovation across studies. R&D and patent statistics are widely used indicators of national innovation as reviewed by Fagerberg, Sroholec and Verspagen (2010). However, both indicators have their pros and cons.

R&D expenditure, as a proxy for innovation input, measures part of the resources that are used for developing new products or processes and increasing the stock of knowledge. Even though it does not fully represent all sources of innovation inputs, due to its data availability across countries, R&D is considered a key explanatory variable, especially in endogenous growth empirical models such as those by Rivera–Batiz & Romer (1991) and Aghion & Howitt (1992). R&D investment is found to result in positive economic growth and increased productivity of OECD countries in the study of Pottelsberghe & Lichtenberg (2001). Considered as the outcome of prior R&D investments, patent statistics are often used as proxies for innovation outputs (Grossman and Helpman 1991a). On one hand, patent data is heavily affected by the characteristics of national systems at different times. Criteria for patent grants such as novelty, non–obviousness, and industrial usefulness differ over time and across countries. Besides, not all inventions are patented due to the cost and unsatisfactory enforcement of patent rights, or due to requirements of disclosure in systems like in Europe and Japan. Even though patent data have disadvantages and does not fully reflect outcome of innovation, on the other hand, it contains rich details on inventors and technical areas and are archived systematically. The advantage of long–time series data available for a wide range of countries facilitates the cross–country comparison, which suits to this study. Therefore, in this research R&D and patent data as measures of innovation.

Keller (2004) suggests that R&D expenditure does not accurately represent the improvement of technology in the same period. R&D capital stock constructed from R&D expenditure better reflects technological changes. In endogenous growth theory, innovation resulting from the accumulation of R&D serves as the main input for new knowledge production. Griliches (1979) and Coe & Helpman (1995) also find cumulative domestic R&D an important determinant of an economy's aggregate output level expansion or growth. Past and present effort determine the inputs available for innovation. In turn, innovation enriches knowledge that results from cumulative R&D and contribute to the existing stock of knowledge. Similar to the use of R&D stock, patent stock is presumed to better measure innovation than patent flow data. Based on this reason, to quantify domestic innovation sources, the two variables of R&D capital stock and stock of resident patents are used in this study.

3.2.3 Measuring foreign innovation diffusion in MIEs

In this section, the foreign sources of innovation measured by R&D and patent stocks are reviewed based on the literature on international R&D spillovers and their channels. The direction of foreign innovation to MIEs is also analyzed to identify the foreign innovation partners for MIEs.

When international trade takes place, diffusion of innovation through the spillover of partners' R&D stocks occurs and increases the domestic R&D stock of the receiving country. Pottelsberghe & Lichtenberg (2001) view foreign R&D capital stock measurement as attached to a particular transfer channel and weighting scheme given their inherent complexity. International trade, FDI, and patents are recognized as major channels for cross–border spillover of innovation due to the data availability in studies by Pottelsberghe & Lichtenberg (2001), Crispolti & Marconi

(2005), Keller (2010), Fagerberg, Sroholec and Verspagen (2010), Ang & Madsen (2013), and Kim & Park (2017). Keller (2010) explains that firms import intermediate goods embodying foreign firms' technology to become acquainted with the characteristics of goods, learn about foreign technologies, and increase domestic production efficiency. Coe & Helpman (1995) conclude that a country's TFP growth depends on both its R&D efforts and on foreign R&D that spills over through imports. The same conclusion is maintained in their following study in 2009. Xu & Wang (2001) find that foreign R&D spillovers embodied in trade had a sizeable impact on TFP of 21 OECD countries during 1971–1990. Crispolti & Marconi (2005) conclude similarly on the role of import–embodied R&D spillovers in the study on innovation diffusion from the USA, Japan, and the EU to 45 developing countries between 1980 and 2000. Krammer (2010) analyzing 47 economies and Ang & Madsen (2013) in their study of the six Asian economies reach the same conclusion about the role of import channel.

Empirical results show mixed effects of R&D spillovers embodied in FDI inflow. Pottelsberghe & Lichtenberg (2001) conclude that inward FDI is not significant for spillover and does not impact the domestic productivity of OECD countries in the 1970s and 1980s. Xu & Wang (2001) find no evidence of the impact of inward FDI in 13 OECD countries during 1983–1990 when applying the C&H weighting scheme while finding a significant impact of inward FDI when applying the Lichtenberg & Pottelsbergh (1998) weighting scheme. Kim & Park (2017) estimate that foreign R&D capital stock embodied in inward FDI is fairly significant in the 1990s, but insignificant in the 2000s for TFP in 27 OECD countries. Other studies find that FDI brings significant positive technological spillovers and contributes to productivity growth (Crispolti & Marconi 2005; Fu, Pietrobelli and Soete 2011; Ang & Madsen 2013).

Nonresident patents are found to contribute greatly to the spillover of R&D such as in the study of Madsen (2008) on the group of 16 OECD countries about the effect of international patent stock on TFP. Ulku (2004) and Ang & Madsen (2013) note a similar conclusion. Kang, Nabeshima, and Cheng (2015) find significant contributions of nonresident patents to the transition from UMI to high–income level.

Aside from innovation diffusion channels, the direction of foreign innovation to MIEs is also crucial for analysis. In this study, international innovation spillover from high–income countries to MIEs is the focus. Grossman & Helpman (1991b) reason that innovation highly concentrates in a small group of developed economies as shown in R&D and patent statistics.

Eaton & Kortum (1999) and Fu, Pietrobelli and Soete (2011) claim that most innovation activities concentrate in the USA, Japan, and a few European countries. Groundbreaking innovation is costly and may only be pursued with high research capacity and well–connected national innovation systems. Low– and middle–income countries seem to be technology followers, and their technical progress might rely upon the transfer and adoption of innovation from high–income countries (Coe, Helpman and Hoffmaister 1997; Zanello et al. 2016; Fagerberg, Sroholec and Verspagen 2010).

Embarking on the review of channels and directions of international R&D spillovers to MIEs, this study focuses on foreign innovation diffusion from high–income to MIEs. Foreign innovation efforts are quantified through the three variables of (1) FDI–embodied foreign R&D capital stock; (2) import–embodied foreign R&D capital stock; and (3) stock of foreign patents.

3.3 Research Strategy

To investigate the research question of whether the domestic or foreign source of innovation matters more for MIEs to move up the income ladder, the data is described in this section. The construction of variables to estimate the impact of indigenous vs. foreign innovation efforts and the duration in each middle–income subcategory on the probability of MIEs moving up the income rank is detailed. The duration model that is suitable to quantify the impact of innovation efforts on the probability of attaining the next income rank for MIEs is also described under the econometric estimation method. The application of discrete–time hazard models (DTHMs) of duration analysis to confirm the two hypotheses is then detailed.

3.3.1 Data

Aggregate national–level data between 1980 and 2018 of 61 countries are used in this paper (Appendices 1 and 2). Data is organized in the format that each discrete unit of one year for each country is treated as a separate observation. The working sample for LMICs consists of 392 observations for 36 countries, of which 19 obtain the UMI status, and 17 countries still stay in the LMI group by 2018 (details of countries, year of moving to the UMI rank, and duration in LMI rank can be found in Appendix 1). The estimation for UMICs includes 483 observations for 44 countries, among which 18 obtain the high–income status, and 26 countries remained in UMI rank by 2018 (details of countries, year of moving to the UMI rank, and duration in LMI rank can be found in Appendix 2).

3.3.2 Transition to the higher–income rank

In this paper, the transition from LMI to UMI, and from UMI to high–income rank are identified as events of duration analysis, the dependent variable of the study. The time to event, or duration, is the length of time a country stays in each income category of LMI before moving to UMI, or in the UMI category before attaining high–income status by the end of the study period (2018).

With the application of the discrete–time hazard model (DTHM) of duration analysis, the dependent variable takes a binary variable–valued one if a country manages to reach a higher income rank by the end of the study period (2018). If not, the dependent variable takes the value of zero (right–censored) following Jenkins (2005). The inclusion of both complete observations (countries transition to next income category by 2018) and censored observations (countries do not attain the higher income status by 2018), is a significant feature of duration analysis DTHM that enhances the estimation accuracy of the income level transition probability.

3.3.3 Domestic and foreign innovation efforts variables

Drawing from the review in sections 3.2.2 and 3.2.3 on the domestic and foreign sources of innovation efforts that support the MIEs' income transition, independent variables in this study consist of innovation measures of domestic R&D capital stock; foreign R&D capital stock embodied in FDI and imports; resident (domestic) and nonresident (foreign) patent stocks. The effect of economy size of the host country is accounted for by normalizing these measures by population. Details on these variables are as follows.

R&D capital stock per capita

R&D capital stock is calculated based on the flow of gross expenditure on R&D (GERD) by applying the perpetual inventory method (PIM) (Coe and Helpman 1995) as follows:

$$R\&D_S^{t+1} = (1-\delta)R\&D_S^t + R\&D_{exp}^t \tag{3.1}$$

where $R\&D_S^{t+1}$ is R&D capital stock of a country in year $t+1$; $R\&D_S^t$ and $R\&D_{exp}^t$ refers to the R&D capital stock and R&D expenditure of a country in year t; initial value of R&D capital stock is calculated following Griliches (1979)[2]; and δ is the annual R&D capital depreciation rate of 5% [3] following Coe & Helpman (1995) and Lichtenberg & Pottelsbergh (1998). Data for R&D capital stock are from R&D expenditure database of the UNESCO Institute of Statistic and Statistical Yearbook published by UN Statistics. R&D capital stock data is normalized by population to account for the scale effect of economy size.

Stock of resident patents per million population

Indigenous innovation efforts through patents of a country are counted as the sum of patent applications made by resident inventors. Eaton & Kortum (1999) and Ulku (2004) reason that patent application data are more comparable across countries since there might be different time lags between application year and grant year due to different patent examination systems. PIM is used to construct patent stock from patent application data with a 5% depreciation rate:

$$P_S^{t+1} = P^t + (1 - \delta)\, P_S^t \tag{3.2}$$

where P_S^{t+1} represent patent stock in year $t+1$, P_S^t and P^t refer to the patent stock and number of patent applications of a country in year t, the initial value of patent stock is calculated similarly to the initial value of R&D capital stock, and the depreciation rate δ of 5% is applied. Data on patent applications of nonresidents are extracted from the database of WIPO[4] and adjusted by million population.

Foreign R&D capital stock per capita embodied in FDI and imports

Foreign innovation of a country is constructed as weighted sums of R&D capital stocks of its foreign partners. The weighting scheme for foreign innovation embodied in FDI and imports follows Lichtenberg & Pottelsbergh (1998) who believe that a country benefits more from

[2] Initial value of R&D stock is calculated as $R\&D_S = \frac{R\&D_{exp}}{(\delta + g)}$; R&D expenditure of the first year is denoted as $R\&D_{exp}$; given average annual growth rate of the R&D expenditures g (Griliches 1979).

[3] Existing studies use depreciation rates between 5% and 20%

[4] https://www3.wipo.int/ipstats/index.htm?tab=patent

international R&D spillovers when importing or receiving more FDI from countries with relatively higher domestic R&D capital stocks, i.e., higher R&D intensity. Formulas to estimate foreign innovation efforts are as follows.

Foreign R&D capital stock embodied in inward FDI:

$$\mathrm{FI}_{\mathrm{At}}^{\mathrm{FDI}} = \sum_{\mathrm{B}=1}^{\mathrm{x}} \mathrm{FDI}_{\mathrm{ABt}} \ \frac{\mathrm{DI}_{\mathrm{Bt}}}{\mathrm{GDP}_{\mathrm{Bt}}};\ \mathrm{A} \neq \mathrm{B}. \tag{3.3}$$

Import–embodied foreign R&D stock:

$$\mathrm{FI}_{\mathrm{At}}^{\mathrm{IMP}} = \sum_{\mathrm{B}=1}^{\mathrm{x}} \mathrm{IMP}_{\mathrm{ABt}} \ \frac{\mathrm{DI}_{\mathrm{B}}^{\mathrm{t}}}{\mathrm{GDP}_{\mathrm{Bt}}};\ \mathrm{A} \neq \mathrm{B} \tag{3.4}$$

where foreign innovation effort of country A at time t embodied in FDI inflow is FI_{At}^{FDI} and in imports is FI_{At}^{IMP}; FDI_{ABt} refers to stock of inward FDI and IMP_{ABt} refers to bilateral imports of country A from country B at time t[5]; GDP and R&D capital stock of country B are denoted as GDP_{Bt} and DI_{Bt}[6]. As discussed in section 3.2.3, innovation calculated by R&D and patents is conducted mostly in high–income countries. Besides, due to the limited availability of bilateral data, in this study, foreign partners for innovation of MIEs are limited within the TRIAD group of the USA, Japan, and European Union 12[7] following Crispolti & Marconi (2005). A detailed explanation is given in Appendix 3. Data on inward FDI stocks are used to avoid the fluctuation of FDI flow value over time (Ang and Madsen 2013) and are from the UNCTAD database. Data on imports of goods and services bilaterally from TRIAD are recorded annually, 1995 – 2018, by UNCTAD. Stocks of inward FDI and import data are normalized by population to account for the effect of market size of the receiving country.

Stock of nonresident patents per million population

The knowledge spillover from foreign countries through the patent channel is measured by the stock of nonresident patent applications of each country in this paper. Cumulative patents of

[5] Data on FDI and imports of goods and services bilaterally from TRIAD between 1995–2018 are from UNCTAD, data before 1995 are from UN Comtrade database.

[6] Data on R&D and GDP of sending countries are computed from UNESCO Institute of Statistics, UN Statistical Yearbook, and Eurostat.

[7] Belgium, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Luxembourg, Netherlands, Portugal, United Kingdom.

nonresidents in each country annually are calculated similarly to stock of resident patent applications in section 3.4.2, using PIM. Nonresident patent application data from WIPO's database are used and adjusted by population.

3.3.4 Control variables

Human capital

The adoption of foreign innovation depends upon the capabilities of absorption of receiving countries. Human capital plays an important role in determining the absorptive capacity to adopt foreign innovation and develop domestic innovation, as reviewed by Fagerberg, Sroholec and Verspagen (2010). The database constructed by Barro & Lee (2013) for the length of schooling of the population over 15 years of age is used to represent the human capital level of a country. The updates of the data until 2021 is available online.[8] The length of schooling of the population over 15 years of age (average years of schooling of the population over 15 years of age) for each group of primary, secondary, and tertiary education is constructed by Barro & Lee (2013) as follows.

$$S_t^a = \sum_j h_{j,t}^a \, Dur_{j,t}^a \tag{3.5}$$

whereas S_t^a: average years of schooling of age group a (a = 1: 15–19 age group, a = 2: 20–24 age group,… a = 13: 75 and above) in time t; $h_{j,t}^a$ is the fraction of group a having attained the educational level (incomplete vs complete) j = pri, sec, ter; and $Dur_{j,t}^a$ is the duration in years. Barro & Lee (2013) construct the duration data considering the duration system changes of a country over time based on UNESCO Statistical Yearbooks.

Institutional quality

The institutional quality of economies such as the rule of law, regulatory agencies, intellectual property rights (IPRs), etc. can affect the development of domestic innovation and the adoption of foreign innovation from foreign partners of a country. The index of legal structure and property

[8] http://www.barrolee.com/

rights[9] is extracted from the dataset of the Economic Freedom of the World published by the Fraser Institute[10] to reflect institutional quality of the participating economies. This dataset is used since it covers a wide range of countries between 1980 and 2018. Explanations of variables used in this paper and data sources are summarized in Table 3.1.

[9] Under this index, there are five areas of (1) size of government, (2) legal structure and property rights, (3) access to sound money, (4) freedom to trade internationally, and (5) regulation of credit, labor, and business.
[10] Economic Freedom of the World Database: https://www.fraserinstitute.org/economic–freedom/map?geozone=world&page=map&year=2018

Table 3.1. Summary of variables and data sources

Variable	Explanation	Data source
Event (event)	Binary dependent variable valued one if the country had transitioned to the next income level by the end of the study period and valued zero if the country had not.	World Bank GNI per capita historical data
Duration (dur)	Number of years since a country reached one income category.	
R&D (log value) (lndi_rd)	Domestic R&D capital stock per capita, annual value calculated from GERD recorded at the beginning of the year. Unit: USD, constant 2010 prices.	UNESCO Institute of Statistic and UN Statistical Yearbook
FDI (log value) (lnfi_fdi)	Foreign R&D capital stock per capita embodied in inward FDI, from TRIAD. Unit: USD, constant 2010 prices.	UNCTAD and UN Comtrade Database
Imports (log value) (lnfi_imp)	Foreign R&D capital stock per capita embodied in imports, from TRIAD. Unit: USD, constant 2010 prices.	
Resident patents (log value) (lndi_pat)	Stock of resident patent applications per million population.	WIPO
Nonresident patents (log value) (lnfi_pat)	Stock of nonresident patent applications per million population.	
Human capital (hc)	Human capital quality based on the length of schooling of the population above 15 years of age.	Barro & Lee (2013) and its online updated dataset until 2021.
Institutional quality (inst)	Quality of institutions in an economy, measured through the legal structure and property rights index.	Economic Freedom of the World

3.3.5 Econometric estimation method: Discrete–time hazard models

In this section, the duration model that is suitable to quantify the impact of innovation efforts on the probability of attaining the next income rank for MIEs is described. The application of discrete–time hazard models (DTHMs) of duration analysis to confirm the two hypotheses is then detailed.

The duration analysis, or so–called survival analysis, time–to–event analysis, uses regression models to quantify the impact of explanatory variables on the likelihood of survival or failure toward a specific event (Jenkins 2005). Duration analysis is limited in existing studies of MIEs and the support of innovation to their growth at the aggregate level. The duration model in innovation study is more prevalent for firm–level innovation persistence, or innovation spell using microdata. Studies of Le Bas, Cabagnols and Gay (2003), Cabagnols (2006), and Manez, Rochina–Barrachina and Sanchis–Llopis (2015) are among the examples. At aggregate level, Kang, Nabeshima, and Cheng (2015) apply the Cox proportional hazard duration model to investigate the impact of innovation potential on income threshold transition. However, the study constructs variables mainly based on patent data and uses a continuous–time approach which shows limitations in estimations when applying on interval data. This paper tries to improve this shortcoming by employing DTHMs and controlling for unobserved heterogeneity effects.

Data used in this study are recorded annually. The transition to the next income category when it occurs can only be observed in a discrete unit of one year. The DTHM is appropriate in this case according to Allison (1982) who explains that when an event happens at discrete values of time, or data is recorded at a discrete interval of time, DTHM should be applied. The DTHM also has advantages when dealing with tied events,[11] with unobserved heterogeneity (UH), with time–varying predictors (Allison 1982; Jenkins 2005), and with baseline hazard shape, which are the drawbacks of continuous–time hazard models. The DTHM using complementary log–log (cloglog) link is an asymmetrical model and a good fit when binary data under analysis are imbalanced. Other DTHM using logit and probit link functions are symmetric and less flexible functional forms, as claimed by Triguero, Corcoles and Cuerva (2014). The DTHM using cloglog link also deals with censored data, while the probit model does not (Jenkins 2005). With those advantages, the analysis in this paper is based on the cloglog link[12] DTHM.

[11] Events that have the same value of survival time.

[12] Cloglog link function: cloglog(x) = log (–log(1–x)).

Conditional probability is another assumption behind the cloglog link DTHM to estimate the hazard rate. Hazard function quantifies the effect size of explanatory variables using maximum likelihood estimation. In this study, following Allison (1982) the hazard function is written as:

$$h_{ik} = 1 - \exp\left[-\exp\left(\alpha_t + \beta x_{ik}\right)\right] \tag{3.6}$$

where h_{ik} is hazard rate or probability of a country transitioning to the next income category in the next short interval of time, on the condition that the country has maintained its income level and has not reached the next one until now; α_t is a function of time or grouped duration baseline hazard; coefficients β represent the effects of explanatory and control variables x_{ik} of interval k for country i, i.e. domestic R&D, import– and FDI–embodied foreign R&D, resident and nonresident patents as explanatory variables; human capital and institutional quality as control variables. Maximum likelihood estimation[13] aiming to maximize the log–likelihood of the observed data is used to estimate parameters in the hazard function (Allison 1982).

For the baseline hazard α_t, the linear specification, in which duration dependence is summarized by a parametric Weibull specification (Jenkins 2005) is used in this paper. Manez, Rochina–Barrachina and Sanchis–Llopis (2015) reason that by allowing flexible specification, the baseline hazard is informative. The common baseline hazards include linear, higher–order polynomial, and nonparametric specifications of time. However, the polynomial and nonparametric specifications require the inclusion of many additional parameters when a long duration is observed for some countries. They might decrease the statistical power accuracy according to Singer, Willett and William (1993). In this study, the duration used to estimate the baseline hazard is counted from either 1980 or the year a country attained LMI or UMI status until it progresses to the next income category (for complete observations) or until the end of the study period (for censored observations).

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[13]Hess & Persson (2012) incorporate into log–likelihood function the binary dependent variable y_{ik} (value one if the country exits at the end of the observation period and value zero otherwise) as follows:

$$\text{Log–likelihood} = \sum_{i=1}^{n} \sum_{k=1}^{max} \left[y_{ik} \log h_{ik} + \left(1 - y_{ik}\right) \log h_{ik}\right]$$

The cloglog DTHM requires no error term, or assuming that there is no UH according to Singer, Willett and William (1993). Jenkins (2005) highlights that if being ignored, UH might result in the overestimate or underestimate of duration dependence. Manez, Rochina–Barrachina and Sanchis–Llopis (2015) explain that the DTHM can control UH v_i by incorporating it multiplicatively as a random variable taking on positive values. With the mean normalized to 1 and finite variance, and u_i = logv_i, the cloglog function in equation (5) becomes:

$$h_{ik} = 1- \exp [- \exp (\alpha_t + \beta x_{ik} + u_i)] \qquad (3.7)$$

Jenkins (2005) and Kleinbaum & Klein (2005) assume that v_i distributes independently of baseline hazard α_t and x_{ik} while following a distribution such as gamma, normal, and nonparametric. These three distribution assumptions are included for estimations in this study by using the commands of pgmhaz8, hshaz, and xtcloglog of Stata16 program.

3.4 Empirical results

The empirical results for impacts of domestic and foreign innovation efforts on the probability of LMICs and UMICs to move up the income ladder are estimated in three DTHMs. These models control for UH with three distribution assumptions of gamma, normal, and nonparametric. The results obtained are similar with different assumptions of UH for both LMICs (models 1, 2, 3) and UMICs (models 4, 5, 6). Coefficient signs and levels of significance are nearly identical in each group of LMICs and UMICs. Values of log–likelihood are approximate across models with different UH assumptions for both LMICs and UMICs. Values of gamma variance, sigma_u, and m2 that are close to zero suggest that UH is unimportant. The p–value for the likelihood ratio test confirms that UH is statistically insignificant in these models. It can be inferred that results are consistent and robust in three UH specifications for both LMICs and UMICs. Estimation results for each country group of LMI and UMI are detailed below.

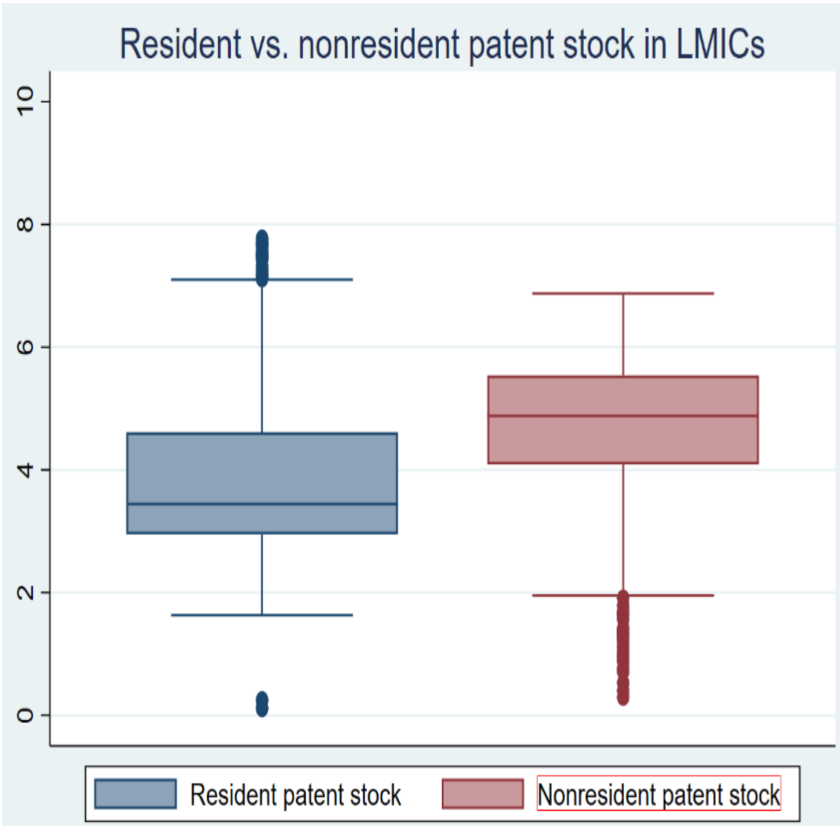
3.4.1 Descriptive statistics

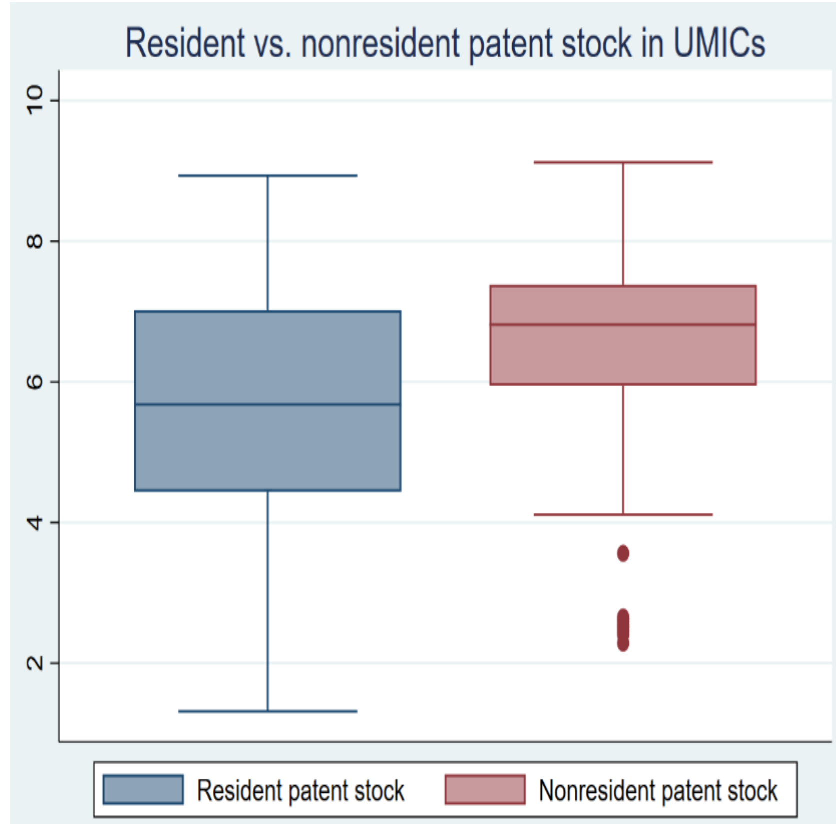
Descriptive statistics of the data used in this study are presented in Table 3.2. The average values of R&D capital stocks, resident and nonresident patents, foreign innovation embodied in FDI and import channels, human capital quality, and institutional quality of UMICs are greater than these average values of the LMIC group. The number of observations for the variables in LMICs and UMICs are in the same range (between 483 and 603 observations).

Table 3.2. Descriptive statistics

Variables	Observations	Mean	Standard Deviation	Min.	Max.
LMICs					
Event (event)	603	0.0315	0.175	0	1
R&D (lndi_rd)	546	3.545	1.422	0.045	6.633
Resident patents (lndi_pat)	593	3.969	1.568	0.106	7.779
FDI (lnfi_fdi)	600	2.987	1.510	0.004	6.774
Imports (lnfi_imp)	536	2.741	1.151	0.000	5.897
Nonresident patents (lnfi_pat)	601	4.646	1.333	0.291	6.875
Human capital (hc)	505	7.017	1.842	3.550	11.15
Institutional quality (inst)	603	4.721	0.798	2	6.95
UMICs					
Event (event)	594	0.027	0.162	0	1
R&D (lndi_rd)	594	5.545	1.270	1.170	7.758
Resident patents (lndi_pat)	594	5.556	1.703	1.316	8.935
FDI (lnfi_fdi)	594	4.619	1.435	0.000	7.188
Imports (lnfi_imp)	594	4.001	1.085	0.446	7.207
Nonresident patents (lnfi_pat)	594	6.604	1.188	2.285	9.121
Human capital (hc)	483	8.637	1.851	4.650	12.73
Institutional quality (inst)	594	5.341	0.973	2.30	7.34

A more detailed comparison of resident vs nonresident patent stock per million population shows that on average values of both variables are greater in UMICs than in LMICs as shown in the box plots in Figure 3.1. Similarly, when comparing values of R&D capital stock, FDI–embodied foreign R&D capital stock, and import–embodied foreign R&D capital stock in the boxplot Figure 3.2, the same trend is noted. The correlation matrices of variables used in the estimations for LMICs and UMICs are in Table 3.3 and Table 3.4. It is noted from these two tables that there is no high correlation coefficient among variables (less than 0.8), therefore, multicollinearity should not be a problem.



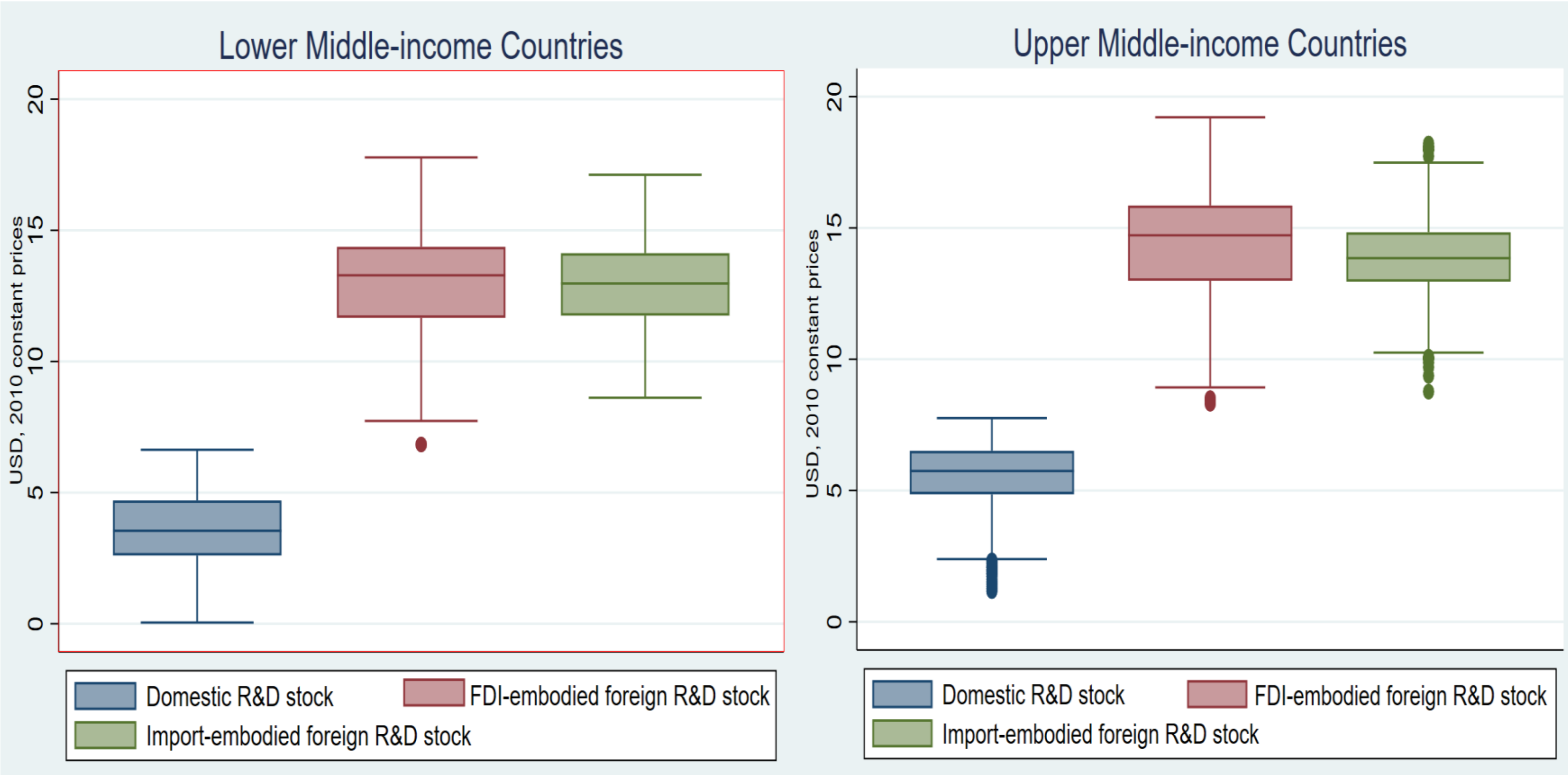


A. Lower Middle–income Countries

B. Upper Middle–income Countries

Figure 3.1 Resident vs. nonresident patent stock per million population in LMICs and UMICs

Source: Author's calculation



A. Lower Middle–income Countries B. Upper Middle–income Countries

Figure 3.2 R&D capital stock, FDI–embodied foreign R&D, and import–embodied foreign R&D in LMICs and UMICs

Source: Author's calculation

Table 3.3. Correlation matrix of variables in regressions of LMI group

	Event (event)	R&D (lndi_rd)	Resident patents (lndi_pat)	FDI (lnfi_fdi)	Imports (lnfi_imp)	Nonresident patents (lnfi_pat)	Human capital (hc)	Institutional quality (inst)
Event (event)	1.000							
R&D (lndi_rd)	0.170	1.000						
Resident patents (lndi_pat)	0.130	0.589	1.000					
FDI (lnfi_fdi)	0.171	0.257	0.087	1.000				
Imports (lnfi_imp)	0.174	0.384	0.124	0.560	1.000			
Nonresident patents (lnfi_pat)	0.143	0.268	0.438	0.047	0.289	1.000		
Human capital (hc)	0.084	0.161	0.461	0.046	–0.075	0.072	1.000	
Institutional quality (inst)	0.095	0.319	0.539	0.131	0.343	0.365	0.242	1.000

Table 3.4. Correlation matrix of variables in regressions of UMI group

	Event (event)	R&D (lndi_rd)	Resident patents (lndi_pat)	FDI (lnfi_fdi)	Imports (lnfi_imp)	Nonresident patents (lnfi_pat)	Human capital (hc)	Institutional quality (inst)
Event (event)	1.000							
R&D (lndi_rd)	0.190	1.000						
Resident patents (lndi_pat)	0.101	0.428	1.000					
FDI (lnfi_fdi)	0.098	0.421	0.036	1.000				
Imports (lnfi_imp)	0.197	0.591	–0.014	0.589	1.000			
Nonresident patents (lnfi_pat)	0.178	0.362	0.527	–0.041	0.230	1.000		
Human capital (hc)	0.097	0.525	0.548	0.434	0.353	0.256	1.000	
Institutional quality (inst)	0.186	0.256	0.164	0.203	0.383	0.315	0.393	1.000

3.4.2 Main results

Lower middle–income countries

The details of empirical results for LMICs on the impact of independent variables on the probability of exiting the current lower middle–income group with three assumptions of UH are presented in Table 3.5. Among all innovation variables of LMICs, foreign innovation efforts embodied in FDI, and foreign patents are statistically significant in affecting the probability of the LMI group to transition to the UMI group, at 90% and 95% confidence levels.[14] LMICs that have higher levels of FDI–embodied foreign R&D capital stock and higher level of foreign patent stock increase their possibility of exiting the LMI group to reach the UMI status.

The importance of FDI–embodied foreign R&D capital for LMICs cannot be compared with any existing studies given the lack of similar research estimating the impact separately for the LMI and UMI groups. The conclusions by Blyde (2003), Crispolti & Marconi (2005), and Ang & Madsen (2013), in which FDI is highlighted as an important channel of diffusing innovation are somewhat comparable. It can infer that FDI contributes to the transition of LMICs to the next income group while generating spillover through the occurrence of imitation effect, demonstration effect, labor turnover, and vertical linkage. Firms in LMICs might observe and acquire new technologies, or marketing techniques of FDI firms within–industry, then adopt those technological innovation. They benefit from imitation effect or demonstration effect in this case (W. Keller 2010). Besides, employees in FDI firms when moving to local firms in LMICs might also transfer what they learn about more advanced technologies of foreign firms and create a learning effect to local firms in LMICs (labor mobility effect). In case of vertical linkage, FDI–embodied foreign technology might be transferred to local supplier (upstream firms) to ensure that those products meet technical specifications, or to buyer (downstream firms) to ensure that equipment functions as designed and local engineers operate and maintain equipment properly (Keller 2004). Reverse engineering effect might take place in this case.

In this paper, interestingly, the unimportance of foreign innovation spillover through the import of more advanced technology and machinery and the more vital role of FDI channel for technology transfer for LMICs are found. It is assumed that due to the lack of matching local

[14] Additional estimations to confirm the robustness of these results are made with only inward FDI stock and nonresident patent stock as independent variables, no control variables included. Similar results are obtained at 90% confidence level with coefficients of 0.621 for nonresident patent stock, and 0.3499 for FDI stock.

absorptive capacity, the import channel is not efficient for foreign innovation spillovers. It might infer that for firms in LMICs, the reverse engineering effect, in which local firms purchase new machines and technology, and gain new knowledge by analyzing these more advanced foreign technologies for adapting and building up innovation capability, does not have a significant role in innovation spillover. This result is different from the findings of Crispolti & Marconi (2005), Krammer (2010), and Ang & Madsen (2013) which emphasize that FDI channel is less significant than the import channel in transmitting foreign technologies to developing countries.

Comparing the importance of foreign over domestic patents, the only similar study was by Kang, Nabeshima, and Cheng (2015), in which foreign patents are not significant for LMICs. The finding of significant importance of foreign patents in transferring international R&D capital in this study is similar to the conclusion of Ang & Madsen (2013), and Madsen (2008). This result shows that technology licensing from foreign partners might be effective in supporting the moving up of the income ladder for LMICs. Foreign patent is one relevant channel of international technology transfer for LMICs to transition to UMI rank. No UH was found consistently in models 1, 2, and 3.

Table 3.5. Estimation results for the LMICs

	Model 1	**Model 2**	**Model 3**
UH distribution	Gamma	Normal	Nonparametric
R&D (lndi_rd)	0.740 (0.116)	0.740 (0.116)	0.740 (0.116)
Resident patents (lndi_pat)	–0.050 (0.911)	–0.050 (0.911)	–0.050 (0.911)
FDI (lnfi_fdi)	**0.603**** **(0.027**)**	**0.603**** **(0.027**)**	**0.603**** **(0.027**)**
Imports (lnfi_imp)	0.806 (0.157)	0.806 (0.157)	0.806 (0.157)
Nonresident patents (lnfi_pat)	**0.686*** **(0.073*)**	**0.686*** **(0.073*)**	**0.686*** **(0.073*)**
Human capital (hc)	0.179 (0.462)	0.179 (0.462)	0.179 (0.462)
Institutional quality (inst)	–0.875 (0.178)	–0.875 (0.178)	–0.875 (0.178)
Duration	0.026 (0.656)	0.026 (0.656)	0.026 (0.656)
Log–likelihood	–40.041	–40.041	–40.041
UH	No (Gamma variance: 0.0000)	No (Sigma_u: 0.0010)	No (m2 intercept: –0.00002)
LR test of no UH	Chibar2: 0.000 Prob.>chibar2: 0.5	Chibar2: 0.000 Prob.>chibar2: 0.5	NA
Number of observations	392	392	392

*Coefficients are reported with p-values in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.*

In conclusion, the estimation results above show that LMICs depend more on the two channels of nonresident patents and FDI–embodied foreign innovation to attain the higher–income status. None of the domestic innovation variables are significant in these estimations. Hypothesis 1.1 which poses that LMICs depend more on foreign innovation diffusion to reach the UMI rank, is therefore supported. This result is unique since no previous similar study was done using national–level data on LMICs. The finding of the greater importance of foreign innovation effort over indigenous one for the LMICs supports the conclusions made by Blyde (2003), Santacreu (2015), and Zanello et al. (2016). The impacts of human capital and institutional quality are not significant for LMICs in this study. The results obtained here show the duration non–dependence on the probability of transitioning to the next income category.

Upper middle–income countries

Estimation results reported in Table 3.6 for UMICs are consistent among the three models. Domestic R&D capital stock is statistically significant at 7.7%, followed by import–embodied foreign innovation effort (significant at 8.3%), to the probability of UMICs transitioning to the high–income category. Positive coefficients of these two variables imply that the higher level of R&D capital stock and import value of foreign technologies a country has, the greater the probability that it will reach the high–income group. [15]

The importance of domestic R&D capital stock is confirmed by most empirical studies on economic development. The role of the import channel as a conduit for transferring foreign R&D to developing countries is similarly found in the studies of Coe & Helpman (1995 and 2009), Xu & Wang (2001), Crispolti & Marconi (2005), and Ang & Madsen (2013). It can be inferred that the import channel supports the transferring of highly codified, complex technologies to UMICs. Purchase of technological goods such as machine–embodied technology, advanced technology, technical processes, and techniques from foreign partners is an effective way for technology transfer and innovation spillover when UMICs transition to the HI rank. The reverse engineering effect from the import channel might build up capability of local firms in UMICs by providing additional information related to new and more advanced technologies. This study finds that institutional quality is also significant for UMICs as similarly concluded by Coe, Helpman and Hoffmaister (2009). Institutional quality might include the quality of legal structure, the effectiveness of government, and the level of intellectual property rights (IPR) protection and has significant impacts on the innovation diffusion process for UMICs. Therefore, enhancing institutional quality of the UMICs such as strengthening the rule of law, IPR, enhancing political stability, and reducing corruption could support the development of domestic innovation and the adoption of foreign innovation from foreign partners. UMICs with weaker and less inefficient

[15] Estimation with R&D capital stock and import–embodied international R&D capital was conducted separately, with no control variables included. Similar results were obtained at the 95% confidence level with coefficients of 1.421 for domestic R&D capital stock, and 1.0426 for import–embodied foreign innovation.

working public institutions, weaker IPR protection might not be able to ensure the development of domestic innovation and facilitate foreign innovation spillovers.

Table 3.6. Estimation results for the UMICs

	Model 4	**Model 5**	**Model 6**
UH distribution	Gamma	Normal	Nonparametric
R&D (lndi_rd)	**0.997*** **(0.077*)**	**0.997*** **(0.077*)**	**0.997*** **(0.077*)**
Resident patents (lndi_pat)	0.309 (0.261)	0.309 (0.261)	0.309 (0.261)
FDI (lnfi_fdi)	–0.033 (0.890)	–0.033 (0.890)	–0.033 (0.890)
Imports (lnfi_imp)	**0.831*** **(0.083*)**	**0.831*** **(0.083*)**	**0.831*** **(0.083*)**
Nonresident patents (lnfi_pat)	–0.147 (0.766)	–0.147 (0.766)	–0.147 (0.766)
Human capital (hc)	–0.161 (0.430)	–0.161 (0.430)	–0.161 (0.430)
Institutional quality (inst)	**1.068**** **(0.039**)**	**1.068**** **(0.039**)**	**1.068**** **(0.039**)**
Duration	0.086** (0.048**)	0.086** (0.048**)	0.086** (0.048**)
Log–likelihood	–47.533	–47.533	–47.533
UH	No (Gamma variance: 0.0004)	No (Sigma_u: 0.0026)	NA
LR test of no UH	Chibar2: 0.000 Prob.>chibar2: 0.5	Chibar2: 0.000 Prob.>chibar2: 0.5	NA
Number of observations	483	483	483

*Coefficients are reported with p-values in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.*

The FDI–embodied foreign innovation effort is not statistically significant in the case of UMICs. Pottelsberghe & Lichtenberg (2001), Xu &Wang (2001), and Kim & Park (2017) conclude similarly that the inward FDI spillover effect is not significant for innovation spillover. It is assumed that for UMICs, the level of absorptive capacity and innovation capability is higher than in LMICs, thus the imitation effect, or demonstration effect are no longer relevant and effective in transferring more advanced foreign technologies. Instead for international technology transfer in the case of UMICs, the reverse engineering effect generated through purchasing foreign technologies, machinery and equipment become significant as concluded above. Patents are not significant in transmitting more advanced technology and support the transition of UMICs to high–income status. It infers that technical information and knowledge sharing through patents, or technology licensing might not be sufficient to support UMICs in moving up its income ladder. This result is opposite to the conclusion made by Eaton & Kortum (1999), Ulku (2004), Madsen (2008), and Ang & Madsen (2013). They emphasize the significance of the spillover of international R&D capital through the patent channel at all levels of development. No UH is found in models 4, 5, and 6.

Overall, UMICs depend more on domestic R&D capital stocks, followed by technology transfer through the import channel to attain high–income status. Hypothesis 1.2 which postulates that UMICs depend more on indigenous innovation effort to attain the high–income category, is supported. This result is in line with previous reports by Eaton & Kortum (1997), Fu, Pietrobelli and Soete (2011), and Santacreu (2015). Building up indigenous innovation capability through R&D capital accumulation is the most important for UMICs to reach high–income status. The conclusion is opposite to the one of LMICs in section 3.4.2, which relies more on the channels of FDI and patents for spillovers of foreign innovation. The quality of institution is found important in supporting UMICs to transition to the high–income rank, which is similarly underlined by Coe, Helpman, and Hoffmaister (2009).

3.4.3 Robustness checks

In sections 3.4.2, the estimation results are consistent in both DTHMs without UH and DTHMs incorporating UH in three assumptions of gamma, normal, and nonparametric distribution. The identical results show that the choice of heterogeneity distribution does not affect the parameter estimates, supporting the conclusion made by Nicoletti & Rondinelli (2010). The model results are robust. Additionally, in this section, data are estimated with logit and probit link DTHMs to confirm the robustness of results for both LMI and UMI groups. Results are presented in Table 3.7.

Estimation results obtained from the logit link DTHM (model 7) and probit link DTHM (model 8) for the LMICs are similar to the results of the cloglog link DTHM with normal distribution assumption of UH (model 2, section 3.4.1). LMICs leverage foreign patents and FDI–embodied foreign innovation efforts to transition to the UMI rank. Hypothesis 1.1, which poses that LMICs depend more on foreign innovation diffusion to transition to the UMI rank, is supported by both logit and probit link DTHMs.

Results obtained for UMICs from both the logit link DTHM (model 9) and probit link DTHM (model 10) show that UMICs depend on indigenous innovation efforts of R&D capital and strengthening governance while being also supported by foreign technology spillovers through import channel (as shown in model 9). The results of the logit link DTHM is consistent with cloglog DTHM estimation (model 5, section 3.4.2). This confirms the robustness of the estimations for UMICs. Slightly higher coefficient values found with probit link model 10 might be due to the omission of censored data. Even though the import channel becomes less significant, the most important role of domestic innovation effort is still valid, and Hypothesis 1.2 which poses that UMICs depend more on indigenous innovation effort to attain the high–income category, is still supported.

Table 3.7. Estimation results with the logit and probit link DTHMs for LMICs and UMICs

	LMICs		**UMICs**	
	Model 7: Logit	Model 8: Probit	Model 9: Logit	Model 10: Probit
R&D (lndi_rd)	0.732 (0.125)	0.242 (0.177)	**1.007*** **(0.086)**	**0.523**** **(0.040)**
Resident patents (lndi_pat)	–0.014 (0.976)	0.069 (0.712)	0.335 (0.243)	0.164 (0.215)
FDI (lnfi_fdi)	**0.655**** **(0.030)**	**0.347**** **(0.025)**	–0.051 (0.849)	–0.060 (0.662)
Imports (lnfi_imp)	0.812 (0.173)	0.342 (0.211)	**0.451*** **(0.093)**	0.372 (0.120)
Nonresident patents (lnfi_pat)	**0.754*** **(0.065)**	**0.424**** **(0.045)**	–0.112 (0.833)	–0.562 (0.826)
Human capital (hc)	0.154 (0.536)	0.033 (0.769)	–0.200 (0.342)	–0.135 (0.197)
Institutional quality (inst)	–0.880 (0.208)	–0.373 (0.275)	**1.173**** **(0.034)**	**0.629**** **(0.020)**
Duration	0.031 (0.611)	0.018 (0.530)	0.916** (0.053)	0.049** (0.046)
Log–likelihood	–40.139	–40.182	–47.561	–47.180
Number of observations	392	392	483	483

*Coefficients are reported with p-values in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.*

Overall, the two hypotheses are supported by all the cloglog, logit, and probit link DTHMs. The estimation results obtained in sections 3.4.2 are therefore robust, and their validity is confirmed.

3.5 Conclusion

This paper examines the importance of domestic and foreign innovation efforts in the possibility of MIEs' transition to higher–income rank. Data of 61 countries between 1980 and 2018 in both categories of LMI and UMI are analyzed. DTHMs of duration analysis are employed. UH is controlled by incorporating it in the models with three different assumptions of its distribution.

The results show that the most important factor for LMICs to successfully exit this income group lies in foreign patent diffusion and FDI–embodied foreign R&D capital stocks. UMICs rely the most on indigenous innovation efforts of domestic R&D capital stocks as the main source of growth, supplemented by foreign R&D spillovers through imports to build up their capacity. Institutional quality referring to legal structure and IPRs is also important for these UMICs in enhancing the innovation capability to transition to the high–income category.

These findings have implications for policymakers that the LMICs aiming to successfully exit this group should focus more on foreign innovation diffused through foreign patents and FDI channel. Policies to attract foreign investment such as easing conditions, registration, and doing business, or enhancing the protection of foreign patents in the jurisdiction of the LMICs, should be the focus. On the contrary, for UMICs aiming to attain high–income status, the foremost policy priority should be strengthening indigenous innovation capabilities through investing in R&D. UMICs need to rely on their own financial investments to build up R&D stocks and evolve to the high–income stage. Investing in R&D also facilitates the industrial structure shift to areas like advanced manufacturing and creating radical innovations and revolutionary technologies. R&D investment will also require enhancing the skill sets of R&D personnel and the absorptive capacity of the labor force. Policies to enhance innovation capabilities through importing foreign technologies and know–how transferred should also be pursued in parallel to speed up the catch–up process (Fu, Pietrobelli and Soete 2011). Strengthening the quality of institutional systems such as legal structure, IPRs, etc. is another parallel policy focus for UMICs targeting to reach the next stage in the economic development process.

Future research is required to deepen understanding of the interactions among different assumptions of baseline hazards with different distribution assumptions of UH in the DTHMs applied in this study. More accurate bilateral import– and FDI–embodied foreign innovation data across countries are needed for measurements of foreign R&D capital spillovers in MIEs given the limited data on developing countries. Human capital composition (different levels of skilled human capital) should be explored to capture more accurately the role of human capital for MIEs' income transition.

Chapter 4 The Role of Human Capital Composition for Innovation of MIEs

4.1 Introduction

In growth theories, from the neoclassical growth model to the new growth theory, scholars such as Solow (1956), Nelson and Phelps (1966), Romer (1990), Grossman and Helpman (1991c), Aghion and Howitt (1992), etc. have underlined that human capital serves as one determinant for the growth of nations, and it is a prerequisite for economic development. On one hand, human capital might affect the output growth of an economy by serving as labor input in the production function. Researchers often postulate that a more educated and higher skilled workforce would positively associate with growth. On the other hand, according to endogenous growth scholars like Benhabib and Spiegel (1994), Vandenbussche, Aghion and Megh (2006), the stock of human capital might enhance a country's ability to develop local technological innovation and adopt foreign technologies and thereby facilitating convergence. In this approach, technological progress or TFP growth is modeled as a function of the educational level. A higher level of human capital is assumed to better create and implement innovation and enhance absorptive capacity for advanced foreign technologies assimilation as stressed by Keller (2004). The poor quality of human capital might act as a constraint to innovation activities, thus hindering development according to Agénor (2017). Additionally, countries, especially middle–income ones, might not have the capacity to absorb large amounts of physical capital from abroad due to the inadequate supplies of suitable labor.

Despite the dual role of human capital in promoting growth emphasized by authors like Benhabib & Spiegel (1994), Keller (2004), and Kneller & Stevens (2006), the understanding of the effects of human capital at different levels of education and skills on innovation enhancement, especially in middle–income countries remain less prevalent in empirical studies. It is in contrast with numerous papers on the human capital contributions to productivity and economic growth (Agénor and Neanidis 2015).

Based on the assumption that different levels of development and innovation capacity require different types of human capital, Vandenbussche et al. (2006), de la Fuente and Domenech (2006) further argue that the way human capital composition shapes the innovation capacity might not be uniform. Cross–country analyses leveraging this approach are not abundant according to Ang, Madsen and Islam (2011). Danquah & Amankwah–Amoah (2017) and Qureshi, et al. (2021) review that among those few studies, the focus is mainly on developed economies like the OECD that are closer to the technological frontier and have more stable institutional system. The understanding of how human capital composition enhances innovation in catch–up economies remains limited.

As an effort to narrow the research gap above, this study aims to examine the innovation enhancing effect of human capital composition in middle–income economies (MIEs). Using panel data at the aggregate national level of 65 MIEs and above from 1985 to 2019, with a focus on middle–income ones, the paper explores the role played by unskilled, skilled, and high–skilled levels of human capital on the innovation capacity of these countries. The panel data regression estimation procedures are applied.

Empirical results of this study show that unskilled human capital is not significant to the innovation capacity of middle–income and high–income countries. Skilled human capital is important for the innovation capacity of lower middle–income countries (LMICs) while being unimportant to upper middle–income countries (UMICs) and high–income countries (HICs). On the contrary, high–skilled human capital is positively significant to the innovation capacity of both UMI and HI groups. Aside from skilled human capital, foreign innovation embodied in the FDI channel is also crucial for LMICs. R&D capital stock and import–embodied international R&D spillover are found to support innovation capacity in UMICs. In HICs, findings highlight the important role of R&D personnel. It is supported by R&D capital stock, FDI embodied foreign innovation and the institutional quality.

The contribution of this study is threefold. First, it contributes to the literature on the role of human capital for innovation at aggregate level. Second, it expands empirical results on the innovation–enhancing effect of the human capital composition. This study postulates that the composition of human capital based on the educational level is insufficient to reflect the importance of human capital to innovation capacity. The categories of skilled human capital proxied through tertiary education, and unskilled human capital proxied through primary and secondary education by Vandenbussche et al. (2006), Ang, Madsen and Islam (2011), and Agénor and Neanidis (2015) are supplemented by the high–skilled human capital of R&D personnel in this study. As the direct labor force involved in innovation activities, R&D personnel, might represent more accurately the vital role of human capital composition for innovation capacity. To the best of the author's knowledge, this is the first attempt to examine the impact of human capital composition on innovation at the aggregate level using these three components of unskilled, skilled, and high–skilled human capital. The inclusion of high–skilled human capital in addition to the educational outcome variables of unskilled and skilled human capital is another uniqueness of the study. Third, this study extends the empirical findings on MIEs by including 44 middle–income countries in the sample of 65 economies. Utilizing aggregate data at the national level is another contribution in this regard given the more prevalent firm–level innovation data in current studies.

The paper continues as follows. The next section reviews the literature on the role of human capital and innovation in economic development, and the study gap on the impact of human capital composition on innovation capacity. Section 4.3 explains the methodology approach, including a framework of research, estimation strategy, and data used in this study. Section 4.4 details estimation results together with the robustness check. Conclusion and implications to policies are made in section 4.5.

4.2 Literature review

4.2.1 The role of human capital and innovation in growth literature

Human capital is considered an important driver of economic growth, and innovation is another vital component of economic development in neoclassical growth models and endogenous growth theories as reviewed by Ang, Madsen and Islam (2011) and Agénor and Neanidis (2015). The link between human capital, innovation, and growth has been the subject of numerous theoretical and empirical studies. Starting from Solow (1956), other scholars like Romer (1990), Grossman & Helpman (1991c), Aghion & Howitt (1992) and (1998) have considered R&D or technological advancement and human capital accumulation as engines of growth by emphasizing the complementarity between these two components of the development process.

Human capital is usually referred to as knowledge, skills, competencies, and attributes embodied in individuals as defined by Becker (1964). Goldin (2016) explains that knowledge and skills that are part of human capital are acquired through education and experience. It is in the same line as Becker (1964) who provides a general theory on the role of human capital in the production process and the incentives to invest in human capital. These investments might be in the form of school education the pre–labor market stage and on–the–job training at the labor market stage. The contribution of human capital in enhancing innovation and economic growth is largely emphasized in these studies. Manca (2012) reviews that human capital is appropriate to represent the absorptive capacity of firms and countries. Danquah and Amankwah–Amoah (2017) reasons that human capital can be utilized to foster innovation activity. More specifically, as elaborated by Deakins & Whittam (2000), at the organizational level, human capital might be associated with the ability to develop business innovation in a firm, or the ability to execute and implement policies in public sector agencies.

Along with human capital, innovation emerges as one important driver stimulating economic development in the neoclassical growth model and endogenous growth theory. Innovation might be recognized as an engine of economic growth, especially for MIEs whose marginal productivity of capital accumulation is diminishing and are seeking new drivers of growth. Types and sources of innovation play different roles across income levels or economic development stages. Fagerberg & Verspagen (2002) reason that countries in early stages of development leverage foreign technologies adoptions, while at later stages of development and relatively closer to the technological frontier, countries leverage indigenous innovation efforts. Similar to this conclusion, Blyde (2003) views that international R&D spillovers are a relatively more important source of productivity gains for developing than for developed or high–income countries. On the contrary, findings by Santacreu (2015) show that growth of developed countries is attributed mainly to domestic innovation.

Scholars often assume that there is a strong connection between innovation and human capital to enhance national–level development. Innovation, a knowledge–intensive activity, depends on human capital to generate ideas and apply knowledge (Mourad and Dirk 2004). Human capital is among the determinant of an economy's capacity to carry out technological innovation and adopt foreign technologies. Nelson and Phelps (1966) reason that the more educated the labor force, the faster the adoption of new technologies. Historically, in the 1950s, the neoclassical growth model by Solow–Swan postulates that the aggregate outputs are produced through a production function of labor and capital. In the long run, a steady–equilibrium economy must rely on innovation as an exogenous source of growth. In the 1990s, endogenous growth economists such as Romer (1990) and Aghion & Howitt (1992) emphasize that technological innovation is determined endogenously within the model from the rate of investment, the size of the capital, and human capital stock, etc. Innovation in R&D sectors uses human capital and existing knowledge stock, and human capital determines the capacity of a nation to innovate as explained by Romer (1990). Human capital promotes productivity growth through facilitating the development of new technologies for domestic innovation, as well as diffusing and adopting new foreign technologies as highlighted by Grossman & Helpman (1991c) and Aghion and Howitt (1992). Keller (2004) elaborates that the successful adoption of foreign technology also requires firms and countries to have certain types of skills.

The contribution of human capital and innovation to growth has been the focus in economic development theories. Human capital serves as labor input in the production function and directly affects economic growth. Indirectly, one might reason that human capital contributes to growth through enhancing innovation for higher technological progress as reviewed by Ang, Madsen and Islam (2011). The dual role of human capital is supported by Keller (2004) and Kneller & Stevens (2006). The link between human capital, innovation, and economic growth has been the subject of numerous theoretical and empirical growth literature, in which the contributions of human capital and innovation to growth are estimated (Agénor and Neanidis 2015). However, the direct relationship between human capital and innovation has not been the focus especially for MIEs, except for a few studies such as by Mourad & Dirk (2004), Stone and Shepherd (2011). In support of this argument, Danquah and Amankwah–Amoah (2017) view that the understanding of how human capital enhances innovations, especially in developing countries remains limited. Qureshi et al. (2021) review that most empirical analyses focused on developed countries which are at or near the global technological frontier, and few analyses delve into innovation patterns in catch–up economies. To contribute to closing this gap, in this paper, the research question is formulated as: ***"How does human capital affect the innovation outputs of MIEs?"***

4.2.2 Innovation capacity enhancing effects of human capital composition

Given its importance, while limitedly studied of the direct relationship between human capital and innovation capacity as reviewed in section 4.2.1, the review of studies on the link between human capital and innovation, especially in MIEs is made in the following section.

Empirical studies on human capital contribution to innovation capacity show mixed findings. Mourad & Dirk (2004) find a positive relationship between human capital proxied through HDI and innovation proxied through patent counts, R&D expenditures, and high–tech export in a study of 59 economies between 1995 and 2004. The results provide significant support to the role of human capital as a catalyst for innovation. Stone and Shepherd (2011) conclude that skilled labor is a crucial determinant of a firm's ability to realize productivity gains. Danquah and Amankwah–Amoah (2017) measure effects of human capital on innovation and technology adoption in 83 countries between 1960 and 2010. Human capital measured by mean years of schooling in the population aged 15 years and over appears to generate a positive and significant impact on the adoption of technology, while its impact on domestic innovation is insignificant.

Given the stylized fact on the underscored role of human capital for innovation in growth theories, the mixed results on the contribution of human capital to innovation are puzzling. It is similar to the problem some scholars face when estimating the contribution of human capital to economic growth using the average human capital stock. For example, Krueger and Lindahl (2001) question the assumption in the influential model of Mincer that the change in a country's average level of schooling should be the key determinant of income growth. De la Fuente & Domenech (2006), Vandenbussche, Aghion and Megh (2006), and Cohen and Soto (2007) by determining a weak correlation between variables of education and economic growth raise skepticism about the relevance of average human capital measures in explaining the growth process.

To solve this puzzle, Vandenbussche, Aghion and Megh (2006) postulate that the growth–enhancing effects of human capital depend on its composition rather than on the average measure of human capital stock. Different human capital skill levels of workers may differently interact with economic growth. At each development stage, or depending on the distance from the technological frontier, a country might find the significant contribution of each human capital component differently. For lower–income countries, incremental innovation and dependence on technological diffusion are often observed. Incremental innovation is postulated to be low–skilled and labor–intensive. However, when an economy approaches the world technologies frontier, groundbreaking innovation is the main engine of growth and requires higher–skilled labor. Empirically, Benhabib & Spiegel (2005) study the sample of 19 OECD countries between 1960 and 2000 and find that the growth–enhancing effect comes from skilled human capital of tertiary education attainment, rather than coming from total average human capital. Manca (2012) suggests that the developed regions succeeding in changing the human capital composition by increasing the share of highly educated workers close the gap with the technological frontier faster. Ang, Madsen and Islam (2011) conclude that the effect of skilled human capital is increasing with proximity to the technological frontier since highly innovative economies are also highly skilled–intensive.

There are limited studies analyzing the human capital composition effect on the growth of countries at different income levels as noted by Ang, Madsen and Islam (2011). Human capital composition effect is mainly studied in developed countries like the OECD. Fewer studies on the innovation capacity enhancing effect of human capital composition are found for developing countries. Among these few, Agénor (2017) reasons that in early stages of development, high–skilled labor matters relatively little, but will become more important when countries advance closer to the technologies frontier and compete intensively against foreign competitors. In UMICs, returns to high–skilled workers may be higher than those of low–skilled workers according to Aghion et al. (2009). Danquah & Amankwah–Amoah (2017) assume that tertiary education and above is crucial for technological innovation as the more educated labor force, the easier it is to master technologies. The adoption and implementation of technology from frontier technology still require high–skilled workers as it is a skill–costly activity according to Manca (2012).

In a few studies on innovation enhancing effect of human capital at different education levels, Vandenbussche et al. (2006), Ang, Madsen, and Islam (2011), and Agénor and Neanidis (2015) decompose human capital level into unskilled human capital (measured by primary and secondary education completion rate), and skilled human capital (proxied through tertiary education completion rate). However, educational outcomes might not be sufficiently representative of human capital impacts on innovation capacity, and tertiary education is not a good enough measure of the high–skilled workforce that can contribute to innovation. There is a gap between the use of human capital education attainment variables and the knowledge and skills of workers in the innovation process.

To address this issue, in this paper, it is reasoned that human capital in R&D sectors or R&D personnel might better represent the human capital necessary for groundbreaking innovation and more accurately reflect the knowledge, skills, and competence required as inputs in the innovation process. Human capital in R&D sectors is categorized as high–skilled human capital measured by the number of R&D personnel per million population. This study differentiates itself from the existing ones which assume tertiary education is sufficient human capital for innovation.

Based on the review of human capital composition effects on different income categories, and the composition of human capital assumed, in this study, the following hypotheses are made.

Hypothesis 2.1: *Skilled human capital is more important than unskilled and high–skilled human capital for the innovation outputs of LMICs.*

Hypothesis 2.2: *High–skilled human capital contributes more than unskilled and skilled human capital to the innovation outputs of UMICs.*

Hypothesis 2.3: *Unskilled human capital is not important for innovation outputs of MIEs.*

In the next session, the methodology approach to verify the research question and confirm these hypotheses will be presented.

4.3 Empirical methodology

In this section, the methodology approach to examine the impact of different levels of human capital on innovation as posed in the research question and its three hypotheses is presented. The estimation design and panel data estimators are described. The data, its sources, and descriptive statistic are introduced next.

4.3.1 Model specification and estimation strategy – Panel data regression

To examine the innovation–enhancing effect of human capital composition in different subcategories of middle–income, this study includes three categories of unskilled, skilled, and high–skilled human capital as analyzed in subsection 4.2.2. It is the expansion of human capital composition in existing empirical studies. The estimation equation takes the following functional form to depict the relationship between the human capital composition and innovation capacity:

$$inno_{it} = \beta_1 hc\_usk_{it} + \beta_2 hc\_sk_{it} + \beta_3 hc\_hs_{it} + \theta' X_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{4.1}$$

In which i denotes country and t denotes time; dependent variable of $innov_{it}$ denotes innovation capacity measured by annual patent application number; hc_usk_{it} proxies unskilled human capital; hc_sk_{it} represents skilled human capital; and hc_hs_{it} denotes high–skilled human capital; X_{it} is a vector of control variables that include R&D capital stocks, foreign innovation embodied in FDI and import channels; and quality of institution; μ_i denotes country–specific fixed effects; η_t captures the unobservable individual invariant time effect; and ε_{it} is error term. Constant terms are also included in these estimations.

Panel data regression is employed in these estimations for each subgroup of LMICs, UMICs, and HICs following Qureshi et al. (2021) and Agénor & Neanidis (2015). Unobserved country–specific effects and time–invariant effects are controlled for in these panel data regressions by including country and year dummies.

The Hausman test (Hausman 1978) is conducted to choose the more relevant models among the FEM and REM. The null hypothesis under the Hausman test is that there is no correlation between the individual effects and the independent variables. The Hausman test result with the chi–square value and its p–value of less than 5% would reject the null hypothesis and confirms the more efficient FEM. An insignificant value of this test would indicate the REM outperforms the FEM. In case the null hypothesis cannot be rejected and confirm the choice of REM, the Lagrange Multiplier (L–M) test following Breusch and Pagan (1980) is conducted. The L–M test results would determine whether the REM or Pooled OLS is more relevant. If the null hypothesis of the test is rejected, REM is indicated to outperform Pooled OLS. In case FEM is found to better fit, F–test results to confirm the relevance of FEM over Pool OLS is necessary. The elaboration on constructions of variables in the estimation equation above and its data sources will follow in the next section.

4.3.2 Variables construction

This section elaborates on the dependent variable of innovation capacity, human capital composition variables of skilled, skilled, and high–skilled human capital, the control variables of R&D investment, FDI–embodied and import–embodied foreign innovation, and institutional quality are made.

Measurement of innovation capacity – A dependent variable

The dependent variable of innovation capacity is measured by patent applications of residents. The use of patent data in the analysis of innovation is due to its advantages in systematically archived for long time series and across countries. It also represents part of the output of innovation generated from innovation input of R&D investment at the aggregate national level. Patent application data are more comparable across countries than patent grants which are heavily depending on the characteristics of each country's patent examination systems (Eaton and Kortum 1999). Data on patent applications of residents is from the database of WIPO and adjusted by million population.

Human capital composition – Explanatory variables

In human capital measurement, educational data is often used because it's a simple approach while education is one of the most important characteristics embodied in workers as reviewed by Collins & Bosworth (1996). Estimating the impact of human capital on economic growth, previous studies might use education indicators of enrollment rate, average years of schooling, literacy rates such as in Barror and Lee (2013), Caselli, Esquivel and Lefort (1996), cognitive skills measured by test score in Eric & Woessman (2012). While enrollment ratios represent human capital investment levels, literacy is a stock variable for human capital (Benhabib and Spiegel 1994).

In this study, human capital is constructed as the fraction of the population having primary, secondary, and tertiary education following Ang, Madsen and Islam (2011). Moreover, it's postulated that the human capital composition based on the educational level is insufficient to reflect the role of human capital to innovation output. The high–skilled human capital of R&D personnel, the direct capital for the innovation process, is assumed to be more relevant. R&D personnel characterizes a key innovation input as it includes professionals who conduct research and improve or develop concepts, theories, models, techniques, instrumentation, and software of operational methods. R&D personnel supplements the skilled and unskilled human capital (Qureshi, et al. 2021).

Unskilled human capital

The total number of people above 15 years of age attaining primary and secondary education per million population represents the unskilled human capital. The unskilled human capital variable is constructed based on the dataset of Barro and Lee (2013). The dataset has been updated online until September 2021[16].

[16] https://barrolee.github.io/BarroLeeDataSet/BLv3.html

Skilled Human Capital

To move up the value chain beyond simple production processes and products, higher education completion labor force is crucial. In this study, it is used as a proxy for skilled human capital. Tertiary education, even though not high–skilled, plays a crucial role in the exchange of ideas and skills necessary for innovation. The skilled human capital is measured by the fraction of the population over the age of 15 completing tertiary education in the dataset of Barro and Lee (2013).

High–skilled Human Capital

Aside from education, the level and standard of research activity in an economy are prime determinants of the innovation capacity of a nation. Human capital employed in R&D sectors serves as direct human capital inputs for innovation activities. R&D personnel consists of people performing R&D, highly trained scientists, and engineers (researchers), technicians with a high level of experience and training, and supporting staff who contribute directly to carrying out R&D activities (OECD/Eurostat 2018). In this study, high–skilled human capital is measured by the number of R&D personnel full–time equivalent (FTE) as a proportion of the population extracted from UNESCO Statistics and UN Statistical Yearbooks.

Control variables

The following control variables are included in the regressions: R&D capital stock; FDI– and import–embodied foreign innovation; and institutional quality.

R&D capital stock per capita

R&D variable as input of innovation account for knowledge stock in the R&D sector. R&D investment is required for developing new technologies and enabling a firm or country to understand and adopt innovation appropriately (Keller 2004). R&D capital stock is calculated based on the gross expenditure on R&D by applying the perpetual inventory method (PIM) (Coe and Helpman 1995) as follows.

$$R\&D_S^{t+1} = (1 - \delta)\, R\&D_S^t + R\&D_{exp}^t \tag{4.2}$$

where $R\&D_S^{t+1}$ is R&D capital stock of a country in year $t+1$; $R\&D_S^t$ refers to the value of R&D capital stock in year t [17]; $R\&D_{exp}^t$ is R&D expenditure of a country in year t; and δ is the annual R&D capital depreciation rate of 5% following Coe & Helpman (1995) and Litchtenberge & Pottelsbergh (1998). R&D capital stock data is normalized by population to account for the scale effect of economy size.

Foreign R&D capital stocks per capita embodied in FDI and imports

Foreign innovation of a country is constructed as weighted sums of R&D capital stocks of its foreign partners. The weighting scheme for foreign innovation embodied in FDI and imports follows Litchtenberge & Pottelsbergh (1998) in this study with the following formulas.

Foreign R&D capital stock embodied in inward FDI:

$$\mathrm{FI}_{\mathrm{At}}^{\mathrm{FDI}} = \sum_{\mathrm{B}=1}^{\mathrm{x}} \mathrm{FDI}_{\mathrm{ABt}} \, \frac{\mathrm{DI}_{\mathrm{Bt}}}{\mathrm{GDP}_{\mathrm{Bt}}}; \ \mathrm{A} \neq \mathrm{B}. \tag{4.3}$$

Import–embodied foreign R&D stock:

$$\mathrm{FI}_{\mathrm{At}}^{\mathrm{IMP}} = \sum_{\mathrm{B}=1}^{\mathrm{x}} \mathrm{IMP}_{\mathrm{ABt}} \, \frac{\mathrm{DI}_{\mathrm{B}}^{\mathrm{t}}}{\mathrm{GDP}_{\mathrm{Bt}}}; \ \mathrm{A} \neq \mathrm{B} \tag{4.4}$$

where foreign innovation effort of country A at time t embodied in FDI inflow is FI_{At}^{FDI} and in imports is FI_{At}^{IMP}; FDI_{ABt} refers to the stock of inward FDI and IMP_{ABt} refers to bilateral imports of country A from country B[18] at time t; GDP and R&D capital stocks of country B are denoted as GDP_{Bt} and DI_{Bt}.

Institutional quality

The innovation capacity of a country is highly affected by its institutional quality such as the rules of law, regulatory agencies, intellectual property rights, etc. The index of legal structure and

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[17] Initial value of R&D stock is calculated as $\mathrm{R\&D_S} = \frac{\mathrm{R\&D_{exp}}}{(\delta + \mathrm{g})}$; R&D expenditure of the first year for which data of R&D expenditure are available is denoted as $\mathrm{R\&D_{exp}}$; given average annual growth rate of the R&D expenditures g over the period for which published R&D data are available (Griliches 1979).

[18] Due to the limited availability of bilateral data, in this study, foreign partners for innovation of MIEs are limited within the TRIAD group of the USA, Japan, and European Union 12 following Crispolti & Marconi (2005).

property rights[19] is extracted from the dataset of the Economic Freedom of the World published by the Fraser Institute to reflect institutional quality of the participating economies. Among various indices for institutional quality, this dataset is used since it covers a wide range of countries throughout the period of 1985–2019.

4.3.3 Data

The data span 65 countries for the periods of 1985–2019 (a list of countries in each income group is given in Appendix 4). Data of 5–year average for seven periods, i.e., 1985–1989, 1990–1994, 1995–1999, 2000–2004, 2005–2009, 2010–2014, 2015–2019, is constructed to reduce potential volatility and provide a solution to miss–data issue, especially for LMICs. This implies a maximum size of 455 observations for the full sample of all countries. The sample is divided into three groups of income of LMICs, UMICs, and HICs. The classification is based on the data of GNI per capita by the World Bank (2020). The summary of variables and data sources are presented in Table 4.1.

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[19] Under this index, there are five areas of (1) size of government, (2) legal structure and property rights, (3) access to sound money, (4) freedom to trade internationally, and (5) regulation of credit, labor, and business.

Table 4.1. Summary of variables and data sources

Variable	**Explanation**	**Data source**
Dependent variable		
Patents (log value) (lnpat)	Number of resident patent applications per million population.	WIPO
Explanatory variables		
Unskilled human capital (log value) (lnhc_usk)	Number of people above 15 years of age attained primary and secondary education levels per million population.	Barro & Lee (2013) and its online updated dataset until 2021.
Skilled human capital (log value) (lnhc_sk)	Number of people above 15 years of age attained tertiary education level per million population.	
High–skilled human capital (log value) (lnhc_hs)	Number of full–time equivalent (FTE) R&D personnel per million population.	UNESCO Institute of Statistic and UN Statistical Yearbook
Control variables		
R&D capital (log value) (lnrd)	Domestic R&D capital stock per capita, annual value calculated from GERD recorded at the beginning of the year. Unit: USD, constant 2010 prices.	UNESCO Institute of Statistic and UN Statistical Yearbook
FDI–embodied foreign innovation (log value) (lnfdi)	Foreign R&D capital stock per capita embodied in inward FDI, from TRIAD. Unit: USD, constant 2010 prices.	UNCTAD and UN Comtrade Database
Import–embodied foreign innovation (log value) (lnimp)	Foreign R&D capital stock per capita embodied in imports, from TRIAD. Unit: USD, constant 2010 prices.	
Institutional quality (inst)	Quality of institutions in an economy, measured through the legal structure and property rights index.	Economic Freedom of the World

4.4 Estimation results

In this section, estimation results based on the methodology in the previous section are presented. The relationship between the human capital composition of unskilled, skilled, and high–skilled to innovation capacity are estimated while controlling for the effects of R&D capital stocks, FDI– and import–embodied foreign innovation, and the instructional quality. To assess the robustness of these results, estimations are then conducted with alternative measure of human capital composition, and alternative measure of innovation capacity.

4.4.1 Descriptive statistics

Descriptive statistics for patents and human capital composition of unskilled, skilled, and high–skilled levels during the period of 1985–2019 across the three income groups are presented in Table 4.2.

Among 65 countries included in the study, there are 18 LMICs, 26 UMICs, and 21 HICs. Data on patent applications of residents show that maximum value belongs to the group of HICs, followed by UMICs and LMICs. Details on distribution of patent applications across different income groups is depicted in Figure 4.1. Similar to the data on patents, the maximum value of R&D capital stock per capita, institutional quality, high–skilled human capital, skilled human capital, and unskilled human capital of HICs are greater than UMICs. Those values of UMICs are greater than those of LMICs. Comparison of mean value of different human capital skill levels across the three income groups show similar pattern (Figure 4.2).

Table 4.2. Descriptive statistics

Variables	Observations	Mean	Standard Deviation	Min.	Max.
LMICs (18 countries)					
lnpat	120	0.671	1.732	–4.843	3.674
lnhc_usk	126	10.575	0.930	7.378	12.520
lnhc_sk	119	8.065	0.494	6.532	9.167
lnhc_hs	92	6.078	1.132	3.305	8.524
lnrd	95	3.116	1.435	–0.296	5.567
lnfdi	121	2.506	1.712	0.001	6.681
lnimp	126	2.010	1.263	0.000	4.547
inst	126	4.324	0.857	2.527	5.872
UMICs (26 countries)					
lnpat	178	2.570	1.200	0.008	5.626
lnhc_usk	174	11.808	0.952	8.517	13.102
lnhc_sk	182	10.869	1.000	4.605	12.527
lnhc_hs	182	6.557	1.162	4.102	9.246
lnrd	178	5.747	0.976	2.889	8.206
lnfdi	180	3.789	1.714	–0.991	7.029
lnimp	181	4.342	1.078	1.526	6.434
inst	180	4.943	0.795	2.000	6.950
HICs (21 countries)					
lnpat	144	4.715	1.703	–0.089	8.071
lnhc_usk	147	12.720	0.430	11.491	13.490
lnhc_sk	147	13.151	0.223	12.596	13.663
lnhc_hs	147	7.909	1.044	5.085	9.856
lnrd	142	6.986	1.377	2.759	9.555
lnfdi	138	5.763	1.109	2.541	8.519
lnimp	145	5.014	1.246	2.102	7.785
inst	147	6.367	0.923	3.570	7.981
All countries (65 countries)					
lnpat	442	2.792	2.175	–4.843	8.071
lnhc_usk	447	2.550	1.165	7.378	13.490
lnhc_sk	448	2.893	1.244	4.605	13.663
lnhc_hs	421	6.946	1.348	3.305	9.856
lnrd	415	5.660	1.856	–0.296	9.555
lnfdi	426	4.050	2.005	–0.991	8.519
lnimp	431	3.966	1.648	0.000	7.785
inst	452	5.231	1.186	2.000	7.981

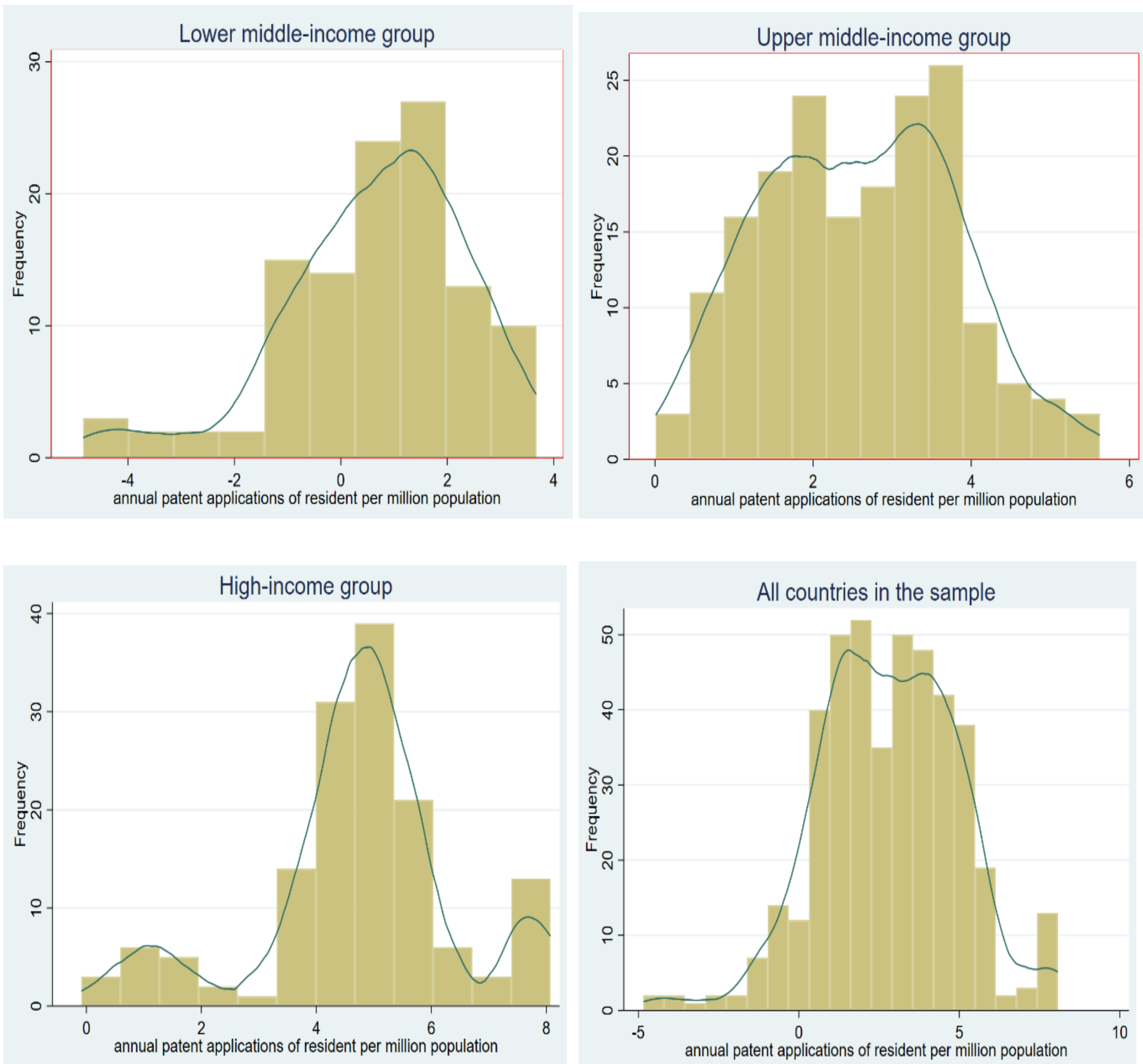

Figure 4.1 Distribution of patent applications across different income groups

Source: Author's calculation

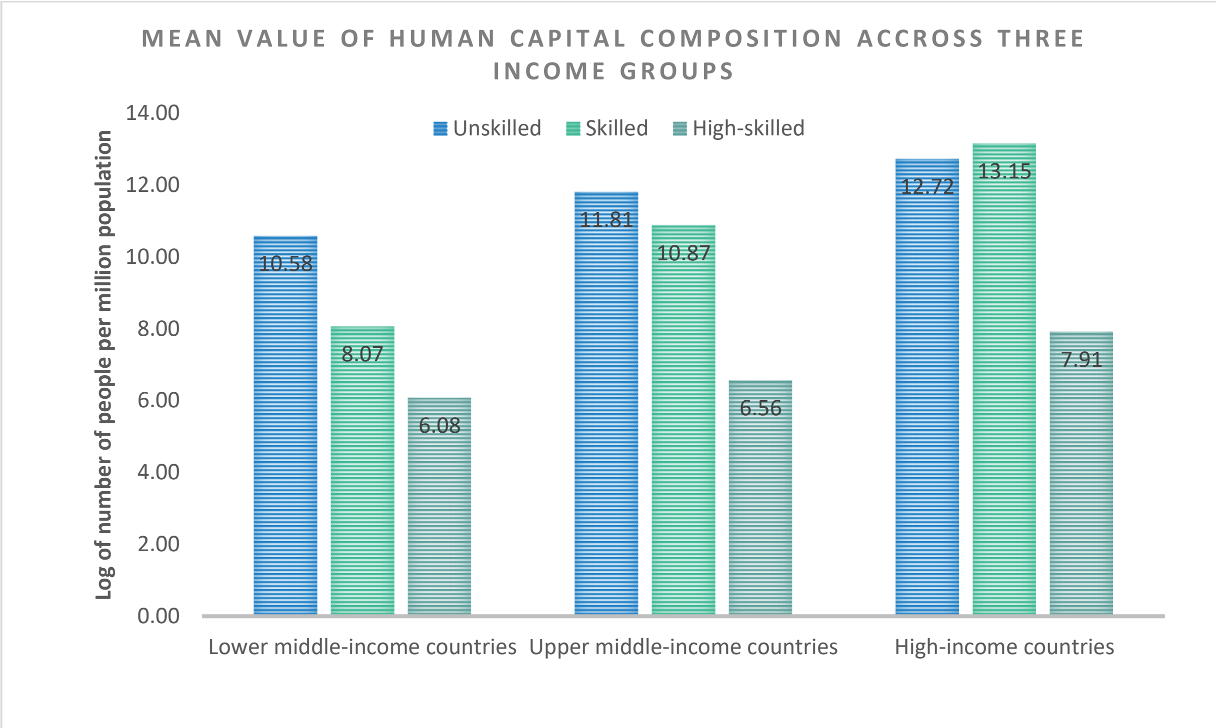

Figure 4.2 Mean value of human capital composition across three income groups.

Source: Author's calculation

Preliminary observation on data show that there exists a positive correlation between human capital composition variables and the innovation output variables. This pattern applies for unskilled, skilled, and high–skilled human capital variables across three income groups. Figures 4.3, 4.4, and 4.5 depict this correlation among human capital composition across LMICs, UMICs, and HICs. This preliminary trend confirms the assumption on that overall human capital brings a positive impact to innovation.

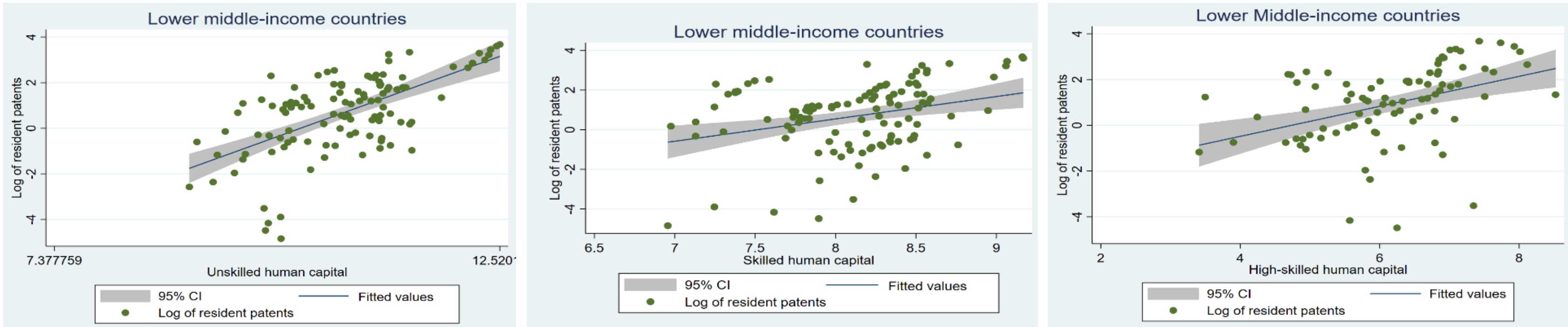

Figure 4.3 Correlations of innovation outputs and human capital composition variables in LMICs

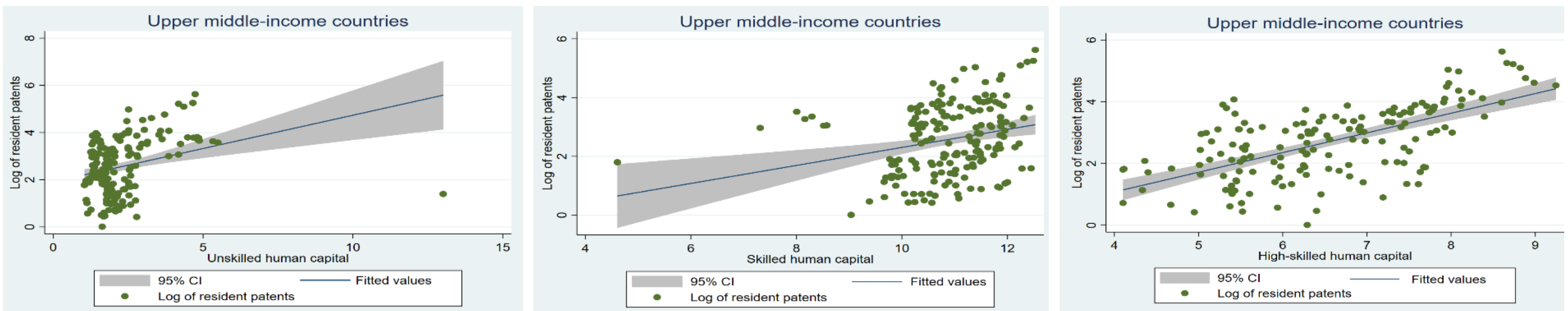

Figure 4.4 Correlations of innovation outputs and human capital composition variables in UMICs

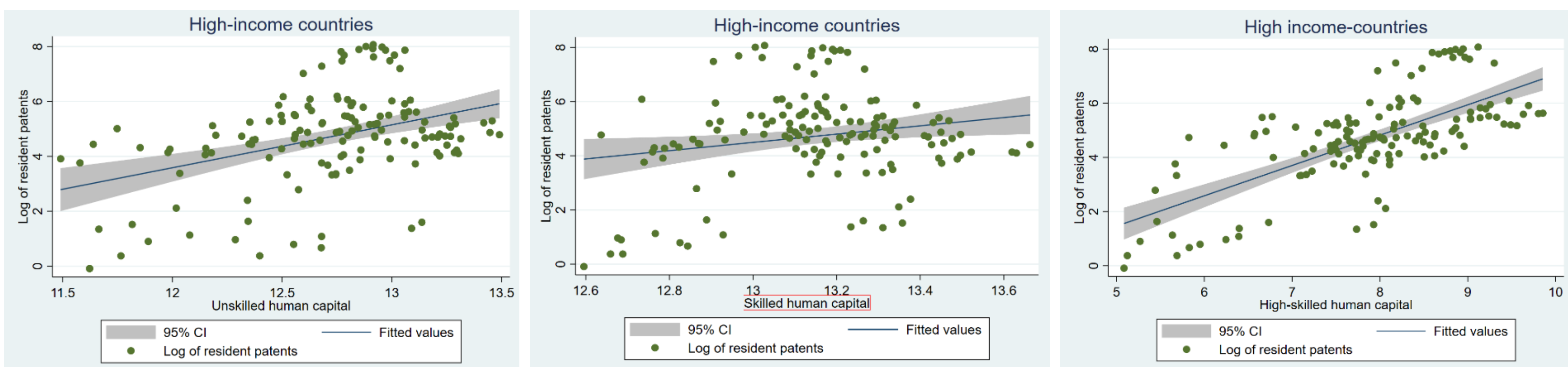

Figure 4.5 Correlations of innovation outputs and human capital composition variables in HICs

Correlation metrics for the variables for each group of LMICs, UMICs, HICs, and a full sample of all countries are described from Table 4.3 to Table 4.6 below. In these matrices, correlation coefficients among variables are lower than 0.8. It is considered that no high correlation coefficients among variables are found. Thus, the concern about potential issues caused by multicollinearity is low.

Table 4.3. Correlation matrix of variables in regressions of LMI group

	lnpat	lnhc_usk	lnhc_sk	lnhc_hs	lnrd	lnfdi	lnimp	inst
lnpat	1.000							
lnhc_usk	0.583	1.000						
lnhc_sk	0.287	0.506	1.000					
lnhc_hs	0.356	0.385	0.193	1.000				
lnrd	0.513	0.626	0.102	0.598	1.000			
lnfdi	0.388	0.524	0.314	0.078	0.512	1.000		
lnimp	0.238	0.405	0.375	0.071	0.356	0.768	1.000	
inst	0.302	0.243	0.107	0.241	0.081	0.025	–0.212	1.000

Table 4.4. Correlation matrix of variables in regressions of UMI group

	lnpat	lnhc_usk	lnhc_sk	lnhc_hs	lnrd	lnfdi	lnimp	inst
lnpat	1.000							
lnhc_usk	0.492	1.000						
lnhc_sk	0.269	0.181	1.000					
lnhc_hs	0.624	0.396	0.332	1.000				
lnrd	0.614	0.210	0.337	0.570	1.000			
lnfdi	0.439	0.210	0.283	0.356	0.433	1.000		
lnimp	0.206	0.147	0.397	0.275	0.248	0.392	1.000	
inst	0.245	0.155	0.252	0.284	0.301	0.300	0.323	1.000

Table 4.5. Correlation matrix of variables in regressions of HI group

	lnpat	lnhc_usk	lnhc_sk	lnhc_hs	lnrd	lnfdi	lnimp	inst
lnpat	1.000							
lnhc_usk	0.378	1.000						
lnhc_sk	0.139	0.618	1.000					
lnhc_hs	0.662	0.367	0.302	1.000				
lnrd	0.710	0.227	0.079	0.681	1.000			
lnfdi	0.528	0.187	0.147	0.419	0.560	1.000		
lnimp	0.239	0.196	0.150	0.436	0.624	0.516	1.000	
inst	0.503	0.005	0.052	0.450	0.482	0.625	0.348	1.000

Table 4.6. Correlation matrix of variables in regressions of all countries

	lnpat	lnhc_usk	lnhc_sk	lnhc_hs	lnrd	lnfdi	lnimp	inst
lnpat	1.000							
lnhc_usk	0.422	1.000						
lnhc_sk	0.319	0.182	1.000					
lnhc_hs	0.723	0.298	0.464	1.000				
lnrd	0.719	0.477	0.152	0.690	1.000			
lnfdi	0.639	0.331	0.392	0.551	0.623	1.000		
lnimp	0.500	0.455	0.078	0.443	0.683	0.578	1.000	
inst	0.643	0.381	0.422	0.606	0.584	0.586	0.439	1.000

4.4.2 Main results

In this section, the analysis of the impact of different human capital skill groups on the innovation capacity of LMICs and UMICs is presented. The results of the Hausman test in Table 4.7 reject the null hypothesis. The chi–square value ranges from 22.10 (LMICs) to 63.62 (UMICs) in those four models, with significant p-values of less than 5% of this test for regressions of LMICs, UMICs, HICs, and all countries. The results of the Hausman tests indicate that the FEM is more efficient for the samples and outperforms the REM in these estimations.

Table 4.7. Results of Hausman tests for FEM vs. REM

	Lower Middle–income	**Upper Middle–Income**	**High–Income**	**All Countries**
Chi–square test value	22.10	63.62	25.58	27.01
P–value	0.037	0.000	0.019	0.012

To confirm the fit of FEM over the Pooled OLS model, the results of F-test for u_i=0, or to confirm the null hypothesis of Pool OLS being more efficient than REM is presented. The results of the F-test and the significant p-values of less than 1% in all models (Table 4.8) support that FEM is more efficient than the Pooled OLS. Thus, the null hypothesis is rejected, and FEM is concluded as more appropriate than Pooled OLS model in this study.

Table 4.8. Results of F-test that all u_i=0 for FEM vs. Pooled OLS models

	Lower Middle–income	**Upper Middle–Income**	**High–Income**	**All Countries**
Chibar2	32.08	18.25	15.41	20.18
P–value	0.000	0.000	0.000	0.000

The results of the estimation by panel FEM are presented in Table 4.9 for four groups of LMICs, UMICs, HICs, and all countries. The results in Table 4.9 show that unskilled human capital is insignificant to all groups of LMICs, UMICs, and HICs. The effect of skilled human capital is only significant and positive for LMICs. On the contrary, high–skilled human capital is statistically significant for UMICs and HICs. In Table 4.9, results of both FEM and REM are presented. Even though FEM is found to be relevant to the dataset of this study, the identical result estimations of both FEM and REM support the robustness of the results.

Lower middle–income countries

In model 1 of Table 4.9, results for the group of LMICs show that among human capital variables, only the skilled human capital of tertiary education completion workforce is statistically significant for innovation capacity (at 1% significance level). The positive and significant coefficient of skilled human capital infers that for LMICs who have just moved away from the low–income level and are still technology followers, to efficiently assimilate foreign advanced technologies and adapt to local conditions, the skilled workforce is the most important. The unskilled human capital of primary and secondary education completion is at the basic education level and is not required for enhancing innovation in LMICs (Manca, F 2012). However, the high–skilled human capital that could promote innovation of new technology might yet to be required. R&D personnel or high–skilled human capital has not shown its importance perhaps because innovation is not yet at the groundbreaking level. Hypothesis 2.1 is confirmed by these results.

The important role of the skilled human capital of tertiary education for LMICs to facilitate the diffusion of technologies echoes the conclusion of Aghion et al. (2009) that in LMICs, the returns to lower–skilled workers is higher than those of high–skilled workers. It is contrary to Ang, Madsen and Islam (2011) who demonstrate that the innovation–enhancing effect of tertiary education attainment is generated only in high–income countries, while it does not contribute to innovation– and growth–enhancing effects in LMICs.

The insignificant role of the unskilled human capital and significant role of skilled human capital in LMICs might be explained by Vandenbussche et al. (2006). They propose that the marginal increase in the unskilled human capital enhances productivity growth when a country is further away from the technology front runner, and tertiary education is increasingly important for growth when a country gets closer to the technological frontier. It is also similar to conclusion by Ang, Madsen and Islam (2011).

The coefficient of FDI–embodied foreign innovation is positive and significant at 1% significance level. The importance of the FDI channel in transferring foreign technologies and knowledge correspond the results of studies by Blyde (2003), Crispolti & Marconi (2005), and Ang and Madsen (2013). The import–embodied foreign innovation is found not significant for

LMICs. The results may reflect that the spillover effect of innovation resulting from foreign trade is limited. It can be assumed that the import channel is not effective in transferring foreign innovation may be due to the lack of matching local absorptive capacity. Reverse engineering effect might not take place in this case, while demonstration effect through FDI might happen.

Table 4.9. Estimation results of human capital composition effects on innovation capacity

Dependent variable: resident patent application (lnpat)	**Model 1: Lower Middle–income**		**Model 2: Upper Middle–Income**		**Model 3: High–Income**		**Model 4: All countries in the sample**	
	FE	RE	FE	RE	FE	RE	FE	RE
Unskilled human capital (lnhc_usk)	0.022 (0.314)	0.032 (0.348)	0.004 (0.097)	0.132 (0.134)	0.283 (0.072)	0.350 (0.481)	0.062 (0.155)	0.007 (0.121)
Skilled–human capital (lnhc_sk)	**1.801***** **(0.443)**	**1.337***** **(0.344)**	0.047 (0.055)	0.002 (0.048)	–0.498 (0.720)	–0.863 (0.805)	0.040 (0.076)	0.049 (0.073)
High–skilled human capital (lnhc_hs)	0.116 (0.151)	0.096 (0.104)	**0.211**** **(0.093)**	**0.259***** **(0.076)**	**0.638*** **(0.354)**	**0.568**** **(0.237)**	**0.297***** **(0.087)**	**0.324***** **(0.078)**
R&D capital (lnrd)	0.154 (0.176)	0.356 (0.222)	**0.306**** **(0.141)**	**0.322***** **(0.124)**	**0.257**** **(0.105)**	**0.345***** **(0.103)**	**0.300***** **(0.093)**	**0.406***** **(0.088)**
FDI–embodied foreign innovation (lnfdi)	**0.302***** **(0.097)**	**0.359**** **(0.150)**	–0.057 (0.099)	–0.067 (0.076)	**0.349**** **(0.143)**	**0.325**** **(0.131)**	**0.156***** **(0.058)**	**0.232***** **(0.056)**
Import–embodied foreign innovation (lnimp)	–0.112 (0.177)	0.001 (0.239)	**0.380**** **(0.176)**	**0.274*** **(0.153)**	–0.189 (0.196)	–0.208 (0.175)	–0.020 (0.125)	0.037 (0.101)
Institutional quality (inst)	0.171 (0.173)	0.207 (0.211)	0.030 (0.055)	0.274 (0.153)	**0.502**** **(0.187)**	**0.410***** **(0.147)**	**0.156*** **(0.106)**	**0.186*** **(0.099)**
Constant	–15.284 (3.090)	–12.891 (3.670)	–2.911 (1.229)	–0.809 (1.791)	4.092 (0.580)	1.911 (0.653)	2.040 (0.944)	–3.532 (0.592)
No. of observations	90	90	174	174	138	138	413	413
No. of groups	17	17	26	26	21	21	63	63
F-test/ WaldChi2	274.99	304.63	36.78	234.81	14.29	407.23	216.00	240.06
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R–squared	0.249	0.364	0.345	0.478	0.555	0.661	0.676	0.730
Country fixed effects	Yes		Yes		Yes		Yes	
Time fixed effects	Yes		Yes		Yes		Yes	

*Coefficients are reported with robust standard errors in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.*

Upper middle–income countries

In model 2 (Table 4.9), results for UMICs show that similar to the LMIC group, unskilled human capital is statistically insignificant to the innovation capacity of UMICs. However, skilled human capital no longer plays an important role in UMICs' innovation level. The coefficient of the high–skilled human capital of R&D personnel is positive and significant to the innovation capacity of UMICs (at 10% significance level in FEM). It can be presumed that UMICs have moved up the income ladder and reached a certain level of innovation capacity, therefore, to foster technological innovations and adopt foreign innovation for UMI group, R&D personnel roles is exceeding the role of unskilled and skilled workers. These results support the finding of Vandenbussche et al. (2006) in which the highly educated workforce is the main driver of growth and innovation. However, it is not completely identical since in this study high–skilled people are considered R&D personnel, while Vandenbussche et al. (2006) consider tertiary education is highly skilled. Similarly in a study using aggregate level patent application data of 17 OECD countries between 1973 and 2006, Furman, Porter, and Stern (2002) conclude that R&D personnel or human capital in the R&D sector is positively significant to innovative capacity. Innovation capacity is driven by R&D manpower. It is contrary to the finding of Ulku (2007) who use aggregate patent and R&D data in 41 countries and find that the increase in the ratio of researchers to total labor forces increases innovation in only the large market of OECD countries. Results of this study confirm Hypothesis 2.2.

High–skilled human capital possesses a sufficient level of skills to exploit the sophisticated tools and techniques, latest technologies and therefore contribute positively to the enhancement of national aggregate innovation capacity. UMICs that need to develop and implement cutting–edge technologies to converge with the high–income group, and HICs that need to maintain their indigenous innovation capability require more R&D personnel. These high–skilled personnel with more technical and specialized education are required for UMICs and HICs. High–skilled human capital might also ease the adoption of new technologies from foreign partners, with sophisticated technology transfers and diffusion.

The coefficient for import–embodied foreign innovation is positive and significant at 5% level. The result of a positive and significant impact of R&D capital stock at 5% level of significance underlies the role of R&D capital stock that are prevalent in empirical studies on economic development. It can be postulated that the innovation spillover effect through imports of high-tech and machinery and its adoption in UMICs require a sufficient level of absorptive capacity. The role of the import channel in diffusing the R&D of foreign partners is similarly concluded by Coe & Helpman (1995) and (2009), Xu & Wang (2001), Crispolti & Marconi (2005), and Ang & Madsen (2013).

The findings of the unimportant of unskilled human capital for LMICs and UMICs confirm hypothesis 2.3. It is also the same as the conclusion of Agénor (2017) that primary and secondary education measures do not matter significantly for innovation capacity. Unskilled human capital with a basic level of capacity to utilize information might be more relevant for imitation in low–income economies than innovation in MIEs.

Expanding the estimation results on the role of the human capital level of education and skills to the group of HICs and all countries in model 3 and 4, the robustness of the results in LMICs and UMICs are confirmed. Unskilled human capital is repeatedly insignificant in regression for both HICs and all countries. For HICs, the high–skilled human capital of R&D personnel is the only important group among the labor force. Its p–value of the coefficient is positive and significant at 10%. Together with high–skilled human capital, R&D capital stock, FDI embodied foreign innovation, and the quality of institution are found vital for strengthening the innovation capacity of HICs. These results confirm the assumption on the role of R&D and institutional quality in most empirical studies for HICs development. While R&D and institutional quality are vastly recognized in the literature for its innovation–enhancing effects, the positive and significant role of FDI–embodied foreign innovation found in this research is not consistent in existing literature. Xu (2000) explains that in the case of HICs, the FDI channel transfers the more complex technology that might require a certain level of human capital quality to absorb and utilize. This condition might yet to be met by UMICs. However, FDI–embodied foreign innovation in HICs might be different from LMICs, in which the technology transfer is less complicated. Besides, the fact that HICs possess a relatively higher quality of governance, and a more stable business environment than LMICs and UMICs might also be a reason explaining a positive and significant FDI–embodied foreign innovation of HICs in this case.

In model 4, estimation for the full sample of all countries that are included in this study (all countries included in models 1, 2, and 3) is conducted. The list of all countries included in model 4 is available in Appendix 4. Estimated coefficients for high–skilled human capital are both positive and significant at 1% significance level. This result implies that high–skilled human capital is more important than skilled and unskilled human capital for the innovation capacity of all countries that obtained the level of middle–income and above.

In conclusion, the results highlight the importance of human capital for national innovation. Both skilled and high–skilled human capital plays a role in innovation capacity in MIEs, while unskilled human capital does not necessarily foster innovation. Skilled human capital is more vital for LMICs, while high–skilled human capital is required for UMICs and HICs. The three hypotheses are supported. One small note for the result of this section is that since the possibility of reverse causality cannot be completely avoided, these results should be interpreted with caution before resulting in policy implications.

4.4.3 Robustness checks

For robustness check, regressions are re–run under different modifications and by using FEM. The various modifications include the estimation without control variables, estimation with alternative measures of the human capital composition of average duration of schooling, and estimation with an alternative measure of innovation capacity using both data on patent applications and utility models. The results confirm the robustness of the estimations in section 4.4.2. The relevance of FEM is confirmed through the Hausman tests.

No control variables

In the first set of robustness checks, only the main variables of human capital composition are included in the FEM. The results of estimations in models 5, 6, and 7 presented in Table 4.10 confirm the robustness of the main results in section 4.4.2 (Models 1, 2, and 3).

Table 4.10. Estimation models without control variables

Dependent variable: resident patent application (lnpat)	**Model 5: Lower Middle–income**	**Model 6: Upper Middle–Income**	**Model 7: High–Income**
Unskilled human capital (lnhc_usk)	0.518 (0.387)	0.008 (0.102)	–0.029 (0.062)
Skilled–human capital (lnhc_sk)	**0.814***** **(0.245)**	–0.044 (0.073)	0.588 (0.358)
High–skilled human capital (lnhc_hs)	0.128 (0.142)	**0.360***** **(0.072)**	**0.523***** **(0.137)**
R&D capital (lnrd)	NA	NA	NA
FDI–embodied foreign innovation (lnfdi)	NA	NA	NA
Import–embodied foreign innovation (lnimp)	NA	NA	NA
Institutional quality (inst)	NA	NA	NA
Constant	–9.660 (3.677)	3.932 (1.512)	–3.482 (4.776)
No. of observations	92	174	144
No. of groups	18	26	21
Wald chi2	37.27	130.52	74.23
Prob > chi2	0.000	0.000	0.000
R–squared	0.393	0.357	0.473
Country fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes

*Coefficients are reported with robust standard errors in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.*

For LMICs, the skilled–human capital proxied by tertiary education completion is the only significant variable (at 1%), with a positive coefficient. For UMICs and HICs, high–skilled human capital is confirmed to be significant (at 1%) to the innovation capacity of those groups. Their positive coefficients imply that the larger number of R&D personnel, the bigger contribution this group makes to aggregate innovation outcomes.

Alternative measures of human capital

The human capital composition can be constructed by the average years of schooling. In the second robustness check, skilled and unskilled human capital is measured by the length of schooling in the Barro and Lee database. The educational variable for unskilled human capital is constructed based on the total length of primary and secondary education of the population over the age of 15. For skilled human capital, the total length of schooling until finishing tertiary education of the population over the age of 15 is counted.

The length of schooling of the population over 15 years of age (average years of schooling of the population over 15 years of age) for each group of primary, secondary, and tertiary education is constructed by Barro & Lee (2013) as follows.

$$S_t^a = \sum_j h_{j,t}^a \, Dur_{j,t}^a \tag{4.5}$$

whereas S_t^a: average years of schooling of age group a (a = 1: 15–19 age group, a = 2: 20–24 age group, …. a = 13: 75 and above) in time t; $h_{j,t}^a$ is the fraction of group a having attained the educational level (incomplete vs complete) j = pri, sec, ter; and $Dur_{j,t}^a$ is the duration in years. Barro & Lee (2013) construct the duration data considering the duration system changes of a country over time based on UNESCO Statistical Yearbooks.

Estimation results using alternative measures of human capital and FEM in Table 4.11 confirm that the main estimation results are robust. The signs of coefficients for human capital composition variables, and patent stock for innovation capacity remain unchanged.

Table 4.11. Estimation models with alternative measures of human capital

Dependent variable: resident patent application (lnpat)	**Model 8: Lower Middle–income**	**Model 9: Upper Middle–Income**	**Model 10: High–Income**
Unskilled human capital (lnhc_usk)	–5.665 (4.114)	1.566 (2.902)	0.032 (0.056)
Skilled–human capital (lnhc_sk)	**7.787**** **(4.031)**	–1.553 (2.938)	0.096 (0.950)
High–skilled human capital (lnhc_hs)	–0.042 (0.099)	**0.235***** **(0.089)**	**0.765***** **(0.199)**
R&D capital (lnrd)	0.343 (0.174)	0.298** (0.131)	**0.208**** **(0.091)**
FDI–embodied foreign innovation (lnfdi)	**0.385**** **(0.157)**	–0.016 (0.079)	0.111 (0.094)
Import–embodied foreign innovation (lnimp)	–0.043 (0.204)	**0.330**** **(0.162)**	–0.066 (0.109)
Institutional quality (inst)	0.178 (0.282)	–0.004 (0.067)	**0.257***** **(0.138)**
Constant	–0.746 (2.007)	1.727 (0.671)	–1.466 (1.647)
No. of observations	82	150	128
No. of groups	16	26	20
Wald chi2	47.62	239.44	328.19
Prob > chi2	0.000	0.000	0.000
R–squared	0.532	0.355	0.681
Country fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes

*Coefficients are reported with robust standard errors in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.*

Alternative measure of innovation capacity

In addition to patent application data, utility model application data from the WIPO[20] is added to reflect the innovation capacity in models 11, 12, and 13. Utility model data is part of the WIPO's intellectual property statistics database available for a wide range of countries worldwide.

[20] https://www3.wipo.int/ipstats/index.htm?tab=utility

Table 4.12. Estimation models with alternative measures of innovation capacity

Dependent variable: resident patent and utility models application (lnpu)	**Model 11: Lower Middle–income**	**Model 12: Upper Middle–Income**	**Model 13: High–Income**
Unskilled human capital (lnhc_usk)	0.077 (0.197)	–0.195 (0.155)	0.032 (0.056)
Skilled–human capital (lnhc_sk)	**0.645**** **(0.257)**	0.040 (0.073)	0.096 (0.950)
High–skilled human capital (lnhc_hs)	0.128 (0.109)	**0.432***** **(0.142)**	**0.765***** **(0.199)**
R&D capital (lnrd)	0.506 (0.191)	0.251 (0.180)	**0.204*** **(0.124)**
FDI–embodied foreign innovation (lnfdi)	**0.811***** **(0.136)**	–0.027 (0.145)	0.111 (0.094)
Import–embodied foreign innovation (lnimp)	–0.105 (0.258)	0.289 (0.183)	–0.066 (0.109)
Institutional quality (inst)	–0.402 (0.200)	–0.055 (0.086)	**0.257**** **(0.138)**
Constant	–6.717 (3.372)	–0.055 (0.088)	–1.466 (1.647)
No. of observations	90	174	138
No. of groups	17	26	21
Wald chi2	184.94	294.02	328.19
Prob > chi2	0.000	0.000	0.000
R–squared	0.553	0.474	0.681
Country fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes

*Coefficients are reported with robust standard errors in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.*

Utility models are a form of patent–like protection for minor or incremental innovations. Utility models are closely related to the patent system however it is applied to discoveries that are not enough inventive or do not bring high enough level of novelty. The utility model applications data of each country for a given year are constructed by summing up all utility applications of resident inventors. The main estimation results shown in Table 4.12 confirm that the signs of coefficients for human capital composition variables, and innovation capacity remain unchanged.

4.5 Conclusion

Investment in human capital is paramount to speed up a country's development. Defining appropriate priority in human capital investment according to stages of development would facilitate the convergence journey more efficiently. Contributing to this topic, this study examines the role of human capital composition at a different level of skills to innovation at aggregate level of MIEs and above. The three categories of high–skilled human capital proxied through the number of R&D personnel, skilled human capital proxied through tertiary education, and unskilled human capital proxied through primary and secondary education are used to estimate the innovation–enhancing effect of the human capital composition. To the best of the author's knowledge, this is the first paper examining the impact of human capital composition on innovation at the aggregate level and the first paper using the combination of these three human capital variables. A panel of data of 65 countries covering three income levels of LMI, UMI, and high–income throughout 1985–2019 is used.

Results show that the innovation capacity enhancing effects of high–skilled human capital increase when countries reach UMI and HI levels. It implies that UMICs and above if concentrating on fostering the R&D personnel who are directly involved in the innovation process will be able to elevate the level of innovation capacity. UMICs, those that move closers to the technological frontier, should invest more to enlarge the pool of high–skilled R&D personnel. Imports of foreign technologies are found to be significant for UMICs. For high–income countries, the quality of institutions and foreign innovation spillover through FDI plays a vital role. R&D capital stocks are crucial for both UMICs and HICs. However, since the possibility of reverse causality cannot be excluded, the result implications above should be taken with caution.

For LMICs, the skilled level of human capital is found to be the most important part of the workforce that contributes to innovation capacity enhancement. By contrast, R&D personnel of high–skilled human capital is not contributing to the innovation capacity of LMICs. Given the assumption that innovation activities of LMICs are mainly from adopting foreign technological progress else where, this finding suggests that the larger pool of skilled–level workforce, the more positive results of innovation outcomes are yielded. LMICs should continue to invest in having a higher number of adults who complete tertiary education. Aside from human capital, the study also confirms the role of FDI–embodied innovation to strengthen the innovation capacity of LMICs.

Unskilled human capital is confirmed to not play an important role for both middle–income and high–income countries in fostering innovation capacity. However, obtaining the basic level of education of secondary education at the minimum would be the prerequisite for continuing study at higher levels.

Policies for the development of human capital for innovation if considering the importance of each level of human capital composition at each level of economic development might result in the more efficiently use of the limited resources.

Chapter 5 Impact of Competition from Informal Firms on Innovation of Formal Manufacturing Firms in MIEs

5.1 Introduction

The informal economy is a notable phenomenon of emerging and developing economies (Dabla-Norris, Gradstein and Inchauste 2008). The informal economy represents a significant share of output and employment in middle–income economies (MIEs) with many economic activities occurring. Estimated size of the informal economy being compared with the official GDP shows that nearly 30% of the GDP in Latin America, more than 50% in India, and over 60% of the total GDP of Sub–Saharan Africa are coming from the informal economy (Charmes 2016). The International Labor Organization (ILO) (2018) estimates that more than 60% of the world's employed population, or 2 billion workers worldwide, earn their livelihoods in the informal economy. Region–wise, 85.8% of African workers, 68.2% of Asian and Pacific workers, and almost 40% of American workers are employed in the informal economy. The proportion has continued to grow in recent decades (Charmes 2016). In studying the innovation of an economy, especially MIEs, it is critical to recognize the existence of a dual–economy system. Even though the informal sector has been considered as a sector bringing negative effects, there is a counterargument that this sector is a crucial component of the economy, in both employment and wealth creation.

The informal economy exists in all countries regardless of the level of socio–economic development. However, the ILO (2018) estimates that the level of socio–economy development is positively correlated to the size of formality. More specifically, MIEs and low–income countries have higher shares of informal employment than high–income countries (69.6% vs. 18.3% of the employed population) (ILO 2018). MIEs and low–income countries represent 82% of world employment, but 93% of the world's informal employment is in these countries. Aside from the large share of informal employment, the large informal economy might also imply the coexistence of numerous informal sector firms (Fu, X. , Mohnen, P. and Zanello 2018). Formally registered firms must therefore compete against informal producers (Mendi and Costamagna 2017). The World Bank Enterprise Survey (WBES) reveals that the competitive behavior of informal enterprises is one of the top three obstacles formal businesses face (Distinguin, Rugenmintwari and Tacnegn 2016, Mendi and Costamagna 2017, Avenyo, Konten and Mohnen 2021).

The severe competition stemming from informal firms might constrain formal firms' choice of innovation strategies and outputs (Mendi and Costamagna 2017). Williams and Bezeredi (2018) also suggest that unfair competition from the informal sector brings a negative impact on formal firms' performances. Innovation mainly happens at the firm–level and mainly in formal firms (Shekar 2021), because only the formal sector firms possess strong capabilities and resources for innovation activities (Charmes 2016). The impact of informal competition on innovation activities of formal firms is therefore vital to study. Besides, the issue of informal competition is further exacerbated by the limited law enforcement in MIEs (Distinguin, Rugenmintwari and Tacnegn 2016). Policymakers, for the purpose of job creation, might cautiously intervene in regulating the informal economy. Considering the size of the informal economy in developing countries, it is more critical for scholars to explore different ways in which formal and informal firms innovate, interact, and the impact it has on growth of an economy (Fu, X. , Mohnen, P. and Zanello 2018).

Innovation has been assumed to be a driver of economic growth in MIEs and contributes largely to cross country differences in per capita incomes (Hall and Jones 1999). Despite a noticeable upsurge in the number of studies on informal competition consequences, empirical evidence on the impact of informal competition and innovation remains insufficiently analyzed (Shekar 2021). Mendi and Costamagna (2017) review that the economic implications of competition caused by informal enterprise activities are under–researched in literature. Among the limited number of studies, the existing analyses tend to focus on a limited number of countries, on a specific region, or limited by the type of firms like only SMEs. There has been no cross–country study focusing on firms of middle–income countries on the large scale. More thorough studies to bring more insights into the impact of informal sector on formal sector firms in middle–income countries are required.

Motivated to bridge the research gaps above, this study utilizes the large dataset of the World Bank Enterprise Surveys (WBES) of 68,568 manufacturing firms in 92 countries between 2006 and 2019. This research aims to make the following contribution to the existing literature. First, it extends the empirical results and gives more insights into the inconclusive debate of whether informal economy and the competition caused by informal firms are beneficial or detrimental to firms' innovation activities. The empirical evidence from studying a large scale of 68,568 manufacturing firms in 92 MIEs also brings implications for the innovation strategy of firms in MIEs to stay competitive in the market. Second, the study findings will provide useful inputs for policymakers in MIEs to deal with the phenomenon of informal competition while enhancing innovation of a country. The research question is formulated as: ***"How does the competition caused by informal firms affect the innovation of formal manufacturing sector firms in MIEs?"***

The results of this study show that informal competition brings a positive and significant impact on the innovation outputs of formal firms. It confirms the escape–competition effect in which the informality incentivizes formal firms to innovate in MIEs. The main conclusion stays valid when being checked by the alternate measure of informal competition and alternate measure of innovation activities. Besides, when disaggregating the sample of manufacturing firms in MIEs by region, the main results remain unchanged and confirm the robustness of the estimations. The rest of the paper is organized as follows. Section 5.2 introduces the background of the informal economy, the informal competition caused by unregistered firms, and its impact on the formal firms' innovation. Section 5.3 presents the research strategy to examine the research question and test the hypothesis. Section 5.4 describes the main empirical results and the robustness checks of the estimations. Section 5.5 concludes the paper.

5.2 Literature review

In this section, a basic understanding of and approaches to the phenomenon of the informal economy, the competition between registered and unregistered firms, and the impact of such competition on the innovation activities of formal firms are discussed.

5.2.1 Informal economy

The informal economy is a specific area of economic activity that has emerged in all countries. In developing countries, the informal economy phenomenon is more prevalent and represents a significant part of these economies. Over the last four decades, the economic and social roles of the informal economy for growth and employment have attracted significant attention from academic and policy studies, especially in developing countries.

Despite a growing literature on the term "informal economy" and its causes and effects, there isn't any commonly agreed definition and measurement for this concept as reviewed by Schneider (2005), Choi and Thum (2005), Buehn & Schneider (2012), Schneider and Enste (2013), and Lee, Alba and Park (2018). Fleming, Roman and Farrell (2000) review that economic activity falling outside the purview of government accounting is known by various names such as shadow, informal, hidden, underground, gray, and parallel economy. Despite decades of study on the issue, little agreement has been reached on the concept of the informal economy. Fleming, Roman and Farrell (2000) explain that the differences in the definitions of the informal economy stem from different research objectives and the different contexts of the informal economy. Overall, the informal economy might be defined in terms of the number of employments or based on the estimated value of the informal economy in comparison with and as a percentage of the official GDP.

The ILO looks into the employment aspect of the informal economy by defining the informal sector in 1972, then in 1993, and in 2002. To define the informal economy, the ILO (2002) refers to *all economic activities by workers and economic units that are in law or in practice not covered or insufficiently covered by the formal arrangement*. The ILO (2018) provides statistical profiles of the informal economy at the global level focusing on the *measures of informal employment and employment in the informal sector* for more than 100 countries. Their statistics on informal employment are disaggregated by sex, age, level of education, status in employment, and other socio–economic characteristics. The informal economy does not cover illicit activities according to the ILO (2018).

Defining the informal economy based on employment measures is not the only focus. Economists, statisticians, and policymakers are also interested in economic activity more generally. There are other definitions that focus on activities that involve the provision of goods and services in exchange for remuneration, but which are not covered or insufficiently covered by formal arrangements (Charmes 2016). In addition, other terms such as shadow economy, hidden economy, gray economy, black economy, unofficial economy, underground economy, or cash economy are also used to refer to the phenomenon of informal economy by different scholars. Schneider and Enste (2000), Choi and Thum (2005), La Porta and Shleifer (2014), Buehn & Schneider (2012), Lee, Alba, and Park (2018), Medina and Schneider (2018) use the broad working definition of the shadow economy, or informal economy that cover all unregistered economic activities contributing to the GDP but is unreported officially even though it should be added to the calculation of the GDP. Schneider & Enste (2000) and Schneider (2005) specify that *the informal economy includes all market–based production of goods and services that are deliberately concealed from public authorities to avoid payment of income, value–added, or other taxes; to avoid payment of social security contributions; to avoid having to meet certain legal labor market standards, such as minimum wages, maximum working hours, safety standards, etc.; and to avoid complying with certain administrative procedures, such as completing statistical questionnaires or administrative forms.* Similar to the approach of the ILO, this definition does not include economic activities that violating the penal codes as highlighted by Buehn & Schneider (2012). In this research, the approach to define and measure the informal economy of Schneider (2005) is adopted.

From the angle of motivation of firms to operate in the informal economy, the emergence of informal economy might either be a strategy of last resort to escape poverty or a voluntary choice to exit from the formal economy to reduce taxation and regulation burden (Dell'Anno 2021). A two–lens framework by the World Bank (2007) also focuses on either firms' exclusion from the governments' benefits or voluntary exit decisions based on cost–benefit calculations. In the former case, due to the insufficient number of employments in the formal sector, employment has to go into the informal sector. Firms like the micro, small and medium enterprises (MSMEs) with too few numbers of paid employees, or under a certain size of threshold that produce goods and services for sale are not able to register in the formal sector is another example. MSMEs are not counted as part of the formal economy and are not regulated by the law (WIPO 2013). Schneider and Enste (2013) explain that informal employment is not covered by law due to short contracts, or casual jobs, or below the threshold for social protection. In this case, "exclusion" is the reason for the existence of an informal economy. Informal economic activities could be considered legally exempt categories of productive activities. In the latter case of voluntary choice, Maloney (2004) and Dell'Anno (2021) reason that to avoid legal, registration, and tax system burden, voluntary entrepreneurial small firms choose to stay out of the formal economy. Kanbur (2017) explains that entrepreneurs require capital to pay startup costs and employment tax, and some might opt to not register to avoid these costs. The World Bank (2007) terms this approach as an exit approach, in which firms choose their level of engagement with the institutions of the government depending on their judgment of the benefits gained from the formality and the government effort and capability of enforcement.

At the firm level, over half of enterprises globally are shown to operate on an unregistered basis (Williams and Bezeredi 2018). However, there is no widely accepted definition for informal firms. Fu, Mohnen and Zanello (2018) summarize that scholars have used different criteria such as based on firm size, status of registration, social security contributions of employers, legal forms of organization, or characteristics of financial account to refer to the informal firms.

Charmes (2012) and Routh (2022) reason that since varied economic activities do not resemble the characteristics of orthodox contractual waged employment, they are termed informal. Hart (2006) elaborates that the term informal is used to highlight economic activities that are not organized in the same institutional form like of the industrial production process characterized by formal employment contract. Buehn and Schneider (2016) explain that the shadow economy includes economically legal but hidden activities. Informal economy is not prosecuted in many countries even though certain regulations and administrative rules are ignored, or not enforced. Supporting this view, the ILO defines informal economy as economic activities that operate outside the law because of the lack of formal legal coverage or because of the law is not enforced (ILO 2002). Additionally, authors such as Azuma and Grossman (2008) emphasize that it is the choice of a policy due to the inability of the state. Therefore governments, especially in middle–income ones are tolerating informal economy.

5.2.2 Impact of competition from informal firms on innovation activities of formal firms

While firms in the informal economy are typically small, inefficient, unproductive and stagnant (La Porta and Shleifer 2014), they focus mostly on the short–run and invest less on innovation as specified by Eilat and Zinnes (2002), Fu, Mohnen, and Zanello (2018), and Kraemer–Mbula and Wunsch (2016). Innovation is likely to happen in the firms of the formal sectors, with stronger capabilities and resources for innovation activities (Charmes 2016). Formal firms might also have more human and capital resources for innovation activity collaborations with other firms including foreign institutions. This difference in innovation capabilities and investment between firms in the formal and informal economy shapes the innovation adoption and diffusion landscape. Innovation strategies of formal firms under the impact of informal economy firms are vital to the aggregate innovation level of a country.

The existence of the informal economy might cause severe competition between formal and informal firms as both are competing for the same customer and resources (McGahan 2012). The competition might be found through prices of products because firms in the informal economy has lower entry costs than firms in the formal sector as explained by Aveyno, Konte and Mohnen (2021). In support of this argument, Williams and Bezeredi (2018) specify that informal firms despite being inefficient compared with formal firms, with cost advantage from evading taxes and regulatory obligations, avoidance of social insurance contributions, and lower entry cost, could undercut prices of more productive competitors, stay in business and compete with formal sector firms on price. Through price competition, the informal sector firms bring unfair competition to formal firms and might hurt the performance of formal firms. Williams and Bezeredi (2018) provide evidence from a study on firms of three South–East European countries. In their studies, enterprises who state that their competitors participate in the informal economy have significantly lower annual sales growth rates compared with those who do not report informal economy competition. Mendia and Costamagna (2017) also view that formal firms operating in an environment of widespread informal firms are likely to be negatively affected by the competition from informal firms. On the contrary, the fear of losing market share to informal competitors might force firms to cut costs, improve management practices, improve training, and improve the use of labor to enhance the firm performance. In this case, it might be presumed that the formal firms are pressured by informal competitors like by other competitors from the formal economy as in the explanation of Nickell (1996).

In terms of innovation, the competition stemming from the presence of firms operating in the informal economy might constrain formal firms' choices of innovation strategies and its innovation activities (Eilat and Zinnes 2002, Mendi & Costamagna 2017, Shekar 2021). It will then affect formal firms' innovation outputs captured in innovation statistics of patent counts (Fernández, Velasco and Fanjul-Suarez 2018). In the case where competition brings a negative effect on innovation, scholars term it as "Schumpeterian effect" (Avenyo, Konte and Mohnen 2021). However, there are cases where competition has a positive effect on innovation and is termed as "escape–innovation effect" as elaborated in Aghion et al. (2001). Analysis on the impact of informal sector competition on formal sector innovation using firm-level data are inclusive in proving either "Schumpeterian effect" or "escape–competition effect" (Avenyo, Konte and Mohnen 2021).

On one hand, analyzing the negative impact of informal competition on innovation efforts, (or the "Schumpeterian effect"), Schumpeter (1942) reasons that less competition might reduce the uncertainty associated with rivalry between competing firms, increasing the results of R&D investment and its return-on-investment rate. On the contrary, higher competition might result in lower innovation efforts by firms in different ways. First, firms in the formal economy are forced to compete against informal firms for the same resources. The constraints on resources then limit their innovation choices (Mendi and Mudida 2018). Second, via competition in the product market, informal producers may disrupt formal firm's innovation activities and their innovation decisions (Eilat, Y and Zinnes, C. 2002). Empirical results supporting the argument that the presence of informal economy might dampen innovation include the ones of Mendi and Costamagna (2017). They test the effect of competitive pressure caused by informal producers on the likelihood of formal firms introducing new products and processes, as well as explore the impact on formal firms' resource allocation for innovation activities. They find that formal firms are likely to be negatively affected by the activities of informal firms. The presence of the informal sector alters the potential payoff from innovation and incentives for formal firms to innovate. Mendi and Mudila (2018) also view that competition with firms in the informal sector negatively influences the introduction of innovative products and processes, especially when the informal firm's products are close substitutes for those of formal firms.

Opposite to the "Schumpeterian effect" is the "escape–competition effect" as termed by Aghion et al. (2001). The escape–competition effect refers to the situation in which the increased competition serves as an incentive to escape market rivalry by stimulating innovation activities (Aghion, et al. 2001). The fear of losing market share to informal firm may lead formal firms to invest more in innovation, introducing new or improved products and processes. In this case, the increased competition results in more incentive to invest (Aghion, et al. 2001). More intense competition might increase incremental profits from innovation and thereby encourage R&D investment. However, Aghion et al. (2001) also emphasizes that it might apply in industry with similar technologies and equally efficient only. Empirically, competition with informal firms in product markets might affect formal firm's decision to innovate, or to introduce new and innovative products and processes according to Mendi and Costamagna (2017), Fernandez et al. (2018), Aveyno, Konte and Mohnen (2021) and Shekar (2021). Findings by Aveyno, Konte and Mohnen (2021) show that informal sector competition pressurizes firm to innovate more, differentiate their product and reduce cost to remain competitive on the market. They also note a positive impact on formal firms' R&D investment by the informal sector competition. Shekar (2021) similarly suggests that through competition with the informal sector, formal sector enterprises are incentivized to innovate, or the impact of escape competition effect is found.

The controversy of whether the impact of informal competition on innovation of formal firms is negative or positive remains inconclusive. Studies examining the impact of informal competition on innovation of firms using firm–level dataset tend to focus on specific country, or region, or SMEs. Among those, Mendi and Costamagna (2017) estimate the effects of informal competition on the likelihood of formal firms' innovation in Africa and Latin America. Amin (2021) conducts a preliminary study on the impact of informal competition on the likelihood of R&D spending by firms in a large number of countries. However, it is limited only to SMEs. Aveyno, Konte and Mohnen (2021) analyze the impact of informal market competition on product innovation of firms in Sub–Saharan Africa. To expand the empirical findings on this on–going debate, this study explores a larger dataset of manufacturing firms in a bigger number of countries.

In the context of MIEs who are considered technological laggards and need to catch up with leading–edge technologies from the technological frontier, Aghion et al. (2001) specify that competition might be outweighed by the increased incentive for firms to innovate for the purpose of escaping competition. In this case, competition yields a positive effect on innovation and growth. Similarly, Shekar (2021) elaborates that in low technological industries that are prevalent in MIEs, the growing competition acts as an incentive for escaping market competition. Based on these arguments of Aghion et al. (2001) and Shekar (2021) which take into account the innovation characteristics of MIEs, despite the mixed empirical evidence on whether the "Schumpeterian effect" or "escape–competition effect" occurs, I assume that with the focus on MIEs, the observations of Aghion et al. (2001) and Shekar (2021) might be applicable in this study. The following hypothesis is made.

Hypothesis*: The competition caused by informal firms induce innovation of formal manufacturing firms in MIEs.*

To confirm the hypothesis, in the next section, the strategy to study the impact of informal competition by unregistered firms and innovation activities of manufacturing firms will be detailed.

5.3 Research strategy

In this section, the sources of data, construction of variables, and the estimation methodology employed in this study are presented.

5.3.1 Data

The study utilizes the World Bank's Enterprise Survey (WBES) data. The WBES covers a large number of firms in more than 100 countries, mainly the developing ones. Even though the WBES focus is not on innovation and informal competition, it includes questions to provide information on level of obstacles caused by practices of firms in the informal sector to formal firms' activities, and information on whether a firm introduced any new product or services within three years, or new product and services that are also new to the main market of the firm. For this study, a dataset containing 68,568 manufacturing firms from 92 middle–income countries between 2006 and 2019 extracted from the WBES is used. A list of countries in MIEs, both LMI and UMI groups is presented in Appendix 5. There are 47 countries belonging to the LMI category, and 45 countries belonging to the UMI category. Data of WBES are supplemented by other dataset such as the World Development Indicators by the World Bank, the Economic Freedom of the World dataset by the Fraser Institute, and the human capital dataset by Barro and Lee (2013) and its online updates until 2021.

5.3.2 Estimation methodology – Probit regression

To quantify the impact of informal competition on the innovation activities of formal firms in MIEs, the estimation equation is formulated below.

$$inno_{ij} = \alpha + \beta_1 ifc_{ij} + X_{ij} + Y_j + year + ind + region + \varepsilon_{ij} \tag{5.1}$$

in which i denotes firm, j denotes country to which a firm belongs; dependent variable of $inno_{ij}$ denotes innovation activities of firm i; ifc_{ij} proxies informal competition that formal firm i of country j face from the informal sector firms; X_{ij} include firm characteristics control variables; Y_j includes country–specific control variables; $year$ captures the year fixed effects (a set of dummy variables for the survey year); ind captures industry fixed effects (set of dummy variables for the manufacturing subsector to which a firm belongs); $region$ captures specific characteristics of region where a firm belongs; and ε_{ij} is error term. Constant term is also included in the estimation.

Since the dependent variable is binary, the maximum likelihood probit model is employed in these estimations for MIEs following Distinguin, Rugenmintwari and Tacnegn (2016), Mendi and Costamagna (2017), Khatiwada and Arao (2020), and Amin (2021).

5.3.3 Variables

Dependent variable

The innovation activities of firms in this study are measured by the introduction of new products and/or new services that are also new to the main market of the firm. The WBES includes a question of whether a firm introduced any new or significantly improved products or services within 3 years prior to the survey, and whether the firms introduced new products or services that are also new to its main markets. In the former case, even though it is an innovation to a firm, the same might have been introduced by other firms. This type of innovation is the lowest degree of novelty. In the latter case, when a firm introduces new products or services that are also new to the market the level of novelty is higher compared with the first case. Thus, answers of firms to this question are used to proxy innovation activities of firms.

Explanatory variables

Capturing the magnitude and impact of the informal sector and its competition with formal firms is not easy because of its intrinsic nature. The WBES ask firms if they compete against informal sector firms by answering yes or no, and if the practices of competitors in the informal sectors present no obstacle, minor obstacle, moderate obstacle, major obstacle, very severe obstacle to the firm's operations. However, responses to these questions cannot be used directly as they are likely to be endogenous to the responses of whether the firm spends on R&D activities. To mitigate this endogeneity issue, the approach of cell average of informal competition to formal firms might offer a solution. The competition between formal firms and informal firms is proxied through the proportion of all other formal firms in the same cell (such as same country or industry) that compete against informal firms (Distinguin, Rugenmintwari and Tacnegn (2016), Mendi and Costamagna (2017), Aveyno, Konte and Mohnen (2021), Amin (2022)). The use of cell average might also limit potential measurement errors caused by missing data (Amin 2022). Country–

average level of informal competition is used in this study because manufacturing firms that are located in the same country are presumed to face a similar level of competition intensity caused by unregistered firms. The technique of using the proportion of firms in the same country that competes against informal firms to proxy the informal competition level is also applied by Distinguin, Rugenmintwari and Tacnegn (2016) who utilizes WBES data to analyze how informal competition affects access to finance of formal firms, or Mendi and Costamagna (2017) who assess the impact of informal competition on firms' performances, or Amin (2022) who examines the effect of informal competition on employment growth.

Control variables

The R&D investment of a firm is one factor affecting the introduction of new products or new processes. Besides, the coexistence of informal and formal economy might limit resources and investment in innovation of firms in formal economy as explained by Mendi & Mudida (2018). A variable for the R&D activity of a firm is constructed by utilizing the answers of the WBES to the question of whether a firm conducted R&D activity in the last fiscal year. A dummy variable of *rd* valued one if a firm has spent on R&D activity in the last fiscal year and valued zero otherwise proxies for R&D activity of firms.

The study also takes into account the observable firm characteristics as control variables such as size, age, whether a firm belongs to a group of firms (affiliation), export revenue as a percentage of total revenue, foreign ownership of the firm, access to finance, and manager's experience. Amin (2021) reasons that large firms and firms with greater market power are more likely to invest in innovation activity. Larger firms benefit more from economies of scale and scale of innovation investment while having more resources for innovation. On the contrary, small firms are advantageous on the efficiency in performing innovation activity (Amin 2021). A firm's age is also assumed to link to innovation activity based on the assumption that only efficient firms grow and survive over time. Older firms also have more experience and knowledge accumulated. However, young firms might incline to take risks and explore new ideas more than organizational rigid old firms. Whether a firm is affiliated to larger establishment might affect its access to technology, know–how, market information, human resources within the group and therefore affect innovation activities. Exporting firms operate in a more dynamic and competitive market. Hence, it might matter to the motivation to innovate of firms, whether they are exporters.

Exporting markets create a better learning opportunity for new technologies or divide the innovation investment over a larger market of domestic and foreign ones. Firms with foreign ownership might have better access to new technologies, greater access to foreign markets, or benefit more from foreign spillover effects to incentivize innovation. Therefore, the proportion of a firm's ownership by foreign partners is included as one control variable. Better access to finance in general also matters to innovation decisions. Data extracted from the answer to the question indicating whether a firm has an overdraft facility is used as one control variable for this purpose. In terms of access to finance, a certain level of overdraft facility given to a firm would stimulate its performance and productivity, as well as investment in R&D. Overdraft facility as used in the WBES refers to a flexible account that allows firms to draw upon in the event their account balance becomes negative (Laborda Castillo, L. and Salem, D. 2013). It is also presumed that the higher the industry–specific experience of the top manager, the higher the likelihood of innovation for the firm.

Additionally, a set of country characteristic variables such as institutional quality regarding rules of law, business regulations, IPR protection, government effectiveness affect a firm's innovation as concluded by Fu, Mohnen and Zanello (2018). The availability of human capital in a country and its quality is likely to have a positive impact on the innovation effort of firms. A country's level of economic development (proxied by its GDP per capita), or its market size (proxied by its population) also matters to the firms' innovation. To limit the effect of potential endogeneity issues, these variables are proxied by country–level data variables by the World Bank WDI, the Fraser Institute, and the database of Barro and Lee (2013) updated in 2021.

The WBES data are collected in different years with different intervals across countries. The potential effect of an annual global shock to innovation activity is accounted for by including dummy variables indicating the year the WBES was conducted in a particular country (year fixed effects). Industry dummy variables of 21 sub–manufacturing sectors[21] are also included.

[21] Manufacturing sub-sectors include (1) Manufacture of food products and beverages, (2) Manufacture of textiles; (3) Manufacture of wearing apparel; (4) Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness, and footwear; (5) Manufacture of wood and of products of wood; (6) Manufacture of paper and paper products; (7) Publishing, printing and reproduction of recorded media; (8) Manufacture of coke, refined petroleum products; (9) Manufacture of chemicals and chemical products; (10) Manufacture of rubber and plastics products; (11) Manufacture of other non–metallic mineral products; (12) Manufacture of basic metals; (13) Manufacture of fabricated metal products, except machinery and equipment; (14) Manufacture of machinery and equipment; (15) Manufacture of office, accounting and computing machinery; (16) Manufacture of electrical machinery and apparatus; (17) Manufacture of radio, television and communication equipment and apparatus; (18) Manufacture of

Innovation intensity varies across different industry sectors (industry–fixed effects). Similarly, region control dummy variables are included to count for factors associated with differences across regions where firms are located (region–fixed effects). The summary of variables, its definition, and data sources is presented in Table 5.1.

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medical, precision and optical instruments, watches and clocks; (19) Manufacture of motor vehicles, trailers and semi–trailers; (20) Manufacture of other transport equipment; (21) Manufacture of furniture; and (22) Other manufacturing.

Table 5.1. Summary of variables and data sources

Variable	Explanation/ Definition	Data source
Dependent variable		
Firm innovation (inno)	A dummy variable valued one if the answer is yes and valued zero otherwise to the following question of whether a firm as new product/service that is also new to the establishment's main market.	World Bank Enterprise Survey[22] (WBES) 2006–2019
Independent variables		
Informal competition (ifc)	Country–level average of informal competition faced by formal firms (cell average method following Amin (2021). It is proxied by the proportion of all other formal firms in the same cell (country) that report competition against informal firms.	WBES 2006–2019
Firm characteristic control variables		
R&D activity (rd)	A binary variable valued one if the firm spent on R&D activity during the last fiscal year and valued zero otherwise.	WBES 2006–2019
Firm age (age)	Number of years since its establishment.	WBES 2006–2019
Firm size (log value) (lnfsize)	Natural log of the total number of permanent, full–time employees at the last fiscal year.	WBES 2006–2019
Affiliation to larger establishment (affi)	A binary variable valued one if the firm is part of a larger firm and valued zero otherwise.	WBES 2006–2019
Managerial experience (mag_exp)	Number of years of working experience in the sector that the top manager has.	WBES 2006–2019
Export (expo)	Percentage of sales of direct exports.	WBES 2006–2019

[22] Data of the WBES on question h2 is used to construct the variable of *inno,* question h8 for the variable of *rd,* question a7 for the variable of *affi,* question d3c for the variable of *expo*, question b2b for the variable of *fore,* question k7 for the variable of *fin.*

Variable	Explanation/ Definition	Data source
Foreign ownership (fore)	Proportion of firm's ownership that is with individuals or foreign organizations. The answer is extracted from the question of percentage owned by private foreign individuals, companies or organizations.	WBES 2006–2019
Access to finance (fin)	A binary variable valued one if the firm answers yes to the question of "Does this establishment have an overdraft facility?", and valued zero if the firm answers no.	WBES 2006–2019
Country specific control variables		
Population (log value) (lnpop)	Natural log of population of a country.	WDI
Institutional quality (inst)	Quality of institutions in an economy, measured through the legal structure and intellectual property rights (IPR) protection index.	Economic Freedom of the World
Skilled human capital (log value) (lnhc_sk)	Natural log of the number of people above 15 years of age attained tertiary education level per million population.	Barro & Lee (2013) and its online updated dataset until 2021
Year specific control variable		
Year fixed effect (year)	Year dummies.	WBES 2006–2019
Industry specific control variable		
Industry fixed effect (ind)	Dummy variables of manufacturing sub-sector following ISIC 2–digit level classification (22 subsectors).	WBES 2006–2019
Region specific control variable		
Region fixed effects (region)	Dummy variables proxying 6 regions that the firm is located: AFR (Africa), EAP (East Asia and Pacific), ECA (Eastern Europe and Central Asia), LAC (Latin America and Caribbean), MNA (Middle East and North Africa), SAR (South Asia).	WBES 2006–2019

5.4 Empirical results

The estimation results based on the probit model showing the impact of competition caused by informal firms on the innovation activities of formal manufacturing firms in 92 MIEs are presented in this section. The robustness of the results is tested with an alternate dependent variable, a different measure of informal competition, and by using the logit model.

5.4.1 Descriptive statistics

Summary statistics of the variables used in the analysis for formal manufacturing firms in MIEs are shown in Table 5.2. The correlation matrix of all variables is presented in Table 5.3. For each variable, the number of observations, its average, standard deviation, and minimum and maximum values are reported. The correlations among the independent variables in Table 5.3 indicate that coefficients among those variables are lower than 0.8. It might be considered that no potential multicollinearity problem is detected.

Table 5.2. Descriptive statistics

Variables	Observations	Mean	Standard Deviation	Min.	Max.
Firm's innovation (inno)	68,568	0.183	0.387	0	1
Informal competition (ifc)	68,568	51.704	15.774	7.2	90.1
R&D (rd)	68,568	0.168	0.374	0	1
Firm age (age)	68,568	29.074	15.822	0	125
Firm size (lnfsize)	68,254	3.633	1.432	0	12.030
Affiliation to larger establishment (affi)	68,568	0.148	0.355	0	1
Managerial experience (mag_exp)	68,568	17.502	8.724	1	40
Export (expo)	68,254	8.761	23.546	0	100
Foreign ownership (fore)	68,568	5.463	19.151	0	100
Access to finance (fin)	68,568	0.407	0.491	0	1
Population (lnpop)	68,568	17.833	1.708	13.264	21.014
Institutional quality (inst)	68,568	4.711	0.794	2.330	7.060
Skilled human capital (lnhc_sk)	68,173	9.781	1.500	6.976	12.527

Out of 68,568 firms in the sample, 56,002 firms (81.67%) respond that they did not have new product/ process that is also new to the firms' main market, while 12,566 firms (18.33%) had (illustration in Figure 5.1). The mean value of the variables of innovation equals 0.183 and the standard deviation is 0.387. In terms of the level of informal competition, 51.7 % of firms consider competition from informal enterprises as a major constraint.

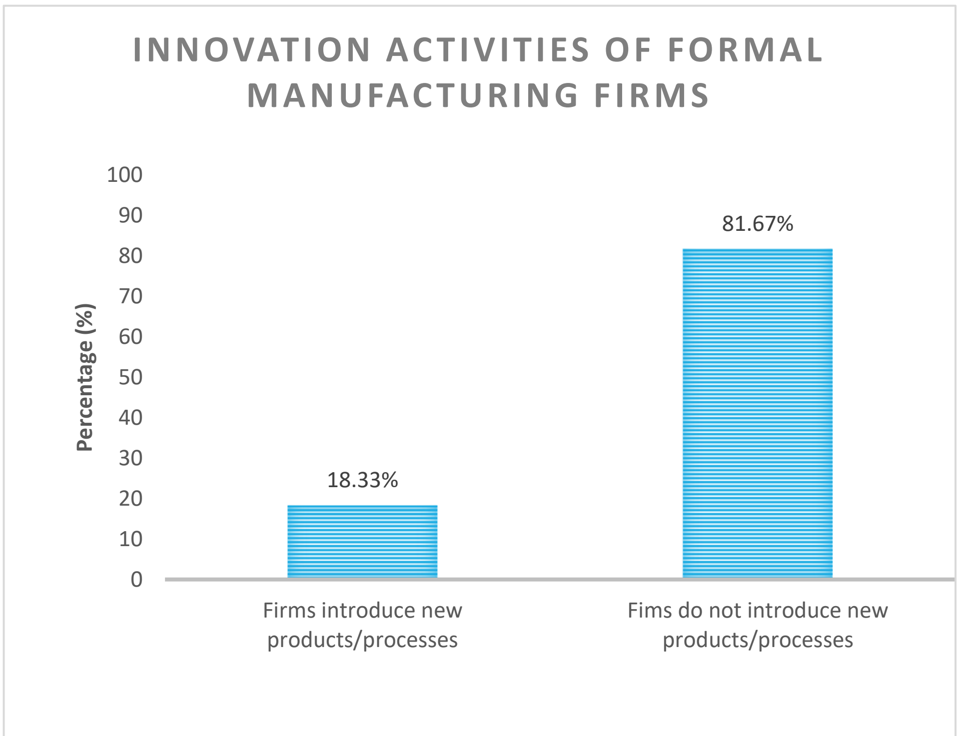

Figure 5.1 Innovation activities of formal manufacturing firms

Source: Author's calculation

For the R&D activities of firms (*rd*), the mean value of the variable equal 0.168 and the standard deviation is 0.374. Approximately 16.77% of firms in the sample spent on R&D activities in the last fiscal year covered by the WBES, while 83.23% of firms in the sample didn't. On average, each of these manufacturing firms has 144 staff. The average age of firms is 29 years, with its manager having 17.5 years of experience. The majority of firms are owned by domestic shareholders, with 5% on average being owned by foreign shareholders. Regarding export, 8.76% of firms perform export activities. In the dataset, 11.95% of firms are located in Africa, 16.12% of firms are in East Asia and Pacific, 23.82% of firms are in Eastern Europe and Central Asia, 21.89% of firms are located in Latin America and the Caribbean, 8.69% of firms are located in the Middle East and North Africa, and 17.53% of firms are located in South Asia. The geographical distribution of manufacturing firms in the dataset is illustrated in Figure 5.2.

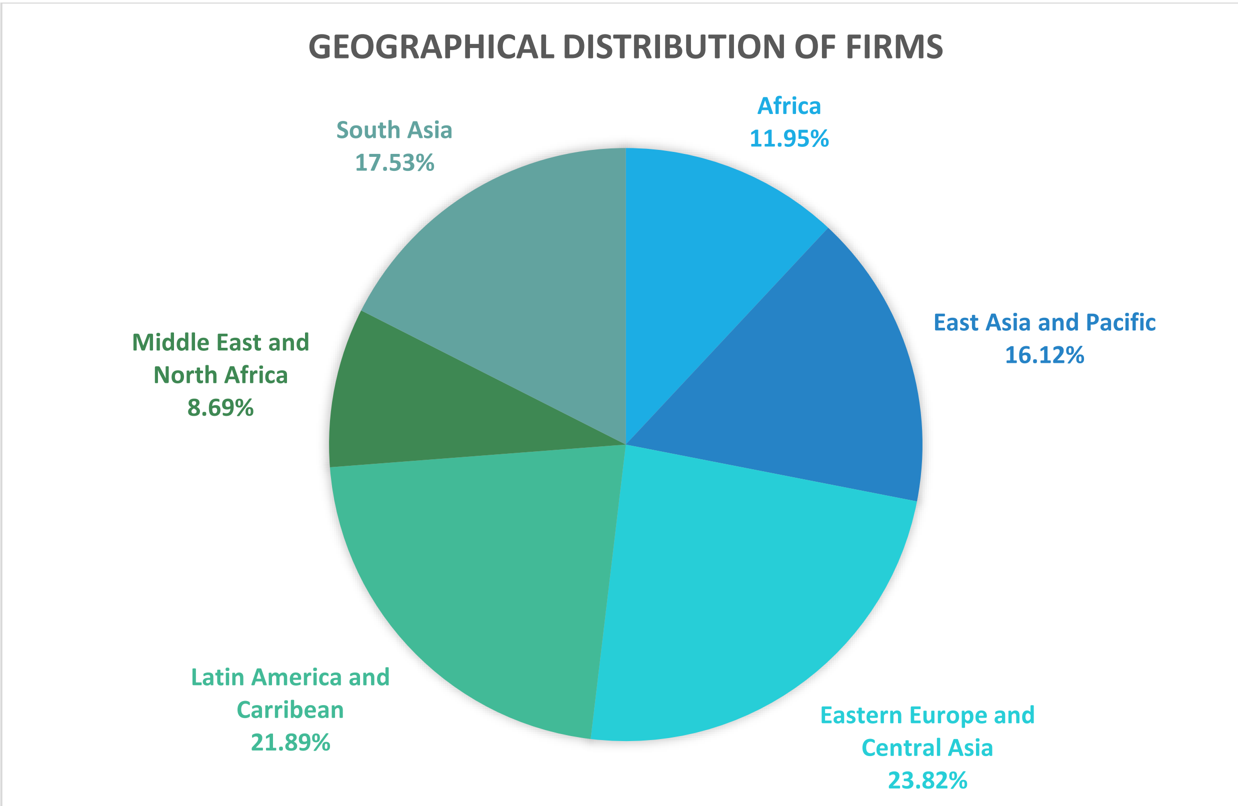

Figure 5.2 Geographical distribution of firms

Source: Author's calculation

Table 5.3. Correlation matrix of variables

	inno	ifc	rd	age	lnfsize	affi	mag_exp	expo	fore	fin	lnpop	inst	lnhc_sk
inno	1.000												
ifc	–0.006	1.000											
rd	0.272	–0.006	1.000										
age	0.016	0.062	0.058	1.000									
lnfsize	0.034	–0.049	0.064	0.176	1.000								
affi	0.024	0.009	0.042	0.068	0.237	1.000							
mag_exp	–0.027	0.073	–0.014	0.007	0.006	–0.009	1.000						
expo	0.036	–0.049	0.014	0.006	0.111	0.034	0.106	1.000					
fore	–0.004	–0.009	0.011	0.030	0.190	0.112	0.010	0.065	1.000				
fin	0.048	0.041	0.182	0.087	0.043	0.036	0.014	0.004	0.013	1.000			
lnpop	0.062	–0.072	0.027	–0.033	0.071	–0.004	–0.007	–0.007	–0.065	0.032	1.000		
inst	–0.099	–0.086	0.090	–0.022	0.038	0.002	–0.017	–0.037	0.040	0.182	0.011	1.000	
lnhc_sk	–0.037	0.038	0.029	–0.002	0.032	0.030	0.068	0.025	0.078	0.134	–0.238	0.328	1.000

5.4.2 Estimation results

Main estimation results for MIEs

Impact of competition caused by informal firms

This section reports the empirical results of the estimations based on the probit regressions. Table 5.4 reports coefficients from estimations, along with the corresponding marginal effects, robust standard errors and statistical significance p-values for formal manufacturing firms in MIEs.

Model 1 reports the results solely with the main variable of interest, i.e. the impact of informal competition on the innovation activities of formal firms. Subsequently, in model 2, a variable of the R&D activity of firms is added. A full set of firms' characteristics control variables are incorporated in model 3, and then country characteristics variables are added in model 4. The results of estimations are consistent across model 1 to model 4. One notable finding from the estimation results is that the informal competition caused by the unregistered firms induces the innovation outputs of formal firms in MIEs. The positive value of the coefficient (statistically significant at 1% level) of the informal competition variable might be interpreted that informal sector competition force firm to innovate more. Under the effect of competition from unregistered firms, formal firms might introduce innovation to stay competitive and open up new market segments (Avenyo, Konte and Mohnen 2021), and differentiate their product to survive. It might also be explained that the fear of losing market share to informal firms may force formal firms to invest more in innovation, introduce new or improved products and processes. Through competition with the informal sector, formal sector enterprises are incentivized to innovate (Shekar 2021). The escape–competition effect for manufacturing sector firms is found in this case, similar to the estimation of Aveyno, Konte and Mohnen (2021) for the industry–level informal competition in sub–Saharan Africa. It is opposite to the conclusion in a study by Shekar (2021) that the informal sector negatively influences the introduction of product innovation of firms in the formal sector. Confirming Shekar's conclusion, Fernández, Velasco and Fanjul–Suarez (2018) state that in regions with higher levels of informal economy share, there is less incentive for the firms to innovate and invest in new products because informal firms cause more fierce competition and stronger obstacles to formal firms' innovation (Mendi and Costamagna 2017).

Because probit regression is a non–linear function of regressors, the coefficients reported above can only show the direction of the impact of independent variables. Thus, the marginal effects of informal competition on the probability of the firm introducing new products/processes are presented. The marginal effects of the independent variables of interest imply that a 1% increase in the percentage of firms in the same country face informal competition, the probability that a firm introducing new products/ processes that is also new to its main market increase by 0.1% (model 4). One small note for the result of this section is that since the possibility of reverse causality cannot be completely avoided, these results should be interpreted with caution before resulting in policy implications.

Table 5.4. Estimation results of informal competition impact on formal firms' innovation

Dependent variable: new product/process of firm that is also new to its main market	**Model 1**		**Model 2**		**Model 3**		**Model 4**	
	Coefficient	Marginal effect	Coefficient	Marginal effect	Coefficient	Marginal effect	Coefficient	Marginal effect
Informal competition (ifc)	**0.007*** (0.001)**	**0.000* (0.000)**	**0.007*** (0.001)**	**0.000*** (0.000)**	**0.004*** (0.001)**	**0.000*** (0.001)**	**0.004*** (0.001)**	**0.001*** (0.000)**
R&D (rd)			**0.974*** (0.014)**	**0.221*** (0.003)**	**0.921*** (0.014)**	**0.227*** (0.003)**	**0.921*** (0.014)**	**0.218*** (0.004)**
Firm age (age)					0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Firm size ((lnfsize)					0.012 (0.004)	0.003 (0.001)	0.005 (0.004)	0.001 (0.001)
Affiliation to larger establishment (affi)					0.021 (0.017)	0.005 (0.004)	0.017 (0.017)	0.006 (0.004)
Managerial experience (mag_exp)					**–0.004*** (0.001)**	**–0.001*** (0.000)**	**–0.005*** (0.001)**	**–0.001*** (0.000)**
Export (expo)					**0.002*** (0.001)**	**0.000*** (0.001)**	**0.001*** (0.001)**	**0.000*** (0.001)**
Foreign ownership (fore)					0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)
Access to finance (fin)					**0.078*** (0.012)**	**0.019*** (0.003)**	**0.034* (0.012)**	**0.009*** (0.012)**
Population (lnpop)							**0.009** (0.004)**	**0.000** (0.001)**
Institutional quality (inst)							**0.095*** (0.004)**	**0.022*** (0.001)**
Skilled human capital (lnhc_sk)							**0.022*** (0.005)**	**0.006*** (0.005)**
Industry fixed effect (ind)	Yes		Yes		Yes		Yes	
Region fixed effect (region)	Yes		Yes		Yes		Yes	
Year fixed effect (year)	Yes		Yes		Yes		Yes	

Dependent variable: new product/process of firm that is also new to its main market	**Model 1**		**Model 2**		**Model 3**		**Model 4**	
	Coefficient	Marginal effect	Coefficient	Marginal effect	Coefficient	Marginal effect	Coefficient	Marginal effect
Constant	–0.224*** (0.043)		–0.102*** (0.045)		–0.117*** (0.050)		–0.905*** (0.092)	
Wald Chi2	1063.05		5924.83		5984.85		6367.75	
Prob.> Chi2	0.000		0.000		0.000		0.000	
Pseudo R2	0.014		0.090		0.092		0.102	
Number of observations	68,568	68,568	68,568	68,568	68,210	68,210	67,818	67,818

*Coefficients are reported with robust standard errors in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.*

Impacts of other factors

Among the control variables on the firms' characteristics, R&D activities (*rd*) impact on the introduction of new products/processes of formal firms has a positive coefficient that is statistically significant at 1%. This result is in line with the vastly discussed literature suggesting that R&D investment serves as the input of the innovation process. Export activities and access to finance are also found beneficial to the innovation activities of firms in this study. The coefficient of the export activities variable (*expo*) shows the positive impact and is statistically significant at 1% for manufacturing firms in MIEs. This result is similar to the conclusion by Aveyno, Konte and Mohnen (2021) and Amin (2021) who conclude that greater exporting activity of firms results in a higher innovation rate. It can be concluded that manufacturing firms in MIEs that have export activities might benefit from the opportunity of accessing dynamic markets and better acquiring new advanced technology. Access to finance (*fin*) variable is positively impacting innovation activities of manufacturing formal firms. Its coefficient is positive and statistically significant at 10%. Amin (2021) similarly finds that firms that have an overdraft facility have a significantly higher rate of innovation than others. Laborda Castillo and Salem (2013) also conclude that overdraft facility has positive impact and is significant to innovation investment of firms.

On the contrary to the importance of export and access to finance, in this study the factor of age, size, whether a firm is an affiliation of a bigger establishment, and foreign ownership do not have impact on manufacturing firms' innovation in MIEs. The unimportant roles of the age of firms (*age*) and affiliation to a larger establishment (*affi*) noted in this study are opposite to the advantage of being part of a bigger establishment and positive effect of a firm's age to yield higher rate of innovation by Aveyno, Konte and Mohnen (2021). Mendi and Constamagna (2017) also conclude that young and smaller firms have significantly higher innovation activities. In terms of the impact of firm size (*lnfsize*), some researchers find that smaller companies may have advantages in terms of quick decision–making, willingness to take risks, and flexibility in responding to new market opportunities. Therefore, medium and small companies may have a bigger tendency to innovate (Chudnovsky, A. and G. 2006). Other researchers argue that larger firms have advantages thanks to the scale and availability of specialist resources which create better conditions for innovation. Amin (2021) and Aveyno, Konte and Mohnen (2021) find that larger firm size is associated with higher innovation activity of R&D. However, the findings in this paper do not support any of those conclusions on the role of firm size in innovation outputs.

The finding about the insignificant role of foreign ownership of firms (*fore*) to its innovation activity in this study validates the results of Aveyno, Konte and Mohnen (2021) and is opposite to the conclusion that firms benefit from knowledge spillovers that originate from foreign partners that holding share in the company by Amin (2022).

Managerial experience (*mag_exp*) brings a negative and significant impact on the innovation of firms in MIEs (at 1%). This finding is similar to the estimation of Aveyno, Konte and Mohnen (2021) for the informal competition effect on formal firms' performance and its product innovation at the local region level. Goll, Johnson, and Rasheed (2008) explain that degree of risk–averse rises with higher level of manager's experience. The experienced manager is not willing to take unprecedented and novel strategies. This finding is different from the conclusion of Aveyno, Konte and Mohnen (2021) when estimating across sectors that the experience of managers is not significant to the introduction of product innovation or of the conclusions of Mendi and Costamagna (2017) and Amin (2021).

Country characteristic control variables such as skilled human capital for innovation (*lnhc_sk*), size of the market (*lnpop*), and quality of institution (*inst*) show positive signs and are statistically significant at 1% for firms in MIEs. It confirms that a higher level of human capital is associated with a higher innovation rate, as prevalent in the existing literature.

Overall, the hypothesis that *"competition caused by informal firms induce innovation activities of formal manufacturing firms in MIEs"* is supported by the results of this study. The more fierce competition the informal sector brings, the more innovative formal firms are found.

Estimation results for LMICs and UMICs

The finding results are then checked separately by each group of LMI and UMI. Table 5.5 shows estimation results for LMICs (model 5) and UMICs (model 6). The estimation result of MIEs (model 4) are presented for comparison.

Table 5.5. Estimation results for LMICs and UMICs

Dependent variable: new product/process of firm that is also new to its main market	**Model 4 (MIEs)**	**Model 5 (LMICs)**	**Model 6 (UMICs)**
Informal competition (inf)	**0.004*** (0.001)**	**0.006*** (0.001)**	**0.004*** (0.001)**
R&D (rd)	**0.921*** (0.014)**	**0.921*** (0.021)**	**0.977*** (0.022)**
Firm age (age)	0.000 (0.001)	–0.001 (0.001)	**0.002*** (0.001)**
Firm size (lnfsize)	0.005 (0.004)	**0.025*** (0.006)**	0.013 (0.007)
Affiliation to larger establishment (affi)	0.017 (0.017)	–0.915 (0.023)	**0.125*** (0.028)**
Managerial experience (mag_exp)	**–0.005*** (0.001)**	–0.000 (0.001)	**–0.005*** (0.001)**
Export (expo)	**0.001*** (0.001)**	**0.002*** (0.001)**	0.000 (0.001)
Foreign ownership (fore)	0.001 (0.001)	0.000 (0.001)	**0.002*** (0.001)**
Access to finance (fin)	**0.034* (0.012)**	**0.060*** (0.017)**	**0.057** (0.020)**
Population (lnpop)	**0.009** (0.004)**	**0.040*** (0.006)**	**0.031*** (0.007)**
Institutional quality (inst)	**0.095*** (0.004)**	**0.099*** (0.005)**	**0.103*** (0.019)**
Skilled human capital (lnhc_sk)	**0.022*** (0.005)**	**0.211*** (0.010)**	**0.102*** (0.011)**
Industry fixed effect (ind)	Yes	Yes	Yes
Region fixed effect (region)	Yes	Yes	Yes
Year fixed effect (year)	Yes	Yes	Yes
Constant	**–0.905*** (0.092)**	**–2.930*** (0.161)**	**–4.061*** (0.240)**
Number of observations	67,818	36,975	30,842
Wald Chi2	6367.75	3401.34	3193.81
Prob.> Chi2	0.000	0.000	0.000
Pseudo R2	0.102	0.109	0.145

*Coefficients are reported with robust standard errors in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.*

Results from the estimations in models 5 and 6 show the positive impact of competition caused by informal firms on the innovation outputs of firms in both LMI and UMI groups (statistically significant at 1% level). The escape competition noted for LMICs and UMICs is similar to the result in model 4 for the whole sample of MIEs. Besides, in both LMICs and UMICs, R&D investment brings a positive impact on the innovation of formal manufacturing firms (statistically significant at 1% in both models 5 and 6).

Unlike the variable of competition caused by informal firms, the other control variables for firm characteristics show mixed findings. The only firm characteristic variable that is found consistent with the conclusion of model 4 is access to finance (*fin*). It means that access to finance is supportive of the innovation activities of firms in both LMICs (statistically significant at 1%) and in UMICs (significant at 5%). This result confirms that access to finance holds the key to conducting innovation activities of firms in MIEs. On the contrary, the other variables show different results for LMICs and UMICs. The export activities (*expo*) and size of firms (*lnfsize*) positively impact the innovation of firms in LMICs (significant at 1%), while it is insignificant for firms in UMICs. Larger firms and firms with export activities in LMICs are more likely to perform innovation activity. It might infer that firms in LMICs acquire better new advanced technology from their exporting markets to enhance their innovation activities than firms in UMICs. Foreign ownership (*fore*) and whether a firm is affiliated with a larger company (*affi)* positively impact firms in UMICs (significant at 1%), while these variables do not play a significant role in the innovation of firms in LMICs. It might be presumed that in UMICs foreign ownership and being affiliated to a bigger company can bring better access to more advanced technology and better access to foreign markets for technological spillovers. The age of a firm (*age*) is noted as insignificant to innovation of firms in LMICs, while older firms in UMICs have better innovation results (significant at 1%). This result implies that in UMICs, older firms with better knowledge accumulated might have more innovation activities and outputs, while in LMICs it is not the case. The factor of managerial experience (*mag_exp*) does not impact the innovation output of firms in LMICs, but it is an element that might prevent innovation activities of firms in UMICs (significant at 1% level). These results confirm that the industry–specific experience of the managers does not necessarily enable firms in MIEs to be more innovative. The mixed results for these firm characteristics variables are also noted in existing empirical studies by other scholars. There might be different reasons explaining those mixed results. Within the scope of this thesis, there is not sufficient detail to determine and confirm the causes of these differences in the two income ranks. It should be further explored in future studies focusing on these firms' characteristics at different country income levels of LMI and UMI separately.

Country characteristic control variables such as skilled human capital for innovation (*lnhc_sk*), size of market (*lnpop*), and quality of institution (*inst*) show positive signs and statistically significant (at 1% level) in both models 5 and 6 for LMICs and UMICs. The role of human capital and the quality of institution in innovation output are underlined by these results. These results are identical to results of model 4.

Extension to regional level informal competition

The finding results are then checked separately by each region covered in this study. Table 5.6 shows estimation results by regions (model 7 to model 12). There are six regions of East Asia and Pacific (EAP) (model 7), South Asia (SAR) (model 8), Eastern Europe and Central Asia (ECA) (model 9), Latin America and Caribbean (LAC) (model 10), Middle East and North Africa (MNA) (model 11), and Africa (AFR) (model 12) included in this study. Overall, it confirms that the innovation–inducing effect of informal competition on the formal manufacturing firms is prevalent in MIEs across regions. When breaking down by region, the escape–competition effect holds only for four regions of SAR, ECA, LAC, MNA, while the Schumpeterian effect hold for other two regions of AFR and EAP.

Table 5.6. Estimation results of informal competition impact on formal firms' innovation by region

Dependent variable: new product/process of firm that is also new to its main market	**Model 7 East Asian and Pacific region (EAP)**	**Model 8 South Asian region (SAR)**	**Model 9 Eastern Europe and Central Asian region (ECA)**	**Model 10 Latin American and Caribbean region (LAC)**	**Model 11 Middle East and North African region (MNA)**	**Model 12 African region (AFR)**
Informal competition (ifc)	**–0.055*** (0.001)**	**0.071*** (0.003)**	**0.001*** (0.002)**	**0.011*** (0.001)**	**0.021*** (0.003)**	**–0.006*** (0.001)**
R&D (rd)	**0.898*** (0.046)**	**0.940*** (0.031)**	**1.131*** (0.038)**	**0.835*** (0.028)**	**1.092*** (0.067)**	**1.060*** (0.050)**
Firm age (age)	0.001 (0.002)	0.001 (0.001)	0.000 (0.001)	–0.001* (0.001)	0.003** (0.002)	–0.002* (0.001)
Firm size (lnfsize)	–0.033** (0.013)	0.038*** (0.011)	0.010 (0.010)	0.018* (0.010)	0.037** (0.017)	–0.019 (0.014)
Affiliation to larger establishment (affi)	0.081 (0.055)	0.013 (0.039)	0.159*** (0.045)	0.038 (0.037)	0.059 (0.058)	–0.068 (0.043)
Managerial experience (mag_exp)	–0.002 (0.002)	–0.002 (0.002)	**–0.003** (0.001)**	**–0.008*** (0.001)**	–0.002 (0.003)	**–0.009*** (0.002)**
Export (expo)	0.001 (0.001)	**0.001** (0.001)**	**0.001** (0.001)**	0.001 (0.001)	0.001 (0.001)	**0.002*** (0.001)**
Foreign ownership (fore)	**0.002** (0.001)**	**0.004* (0.003)**	**0.001* (0.001)**	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)
Access to finance (fin)	0.019 (0.044)	**0.357* (0.029)**	**0.060** (0.028)**	0.012 (0.028)	**0.187*** (0.053)**	0.036 (0.038)
Population (lnpop)	0.020 (0.018)	**0.276** (0.022)**	**0.018** (0.011)**	**0.239*** (0.011)**	**0.078*** (0.242)**	0.242 (0.017)
Institutional quality (inst)	**0.064*** (0.020)**	**0.416*** (0.032)**	**0.040*** (0.028)**	**0.169*** (0.028)**	**0.175*** (0.056)**	**0.458*** (0.030)**
Skilled human capital (lnhc_sk)	**0.160*** (0.015)**	**0.160*** (0.046)**	0.008 (0.009)	**0.232*** (0.013)**	0.031 (0.004)	**0.353*** (0.028)**

Dependent variable: new product/process of firm that is also new to its main market	**Model 7 East Asian and Pacific region (EAP)**	**Model 8 South Asian region (SAR)**	**Model 9 Eastern Europe and Central Asian region (ECA)**	**Model 10 Latin American and Caribbean region (LAC)**	**Model 11 Middle East and North African region (MNA)**	**Model 12 African region (AFR)**
Industry fixed effect (ind)	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect (year)	Yes	Yes	Yes	Yes	Yes	Yes
Constant	–290.8*** (13.512)	690.604*** (18.779)	–98.47*** (7.717)	–273.8*** (7.074)	56.443** (23.463)	–76.109*** (8.247)
Number of observations	10,971	11,941	16,228	14,945	5,628	8,105
Wald Chi2	866.57	3322.45	1400.74	2719.01	429.69	879.45
Prob.> Chi2	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R2	0.148	0.255	0.106	0.209	0.116	0.123

*Coefficients are reported with robust standard errors in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.*

In the EAP and AFR regions, results show that the higher informal competition pressure, the fewer innovation activities are conducted. The “Schumpeterian effect” is found in these regions. The result for the African region is slightly similar to the conclusion of Aveyno, Konte and Mohnen (2021) that the local informal competition has a negative effect on the product innovation intensity of formal firms, or the "Schumpeterian effect" exists. However, this result does not remain the same at the industry level in Sub–Saharan African countries. Regarding the EAP region, in the absence of similar studies, estimation result of this section could not be compared with previous ones. On the smaller scale, the study on manufacturing formal firms in India by Shekar (2021) finds the presence of the “Schumpeterian effect” where in manufacturing enterprises, informal sector competition is harmful to innovation. However, this result is not valid for informal sector competition at the industry level in India, in which the “escape–competition effect” is determined.

One possible explanation for the Schumpeterian effect taking effect in the AFR region could be sourced from the work by Aveyno, Konte and Mohnen (2021). These authors find that in the Sub–Saharan African region there exists the outsourcing of economic activities between formal and informal firms. The outsourcing activities might allow unregistered firms to take advantage of the knowledge spillover from the formal firms to enhance their capacity, expand market size, and perform better with product innovations and then negatively affect the formal firms. While no empirical work could be found to explain the negative impact of competition brought by unregistered firms in the EAP region, in future research, the factor of outsourcing activities among informal and formal firms should be explored and examined with a larger dataset of a country or a region and with the more proper measurements of outsourcing business activities between the formal and informal firms.

On the contrary to the Schumpeterian effect taking place in the two regions above, in the other four regions of South Asia (SAR), Eastern Europe and Central Asia (ECA), Latin America and Caribe (LAC), and Middle East and North Africa (MNA), estimation results show the escape–competition effect. Among these four regions benefiting from the innovation–inducting effect of informal competition, SAR region tops the list with higher level of positive impact, while in other regions of ECA, LAC, MNA, the impact is positive but at a lower level compared with the SAR region.

The positive impact of informal competition on product innovation in firms in SAR, ECA, LAC, and MNA regions might be due to the institutional factors. Overall, the impact of institutional quality is quite consistent across regions and consistent with the main model results. Manufacturing firms' innovation activities in all the regions are expanded with the higher institutional quality. However, one commonality of institutional factors in these four regions is that there have been regulation reforms and it might impact the nature of competition and informality. In the SAR region, compared with the average of emerging and developing countries, the level of corruption is higher, the level of government effectiveness is lower, and the business environment in this region is less favorable (World Bank 2022). However, there have been efforts for regulations reforms as explained by Shekar (2021) when detailing the impact of the informal competition on innovation outcomes in Indian manufacturing firms. It might be one possible reason explaining why the SAR region tops the escape competition effect and is worth studying further in the future. In the ECA region, some countries have succeeded in reducing burdens for tax compliance and tax rates, enhancing flexible labor market regulations (World Bank 2022). Besides, several economies in ECA are among the most remittance–reliant in the world with remittances helping establish small businesses, which tend to be informal. Additionally, owing to reforms of the post–European Union accession process, this region might have better quality, more effective government, more strengthened regulatory systems, and less corruption (World Bank 2022). Those reasons might be contributing to shaping the nature of informal competition and its impact on innovation of formal firms in this region. Similarly, in LAC there are trade liberalization reforms and improvements in the business climate. In MNA, changes in institutions due to the armed conflicts might have some impact on the informal competition and the informal economy (World Bank 2022). Referring to the EAP and AFR regions that experience the Schumpeterian effect, there haven't been significant institutional reforms noted. In the absence of previous studies with clearer explanations for regional differences, future research might consider studying in–depth the different institutional factors impacting the informal economy for a more thorough understanding and to determine better the cause of this fact.

Estimations on the positive impact of R&D investment is similar across regions and consistent with the main model results. R&D investment results in the expansion of innovation activities in formal manufacturing firms in MIEs in all six regions. The result of managerial experience negatively affects the innovation activities of firms is confirmed for the regions of

ECA, LAC, and AFR; while being not significant for the regions of EAP, SAR, MNA. Affiliation to a larger establishment continues to show an insignificant impact in most regions, which is consistent with the result of the main model. Only in ECA region, the affiliation with a bigger company might positively enhance the innovation activities of the firm. In terms of export, foreign ownership, and access to finance, the positive impacts are noticed in 3 regions, while being insignificant in other regions (similar to model 4). In SAR and ECA regions, the innovation–enhancing effect of export, foreign ownership, and access to finance are found with positive and statistically significant coefficients. The characteristics of age and size of firms show the heterogeneous impact on a firm’s innovation. For firm age, it’s significant and positively impacting the MNA region, while negatively impacting innovation of firms in LAC and AFR regions. The size of a firm is statistically significant and negatively affects the EAP region, while the bigger firms in SAR, LAC, and MNA regions, the more innovative they are.

5.4.3 Robustness checks

To check the robustness of the results in section 5.4.2, the estimations are re–run in three sets of robustness checks with different variables and a different estimation method. In these models, results are similar to the main estimations in model 1–4.

Different measure of informal competition

In the first robustness check, the alternate proxy of informal competition measured by the country–average proportion of formal firms reporting practices of informal firms reported as obstacles is used (model 13). It's different from the main estimations (model 1–4) which use the country average percentage of firms reporting facing informal competition from unregistered firms to represent informal competition. The results of this estimation are shown in Table 5.7 (model 13) and are consistent with the main results in section 5.4.2, model 1–4. The innovation–inducing effect of informal competition remains, while the positive impact of R&D, export activities, and access to finance are found. The negative impact of managerial experience stays unchanged compared with model 4. The results of model 13, therefore, confirm the robustness of the result in the main model 1–4.

Table 5.7. Estimation results with a different measure of informal competition

Dependent variable: new product/process of firm that is also new to its main market	**Model 13**
Informal competition (ifc): practices of competitors in informal economies as major constraints to formal firms	**0.003*** (0.001)**
R&D (rd)	**0.922*** (0.014)**
Firm age (age)	0.000 (0.001)
Firm size (lnfsize)	0.004 (0.004)
Affiliation to larger establishment (affi)	0.018 (0.017)
Managerial experience (mag_exp)	**–0.005*** (0.001)**
Export (expo)	**0.001*** (0.001)**
Foreign ownership (fore)	0.001 (0.001)
Access to finance (fin)	**0.034*** (0.012)**
Population (lnpop)	**0.020** (0.004)**
Institutional quality (inst)	**0.087*** (0.004)**
Skilled human capital (lnhc_sk)	**0.019*** (0.005)**
Industry fixed effect (ind)	Yes
Region fixed effect (region)	Yes
Year fixed effect (year)	Yes
Constant	**–0.890*** (0.094)**
Number of observations	67,818
Wald Chi2	6343.03
Prob.> Chi2	0.000
Pseudo R2	0.102

*Coefficients are reported with robust standard errors in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.*

R&D activity as dependent variable for innovation

In the second set of robustness check, the R&D activity is used as a measure of the dependent variable of the innovation activity of firms (model 14). The results of estimations are presented in Table 5.8. Overall, the conclusion that competition with unregistered firms enhances the innovation activities of formal firms holds its validity. It is consistent with the main findings from section 5.4.2 above. Even though the significance level of impact of some other control variables is different, with an unchanged conclusion of the main independent variable, it can imply that the result of estimations in section 5.4.2 for main results is robust.

Table 5.8. Estimation results with R&D activity as a measure of the firm's innovation

Dependent variable: RD activity	**Model 14**
Informal competition (ifc)	**0.002*** (0.001)**
Firm age (age)	**0.003*** (0.003)**
Firm size (lnfsize)	**0.046*** (0.001)**
Affiliation to larger establishment (affi)	**0.075** (0.004)**
Managerial experience (mag_exp)	**0.002*** (0.001)**
Export (expo)	**0.001** (0.000)**
Foreign ownership (fore)	0.001 (0.001)
Access to finance (fin)	**0.453* (0.012)**
Population (lnpop)	**–0.026*** (0.004)**
Institutional quality (inst)	**0.111*** (0.005)**
Skilled human capital (lnhc_sk)	**0.019*** (0.004)**
Industry fixed effect (ind)	Yes
Region fixed effect (region)	Yes
Year fixed effect (year)	Yes
Constant	–2.283
Number of observations	67,818
Wald Chi2	3108.24
Prob.> Chi2	0.000
Pseudo R2	0.057

*Coefficients are reported with robust standard errors in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.*

Logit model estimation

The last robustness check is conducted by applying logit model estimation in Model 15. The estimation result is presented in Table 5.9. The main estimation result of the innovation–inducing effect of informal competition remains the same. Impacts of other firms' characteristics variables on the innovation of manufacturing formal firms are consistent with the main estimation in model 4 which employs probit regression.

Table 5.9. Estimation results by a logit model

Dependent variable: new product/process of firm that is also new to its main market	**Model 15**
Informal competition (ifc)	**0.007*** (0.001)**
R&D (rd)	**1.573*** (0.024)**
Firm age (age)	0.000 (0.001)
Firm size (lnfsize)	0.012 (0.008)
Affiliation to larger establishment (affi)	0.019 (0.030)
Managerial experience (mag_exp)	**–0.009*** (0.001)**
Export (expo)	**0.002*** (0.001)**
Foreign ownership (fore)	0.001 (0.001)
Access to finance (fin)	**0.055** (0.022)**
Population (lnpop)	**0.026*** (0.007)**
Institutional quality (inst)	**0.174*** (0.008)**
Skilled human capital (lnhc_sk)	**0.047*** (0.009)**
Industry fixed effect (ind)	Yes
Region fixed effect (region)	Yes
Year fixed effect (year)	Yes
Constant	**–1.748*** (0.167)**
Number of observations	67,818
Wald Chi2	6178.76
Prob.> Chi2	0.000
Pseudo R2	0.101

*Coefficients are reported with robust standard errors in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.*

5.5 Conclusion

The large informal economy is one characteristic featuring the developing economies' landscape. The existence of firms in the informal economy affects the operation and innovation activities of the formal firms. This paper focuses on the study of the impact of informal competition on innovation in formal manufacturing firms in MIEs. The data set from WBES between 2006 and 2019 of 68,568 firms across 92 MIEs, including 47 LMICs and 45 UMICs, are utilized. This study contributes to the literature by examining the effect of informal competition on the innovation activities of formal manufacturing firms in a large sample of middle–income countries. To the best of the author's knowledge, the topic is relatively under investigated by other scholars. Secondly, the choice of the dependent variable by country–average level of informal competition is more robust in dealing with endogeneity issues caused by informal competition measures using firm–level data (Amin 2022).

This study reveals that the competition caused by the informal firms is more likely to induce innovation activities of the formal firm through the introduction of new products and processes that are also new to the main market of the firms. The escape–competition effect is confirmed in this study on a large sample of formal manufacturing firms of MIEs. R&D investment positively affects the innovation outputs of formal manufacturing firms as consistently concluded in the existing literature. While a firm's age, size, being affiliated to a larger company, and share of foreign ownership are found to not affect the innovation activities of formal firms, export and access to finance are important to foster innovation activities of formal firms. The length of the manager's experience, on the contrary, might negatively affect firms' innovation activities of firms covered in this study. Robustness checks of the results validate the consistency of the main estimation findings. Breakdown of results by six regions in this study show a slightly differences in direction and significant level of impact for each variable by region. However, the breakdown of the estimation results by LMI and UMI groups confirm the robustness of main estimation results. Since the possibility of reverse causality cannot be excluded, the result implications presented here should be taken with caution.

The empirical results of this study might bring some implications on how to deal with the phenomenon of informality in MIEs. An informal economy to which a large number of firms and employments are belonging is perceived as hampering the formal sector. The perception that informal competition is unhealthy to the formal sector dominates. Therefore, for many decades, there have been debates going on with a policy approach of eradicating the informal economy and formalizing the unregistered firms. However, the findings of this study suggest that the informal firms might not only bring negative impacts to formal firms, and therefore efforts by policymakers in MIEs to reduce the size of the informal sectors should be carefully considered when they aim to elevate the innovation activities of formal manufacturing firms. This implication should be further investigated in the specific context of each country and for other sector other than manufacturing. Another implication could be made from the result of this study regarding the development of the National Innovation System (NIS) in MIEs. The finding provides useful evidence to pinpoint the informal firms as one actor in the NIS of MIEs. There might be a need for policymakers to consider this element when building any policy or plan for NIS development in MIEs. The statistics of firms for developing NIS are usually rooted in the national accounts which often exclude the statistics of the informal sector. More statistics of informal firms and estimation of its impact on formal firms should be included in the NIS development process. This recommendation is partially aligned with the ones made by Aveyno, Konte and Mohnen (2021) and Shekar (2021) regarding the role of informal firms in the NIS.

Future research might investigate the different impacts of informal competition on innovation activities measured through product and process innovation separately. Since the imitation effect toward product and process innovation are not identical, the level of intensity of informality on process innovation vs. product innovation varies. However, given the limitation of the dataset across countries of WBES, in which the question in the cross–country dataset did not separate product vs. process innovation, it is not possible to examine further. The results of the positive impact of informal competition on innovation activities of firms in MIEs, even though interesting should be interpreted carefully and further examined in the context of a specific country for policymaking toward informality. Future studies might explore the impact of informal competition on the innovation activities of firms in low–income countries and high–income countries to validate if the results remain the same with MIEs.

Chapter 6 Conclusions and Implications for Future Studies

This chapter provides summaries of key findings from those three empirical studies. Based on those results, implications for policymaking are presented. The chapter also discusses the limitation of this thesis and suggestions for future research.

6.1 Key findings

The thesis includes three separate empirical studies exploring the role of the innovation in MIEs development and related factors impacting innovation of MIEs. Focusing on the overall topic of innovation in MIEs, each study is presented in one chapter (Chapters 3, 4, and 5) with different econometric techniques applied for estimations and from different perspectives of innovation for MIEs. In Chapter 3, the comparison of the role of indigenous and foreign innovation efforts to the probability of LMICs and UMICs transitioning to the next income category is examined. In Chapter 4, the focus is on the role of human capital composition to the innovation outputs of MIEs at the aggregate national level. In Chapter 5 the issue of the informal competition caused by unregistered firms to the innovation activities of formal manufacturing firms in MIEs is examined. Both country–level and firm–level data are used in this thesis. Data at country level between 1980 and 2019 for 61 countries are included in Chapter 3. The country–level data of 62 countries between 1990 and 2019 is used in Chapter 4. Chapter 5 uses firm–level data from 68,568 firms of 92 MIEs between 2006 and 2019. The answer to each research question corresponding to the three research papers in Chapters 3, 4, and 5 can be summarized as follows.

6.1.1 Indigenous and foreign innovation efforts for MIE growth

Research question 1**:** *How are indigenous and foreign innovation efforts different in contributing to the transition of MIEs to the next income category?*

Hypothesis 1.1: *LMICs depend more on foreign innovation diffusion to attain UMI status.*

Hypothesis 1.2: *UMICs depend more on indigenous innovation effort to attain the high–income rank.*

The analysis in Chapter 3 provides the answer to research question 1. Chapter 3 examines whether the domestic or foreign innovation efforts matter more to the possibility of MIEs' transition to higher–income rank. Results show that LMICs depend on foreign innovation spillovers more than domestic sources to move to the next income group. The most crucial factor for LMICs to successfully exit this income group lies in foreign patent diffusion and FDI–embodied foreign R&D capital stock. One explanation can be made is that the spillover effect from foreign patents and FDI occurred via demonstration effect, labor mobility, or the imitation of new technologies is stronger for the group of LMICs to transition to the next income group than spillover through other channel like imports. It can assume that due to the lack of matching local absorptive capacity, the import channel is not efficient for foreign innovation spillovers. On the other hand, domestic innovation R&D capital stock is found to be insignificant to the probability of LMICs' transitioning to the UMI rank. This result is unique since no previous similar study was done using national–level data on LMICs.

On the contrary, UMICs rely more on indigenous innovation efforts than on foreign sources to attain high–income status. The indigenous innovation effort of domestic R&D capital stock serves as the main source of growth, supplemented by foreign R&D spillovers through imports to build up their innovation capacity. Institutional quality is also important for these UMICs in enhancing the innovation capability to transition to the high–income category. Investing in domestic R&D, followed by adopting foreign innovation diffusion through the import channel is the order of priority these UMICs should follow in the effort to obtain the high–income rank. An explanation can be made that UMICs have moved closer to the technological frontier and to aim for more ground–breaking innovation they might need to build up their indigenous capabilities to a sufficient level. It can also be explained that the import–embodied foreign innovation channel supports better the transferring of more complex technologies to UMICs. The import channel, therefore, outweighs the FDI channel in playing a role to spill over foreign innovation for UMICs. Based on the conclusions above the two hypotheses 1.1 and 1.2 are supported.

6.1.2 Human capital for innovation of MIEs

Research question 2: *How does human capital affect the innovation outputs of MIEs?*

Hypothesis 2.1: *Skilled human capital is more important than unskilled and high–skilled human capital for the innovation outputs of LMICs.*

Hypothesis 2.2: *High–skilled human capital contributes more than unskilled and skilled human capital to the innovation outputs of UMICs.*

Hypothesis 2.3*: Unskilled human capital is not important for innovation outputs of MIEs.*

The empirical analysis in Chapter 4 provides the answer to research question 2. Chapter 4 investigates the role of human capital composition at different levels of skill (unskilled, skilled, and high–skilled) to innovation at the aggregate level of MIEs and above. The high–skilled human capital is measured by the number of R&D personnel, while the skilled human capital is measured by number of people attained tertiary education level, and the unskilled human capital is proxied through number of people attained primary and secondary education level. Results show that the innovation capacity–enhancing effects of high–skilled human capital increase when countries reach UMI and HI levels. For UMICs, those that move closers to the technological frontier, the country should invest more to enlarge the pool of high–skilled R&D personnel. Imports of foreign advanced technologies and machinery are found to be significant for UMICs. For high–income countries, the quality of institutions and foreign innovation spillover through FDI plays a vital role. R&D capital stock are crucial for both UMICs and HICs. For LMICs, the skilled level of human capital is found to be the most important part of the workforce that contributes to innovation capacity enhancement. By contrast, R&D personnel of high–skilled human capital is not contributing to the innovation outputs of LMICs. Given the assumption that the innovation activities of LMICs are mainly from adopting foreign technological progress, this finding suggests that the larger pool of skilled–level workforce, the more positive results of innovation outcomes are yielded. LMICs should continue to invest in having a higher number of adults who complete tertiary education. Aside from human capital, the study also confirms the role of FDI–embodied innovation to strengthen the innovation capacity of LMICs. Unskilled human capital is confirmed to not play an important role for both middle–income and high–income countries in fostering innovation capacity. However, obtaining the basic level of education of secondary education at the minimum would be the prerequisite for continuing study at higher levels.

The results above confirm the validity of the three hypotheses 2.1, 2.2, and 2.3. Unskilled human capital is insignificant to all groups of LMICs, UMICs, and HICs. The effect of skilled human capital is only positive and significant for LMICs. On the contrary, high–skilled human capital is positive and significant for both UMICs and HICs.

6.1.3 Informality and innovation of formal firms in MIEs

Research question 3: *How does the competition caused by informal firms affect the innovation of formal manufacturing sector firms in MIEs?*

Hypothesis 3.1: *The competition caused by informal firms induce innovation of manufacturing firms in MIEs.*

The empirical study in Chapter 5 responds to research question 3. Chapter 5 examines the impact of informal competition on innovation in formal manufacturing firms in MIEs. Results show that informal competition impact is positive and significant to the innovation outputs of formal manufacturing firms. It confirms the escape–competition effect in which innovation incentivizes formal manufacturing firms to innovate in MIEs.

More elaborately, this study reveals that under the effect of competition caused by unregistered firms, formal manufacturing firms might introduce new products and processes that are also new to the main market of the firms to stay competitive. The escape–competition effect is confirmed in this study on a large sample of formal manufacturing firms of MIEs. R&D investment positively affects the innovation outputs of formal manufacturing firms as vastly concluded in the existing literature. Explanation might be added that due to the fear of losing market share to informal firms, formal firms are forced to invest more in its innovation. While a firm's age, size, being affiliated to a larger company, and share of foreign ownership is not found to affect the formal manufacturing firms' innovation activities, export and access to finance are important to foster innovation activities of these formal firms. The length of the manager's experience, on the contrary, might negatively affect the innovation activities of firms covered in this study. The breakdown of results by six regions in this study shows a slight difference in direction and the significant levels of impact for each variable by region. However, the escape–competition effect is dominant across these six regions. Besides, the breakdown of the estimation results by LMI and UMI groups confirms the validity of the main estimation results in the sample of all 92 MIEs. Robustness checks of the results also validate the consistency of the main estimation findings.

The validation of hypotheses through estimation results in Chapters 3, 4, and 5 can be summarized in Table 6.1 below.

Table 6.1. Summary of hypotheses validation

	Hypotheses	**Confirmation**
Hypothesis 1.1	LMICs depend more on foreign innovation diffusion to attain UMI status.	Supported
Hypothesis 1.2	UMICs depend more on indigenous innovation effort to attain the high–income category.	Supported
Hypothesis 2.1	Skilled human capital is more important than unskilled and high–skilled human capital for the innovation outputs of LMICs	Supported
Hypothesis 2.2	High–skilled human capital contributes more than unskilled and skilled human capital to the innovation outputs of UMICs.	Supported
Hypothesis 2.3	Unskilled human capital is not important for innovation outputs of MIEs.	Supported
Hypothesis 3.1	Competition caused by informal firms induces innovation of manufacturing firms in MIEs	Supported

6.2 Policy implications

In order to avoid the potential issues that MIEs might face as mentioned in section 2.2.2, while successfully transitioning to the higher income rank, government participation and policy intervention to promote innovation in these MIEs might be required. The growth trajectories of the countries that successfully evolve to the high–income status of Japan and the Asian tigers, i.e., Hong Kong, Republic of Korea (South Korea), Singapore, and Taiwan, are also indicative of the role of government policies. In this section, implications for policymakers based on the analysis and findings of the three empirical studies in Chapters 3, 4, and 5 will be outlined.

6.2.1 Identify different priorities according to each middle–income sub–category in the innovation roadmap

Governments have drafted national roadmaps of innovation or innovation strategies to enhance the contribution of innovation to economic growth. The empirical findings of this thesis might imply that MIEs could detail in their innovation roadmaps different priorities according to each step in the middle–income rank, cross–cutting different pillars of the roadmap. Some inputs might be included based on the empirical results of this study as follows.

At the rank of LMI, the results of Chapter 3 propose that a country should focus more on attracting foreign innovation diffusion. Foreign innovation diffused through foreign patents and FDI channel is the most important at this income stage. Therefore, policies to attract foreign investment such as easing conditions, registration, and doing business, or enhancing the protection of foreign patents in the jurisdiction of the LMICs could be the focus of this phase. In terms of human capital development, at the phase of LMI rank, the skilled human capital of tertiary education is the most important part of the workforce that contributes to innovation capacity enhancement. LMICs should continue to invest in having a higher number of adults who complete tertiary education. R&D personnel of high–skilled human capital is yet to contribute to the innovation capacity of LMICs. Therefore LMICs should develop high–skilled human capital over the long term. Besides, combined with the important role of FDI in the growth of the LMICs, in long term, these countries should consider attracting FDI into higher–skilled sectors, instead of FDI in the labor–intensive sectors which take advantage of low–cost labor. In this way, FDI spillover effects might yield better outcomes in the long run.

At the rank of UMI, with the target of reaching the high–income status, the UMI group should prioritize strengthening indigenous innovation capabilities. The foremost policy priority for UMICs should be fostering R&D investment in an efficient way. Investing in R&D also facilitates the industrial structure shift to areas like advanced manufacturing and creating radical innovations and revolutionary technologies. It will also enhance the skill sets of R&D personnel and the absorptive capacity of the labor force. Policies to enhance innovation capabilities through importing foreign technologies should also be pursued in parallel to speed up the catch–up process. Strengthening the quality of institutional systems such as legal structure, IPRs, etc. is another parallel policy focus for UMICs. Effective policies toward the high value–added such as high–tech manufacturing sectors, that are the footsteps of successful economies surpassing the middle–

income rank like Republic of Korea and Taiwan, might be examples to learn for UMICs to elevate innovation capability and economic growth (Ezell and Atkinson 2010). In Chapter 4, results show that the innovation capacity–enhancing effects of high–skilled human capital increase when countries reach the UMI level. It implies that in both short and long terms, UMICs should prioritize enlarging the pool of high–skilled R&D personnel and fostering the quality of R&D personnel who are directly involved in the innovation process.

6.2.2 Policy approach to the informal economy phenomenon and the role of informal sector firms in the national innovation systems (NIS) of MIEs

In Chapter 5, the empirical results of this study have brought some implications on how to deal with the phenomenon of informality in MIEs. An informal economy to which a large number of firms and employments belong is perceived as unhealthy to the formal sector. A somewhat negative perception dominates regarding the impact of informal sector enterprises and their activities on formal firms (Shekar 2021). Therefore, there have been efforts and policy approaches to formalize or reduce the size of the informal economy, limiting the activities of informal firms. However, the findings of this study suggest that efforts by policymakers in MIEs to eliminate the informal sectors should be carefully studied if they target to elevate the innovation activities of formal manufacturing firms. Country–specific situations and data should be investigated in detail to conclude each country's policymaking while considering the aggregate data result in this study.

Another implication could be made from the result of this study about the development of the National Innovation System (NIS) in MIEs. While many governments consider creating and fostering an effective NIS in the country, little attention has been given to the informal sector enterprises. The finding of this study provides interesting evidence to pinpoint the informal firms among the actors in the NIS of MIEs. There might be a need for policymakers to consider this element when building any policy or plan for an MIE's NIS development. Policy analysts might also look more in–depth in the interaction of these informal sector firms with other actors in the NIS. Taking into account the role of informal firms as one component of the NIS is also a recommendation made by Aveyno, Konte and Mohnen (2021) and Shekar (2021).

6.3 Thesis limitations and implications for future studies

Despite the efforts I have made to build up a comprehensive analysis of the innovation in MIEs, this thesis might contain some drawbacks caused by the limited availability of data, the limited scope of research, and the limitation due to the estimation methodologies applied.

The first drawback lies in the limited data availability for MIEs. In Chapter 3, the more accurate bilateral import– and FDI–embodied foreign innovation data across countries are needed for the measurements of foreign R&D capital spillovers. Measuring domestic and foreign innovation efforts based on data of R&D and patent stock has been a long challenging task due to the different depreciation rates assumed. In future studies concerning innovation measures and innovation efforts, the use of data from innovation indices published by different international organizations could be explored. Since the time coverage of this study is quite long, this thesis could not apply data based on composite innovation indices. In Chapter 4, for data on the human capital composition of unskilled, skilled, and high–skilled levels, future studies might consider the use of other human capital indexes published by international organizations such as PISA by the OECD or human capital development indexes by the UNDP for expanding the results of this thesis if possible. In Chapter 5, the use of the WBES brings advantages of wide coverage of countries, however, it also contains limitations such as the time coverage of data. The data are collected at different intervals for different countries, some countries have more available data than others, i.e., with a greater number of firms, and the frequency of data collection is higher than for other countries. Besides, this thesis focuses on the manufacturing sector because it's one important sector for innovation. Future studies can consider other sectors of the WBES or explore other databases if available on the other measure of innovation of new to the world innovation. Another aspect that future studies might investigate is firm characteristics or any other factor that affects the choice of firms to pursue an escape competition strategy should be explored. Escape competition strategy might require financial resources that not all formal firms can do. Within the dataset of this thesis, it is not possible to examine this issue.

The second drawback lies in the limitation of the estimation methodology. In Chapter 3, the application of the survival analysis discrete–time hazard models requires an assumption of baseline hazard and an assumption of the distribution of the unobserved heterogeneity. Although this study tried to test different assumptions of UH distributions and the linear specification of duration dependence (Weibull specification) as a baseline hazard, it could not estimate with other baseline hazards such as the higher–order polynomial, and nonparametric specifications of time. It is because given the long data coverage of this study (1980–2018), the polynomial and nonparametric specifications of baseline hazards become too heavy with many additional parameters. Future research might look into the combinations of different assumptions of baseline hazards with different distribution assumptions of UH in the DTHMs to expand the results and understanding of the specific region or country if possible. In Chapter 5, the estimation might suffer from the endogeneity issue as mentioned in the above analysis and as cautioned by scholars. Even though the cell average technique is applied in this thesis, other econometric techniques to limit the impact of this issue could be explored in future studies to tackle this shortcoming when relevant.

The third drawback lies in the limited scope of this study. Future research might look into the different impacts of informal competition on innovation activities measured through product and process innovation separately. Since the imitation effect toward product and process innovation are not identical, the level of intensity of informality on process innovation versus product innovation varies. However, given the limitation of the dataset across countries of WBES, in which the question in the cross–country dataset did not separate product vs. process innovation, it is not possible to examine it separately. Future studies might approach this topic by differentiating product and process innovation and exploring other relevant databases. The results of the positive impact of informal competition on innovation activities of firms in MIEs, even though interesting should be interpreted carefully and further examined in the context of a specific country for policymaking toward informality. Future studies might explore the impact of informal competition on the innovation activities of firms in low–income countries and high–income countries to validate if the results remain the same with the results for MIEs. Since the database of the WBES includes limited numbers of firms from high–income countries and low–income countries, it is not possible to study for these two groups and should be left for future studies.

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APPENDICES

Appendix 1. List of countries and duration in lower middle–income rank between 1980 and 2018 in Chapter 3

	Country	Years in LMI rank	Year of moving to upper middle–income rank	Duration in LMI rank (years)	Value of dependent variable in estimation
1.	Argentina	1980–1990	1991	10	1
2.	Armenia	2002–2016	2017	14	1
3.	Azerbaijan	2003–2008	2009	5	1
4.	Bangladesh	2014–2018	NA	4	0
5.	Belarus	1994–2006	2007	12	1
6.	Brazil	2002–2005	2006	3	1
7.	Bulgaria	1989–2005	2006	6	1
8.	Cambodia	2005–2018	NA	13	0
9.	China	1997–2009	2010	12	1
10.	Colombia	1997–2007	2008	10	1
11.	Costa Rica	1980–1999	2000	19	1
12.	Ecuador	1980–2018	NA	28	0
13.	Egypt, Arab Rep.	1995–2018	NA	13	0
14.	El Salvador	1980–2018	NA	13	0
15.	Honduras	1999–2018	NA	9	0
16.	India	2007–2018	NA	11	0

	Country	Years in LMI rank	Year of moving to upper middle–income rank	Duration in LMI rank (years)	Value of dependent variable in estimation
17.	Indonesia	2003–2018	NA	15	0
18.	Iran, Islamic Rep.	1990–2008	2009	18	1
19.	Kyrgyz Republic	2013–2018	NA	5	0
20.	Lao PDR	2010–2018	NA	8	0
21.	Moldova	2005–2018	NA	13	0
22.	Mongolia	2007–2018	NA	11	0
23.	Pakistan	2008–2018	NA	10	0
24.	Paraguay	1987–2013	2014	26	1
25.	Peru	1980–2007	2008	27	1
26.	Philippines	1980–2018	NA	28	0
27.	Romania	1990–2004	2005	14	1
28.	Russia Federation	1992–2003	2004	11	1
29.	Sri Lanka	1997–2017	2018	20	1
30.	Thailand	1980–2009	2010	29	1
31.	Tunisia	1997–2009	2010	12	1
32.	Türkiye	1980–2003	2004	23	1
33.	Ukraine	2002–2018	NA	16	0
34.	Uzbekistan	2009–2018	NA	9	0

	Country	Years in LMI rank	Year of moving to upper middle–income rank	Duration in LMI rank (years)	Value of dependent variable in estimation
35.	Venezuela, RB	1980–1986	1987	6	1
36.	Vietnam	2009–2018	NA	9	0

Notes: Lower–middle income countries have GNI per capita between USD1,036 and USD4,045 (World Bank 2020).

Appendix 2. List of countries and duration in upper middle–income rank between 1980 and 2018 in Chapter 3

	Country	Years in UMI rank	Year of moving to high–income rank	Duration in UMI rank (years)	Value of dependent variable in estimation
1.	Argentina	1991–2018	NA	17	0
2.	Armenia	2017–2018	NA	1	0
3.	Azerbaijan	2009–2018	NA	9	0
4.	Belarus	2007–2018	NA	11	0
5.	Brazil	2006–2018	NA	12	0
6.	Bulgaria	2006–2018	NA	12	0
7.	Chile	1993–2011	2012	18	1
8.	China	2010–2018	NA	8	0
9.	Colombia	2008–2018	NA	10	0
10.	Costa Rica	2000–2018	NA	18	0
11.	Croatia	1995–2007	2008	12	1
12.	Czech Republic	1994–2005	2006	11	1
13.	Estonia	1991–2005	2006	14	1
14.	Greece	1980–1995	1996	15	1
15.	Guatemala	2017–2018	NA	1	0
16.	Hungary	2000–2006	2007	6	1
17.	Iran, Islamic Rep.	2009–2018	NA	9	0
18.	Ireland	1980–1989	1990	9	1

	Country	Years in UMI rank	Year of moving to high–income rank	Duration in UMI rank (years)	Value of dependent variable in estimation
19.	Israel	1980–1986	1987	6	1
20.	Kazakhstan	2006–2018	NA	12	0
21.	Korea, Rep.	1988–2000	2001	12	1
22.	Malaysia	1992–2018	NA	16	0
23.	Mauritius	1992–2018	NA	16	0
24.	Mexico	1990–2018	NA	28	0
25.	Panama	1998–2018	NA	20	0
26.	Paraguay	2014–2018	NA	4	0
27.	Peru	2008–2018	NA	10	0
28.	Poland	1996–2007	2008	11	1
29.	Portugal	1980–1993	1994	13	1
30.	Romania	2005–2018	NA	13	0
31.	Russia Federation	2004–2018	NA	14	0
32.	Saudi Arabia	1990–2003	2004	13	1
33.	Serbia	2006–2018	NA	12	0
34.	Singapore	1980–1987	1988	7	1
35.	Slovak Republic	1996–2006	2007	10	1
36.	Slovenia	1992–1996	1997	4	1
37.	South Africa	1980–2018	NA	38	0

	Country	Years in UMI rank	Year of moving to high–income rank	Duration in UMI rank (years)	Value of dependent variable in estimation
38.	Spain	1980–1986	1987	6	1
39.	Sri Lanka	2018–2019	NA	1	0
40.	Taiwan	1986–1992	1993	6	1
41.	Thailand	2010–2018	NA	8	0
42.	Tunisia	2010–2014	2015	4	1
43.	Türkiye	2004–2018	NA	14	0
44.	Venezuela, RB	1987–2018	NA	31	0

Notes: Upper middle–income countries have GNI per capita between USD4,046 and USD12,535 (World Bank 2020).

Appendix 3. Notes on bilateral imports and inward FDI from TRIAD (Chapter 3)

40% of world R&D is contributed by the US, 18% by Japan, and 30% by the European Union as estimated by the National Science Board (2002, cited in Crispolti & Marconi, 2005). Besides, due to the unavailability of bilateral inward FDI stock data, an additional assumption about the inward FDI positions of TRIAD members is applied following Crispolti & Marconi (2005). They assume that the TRIAD accounts for 100% of the inward FDI in Africa, Asia, and the Central and Latin American regions. The inward FDI's positions of the TRIAD for these regions are calculated in the table below. For European countries, more than 60% of FDI was intra–regional, while R&D from Japan is negligent (European Communities 1998). The ratio in the table below is applied to calculate bilateral inward FDI stocks for each country in this study.

Region	**US**	**Japan**	**EU12**
Africa	27.793%	1.649%	70.557%
Asia	38.711%	29.245%	32.044%
America	52.045%	6.695%	41.261%
Europe	40%	0	60%

Source: Crispolti & Marconi (2005).

Appendix 4. List of countries in each income category in Chapter 4

	Lower Middle–Income Group	**Upper Middle–Income Group**	**High Income Group**
1.	Bangladesh	Argentina	Chile
2.	Cambodia	Armenia	Croatia
3.	Ecuador	Azerbaijan	Czech Republic
4.	Egypt, Arab Rep.	Belarus	Estonia
5.	El Salvador	Brazil	Greece
6.	Honduras	Bulgaria	Hong Kong SAR, China
7.	India	China	Hungary
8.	Indonesia	Colombia	Ireland
9.	Kyrgyz Republic	Costa Rica	Israel
10.	Lao PDR	Guatemala	Italy
11.	Moldova	Iran, Islamic Rep.	Japan
12.	Mongolia	Kazakhstan	Korea, Rep.
13.	Nepal	Malaysia	Mauritius
14.	Pakistan	Mexico	Poland
15.	Philippines	Panama	Portugal
16.	Ukraine	Paraguay	Saudi Arabia
17.	Uzbekistan	Peru	Singapore
18.	Vietnam	Romania	Slovak Republic

	Lower Middle–Income Group	Upper Middle–Income Group	High Income Group
19.		Russia Federation	Slovenia
20.		Serbia	Spain
21.		South Africa	Taiwan
22.		Sri Lanka	
23.		Thailand	
24.		Tunisia	
25.		Türkiye	
26.		Venezuela, RB	

Notes: The World Bank defines four income thresholds based on gross national income (GNI) per capita: low–income, lower than USD1,035; lower–middle income, USD1,036–USD4,045; upper middle–income, USD4,046–USD12,535; and high–income, greater than USD12,536 (World Bank 2020).

Appendix 5. List of lower middle–income and upper middle–income economies in Chapter 5

Lower Middle–Income Economies (47)		Upper Middle–Income Economies (45)	
Angola	Moldova	Albania	Lebanon
Bangladesh	Mongolia	Argentina	Malaysia
Benin	Morocco	Armenia	Mexico
Belize	Myanmar	Azerbaijan	Montenegro
Bhutan	Nepal	Bahamas	Namibia
Bolivia	Nicaragua	Belarus	North Macedonia
Cabo Verde	Nigeria	Bosnia and Herzegovina	Panama
Cambodia	Pakistan	Botswana	Paraguay
Cameroon	Papua New Guinea	Brazil	Peru
Congo, Rep.	Philippines	Bulgaria	Romania
Côte d'Ivoire	Samoa	China	Russian Federation
Djibouti	São Tomé and Principe	Colombia	Serbia
Egypt, Arab Rep.	Senegal	Costa Rica	South Africa
Ecuador	Solomon Islands	Dominica	St. Lucia
El Salvador	Tanzania	Dominican Republic	St. Vincent and the Grenadines
Eswatini	Timor–Leste	Fiji	Suriname
Ghana	Tunisia	Georgia	Sri Lanka
Honduras	Ukraine	Grenada	Thailand

Lower Middle–Income Economies (47)		Upper Middle–Income Economies (45)	
India	Uzbekistan	Guatemala	Tonga
Indonesia	Vanuatu	Iraq	Türkiye
Kenya	Vietnam	Jamaica	Venezuela, RB
Kyrgyz Republic	West Bank and Gaza	Jordan	
Lao PDR	Zimbabwe	Kazakhstan	
Mauritania		Kosovo	

Notes: Lower–middle income countries has GNI per capita between USD1,036 and USD4,044; and Upper middle–income has GNI per capita between USD4,046 and USD12,535 (World Bank 2020).