ABSORPTIVE CAPACITY AND ECONOMIC GROWTH
HOW DOES ABSORPTIVE CAPACITY AFFECT ECONOMIC GROWTH IN LOW- AND MIDDLE-INCOME COUNTRIES?

by

Muhammad Salar Khan
A Dissertation
Submitted to the
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of
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in Partial Fulfillment of
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Doctor of Philosophy
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Committee:

______________________________	David M. Hart, Chair
______________________________	James L. Olds, Chair
______________________________	Maurice D. Kugler
______________________________	Lucas Núñez
	Mark Zachary Taylor, External Reader
______________________________	John S. Earle, Program Director
______________________________	Mark J. Rozell, Dean
Date: __________________________	Summer Semester 2022 George Mason University Fairfax, VA

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Muhammad Salar Khan
Master of Public Policy
Oregon State University, 2017
Bachelor of Science (Hons) in Economics and Politics
Lahore University of Management Sciences, 2013

Director: David M. Hart, James L. Olds, Professors
Schar School of Policy and Government

Summer Semester 2022
George Mason University
Fairfax, VA

DEDICATION

This dissertation is dedicated to my kind mother, supportive siblings, nephew Umar, nieces Fatima, Zainab, Zarlish, and last but not least, my father and uncle, now in the heavens, whose spirits always inspired me to learn and contribute to humanity. May I live up to their expectations!

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LIST OF ABBREVIATIONS AND SYMBOLS

Dollar .... $
Pakistani Rupee .... PKR
National Innovation System .... NIS
Systems of Innovation for Development .... SIDs
Low- and Middle-Income Countries .... LMICs
High-Income Countries .... HICs
National Absorptive Capacity System .... NACS
Science & Technology .... S&T
Science, Technology, and Innovation .... STI
Research & Development .... R&D
Total Factor Productivity .... TFP
Gross Domestic Product .... GDP
International Development Association .... IDA
Multiple Imputation .... MI
Multiple Imputation by Chained Equations .... MICE
Multivariate Normal Distribution .... MVN
Predictive Mean Matching .... PMM
Expectation-Maximization .... EM
Missing Completely At Random .... MCAR
Missing At Random .... MAR
Missing Not At Random .... MNAR
Fraction of Missing Information .... FMI
Castellacci and Natera .... CANA
Muhammad Salar Khan Dataset .... MSK Dataset
Country Policy & Institutional Assessment .... CPIA
Official Development Assistance .... ODA
Logistic Performance Index .... LPI
Economic Complexity Index .... ECI
Human Development Index .... HDI
Information and Communications Technology .... ICT
World Economic Forum .... WEF
Ordinary Least Squares .... OLS
Fixed Effects .... FE
Random Effects .... RE
Standard Deviation .... SD
United States Patent and Trademark Office .... USPTO
Exploratory Factor Analysis .... EFA
Confirmatory Factor Analysis .... CFA
United States Agency for International Development .... USAID
United Nations .... UN

Organization for Economic Co-operation and Development ....OECD
The Observatory of Economic Complexity ....OEC
World Health Organization...WHO
International Monetary Fund .... IMF
United Nations Educational, Scientific and Cultural Organization ....UNESCO
International Labor Organization..ILO
World Trade Organization .... WTO
United Nations Conference on Trade and Development ....UNCTAD
United States .... US
Pakistan ....PAK
Bangladesh...BGD
Federation of Bangladesh Chamber of Commerce and Industries ....FBCCI
Federation of Pakistan Chambers of Commerce and Industry .... FPCCI
Lahore Chamber of Commerce and Industry LCCI
Pakistan Institute of Development Economics ....PIDE
Lahore University of Management Sciences .... LUMS
Institute of Business Administration..IBA
National University of Science and Technology ....NUST
Islamic International University Islamabad ....IIUI
Institute of Management Sciences ....IMSciences
Lahore Chamber of Commerce & Industry LCCI
Public Sector Development Programme ....PSDP
Special Policy Division .... SPD
Technical & Vocational Education Training Authority.. TEVTA
Korean Development Institute .... KDI
Foreign Direct Investment ....FDI
National Vocational &Technical Training Commission .... NAVTTC
World Integrated Trade Solution ....WITS
International Telecommunication Union ....ITU
International Energy Agency ....IEA
World Integrated Trade Solution ....WITS

ABSTRACT

ABSORPTIVE CAPACITY AND ECONOMIC GROWTH
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Muhammad Salar Khan, Ph.D.

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Dissertation Director: Dr. David M. Hart, James L. Olds

This dissertation analyzes the economic growth dynamics of low- and middle-income countries (LMICs) eligible for the World Bank's International Development Association (IDA) support. LMICs are prime candidates for development and innovation, but unfortunately, a lack of a suitable framework and poor data environments dent their value and representation. I cater to those issues by building and testing a framework of growth conditions (*capacities* in this dissertation) using secondary data from 82 LMICs and primary data from fieldwork in Pakistan. Specifically, I address the impact of national-level capacities on economic growth over time while controlling for confounders (including *incoming* skills). Capacities comprise technology and innovation, business environment and finance, human capital, infrastructure, public policy, and social policy, including welfare and inclusion. Inspired by management science and innovation system literature, the first chapter asserts the need for absorptive capacity approaches in measuring

innovation and development processes in LMICs. The second chapter builds a new complete panel dataset with no missing values for 82 LMICs and establishes the reliability and suitability of the dataset in operationalizing the capacities in LMICs. The third chapter builds a framework of capacities in LMICs and tests the framework using machine learning and econometric approaches to examine how capacities affect economic growth in LMICs longitudinally. The fourth chapter classifies LMICs into five clusters to explore trends for policy implications: leading, walking, limping, crawling, and sleeping economies. Economic growth and capacities are higher in leading economies, followed by walking, limping, crawling, and sleeping. The findings highlight the criticality of infrastructure, finance, skilled human capital, and public policy capacities to enhance economic growth. Incoming flows and skills from abroad are also found to be relevant for economic growth in LMICs. Lastly, the fifth chapter conducts research through interviews and secondary content analyses in Pakistan and Bangladesh to ascertain qualitative findings. Analyses confirm the positive effects of some capacities on economic growth as well as the role of confounders in mitigating those effects. Overall, by ranking empirically important capacities for economic growth, I offer suggestions to cash-strapped governments and international organizations such as the World Bank, the UN, and the USAID to make effective investments to achieve sustainable development goals and boost prosperity.

CHAPTER ONE: A THEORETICAL CASE FOR ABSORPTIVE CAPACITIES APPROACHES TO INVESTIGATE NATIONAL INNOVATION SYSTEM IN LOW- AND MIDDLE-INCOME ECONOMIES

Abstract: This review chapter covers some of the founding literature that helps develop our understanding of the National Innovation System (NIS) concept. Subsequently, several versions of NIS, including system-functional approaches, are discussed and compared with narrow R&D and market-based approaches. Finally, the chapter contends that the system-functional and other narrow approaches are limited in application to the developing low- and middle-income countries (LMICs). Thus, it makes a case for more inclusive absorptive capacity approaches and explains how they might be more relevant in investigating the NIS of an LMIC. Such approaches suggest LMICs be strategic in building their innovation base and plead for strong local conditions (capacities) to produce knowledge as well as capture and improvise on incoming knowledge from abroad. The research is important as it provides insights into analyzing and capturing innovation processes in LMICs, which are prime candidates for development and innovation studies and practice.

1. Introduction

As opposed to the classical view of innovation taking place in "silicon valleys" and research and development (R&D) labs, National Innovation System (NIS) framework offers a more comprehensive lens to investigate innovation activities in a country (López-Rubio, Roig-Tierno, and Mas-Verdú, 2021). Studies find NIS is crucial to innovation-based economic growth (Khan, 2022; Casadella and Uzunidis, 2017; Sesay, Yulin, and Wang, 2018). The NIS entails all economic, political, and social factors influencing innovation on a national scale (Khan, 2022). These factors include the financial infrastructure, private and public firms, educational systems, labor markets, culture, regulatory policies, and the quality of innovation institutions, among other factors (López-

Rubio, Roig-Tierno, and Mas-Verdú, 2021; Fagerberg and Srholec, 2017). Countries that have successfully put together these innovation factors have outperformed and earned the returns in greater economic prosperity.

As a standard reference in the literature on innovation and growth (Chaminade, Lundvall, and Haneef, 2018), policymakers worldwide use the NIS concept (Delvenne and Thoreau, 2012). Many organizations, including the Organization for Economic Cooperation and Development (OECD), the United Nations Conference on Trade and Development (UNCTAD), the European Commission as well as the World Bank, have adapted the idea as a vital diagnostic for their analytical perspective (López-Rubio, Roig-Tierno, and Mas-Verdú, 2021; Chaminade, Lundvall, and Haneef, 2018; Godin, 2009; Delvenne and Thoreau, 2012). Several Science & Technology (S&T) think tanks within the US (Atkinson, 2020; Feinson, 2003) and the US National Academy of Sciences use NIS to analyze science and technology policy in the US (Lundvall et al., 2002). Sweden named a new government institution *Vinnova*, 'the Systems of Innovation Authority' (Regeringskansliet, 2015). The institution aims to promote growth by developing Swedish innovation systems.

The NIS literature is particularly promising in presenting a discourse to analyze innovation processes and factors of innovation in high-income countries (HICs). However, low- and middle-income countries (LMICs) remain marginal in the innovation system literature (Lema, Kraemer-Mbula, and Rakas, 2021; Choi and Zo, 2019). As the researchers have conceived the concept in the context of HICs, it does not automatically and directly capture innovation processes and factors in LMICs (Khan, 2022; Delvenne and Thoreau, 2012). Moreover, LMICs have unique political and social circumstances that merit attention. Thus, new approaches incorporating LMICs' circumstances are needed to capture their innovation processes. Such approaches will possibly identify conditions that might strengthen the innovation system in LMICs and ideally highlight the role of various actors in building innovation processes in LMICs.

This review chapter aims to present a theoretical framework to be used in research on the NIS in LMICs. In doing so, the chapter first covers background literature that helps develop our understanding of the NIS concept. Subsequently, several versions of NIS, including *system-functional* approaches, are discussed and compared with narrow *R&D* and *market-based* approaches. The chapter then asserts that NIS and its different versions, including system-functional approaches, do not fully capture innovation processes in LMICs. Furthermore, since such approaches are limited in their application to the LMICs, the chapter finally makes a case for more inclusive absorptive capacity approaches and explains how they might be more relevant in investigating the NIS of LMICs.

Earlier NIS literature has alluded to absorptive capacities approaches (Fagerberg and Srholec, 2017; Juma et al., 2001; Gebauer, Worch, and Truffer, 2012; Choi and Zo, 2019; Casadella and Uzunidis, 2017) but has not quite tried to investigate fully what they may entail. This chapter explains absorptive capacities approaches vis-à-vis other NIS approaches and makes a theoretical case for why such approaches are worth pursuing in investigating the NIS of LMICs.

2. National innovation system

Not long ago, economists considered growth in machinery and the labor force as the prime determinants of economic growth (Solow, 1956). In such conventional approaches, economic growth depends on secular market signals, including the *supply* and *demand* of growth factors and their *market price*. The *observed* growth *unexplained* by these factors is attributed to *total factor productivity* (TFP), expressed as the ability of the system to combine growth factors (Comin, 2010). While it is calculated indirectly as a *residual* from the production function, economists have yet to develop a consensus on what determines the TFP (Kataryniuk and Martínez-Martín, 2018). Some people termed the TFP a “coefficient of ignorance” (Balogh and Streeten, 1963) or a “third factor” (Freeman, 2002). Against this backdrop, researchers developed the National Innovation System (NIS) concept during the last quarter of the 20th century to explain growth dynamics as a function of innovation processes on a system level.

The NIS concept (and literature) flourished quickly across continents (López-Rubio, Roig-Tierno, and Mas-Verdú, 2021; Băzăvan, 2019; Yongabo and Göransson, 2020; Kurpayanidi, 2021; Oh and Yi, 2022; Zygiaris, 2022; Rakas and Hain, 2019; Sharif, 2006; Fagerberg and Sapprasert, 2011). This rapid diffusion of the concept may have been caused by the failure of mainstream macroeconomic theory and policy to explain international competitiveness and economic development satisfactorily (Lundvall et al., 2002). Besides, the co-emergence of *New Growth Theory* (Romer, 1990) in the mid-’80s may have advanced the concept further. In addition, the global financial and economic crises also might have called for a need for innovation policies, as suggested by the NIS framework. For example, Frenkel and Maital (Frenkel and Maital, 2014) assert that resource scarcity after the crises put renewed focus on investigating intelligent ways to make existing resources do more and, thus, on finding ways to stimulate innovation through public policies.

2.1. Institutions and their interactions are central in the NIS literature

Freeman (1987) first used the expression "National System of Innovation" in his study of Japan's technology development (Edquist, 2006). He defined it as "the network of institutions in public and private sectors whose activities and interactions initiate, import, modify and diffuse new technologies." Lundvall (2009) and Nelson (1993) also wrote extensively on national innovation systems. Among others are Patel and Pavitt (1994), Metcalfe (1995), Dosi et al. (1988), and Edquist (2006), who developed mainly similar definitions. For Lundvall et al. (2009), the institutional setup is a vital element of the NIS. Nelson (1993) also emphasizes the institutions and interactions that support technical innovation. Likewise, Patel and Pavitt (1994) acknowledge institutions' importance and linkages in driving technical change. In a similar vein, Metcalfe (1995) considers institutions as central. He defines NIS as "a system of interrelated institutions for creating, storing and transferring the knowledge, skills, and artifacts that define new technologies." Finally, for Edqusit (2006), institutions and organizations, their interactions, and the functions they perform collectively make NIS.

In most of these initial versions of NIS, 'institutions' (actors) and their 'interactions' (linkages) form the cornerstone. While the scholars differ on what organizations and institutions to include as components in the system, they agree on the *systemic* interdependence and interaction of organizations in a country, shaping innovation. It is only through complex interactions among the actors that innovation and technical progress happen. The actors, including political, social, and economic organizations and institutions, their respective functions, and interactions potentially demarcate the boundaries of a NIS. A country is said to innovate if the actors in the country strengthen each other by considering themselves as building blocks of a joint system of knowledge creation and use as well as technology use.

2.2. Narrow and broad approaches within the NIS literature

The scholars of the NIS literature operate with either "narrow" or "broad" approaches to NIS. This classification scheme offers interesting theoretical and political perspectives. Table 1.1 below summarizes the main themes of the two approaches.

Table 1.1: Narrow vs. Broad Innovation Approaches

Theme	Narrow	Broad
Introductory authors	• Nelson (1993)	• List (1841), Freeman (1987), and Lundvall et al. (2002)
Focus	• Science-based learning • Radical innovations • Firm-level STI learning	• STI and DUI learning • User-producer interaction • Incremental innovations • Diffusion of innovations
Building column	• R&D organizations • National science institutions	• Knowledge is the most critical resource • Learning is the most crucial process in the economy
Independent variables	• R&D expenditure • R&D organizations	• Strength of institutions • Linkages among institutions • Policy levers
Dependent variables	• Science-based learning • Outputs such as papers, patents • Radical innovation	• STI learning • Innovations (incremental and radical) • Diffusion of innovations
Policy implications	• Promote science-based learning • R&D expenditure	• Offer conditions to improve learning across an organization • Include institutions affecting learning • Promote experience-based learning and tacit knowledge and diffusion of technologies

Narrow NIS approaches, such as those offered by Nelson (1993), focus on R&D institutions and their interaction with firms (Chung, 2002). Such approaches emphasize the search processes by highlighting science-based organized learning and knowledge (Lundvall et al., 2002). As for innovation processes, the narrow perspectives underscore the importance of radical innovations and emerging technologies. Moreover, these perspectives create science and technology policies, linking R&D institutions to users in the private and public sectors. While strong relationships between users and research producers are beneficial, they may also lead to *lock-in* when a radical shift in technological trajectory occurs.

On the other hand, the broad approach recognizes these narrow institutions and processes and asserts that they are entrenched in a much broader socioeconomic milieu in which cultural attitudes, political influences, and economic policies determine the extent, direction, and relative success of all innovation activities (Freeman, 2002; Lundvall et al., 2002). Such an approach comprises national institutions and organizations that shape human resources and learning processes and build competencies by imparting education, training, and experience-based learning.

The broad approaches highlight *user-producer interaction*, *experienced-based learning*, *tacit knowledge*, and *interactive learning* processes taking place within and across firms/organizations, and that are outcomes of routine procedures, including learning by doing (Lundvall et al., 2002). They present the innovation system as ingrained in 'the national production system' (Freeman, 1987). Since the focus is on the link between innovation and national aggregate performance, the broad approach regards the innovation process as including incremental innovation, the diffusion and use of novel technologies, and the creation of new ideas and techniques (Feinson, 2003).

In general, the broad NIS strands stimulate a more comprehensive set of policies, consisting of industrial policy and policies related to competence building, such as education policy and labor market policy. Such policies impact the design of institutions and organizations related to learning by *doing, using, and interacting* (DUI).

2.3. Why is a nation a worthwhile unit of analysis?

While the choice of national unit for analysis might have been in response to growing globalization (Chaminade, Lundvall, and Haneef, 2018) or could have been in reaction to neoclassical economics focusing on national growth agendas (Lundvall et al., 2002), the pragmatic and policy concerns perhaps make the nation-state a practical choice for analysis in NIS. For Lundvall et al. (2002), a nation is a worthy choice of analysis because of the "policy dimension of the concept." Different countries have different innovation policies and agendas; thus, it makes more sense to consider the national system as an analytical object. In addition to the policy dimension, the unit is worthwhile for logistical purposes. Innovation and long-term "interactive learning" are easily carried out in national settings with few linguistic and cultural barriers to transferring "tacit knowledge." In such environments, a multifaceted system of trust relationships can also be easily managed. Besides policy and logistical concerns, data is centered around nations, thus making the nation a convenient choice of analysis.

2.4. Types of innovation systems and how they relate to NIS

Pioneer literature on NIS (Dosi et al., 1988; Freeman, 1987; Freeman, 2002; Lundvall et al., 2002) stimulated an extensive set of academic work on innovation and led to a branching of the innovation system concept into many other specifications. These specifications emphasize the systemic characteristics of innovation, but they focus on different economic levels than the nation-state. The three main ones are *regional*, *sectoral*, and *technological systems*. Table 1.2 below briefly illustrates the three specifications.

Table 1.2: Three Specifications of Systems of Innovation

Specification	**Theme**	**Literature**
Regional	The regional classification focuses on a regional system. Inspired by the NIS literature, the regional concept combines the work on regional industrial clusters and districts.	Cooke (1996; 2008), Asheim and Isaksen (1997), Fernandes et al. (2021), López-Rubio, Roig-Tierno, and Mas-Tur (2020), Pino and Ortega (2018)
Sectoral	The sectoral system focuses on firms that manufacture specific products and how such firms interact with a broader set of organizations and institutions. Inspired by the NIS perspective, the sectoral system enriches industrial economics and dynamics.	Li et al. (2021), Malerba (2002), Azad et al. (2019)
Technological	Technological systems focus on technology fields. Such systems analyze the evolving interaction between organizations as new technological systems	Carlsson and Stankiewicz (1991), Bergek et al. (2008), Markard, Hekkert, and Jacobsson (2015), Planko et al. (2017)

Specification	Theme	Literature
	emerge and develop. As the technological system evolves, its geographical reach might vary.	

The NIS concept looks pretty ambitious from the literature: it is developed to inspire national economic growth and competitiveness strategies. The other specifications, while very innovative, do not seem as bold; they address specific subsystems within (and sometimes beyond) the NIS. These specifications might be helpful as many interesting interactions related to modern innovation occur in narrow regions or sectors. For instance, the technological system breeds insights useful for science, technology, and innovation (STI) policymakers about supporting emerging technologies. The regional system offers valuable insights for policymakers overseeing regional development. Finally, the sectoral system provides essential insights into industrial policymaking.

2.5. NIS vs. S&T or an R&D Analysis?

Many approaches, including S&T indicator analysis and R&D analysis, are used to research innovation and innovation policies. Such analyses use narrow S&T and R&D metrics to analyze innovation policies (Raghupathi and Raghupathi, 2019). By focusing on one or a few aspects of innovation, these research approaches themselves beneficial may, in the end, be counterproductive due to their limited scope. Unlike these partial approaches, NIS claims to be a systems-based approach to understanding how the nationwide innovation process works. The NIS is more comprehensive by embracing S&T and R&D

as subsystems (Lundvall et al., 2002) and incorporating *activities* performed by institutions (Edquist, 2006). While understanding the complex interactions among innovation actors, NIS prevents the danger public policies based on partial approaches might cause. One example of a partial approach causing harm would be subsidies and public R&D spending that might discourage private enterprises from funding research (Frenkel and Maital, 2014).

3. Activities-based NIS frameworks

All the versions of NIS (Freeman, 1987; Lundvall et al., 2002; Nelson, 1993) consider institutions as central; however, the functions of institutions in these versions are debatable. Alongside Lundvall's broader framework, we have two main activities-based frameworks that differ in views about the functions of institutions: the OECD and Edquist's system-functional frameworks.

The OECD (1999) framework suggests that NIS requires institutions with six different functions: technology and innovation policy formulation; performing R&D; financing R&D; promotion of human resource development; technology diffusion; and promotion of technological entrepreneurship. This OECD approach has been primarily used in investigating the NIS of developed countries. However, some researchers have also used the OECD approach in examining and comparing LMICs' NIS. For instance, Naqvi (2011) employed the OECD analytical framework to analyze NIS Pakistan. Likewise, Chang and Shih (2004) applied the framework to compare the innovation systems of Taiwan and China. While these studies enrich our understanding, other studies argue that employing the OECD framework in LMICs cannot handle the complexities in LMICs and that this application implies a normative agenda of what should happen (Delvenne and Thoreau 2012).

Edquist, on the other hand, proposed a framework of NIS—Systems of Innovation for Development (SID)—constituting "all important factors, including economic, social, political, organizational, institutional and other factors that influence the development, diffusion, and use of innovations" (Edquist, 2004; 2006). The approach offered by Edquist is even broader than Lundvall's approach toward NIS, and it encompasses both the 'narrow' and 'broad' approaches mentioned earlier. Since it is hard to capture all the determinants of innovation, excluding one or some crucial determinants may cause a reduction, which perhaps Edquist wanted to mitigate in his approach.

Edquist's view toward NIS is *system-based,* in line with Ingelstam's idea (2012) of a "system." Edquist's system has *components* that engage and *interact* with one another. Also, such a system performs *activities* or *functions*. Below I will briefly explain these elements.

3.1. Components

For Edquist, the main components in SIDs are institutions and organizations, which may vary in different countries. According to Edquist and Johnson (2000), "organizations are formal structures with an explicit purpose, and they are consciously created." Critical organizations in SIDs include companies (suppliers, customers, or competitors), universities, venture capital organizations, and public innovation policy agencies. In contrast, "institutions are sets of familiar habits, routines, established practices, rules, or laws that regulate the relations and interactions between individuals, groups, and organizations" (Edquist and Johnson 2000). Examples of some SID institutions are patent laws and norms guiding the relations between universities and firms.

3.2 Relations

The SID approach, in general, emphasizes learning processes for the development of innovations. The learning processes, in turn, require active *interactions*—in other words, *relations*—among organizations and institutions. In the Edquist's approach (Edquist and Johnson, 2000; Edquist, 2006), the relations can exist between the same components (relation between firms and universities or relations between a country's patent laws and informal rules), different components (patent laws and norms influencing the relations between universities and firms or public organizations creating standards and formulating/implementing rules *aka* 'innovation policy').

While institutions shape organizations, institutions are also embedded in organizations (Edquist and Johnson, 2000). In other words, a two-way relationship of mutual dependence exists between the two. This relationship impacts innovation processes and, by this means, also the performance and change of SIDs.

Edquist and Johnson (2000) also point out other important but less direct relations, including relations among organizations and functions (or activities). This relationship may not be one-to-one. Several different organizations can perform one function. For example, research can be carried out by institutes, universities, or research-oriented firms. Conversely, actors can perform multiple functions. For instance, universities are the sources of both new knowledge and educated people (human capital).

3.3 Activities

Perhaps because of the nuances in components and relations, Edquist focused on the systems 'activities' or 'functions.' 'Activities' or the 'functions' of the systems are nearly the same as determinants of innovation processes or factors influencing them (Edquist, 2006). According to Liu and White (2001), 'activities' are related to "the creation, diffusion, and exploitation of technological innovation within a system." Liu and White (2001) identify five fundamental activities:

- research (basic, developmental, engineering)
- implementation (manufacturing)
- end-use (customers of the product or process outputs)
- linkage (bringing together complementary knowledge)
- education

These activities go beyond the R&D system, including essential inputs to research activity and the use of research outputs. Others, such as Hekkert et al. (2007), also present a list of activities. Edquist's list is more extensive, assert Borrás and Edquist (2019). The list includes activities (Borrás and Edquist, 2013; Edquist, 2006) related to the provision of knowledge inputs to the innovation process (such as R&D outcomes in the creation of new knowledge and competence building through individual and organizational learning), demand-side activities (i.e., new product markets and new product quality requirements emanating from the demand side), provision of constituents for systems of innovation (for instance, creating/changing new institutions and enhancing entrepreneurship to create new firms), and support services for innovating firms (incubation activities, financing innovation, and consultancy, for example).

Edquist's list could serve as a *checklist* to explain innovation processes (without missing or overemphasizing one activity) or when choosing innovation policy instruments to mitigate policy concerns and achieve policy goals (Borrás and Edquist, 2013). Since an organization can perform multiple activities, and many activities can involve several organizations, the activities presented by Edquist are also a practical way of policy analysis. By simply looking into the performance of activities of private and public organizations, policymakers can effectively analyze the division of labor among them.

By focusing on activities, Edquist's framework adds to the theoretical rigor of the NIS concept. Such an activities-based approach can potentially serve as a basis for international comparison and can identify policy issues within NIS. However, one can argue that activities may not lead to a strong comparison because activities within one country may differ from activities in other countries. More critique of the activities-based approaches is outlined in section five.

4. NIS for different countries

Enjoying strong initial adoption by OECD and other high-income countries, NIS is currently gaining momentum to address some of the profound issues found in LMICs (Casadella and Uzunidis, 2017; Choi and Zo, 2019). Some studies object to the application of NIS in developing countries, asserting that the emphasis of such application is on simplified mapping without encountering complexities in those countries (Delvenne and Thoreau, 2012). One may argue that all the countries, taken as systems, have institutions, policies, and practices, which perhaps allow the application of the NIS concept. However, there are differences and diversities among the countries. Countries' innovation processes are also complex and nuanced (Katz, 2016). In addition, technology development (as advocated by the NIS approach) follows different trajectories across the countries (Castellacci, 2008). Given these assertions, vast generalization of the NIS concept across countries is perhaps futile (Delvenne and Thoreau, 2012). Even within the HICs or LMICs, there is a considerable degree of variation, which leads to country-specific problems and issues for applying the NIS perspective.

Whereas in HICs, the NIS would "serve the role of maintaining or improving an already established level of competitiveness and growth," NIS faces the challenge of explaining "catching up" (Popov and Jomo, 2018; Dobrzanski, 2018) in poor and progressing LMICs (Feinson, 2003). The "catch up" requires the LMICs to be strategic to acquire existing knowledge and technology and then manifest a thorough command and utilization of that knowledge and technology (Dahlman and Nelson, 1995). This, in turn, demands a favorable environment, including local conditions (such as sound infrastructure, healthy business environment and finance, robust institutions, and human capital, among others) in LMICs. Also, since LMICs interact with other countries, they attract *incoming* knowledge (skills, technological cooperation grants, among other inflows). Thus, the "absorptive capacities" approaches this chapter pleads for include both these local conditions (capacities) and incoming knowledge, as depicted below in Figure 1.1.

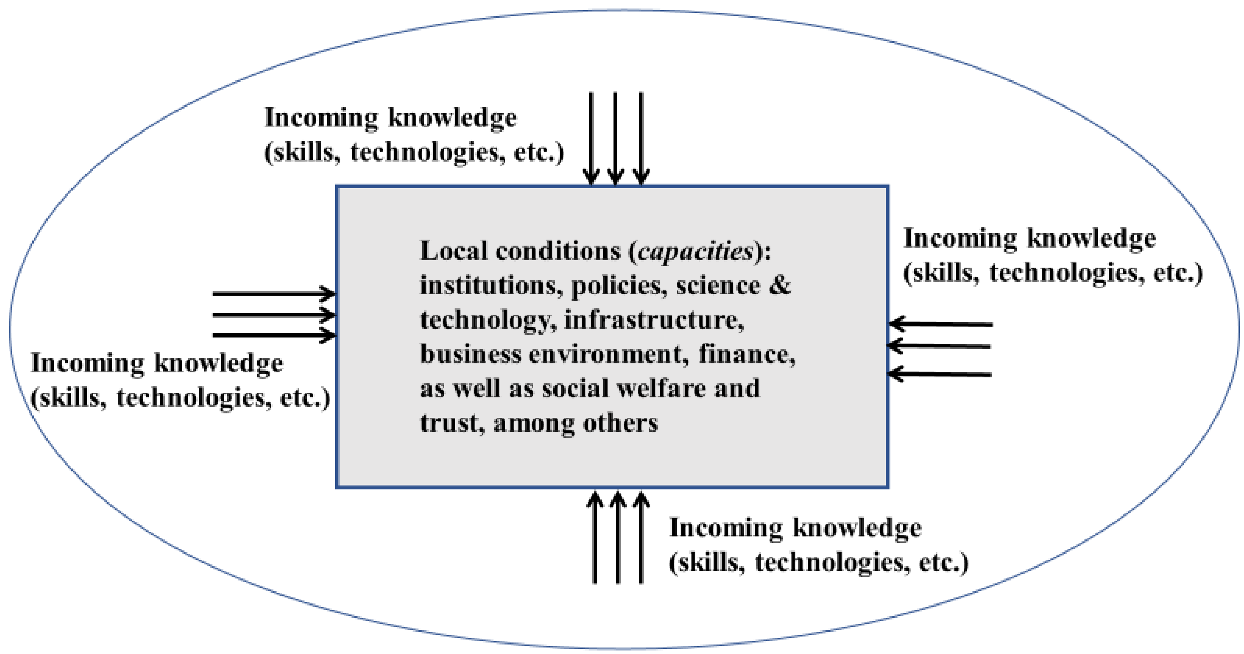

Figure 1.1: Absorptive Capacities Approaches. The figure shows that an LMIC comprises various local conditions (capacities) and attracts incoming knowledge from abroad.

The figure indicates that absorptive capacities highlight two critical elements: capacities (such as institutions, policies, science and technology, infrastructure, business environment, finance, and trust, among others) and incoming knowledge (for instance, skills, technologies, and technological cooperation grants). The adjective 'absorptive' implies that an LMIC absorbs 'knowledge from abroad' and then utilizes the knowledge to create (economic) value subject to the strength of its local conditions (capacities). In case an LMIC's capacities are not strong enough, it won't absorb (or improvise on) that incoming knowledge and hence not covert the incoming learning into economic value. With its focus on developing human capital and other local conditions, NIS offers ways to foster absorptive capacities.

The term "absorptive capacity" appears initially in firm-level literature to indicate a firm as a learning entity (Cohen and Levinthal, 1990). Later, NIS literature also employs (or alludes to) this concept (Dahlman and Nelson, 1995; Narula, 2004; Criscuolo and Narula, 2008; Gebauer, Worch, and Truffer, 2012; Castellacci and Natera, 2016). Charles Edquist, for example, contends "absorption" as one of the four main areas where his proposed SID concept departs from the NIS approach in HICs (Edquist 2005). According to Edquist (2005), the four areas in which SID is distinct from the NIS are given below:

• Product innovations are more critical than process as they affect the product structure

• Incremental innovations are more reasonable than radical ones

• Instead of new innovations, absorptions (diffusion-based on absorptive capacity) are vital

• Innovations in low- and medium-tech areas are more realistic than those in high-tech

Of the above, absorption (absorptive capacity) is more important for LMICs. This capacity refers to the ability to (acquire) learn and implement the technologies and associated practices of already developed countries, argue Dahlman and Nelson (1995). Researchers argue that the advancement of absorptive capacities through various components of the NIS is essential for industrial development and economic growth in LMICs (Khan 2022).

This emphasis on absorptive capacity shifts the priority for LMICs from innovation allocation to learning, including passive and active. Passive learners "absorb the technological capabilities for production, using a kind of 'black box' approach," whereas active learners achieve "technology and its improvements through a deliberate effort" (Juma et al., 2001). Whether a country adapts an active or passive learning approach, this choice has a profound impact on that country's ability to achieve the type of growth that will improve the living standards of its citizens. Juma et al. (2001) contend that passive learners, doomed to remain undeveloped in the long run, depend on spurious competitiveness, such as low wages, natural resource depletion, and state subsidy or protection. On the other hand, active learners bring domestic technological improvements beyond simple technology transfer.

In a similar vein, Viotti (2002) has argued that in the case of technologically lagging economies, learning is defined as "the process (and development) of technical change achieved by diffusion and incremental innovation." In other words, learning is the absorption of existing techniques, i.e., the absorption and incorporation of innovations produced elsewhere and the introduction of improvements. These ideas provide a foundation for studying the NIS of LMICs.

While there are many NIS studies, they are very generic. Most of these studies analyze the NIS of HICs (Zabala-Iturriagagoitia et al., 2021; Marxt and Brunner, 2013; Nelson, 1993). For LMICs, discussions on NIS are yet to be exhausted (Egbetokun et al., 2017; Lema, Kraemer-Mbula, and Rakas, 2021). As technology lagging LMICs establish more efficient NISs to catch up with HICs, investigating their NIS would be beneficial. The term 'innovation' might not mean the output of formal R&D in LMICs, which is the case in HICs (Khan, 2022; Mani, 2002). According to Mani (2002) and Khan (2022), innovation in developing LMICs results not only from R&D activities but also from many other technology activities. Thus, a framework of absorptive capacity, as illustrated here, is needed to capture innovation processes unique to LMICs.

Even within LMICs, a great deal of variation exists. NIS in these countries, therefore, should relate to each country's development level. While developing an absorptive capacity framework for an LMIC, one must consider the country's economic, structural, and institutional development level and its existing capabilities. Following such a consideration, the absorptive capacity approach identifies conditions to upgrade and improve a nation's capacity.

5. Proposed approach to National Innovation Systems of LMICs

This chapter identified multiple approaches to investigating innovation processes in countries. These approaches can be grouped into the following four categories (Table 1.3 in the Appendix summarizes all these approaches):

- Narrow R&D approaches
- Market-based, neo-classical approaches
- Broad activities-based, system-functional approaches
- Absorptive capacities-based approaches

When it comes to LMICs, what could be the right approach? First, all countries—poor and rich—have institutions, policies, and practices if taken as a whole. This fact allows for a universal application of the NIS concept.

However, ignoring variations among countries will be imprudent even when countries have comparable incomes or are in a similar region. Countries and regions' innovation processes are unique to their context, heritage, and history. Moreover, such processes are complex and more nuanced (Katz, 2016). Thus, every country (and region) demands a more dynamic, contextual, historical, and analytical lens of investigation; a one-size-fits-all approach is not appropriate (Delvenne and Thoreau, 2012). Although the narrow R&D, market-based, and activities-based approaches provide a solid foundation for analyzing NISs in LMICs, they lack strong analytical tools to investigate the innovation processes within LMICs (Delvenne and Thoreau, 2012; Lundvall et al., 2002). Consequently, this chapter proposes absorptive capacities approaches in studying the innovation dynamics of LMICs. The following paragraphs critique the existing approaches before further strengthening the theoretical case for absorptive capacities approaches highlighted previously.

The R&D framework, as proposed by Nelson (1993), is more of a narrow S&T or a conventional *science-based* framework. With its emphasis on R&D organizations, the framework focuses on fixed inputs and research outputs (e.g., in Siyanbola et al., 2016). While innovation is an interactive process, this framework is far from capturing dynamic innovation processes in the developed world, let alone LMICs, where innovation processes differ entirely (Khan, 2022). Also, in LMICs, R&D expenditures as shares of GDPs are small, R&D activities are limited, as well as R&D organizations are ineffectual (Edquist, 2006), and there is a low demand for scientific research and knowledge from the productive sector (Vasen, 2011). These countries are not even close to the frontier of traditional and emerging technologies. Thus, the application of the R&D framework might not be valuable for the analysis in LMICs. It is just not rational to expect an LMIC firm with zero or tiny R&D allocation to compete overnight with IBM or Microsoft.

On the other hand, by emphasizing market signals, such as *supply* and *demand* forces, *market price,* and *market equilibrium*, market-based approaches (Martin and Scott, 2000) make a strong case for their universal application. Like R&D approaches, such conventional approaches also specify specific inputs and outputs in evaluating the existing system. Among other problems,[1] the market-based approaches are based on the untenable assumptions of market equilibrium, which is considered 'optimal' and maximizing behavior (Harper, 2018). For such approaches, allocation to innovation is *socially inefficient* than the *ideal norm of perfect competition*. This "market failure" is caused by various factors, including information asymmetry between innovators and investors, knowledge spillovers, and uncertainty about the future of innovative ventures, among other

[1] For example, by assuming that production (innovation) technologies are identical and exogenously given across countries and that returns to scale are constant, market-based approaches assert that all countries (including HICs and LMICs) will converge (Martin 1999). This assertion has been challenged in the new growth theory literature (Romer, 1986, 1994).

factors (Harper, 2018). Such market-based approaches do not work (in general and in LMICs) because they ignore the path-dependent, evolutionary, and dynamic features of innovation processes (Metcalfe, 2001). Because of these features that innovation processes carry, it is impossible to specify any optimal or ideal innovation system. In fact, the innovation system never achieves an ideal equilibrium state (Metcalfe, 2001). Thus, the notion of market failure (or deviation from market equilibrium) also loses its meaning and applicability. Market-based approaches are not useful analysis tools, particularly in LMICs, because their innovation markets are weak (Oliveira and Rodil-Marzábal, 2019). Such markets, like other markets in LMICs, are informal; thus, it is hard to capture them (La Porta and Shleifer, 2014). There also exists a high uncertainty about the prospects of innovation outcomes in LMICs (Lin, Dong, and Wang, 2021). In addition, the policymakers most likely intervene based on factors (such as party affiliation, elite capture, and interest groups) rather than weak price signals.

In contrast to the market failure approaches, researchers following a system-functional approach often speak of 'systemic' problems while focusing on the complex interactions among the various organizations and institutions that constitute the system of innovation (Edquist, 2011). According to this approach, policymakers need to mediate in those areas where the system is not performing well (Chaminade and Edquist, 2006; Edquist, 2001). The literature highlights a range of systemic issues. For instance, Smith (2000) and Woolthius et al. (2005) refer to infrastructure deficiencies, organizational incapabilities, dynamic hindrances entrenched in risk and uncertainty, and cultural as well as regulatory institutional obstacles confronted by innovators, among other blockades.

While the market approaches, as elaborated previously, struggle to conceptualize, or address such institutional and organizational issues, the system-functional approach calls on the government to analyze and mitigate those issues.

The ‘activities’ framework by Edquist for analyzing SIDs follows a systematic approach (Edquist, 2005; 2006). For such an approach, crucial activities that influence innovation processes present a feasible entry point into policy analysis. The approach also recognizes the organizations performing the activities and examines the relations among them. Besides Edquist’s approach, there are several approaches to analyzing activities in NIS. For example, Furman et al. (2002) and Liu and White (2001) also focus on functions related to the innovation process (*innovation process-oriented frameworks*). Similarly, the works of Jacobsson and Bergek (2004) highlight actions associated with the knowledge production, distribution, and utilization process (*knowledge process-oriented frameworks*). Borrás (2004), on the other hand, recognizes the activities of various organizations that impact the innovation system (*organizations-oriented frameworks*). Lastly, OECD (2002) frameworks focus on activities and organizations in NIS that can be influenced by public intervention (*innovation policy-oriented frameworks*).

In general, all the activities-based frameworks enshrine an active role of government and innovation policy. Such frameworks also help resolve some theoretical debates regarding the character and dynamics of NIS and are handy for assessing policy issues within NIS (Edquist, 2006). Yet, these activities-based frameworks may not be the best to follow universally. Firstly, their heavy emphasis on activities might be self-defeating. As NIS evolves, so do the functions of these NIS; therefore, fixing a list of innovation activities might not be productive. Secondly, people have different perceptions of various activities. Some activities are more important than others in different countries. Thus, while the focus on activities does make cross-comparisons of NIS possible, this comparison might not be meaningful. For instance, the NIS of Sweden and Norway might not be compared meaningfully with the NIS of Sub-Saharan Africa. Third, since the activities are abstract and indirect (Golichenko, 2016), it is not entirely clear to what extent the system-activity-based approaches add to the theoretical rigor of the concept.

Moreover, various definitions of system-based approaches specify different sets of institutions and organizations, which makes it confusing to analyze and comprehend. For example, while there is an overarching institution of the state, there are institutions within organizations, e.g., rules for bookkeeping in any ministry or the rules of procedure to run a public office in an LMIC. It is not apparent how the system-based approach deals with all these distinctions.

Despite all the limitations, the activities-based frameworks and, more generally, the system approach on which they are founded seems superior to the conventional 'market failure' approach to specifying and evaluating the grounds for policy intervention. However, the activity-based approach might not be of practical utility, particularly in LMICs. First, the activity-based approaches were ideally developed, keeping the circumstances of HICs into consideration. In the developing LMICs, not only are activities weak, but they are limited and different. Second, a call for government intervention might not be as helpful, as LMICs are not mature democracies. These LMICs are not mostly stable; instead, they are fragile. Political governments within LMICs would also not have immediate and strong incentives to intervene and implement an innovation policy.

What kind of approaches must one investigate for analyzing the innovation systems in the developing LMICs? As mentioned, LMICs have unique political and socioeconomic circumstances. Their innovation processes are distinct from those in HICs. The existing frameworks, developed primarily in HICs, fail to capture innovation processes in LMICs, as also asserted by Delvenne and Thoreau (2012) while critiquing the application of the OECD framework to poor countries. Thus, this chapter contends that absorptive capacities approaches would be more suitable for the analysis of developing LMICs' NIS. Absorptive capacity signifies the ability to (acquire) learn and implement the technologies and associated practices of already developed countries, as earlier argued by Dahlman and Nelson (1995). Researchers discuss the advancement of national absorptive capacities through active and deliberate policy levers as essential for LMICs' development and economic growth (Khan, 2022).

LMICs, by in large, are *lagging* in innovation growth. Even if they intend to catch up with HICs, they might not handle so well all the innovation processes and overcome the obstacles overnight. These countries' firms, institutions, and organizations would have to make persistent and intentional planning to catch up. Initially, they might focus on incremental innovations instead of radical ones (Edquist, 2005). They would need to have active policies for technology assessment, acquisition, imitation, and subsequent diffusion (Dahlman and Nelson, 1995). This, in turn, requires a strong "absorptive capacity." Absorptive capacity thus refers to all the conditions (local conditions alongside the absorption of incoming knowhow) needed to cause successful acquisition, imitation, improvisation, and diffusion of technology (Khan, 2022).

Such an approach deviates from the activities-based approaches to the extent that it does not stress all the advanced activities typically observed in developed NIS. Yet, it is like the system approaches because of its emphasis on interactive learning for the user, producer, and government. Moreover, it includes non-market relationships involving authority, trust, and norm (*social capacity*), which are generally more prevalent in developing LMICs (Winiecki, 2004; Escandon-Barbosa, Urbano-Pulido, and Hurtado-Ayala, 2019).

Absorptive capacity approaches would initially call for need assessment exercises in LMICs. By considering absorptions more critical than innovations, such approaches might divide the LMIC's economy into sectors such as the firms-based economy (businesses, companies, firms), public-based economy (federal organizations and institutions), and household-based economy (individuals and households). The approaches would also develop a set of conditions required to spur innovation-based growth for an overall LMIC-economy. Instead of making innovations in high technology systems, such approaches may consider realistic innovations in low and medium technology areas in line with Edquist's suggestion (2005).

The emphasis on absorptive capacity shifts the priority for LMICs from innovation to learning. In other words, LMICs achieve technical change or growth in TFP by diffusion and absorption of existing techniques. Innovations produced elsewhere will be absorbed, internalized, and further value-added through a deliberate effort. Suppose LMICs want to close the technological gaps. The absorptive capacities approach would plead to close the gaps by learning and absorbing technologies as well as creating the internal capabilities to utilize and improve those technologies, just as pursued by countries such as South Korea. Absorptive capacities approaches are tailored so because they are cognizant of the circumstances in LMICs where innovation results not only from R&D activities but also from many other technology activities. Such approaches consider an LMIC a learning and dynamic entity constantly striving to implement conditions that help it develop local knowledge, capture the incoming knowledge, and improvise on it to spur innovation-based growth. Since these approaches are abreast with social and political realities in LMICs, they better handle the innovation processes in those countries compared to other approaches.

6. Conclusion

This chapter argued for absorptive capacities approaches in analyzing NISs of LMICs. The chapter discussed existing narrow R&D approaches, market-based neoclassical, and activities-based frameworks. While R&D approaches mainly consider R&D organizations as central, market-based approaches find the supremacy of the market. Both these approaches generally operate with fixed inputs and outputs. Unlike these approaches, activities-based approaches focus on activities and enshrine an active role of innovation policy. These NIS approaches provide a foundation for studying innovation systems and processes in LMICs. However, they lack the analytical tools to fully analyze innovation processes unique to LMICs.

Because of the lack of a proper theoretical framework, LMICs rarely are the subject of discussion in innovation studies despite being the prime candidates for innovation and development. An adequate framework is needed to capture the innovation processes in LMICs. The proposed absorptive capacities approaches offer valuable insights and representation to study innovation systems in poor LMICs. By emphasizing the role of active economy-wide learning and competence building, the approaches call for building local conditions (capacities) and incorporating knowhow from abroad.

Economy-wide learning will undoubtedly involve all stakeholders, including public organizations, firms, educational institutes, businesses, nonprofits, and households. Such learning will focus on various local capacities, including human capital, social capital, finance, business environment, science and technology, infrastructure, institutions, and public policies. In light of the absorptive capacities approaches, LMICs will also learn from skills and technologies coming from abroad.

All in all, the current chapter offers a conceptual lens when analyzing NIS in LMICs, which are prime candidates for development studies and practice. The findings from this research provide insights and representation to LMICs in the innovation studies and development literature. The following chapters refine the absorptive capacities approaches and include innovation indicators and other dimensions unique to LMIC

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Appendix

Table 1.3: Summary of Comparisons Among Different Approaches to Innovation

Approach / Indicator	Narrow R&D approaches	Market-based neo-classical approaches	Broad activities-based, system approaches	Absorptive capacity-based approaches
Input	R&D finance	-Market conditions -Market price -Market signals	-R&D expenditure -Policy tools (institutions and linkages)	-Policymaking, planning -Focused infrastructure investment, social interventions, and other capacities -Import of needed commodities and incoming knowhow
Output	-Publications -Graduates -Patents -Trade secrets -No. of researchers	-Export quality -Export volume -New products -Radical innovation	-New products -New processes -STI and DUI learning -Skills -User-producer interaction -Diffusion of innovations	-Improved products and processes -Technology diffusion, improvisation, -Incremental and radical innovation -Learning, competence, skills -Growth

Approach Indicator	Narrow R&D approaches	Market-based neo-classical approaches	Broad activities-based, system approaches	Absorptive capacity-based approaches
			-Incremental innovations	
Reliability	More reliable as it is easily measured	More reliable as it is easily measured	Less reliable as it is hard to measure everything, such as competence building	Somewhat reliable: A strong framework can increase reliability
Assumptions	S&T indicators are magic stick	Optimal equilibrium	Organizations and institutions have functions	-Economies interact with the outside world, and internal conditions can be influenced by policy
Focus	-S&T indicators -Radical innovations -Firm-level STI learning	-Competitiveness -Radical innovations	-Product and process innovations -Marketing, and organizational methods improvement	-Diffusion, imitation, -Process, product innovations -Both radical and incremental innovations
Application	-Organization -Ministry -Economy	-Economy -Industry	Economy	Economy
Role of government	Moderate as there is private R&D too	Null	Maximum	Maximum

Approach / **Indicator**	**Narrow R&D approaches**	**Market-based neo-classical approaches**	**Broad activities-based, system approaches**	**Absorptive capacity-based approaches**
The rationale for government intervention	The inefficiency of the private sector requires central planning and coordination	Market failure	Systemic failures	Systemic failures
Universality	Not applicable to LMICs fully because R&Ds are tiny and ineffective	A limited application where markets are too advanced	Not entirely relevant to LMICs	Applicable to LMICs
Policy implications	-Promotion of science-based learning -R&D expenditure	-Remove market failures -Increase competitiveness in the world market	-Conditions to improve learning across the organization -Consider the institutions affecting learning, -Promote experience-based learning and tacit knowledge and diffusion of technologies	-Conditions to improve learning in the economy, build the capacity of institutions, put in effort in terms of resources, and plan to promote competence and local capacities, -Policy to attract and improvise on incoming knowledge

CHAPTER TWO: ESTIMATING A NEW PANEL DATASET FOR COMPARATIVE ANALYSES OF NATIONAL ABSORPTIVE CAPACITY SYSTEMS, ECONOMIC GROWTH, AND DEVELOPMENT IN LOW AND MIDDLE INCOME ECONOMIES

Abstract: Within the national innovation system literature, the low- and middle-income countries (LMICs) eligible for the World Bank's International Development Association (IDA) support are rarely part of empirical discourses on growth, development, and innovation. One major issue hindering empirical analyses in LMICs is the lack of complete data availability. This work offers a new full panel dataset with no missing values for IDA-eligible LMICs. I use a standard, widely respected multiple imputation method (specifically, *Predictive Mean Matching*) developed by Rubin (1987), which conforms to the multivariate continuous panel data structure at the country level. The incomplete input data consisting of many variables come from publicly available established sources. These variables, in turn, capture six crucial country-level capacities: technological capacity, financial capacity, human capital capacity, infrastructural capacity, public policy capacity, and social capacity. Such capacities are part and parcel of the *National Absorptive Capacity Systems* (NACS). The dataset (MSK dataset) thus produced contains data on 47 variables for 82 LMICs between 2005 and 2019. The dataset has passed a quality and reliability check and can be used for comparative analyses of national absorptive capacities and development, transition, and convergence among LMICs.

1. Introduction

The National Innovation System (NIS) focuses on a broad range of variables, activities, institutions, and their interactions that can foster economic growth and development in countries (Edquist 2006). However, this literature underrepresents the global South. One of the major problems for this lack of reasonable representation stems from the lack of data for low- and middle-income countries (LMICs). By resulting in the exclusion of LMICs in empirical analyses, missing data lead to either positively or negatively biased results that manifest themselves in over and underestimated effect sizes.

Despite the general limitations, several studies have recently investigated NIS and its relationship with growth and development in some developing economies (Choi and Zo 2019; Intarakumnerd, Chairatana, and Tangchitpiboon 2002; Lundvall et al. 2009; Casadella and Uzunidis 2017). Other studies, using capacities as a way to operationalize NIS, have employed available data for diverse samples of countries to estimate the quantitative impact of financial, technological, and social capacities of countries on their economic growth and development process (Khayyat and Lee 2015; Fagerberg and Srholec 2008; 2017; Archibugi and Coco 2005; Gebauer, Worch, and Truffer 2012; Andersson and Palacio Chaverra 2017).

Inspired by the studies on capacities and economic development, Khan (2022) has recently rigorously operationalized a thorough list of capacities that capture innovation, knowledge absorption, and learning processes in LMICs and included those capacities in a formal framework of the National Absorptive Capacity System (NACS). A firm-level concept of "absorptive capacity," as advanced by Cohen and Levinthal (1990), particularly motivates the NACS framework. As a modified version of NIS, NACS considers an LMIC an "economic learning" entity that absorbs, creates, and deploys knowledge, learning, and skills subject to the strength of its local capacities. To study NACS and its evolution in LMICs and to further examine the impact of the framework capacities on economic development in LMICs, complete panel data (country-year observations) on variables that measure capacities are required. Unfortunately, such variables are not wholly available across LMICs eligible for the World Bank's International Development Association (IDA) support that are foci of this study.[2] Hence there is a dire need to fix this problem of missing data for those LMICs, presumably prime candidates for development, learning, and innovation. Therefore, in this chapter, I build a complete and recent dataset on variables constituting capacities within LMICs, using established statistical and machine learning techniques.

Data incompleteness, commonly called the missing data problem, severely hampers empirical research. Various research fields have extensively investigated missing data dynamics, their consequences, and possible remedies (Nugroho and Surendro 2019; Xue et al. 2017; Gilbert and Sonthalia 2018; Enders 2017a; Ginkel et al. 2020; Jones and Tonetti 2020). However, the innovation system and absorptive capacity literature have yet to thoroughly investigate missing data's nuances, processes, and implications. One significant repercussion of missing data is that the current empirical literature on NIS and economic growth suffers from an imbalance. The literature either focuses on many countries within a limited period (Fagerberg and Srholec 2008) or analyzes a few economies for an extended time (Castellacci and Natera 2016; Erdal and Göçer 2015). The former strand of literature

[2] Eligibility for IDA support depends mainly on a country's relative poverty. Relative poverty is defined as GNI per capita below an established threshold, and it is updated annually (1,185 US dollars in the fiscal year 2021). IDA also supports some countries, including several small island economies, that are above the operational cutoff but lack the creditworthiness needed to borrow from the International Bank for Reconstruction and Development (IBRD). Some countries, such as Nigeria and Pakistan, are IDA-eligible based on per capita income levels and are also creditworthy for some IBRD borrowing. They are termed as "blend" countries. http://ida.worldbank.org/about/borrowing-countries

Since IDA eligibility is based off GNI per capita, countries graduate and reinter (reverse graduate in the list). I have data on 82 countries (74 among them are still eligible for IDA resources and 8 countries recently graduated). For a list of IDA graduates, please check: http://ida.worldbank.org/about/ida-graduates can only provide a limited study of the evolution within NIS and NACS, whereas the latter strand prevents analyses in many LMICs. Neither is ideal; while the former is static, the latter is not representative of the LMICs.

This chapter systematically compiles, estimates, and imputes an incomplete dataset to alleviate the missing data problem in LMICs eligible for IDA support. It employs multiple imputation (MI) approach that *efficiently* and *consistently* estimates missing data and generates a panel dataset for 82 LMICs between 2005 and 2019. MI uses state-of-the-art statistical methods to address the missing data problem (Rubin 1996; Enders 2017b). By treating missing variables as outcomes and complete variables as predictors, MI statistical methods either impute all incomplete variables in a single computation step (multivariate regression model) or impute one variable at a time in a series (univariate regression models). Many research fields in physical and biological sciences have embraced such techniques (Miok et al. 2019; Nissen, Donatello, and Van Dusen 2019; Gondara and Wang 2018; Pedersen et al. 2017). This work explicitly employs univariate regression modeling, a variable-by-variable (sequential or chained) predictive mean matching (PMM) technique (Santos and Conde 2020). As an MI conditional modeling approach, PMM imputes missingness dependent on observed data in continuous panel variables that do not have to be normally distributed (Santos and Conde 2020; Morris, White, and Royston 2014; Akmam et al. 2019). This technique returns meaningful imputations that respect the data distribution of the original incomplete dataset (observed dataset).

Castellacci and Natera (2011) conducted a similar data compilation study (CANA hereon). The researchers estimate a CANA dataset for 134 countries between 1980 and 2008 using an MI algorithm developed by Honaker and King (2010). The proposed MSK dataset is similar to CANA dataset as both are panel datasets estimated using novel MI techniques. Similarly, both datasets have a roughly identical structural build of NACS and NIS. For instance, they contend that such systems are measured by dimensions (CANA) and capacities (MSK), which, in turn, are captured by many variables interacting in multiple ways. Although this chapter builds on CANA, it is different in several ways. First, as opposed to the CANA dataset, the MSK dataset estimated here focuses on relatively more data-deficient and economically poor IDA-eligible countries. Secondly, though the MSK dataset employs some of the CANA dataset variables, it has an entirely different functional and operational conception of the capacities and the variables used to operationalize those capacities. Particularly, Public Policy and Social Capacity are operationalized very differently. Additionally, the MSK dataset includes an extended set of other relevant variables to measure capacities (MSK consists of 47 variables for all economies in the dataset, whereas CANA consists of 34 variables for all economies and another seven variables for a restricted set of countries within the dataset). Third, the timeframe for this study is truncated to fifteen years, not only because it is a decent period for panel analysis but also because of pragmatic concerns regarding data availability, particularly on public and social policy capacity variables. The World Bank Group's country offices started collecting these variables in the IDA-eligible countries from 2005 onwards ("Country Policy and Institutional Assessment" 2014).

The last vital distinction worth mentioning is that the CANA dataset is estimated using Honaker and King's (2010) Expectation-Maximization algorithm. The MSK, on the other hand, is estimated using the Multiple Imputation by Chained Equations Predictive Mean Matching (*MICE PMM*) algorithm. Although the *EM* algorithm is efficient and undoubtedly suitable for panel data, it forces a normal distribution on the imputed data regardless of the distribution structure (skewed, unimodal, bimodal) in the observed data (Shireman, Steinley, and Brusco 2017). In contrast, the MICE PMM algorithm preserves the distribution pattern of observed data in the imputed values (Vink et al. 2014), and it has been used for panel data imputation (Kleinke 2017). Besides preserving the distribution pattern in the imputed values, the MICE PMM is best suited for this study because the data structure is heteroskedastic, and associations among variables are nonlinear.[3]

In short, this chapter contributes to the literature by constructing a complete dataset and establishing its relevance for panel analyses of NACS and economic growth, among other analyses, in LMICs. A standard MICE PMM algorithm is employed to construct this dataset. The panel dataset, hence obtained, is complete with no missing values. It consists of 47 variables grouped into six capacities for each country: technological capacity, financial capacity, human capital capacity, infrastructural capacity, public policy capacity, and social capacity. The incomplete (original or observed) dataset is constructed from reputable data sources and contains many missing values (see Table in Appendix B). The

[3] For heteroskedasticity, I checked for variances of the variables in the data. Most of them differed. For instance, variance for *days to enforce contract* is 80 times larger than the variance for *days to start business*. Similarly, I looked at scatter plots for the variables, which showed funnel shaped spread for many variables.

For associations among variables, I looked at scatterplots again. They showed non-linear relationships.

MSK dataset is estimated from this observed dataset, which provides information on 82 LMICs between 2005 and 2019 (total observations are 1,230 country-year observations). A four-way quality check establishes this dataset's reliability and usefulness for researchers interested in panel analyses of absorptive capacity and innovation system, economic development, economic policy, and convergence analysis within LMICs.

The rest of the chapter is shaped as follows. Section 2 gives a brief literature landscape, the association between NIS and NACS, and discusses the missing data and its implications on methodologies. Section 3 further discusses the importance of handling missing data, strategies to address missingness, and underlying missing data mechanisms. Section 4 elaborates on Multiple Imputation and MICE PMM technique. Section 5 discusses the MSK dataset, and the steps taken to develop this dataset. Section 6 carries out a brief descriptive analysis of the MSK dataset, and Section 7 conducts a quality check of the estimated dataset. Lastly, Section 8 concludes by summarizing the results and implications of this work. The Appendix includes graphs and tables, conveying more information on how the database is constructed and other dataset characteristics.

2. From NIS to NACS: Comparative analyses of national systems and growth, and development and the problem of missing data in developing economies

The concept of NIS emerged in the 1990s (Nelson 1993; Freeman 1995; Edquist 1997). It considers systems, activities, institutions, and interactions as the driving force behind economic growth and development (Edquist 2006; López-Rubio, Roig-Tierno, and Mas-Verdú 2021). The strength of these factors explains cross-country differences in growth, development, and innovation. Around the time NIS emerged, Cohen and Levinthal (1990) developed the idea of "absorptive capacity" to explain how learning is consolidated in a firm and how it impacts a firm's growth. In the early 2000s, researchers extended the firm-level concept to a national level (Narula 2004; Criscuolo and Narula 2008). They developed a theoretical framework for aggregating national absorptive capacities upwards from a firm level. Other empirical studies also applied the idea in a national setting (Fagerberg and Srholec 2017). These works used different capacities emerging in NIS literature (technological and social capacities) as proxies for national absorptive capacity. In this essence, NACS is essentially an offshoot of NIS.

Earlier, foundational theoretical and empirical work on NIS focused mainly on prosperous economies (Nelson 1993; Edquist 2001). Later, NIS literature theoretically included developing countries, as they considered developing countries "national economic learning" entities and "imitation" centers (Viotti 2002; Lundvall et al. 2009; Fagerberg and Verspagen 2002). National level capacities literature examining the impact of capacities on economic development also included some developing economies in their analyses (Fagerberg and Srholec 2017). However, because of the lack of data in LMICs, such studies had to compromise operationalizing the complex and multifaceted capacities proposed in NIS and NACS. Similarly, the lack of data on many vital variables perhaps trimmed the list of essential capacities in their analyses.

Another critical challenge that missing data poses is limiting the application of study methodologies in many LMICs. In general, quantitative studies of capacities and development use mainly two different methodologies: panel regression analyses and composite indicator analyses.

Panel regression analyses examine the empirical relationship between a few capacity variables and comparative national differences in GDP per capita growth across countries (Teixeira and Queirós 2016; Ali, Egbetokun, and Memon 2018). While powerful as they consider the dynamic nature of capacities, such panel studies either ignore or drop off many LMICs because longitudinal data for many variables are missing in these countries. As a result, the coefficients of interest obtained through panel analyses do not provide information about the economically poor economies. Using econometric terminology, the estimates from such studies exhibit an upward or downward bias by overestimating or underestimating the effect of *capacities* on *economic growth*.

On the other hand, composite indicator analyses establish a country's comparative standing against other countries by building aggregate or composite indicators that denote different dimensions of technological and social capabilities (Fagerberg and Srholec 2008; 2015). As opposed to panel analyses, the composite analyses consider many countries, including some LMICs. However, since most LMICs have limited data, such studies are usually static (one-year studies), ignoring how NACS evolved. Also, not all LMICs have data on all the variables of interest available for one particular year. Therefore, even composite analyses cannot possibly include all LMICs.

Generally, data availability restricts the number of countries and periods used in the analyses. Both methodologies are challenging for developing countries, particularly for LMICs eligible for IDA resources, which are the focus of this study. This chapter contributes to alleviating the problems stemming from missingness by constructing a new complete panel dataset. A statistical technique called MICE PMM is employed to estimate the missing values in the original incomplete data sources (Rubin 1996). Out of many imputation suites, this chapter considers MICE PMM because they are powerful, efficient, consistent, convenient, and reliable. The following section elaborates on why it is essential to adequately handle missing data and what strategies could be used to deal with missing data.

3. Properly Handling Missing Data- why it is crucial, mechanisms underlying missing data, and strategies to handle missing data

It is essential to carefully consider the missing data problem to obtain accurate estimates of the parameters of interest in any analysis. Missing data pose many dilemmas in data analysis. The chief dilemma is that if a researcher uses original data by excluding subjects with missing data from the study, the researcher will not use all the existing information in the data, most likely causing over-or underestimated parameters (aka ‘biased parameters’). To treat bias in parameters due to the exclusion of subjects in the analysis, a researcher can impute the missing data. During the imputation process, however, the researcher should take utmost care in preserving variability found in existing data and incorporating uncertainty underlying any missing data. Therefore, it is imperative to employ proper and standard imputation methodologies to estimate a reliable dataset.

Provided that the imputation technique is sound, one may get reliable imputations. The first step in getting the imputation technique right essentially means being very mindful of the missing data pattern and what might have caused it. The literature considers three potential mechanisms underlying missing data (Papageorgiou et al. 2018).

Missing Completely At Random (MCAR)- Missing is MCAR if it is genuinely by chance, i.e., missingness is independent of data characteristics. In other words, missingness in MCAR is not related to any nonmissing or missing values in the data set. For example, the random loss of a blood sample in the lab suggests MCAR.

Missing At Random (MAR)- Data exhibits MAR if the missingness is due to observed but not unobserved data. In other words, the observed data explains the missingness. For example, women may be less likely to report their age, regardless of their actual age.

Missing Not At Random (MNAR)- In such a mechanism, missing values explain missingness. For example, individuals with higher salaries may be less willing to answer survey questions about their pay. Another example of MNAR relates to a person not attending a drug test because they took drugs the night before.

Understanding the mechanisms underlying missing data is extremely important to properly handle data. If a researcher fails to understand the missing data pattern and the underlying mechanism and imputes missing values, the missing data may be mistreated. Consequently, results will exhibit insufficient statistical power, upward or downward biases in parameters of interest, under or overestimated standard errors of the parameters, and other inaccurate findings.

Two main strategies are employed to handle missing data: 1) deletion and 2) substitution and imputation (Cook 2021). Deletion (also called complete or available-case analysis) is of two kinds: *pairwise* or *listwise* deletion (Lang and Little 2018). Both these kinds exclude observations with missing values while analyzing data (Lang and Little 2018). Imputation or substitution imputes or substitutes for missing values, and it is also of two main types: single imputation and multiple imputation (Ginkel et al. 2020). Single imputation produces one complete dataset when imputing for missing values. It can be accomplished via several techniques such as mean substitution, mode substitution, nearest neighbor-based imputation, regression, or cold deck imputation (Silva-Ramírez, Pino-Mejías, and López-Coello 2015). Multiple Imputation (MI), on the other hand, produces multiple imputed data sets, employs a statistical analysis model to each one, and eventually merges all analysis results to generate an overall result (Enders 2017b). Based on various data pattern assumptions and underlying data structures, MI is executed in many ways, such as parametric (*Multivariate Normal MI*) or semiparametric approaches (*Multiple Imputation by Chained Equations* including *Predictive Mean Matching*).[4] Another imputation technique, performed in one or many runs, is Expectation-Maximization (EM) algorithm. EM is an iterative algorithm that finds maximum likelihood estimates in parametric models (Honaker, King, and Blackwell 2011). These strategies have both pros and cons (see Appendix A). Of those strategies, this chapter employs Multiple Imputation by Chained Equations (MICE), specifically Predictive Mean Matching (PMM), for imputing missing values that do not observe a normal distribution. MICE PMM is not only

[4] Parametric models are statistical models that have a finite number of parameters. Parametric modeling creates a model for known facts (parameters) about population. An example is normal distribution model with parameters mean and standard deviation. In general, parametric models work well with normally distributed data. On the other hand, nonparametric models have infinite number of parameters and they relax normality assumption. Usually, they assume that the data is not normally distributed. Semiparametric models have both parametric (finite-dimensional i.e., it is easy to research and understand) and nonparametric (i.e., beyond the range of ordinary statistical methods) components. Semiparametric also relaxes normality assumption. More details, see Pace (1995).

a convenient, standard, and reliable technique, but it also gives very accurate and plausible estimates for the data under consideration (Kleinke 2017; Kim and Kim 2020). The next section briefly describes MI, MICE, and PMM.

4. The Multiple Imputation Method and Predictive Mean Matching

Rubin (1987) first introduced multiple imputation methodology as an *efficient* statistical methodology to estimate missing values in a dataset. Several other researchers also explain this technique (Little and Rubin 1989; Rubin and Schenker 1986). Over the years, this methodology has evolved into various methods, catering to missingness in diverse data models. MI overcomes many of the problems associated with deletion and other single imputation techniques (Shi et al. 2020; Afghari et al. 2019). In addition, the methodology returns efficient and accurate estimates and preserves *variability*, which is otherwise lost using other single imputation techniques (such as mean or cold deck imputation).

MI is valid under MAR (*Missing at Random*) assumption (Afghari et al. 2019). Therefore, MI estimates missing values by using available, observed data (Harel et al. 2018).

Since there is uncertainty about missing data values, the estimation process is repeated *m* times (this step refers to the *imputation stage*). From the imputation stage, *m* complete datasets are generated. In the next stage (*analysis stage*), econometric analyses of interest are separately performed on *m* datasets. Finally, all these multiple results are combined (pooled) to obtain a final value of the coefficient of interest, for instance, regression coefficients (*pooling stage*). In short, a standard MI process produces multiple imputed datasets, applies a statistical analysis model to each dataset, and then integrates all analysis results to create an overall result (see Figure 2.1 below).

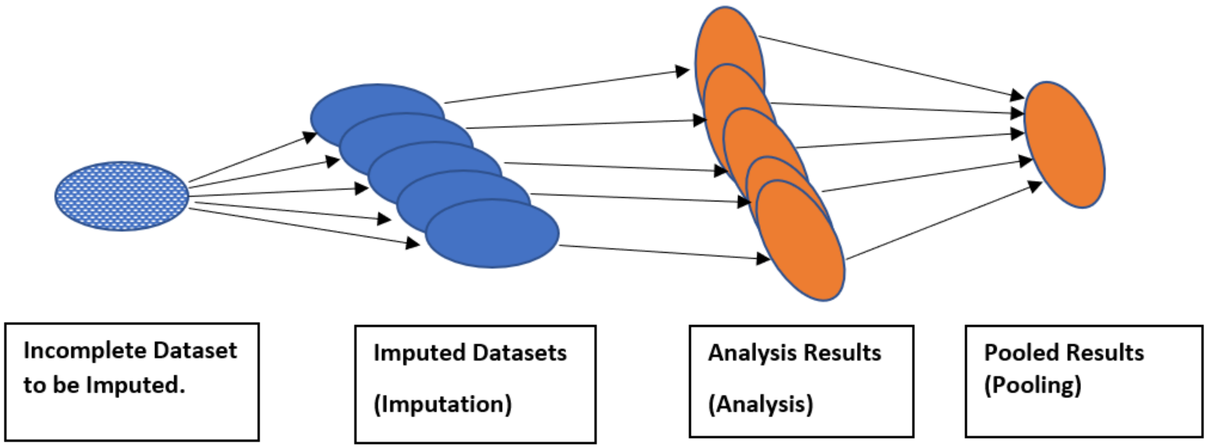

Figure 2.1: Shows a Standard Multiple Imputation Process. In the first step (imputation stage), missing data at hand, shown in white dots, are imputed (all in blue now showing imputation happened) to create m imputed datasets. Following imputation, each imputed dataset is separately analyzed using standard methods (such as OLS regression). Lastly, the analysis results are combined using Rubin’s rules (1987).

Suppose the imputation model at the imputation stage is specified correctly and the data exhibit a normal distribution. In that case, MI yields consistent parameter estimation and confidence intervals that incorporate uncertainty because of the missing data (Morris, White, and Royston 2014). To clarify, the correct specification of an imputation model entails the inclusion of variables considered to predict missingness and variables associated with the variable being imputed and the outcome variable of the analysis model (Morris, White, and Royston 2014; Kg et al. 2006).

One of the common parametric approaches for MI execution is Multivariate Normal distribution (*MVN*). This approach assumes all imputed variables to follow a joint multivariate normal distribution. Conversely, MI by Chained Equations (MICE) is a semiparametric approach that does not take a joint MVN distribution but considers a different distribution for each imputed variable (Zhang 2016b). Unlike MVN, MICE employs a sequential (variable-by-variable) approach while incorporating functional relationships among variables and data characteristics such as ranges. Within MICE, one can either use Linear Regression or Predictive Mean Matching (PMM) for continuous variables. This chapter carries out the PMM technique to impute missing values. PMM relaxes most of the assumptions of parametric MI techniques (Akmam et al., 2019). Hence, it is handy for imputing quantitative variables that are not normally distributed (Lee and Carlin 2017). In the PMM, the missing value for an observation (considered as a 'recipient') is imputed by the observed value from another observation (called a 'donor') with a similar predicted mean outcome as follows (Akmam et al. 2019; Luo and Paal 2021):

In the *imputation* stage, for every missing value, the PMM algorithm structures a small set of donors (typically 5 or 10) from all complete cases that have *predicted* values closest to the predicted value for the missing value. Next, one donor is randomly drawn from the neighborhood pool. The observed value of such a donor is assigned to the missing value. This procedure is conducted *m* times, which generates *m* datasets. After the imputation stage, *analysis* and *pooling* stages follow the same pattern as any standard MI. Like any MI, in the analysis stage *m* times analyses are conducted, and in the pooling stage, these results are combined to get a single estimate.

A more step-by-step computational process within the imputation stage of PMM is explained below:

Suppose there is a variable (X) that has missing values and another set of variables (Vs) to be used to impute X, the software (STATA or R) carries out the following computations in the imputation stage:

1- Firstly, it estimates a linear regression of X on Vs for complete observations (those with no missing values). This step produces a set of coefficients *a*.
2- Secondly, it randomly draws from the "posterior predictive distribution" of *a*.[5] This step generates a new set of coefficients *a**. (this step ensures variability in the imputed values produced later on).
3- Thirdly, the software uses coefficients *a** to generate predicted values for X for all observations.

[5] The posterior predictive distribution is the distribution of possible unobserved values conditional on the observed values (D. R. Williams et al., 2020)

4- Fourthly, for each observation with a missing value of X, the software identifies a set of observations with observed X (called donors or neighbors) whose predicted values are roughly close or similar to the predicted value for the observation with missing data.
5- Lastly, from the neighborhood pool identified, it randomly chooses one donor and designates its observed value to fill in for the missing value.

For each completed dataset, steps 2 through 5 are conducted. The key idea is constructing a right donor pool from where observations with missing data will be matched with observations with available data (Allison 2015). Researchers have answered how many donors or neighbors should be in the donor pool (Morris, White, and Royston 2014; Allison 2015). They assert that the size of the pool depends on sample size. In general, for most situations, these studies suggest k=10 or k=5. The default in the Stata MI command is k=1.

In short, PMM is simple to perform and a versatile method. It relaxes normality distribution assumption, which is not always observed in continuous data. Since PMM imputations are based on observed values in the neighborhood, therefore they are much more realistic. Unlike other techniques such as EM or MVN, PMM does not produce imputations outside the observed values; thus, they overcome the problems with meaningless imputations. Compared to other suites such as Normal Linear Regression imputation, PMM is also less susceptible to model specification, and it can handle many variables irrespective of their distributions (Kleinke 2017). While imputing from the neighboring donor candidates, it incorporates nonlinearities (nonlinear associations among variables) and returns the same distribution for missing data present in the observed data (Kleinke 2017).

5. MSK Panel Dataset

Here I am presenting the main features of the MSK dataset. The dataset has been compiled and estimated after applying the MICE predictive mean matching technique described in the previous section. The complete dataset consists of information for many pertinent variables and for all LMICs eligible for IDA support over time (panel data). Specifically, the dataset contains complete data for 47 variables for 82 countries between 2005 and 2019 (1,230 country-year observations).

This new complete dataset offers ample statistical content to conduct longitudinal comparative country analyses of national absorptive capacity systems (NACS) within LMICs. Among other valuable insights, such analyses illustrate the relative standing of LMICs. Similarly, the dataset's time-series feature enlightens how LMICs' NACS evolved in the last one and a half decades. Immediate use of the dataset would entail estimating the relationship between the variables within the dataset (capacities constituting NACS) and the LMICs' economic development. Such an exercise will offer crucial lessons on economic growth and development to leading and lagging LMICs. Similarly, another use will involve clustering LMICs into different groups based on capacities scores.

Since NACS are multifaceted, any analysis of NACS would involve a large number of possibly relevant variables interacting in many ways. Therefore, the MSK dataset embraces a multidimensional operationalization of NACS. In this dataset, the NACS constitutes six capacities drawn from the literature. In addition, various *incoming* flows from abroad (learning, knowledge, skills, and technology) also may influence the NACS. Figure 2.2 represents these capacities of NACS while alluding to the incoming flows. The six capacities are: 1) Technological capacity, 2) Financial capacity, 3) Human capacity, 4) Infrastructural capacity, 5) Public Policy capacity, and 6) Social capacity. The discussion of these capacities (and incoming flows) and how encompassing they are compared to other narrow definitions of capacities is beyond this chapter's scope (please see Chapter 3 for this discussion). However, the central hypothesized idea behind this dataset's construction is that LMICs that are severely lacking in data need to appreciate that these capacities and their dynamic interaction drive economic development and science, technology, and innovation (STI) in those economies. For this purpose, development economists and STI policymakers need to have access to panel statistical data (country-year observations) on these capacities, which would help them conduct empirical analyses.

Figure 2.2: Shows National Absorptive Capacity System (NACS) and its capacities. These six capacities constitute NACS. Incoming flows mediate capacities within NACS.

Literature on NIS helped identify 64 variables, likely constituting one of these capacities in NACS. After performing imputation analysis, the number of variables decreased—the MSK dataset consists of 47 variables, as shown in Table 2.1. As a matter of good practice, the table also compares descriptive statistics (mean, standard deviation, minimum, maximum, and observation count) of the variables in the new (complete) dataset with descriptive statistics for corresponding variables in the observed (incomplete) dataset. The last column of the table reports the share of missing data present in the original dataset. As can be seen, the missingness is very high for some variables; missingness ranges from 0.89% to about 87%. A quick look at the table shows that descriptive statistics of the two data (complete and incomplete) do not differ much. This is one of the many ways to show that the complete dataset is sufficiently reliable (this will be elaborated in the forthcoming section).

Table 2.1: Descriptive Statistics of New MSK Dataset Vs. Incomplete Observed Dataset (for more details on the variables, please consult Appendix B)

		MSK Dataset					Observed Dataset					
Capacity and Variables	**Variable code**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Missing%**
TECHNOLOGY CAPACITY												
Sci & tech. articles	**tscitjar**	**1230**	**1270.77**	**9395.79**	**0**	**135787.8**	**1,148**	**1236.60**	**9247.52**	**0**	**135787.8**	**6.67%**
Intellectual payments (mil)	**tippay**	**1230**	**65.35**	**492.20**	**-13.92**	**7906**	**818**	**87.80**	**601**	**-13.97**	**7909**	**33.50%**
Voc. & tech. students (mil)	**tsecedvoc**	**1230**	**111698.6**	**253483.79**	**0**	**2300769**	**571**	**121436.2**	**277829.5**	**0**	**2300769**	**53.58%**
R&D expend. % of GDP	**trandd**	**1230**	**.21**	**.16**	**.01**	**.86**	**225**	**0.25**	**0.19**	**0.01**	**0.859**	**81.71%**
R&D researchers (per mil)	**tresinrandd**	**1230**	**162.65**	**225.9**	**5.94**	**1463.77**	**148**	**256**	**317**	**5.93**	**1463.77**	**87.97%**
R&D technicians (per mil)	**ttechinrandd**	**1230**	**57.02**	**63.01**	**.13**	**627.73**	**144**	**55.27**	**70.22**	**0.13**	**627.73**	**88.29%**
High-tech exports (mil)	**thigexperofmanex**	**1230**	**6.23**	**9.29**	**0**	**68.14**	**547**	**5.80**	**8.74**	**0.00008**	**68.14**	**55.53%**
ECI (econ. complexity)	**teciscore**	**1230**	**-.72**	**.63**	**-3.04**	**.82**	**892**	**-0.77**	**0.62**	**-3.04**	**0.82**	**27.48%**
FINANCIAL CAPACITY												
Tax revenue (% of GDP)	**ftaxrpergdp**	**1230**	**16.22**	**11.71**	**0**	**149.28**	**583**	**15.7**	**11**	**0.0001**	**149.28**	**52.60%**
Business startup cost	**fcosbstpropergni**	**1230**	**85.38**	**137.76**	**0**	**1314.6**	**1,154**	**79**	**120.2**	**0**	**1314.6**	**6.18%**
Domestic credit by banks	**fdomcrprsecbybkpergdp**	**1230**	**25.07**	**20.37**	**.5**	**137.91**	**1,100**	**26.3**	**20.85**	**0.5**	**137.91**	**10.57%**
Days to start business	**ftdaystobusi**	**1230**	**35.34**	**37.71**	**1**	**260.5**	**1,154**	**34.48**	**36.45**	**1**	**260.5**	**6.18%**
Days enforcing contract	**fdaystoenfctt**	**1230**	**666.61**	**329.52**	**225**	**1800**	**1,154**	**662.2**	**322.4**	**225**	**1800**	**6.18%**
Days to	**fdaystoregpro**	**1230**	**87.33**	**97.58**	**1**	**690**	**1,104**	**81**	**89.6**	**1**	**690**	**10.24%**

		MSK Dataset					Observed Dataset					
register property												
Openness measure	fopenind	1230	.11	.08	.01	.44	847	0.11	0.08	0.009	0.44	31.14%
Days to electric meter	fdaystoobtelecconn	1230	37.24	33.64	2.5	194.3	153	34.3	31.31	2.5	194.3	87.56%
Business density	fnewbusdenper1k	1230	1.06	1.47	.01	12.31	583	1.19	1.67	0.006	12.30	52.60%
Financial accountholders	faccownperofpop15p	1230	30.94	22.53	1.52	92.97	160	30	19.28	1.52	92.97	86.99%
Commercial banks	fcombkbr1k	1230	10.49	11.99	.27	71.23	1,099	10.58	12.045	0.27	71.23	10.65%
HUMAN CAPITAL CAPACITY												
Primary enrollment (gross)	hprimenrollpergross	1230	103.36	18.18	23.36	149.96	911	103.4	18.15	23.36	149.95	25.93%
Sec. enrollment (gross)	hsecenrollpergross	1230	57.49	25.99	5.93	123.03	711	58.03	26.63	5.93	123.03	42.20%
Primary pupil-teacher ratio	hpupteaprirati o	1230	34.43	14.36	8.68	100.24	751	35.3	14.63	8.68	100.24	38.94%
Primary completion rate	hprimcompra	1230	79.41	20.89	26.1	134.54	735	78.83	20.72	26.09	134.54	40.24%
Govt. expend. on educ.	hgvtexpedupergdp	1230	4.36	2.22	.69	12.9	615	4.06	1.91	0.69	12.90	50%
Human Capital Index 0-1	hhciscale0to1	1230	.42	.09	.29	.69	154	0.43	0.09	0.28	0.69	87.42%
Advanced educ. labor	hlfwithadedu	1230	75.5	10.55	39.97	96.36	265	76.08	10.29	40	96.36	78.46%
Compulsory educ. (years)	hcompeduyears	1230	8.45	2.16	4	15	1,028	8.57	2.16	4	15	16.42%
Industry employment	hempinduspertotem	1230	14.52	7	.64	32.59	1,125	14.08	6.94	0.64	32.59	8.54%
Service employment	hempserpertotem	1230	39.43	15.05	7.16	75.34	1,125	37.8	14.24	7.16	75.34	8.54%
INFRASTRUCTURE CAPACITY												

		MSK Dataset					Observed Dataset					
Mobile subscriptions	imobsubper100	1230	59.12	38.15	.26	181.33	1,219	59.19	38.17	0.26	181.33	0.89%
Access to electricity	iaccesselecperpop	1230	57.02	31.3	1.24	100	1,135	56.77	31.32	1.24	100	7.72%
Broadband subscriptions	ibdbandsubper100	1230	1.97	4.12	0	25.41	1,114	2.02	4.23	0	25.41	9.43%
Telephone subscriptions	itelesubper100	1230	5.31	7.39	0	32.85	1,218	5.29	7.40	0	32.85	0.98%
Energy use (per capita)	ienergyuseperc ap	1230	560.21	392.9	9.55	2246.92	471	553	376.25	9.54	2246.92	61.71%
Logistic perf. Index 1-5	ilpiquoftratran infr	1230	2.18	.33	1.1	3.34	372	2.19	0.32	1.1	3.34	69.76%
Internet users	iindintperpop	1230	16	16.3	.03	89.44	1,209	16	16.33	0.031	89.44	1.71%
PUBLIC POLICY CAPACITY												
CPIA econ. mgmt.	pcpiaeconmgtc l1to6	1230	3.39	.69	1	5.5	1,132	3.40	0.67	1	5.5	7.97%
Public sect. mgmt. & instit	pcpiapsmgandi nscl1to6	1230	3.06	.5	1.4	4.2	1,132	3.06	0.48	1.4	4.2	7.97%
Sructural policies	pcpiastpolclav g1to6	1230	3.3	.54	1.17	5	1,132	3.31	0.52	1.17	5	7.97%
Statistical capacity 0-100	pscapscoravg	1230	59.82	14.89	20	96.67	1,206	59.9	14.87	20	96.67	1.95%
Legal Rights Index 0-12	pstrengthofleg alright	1230	4.83	3.1	0	11	565	5.27	3.05	0	11	54.07%
SOCIAL CAPACITY												
Human resources rating	scpiabdhuman res1to6	1230	3.52	.63	1	4.5	1,132	3.52	0.61	1	4.5	7.97%
Equity of public resc use	scpiaeqofpbres use1to6	1230	3.38	.64	1	4.5	1,132	3.39	0.62	1	4.5	7.97%
Social protection rating	scpiasocprorat 1to6	1230	3.03	.59	1	4.5	1,128	3.04	0.58	1	4.5	8.29%
Social inclusion o..	scpiapolsocincl cl1to6	1230	3.28	.51	1.5	4.3	1,129	3.28	0.50	1.5	4.3	8.29%
National headcount poverty	spovheadcnati onal	1230	38.52	15.13	4.1	82.3	234	35.90	14.20	4.1	82.3	80.98%
Social contributions	ssocialconpero frev	1230	3.23	7.53	0	39.74	569	3.90	8.77	0	39.74	53.74%

The dataset was constructed in five main steps (also illustrated in Appendix C).

Step1- Data collection: In the first step, I collected 64 variables from publicly available databases (see Appendix B for a complete list of variables and their sources). These variables are potentially crucial for measuring the six capacities of countries. This initial dataset (original) contains a large number of missing values for countries and variables of interest.

Step2- Choice of Specification: To multiply impute, the choice of a correct multiple imputation specification is necessary. In *STATA*, either one can employ multivariate normal (MVN) MI or MI by chained equations (MICE).[6] Both these strategies assume a MAR pattern in data before execution. I argue LMICs exhibit MAR pattern. The pattern, by definition, implies that the observed data can explain and predict missingness (Afghari et al., 2019). LMICs can have missing data for a variety of reasons, ranging from poor data infrastructures and meager resources to frequent natural disasters and severe civil conflicts. However, despite missingness in many variables of significance, LMICs offer rich information on poverty indicators, economic development, literacy rates, and demographics. I argue that this rich corpus of data can be employed to explain and predict the missingness pattern for data on other variables, thus justifying the MAR assumption.

Furthermore, since all the variables are continuous, differently distributed, and missingness among them is arbitrary, Rubin's (1987) multiple imputation by chained equations (MICE) best serves this study. Researchers argue that MICE allows sound

[6] One can employ Amelia II in R statistical tool (Honaker et al., 2011). However, Amelia II assumes normality, which is not the case here.

modeling for missing values and provides rigorous standard errors for the fitted parameters (Zhang 2016b; White, Royston, and Wood 2011). MICE treats each variable with missing values as the dependent variable in a regression, with the remaining variables as its predictors. Once MICE is specified, as mentioned earlier, within MICE, one can use either a linear regression *(regress)* or predictive mean matching (*PMM*) specification for continuous variables. Chained imputation with *linear regression* has a severe pitfall as it implements normal distribution on imputed values regardless of the distribution of original values (White, Royston, and Wood 2011). Conversely, PMM caters to this problem by respecting the observed values' distribution pattern. Besides, the use of PMM is robust against other misspecifications in the imputation model (Lee and Carlin 2017). Notably, it is robust against heteroskedastic residuals and nonlinear associations between variables (Lee and Carlin 2017; Kleinke 2017). Since the observed variables are not normally distributed (see kernel density graphs plotted after imputation in Appendix) and their residuals are heteroscedastic, PMM is the most suitable chained imputation for this data.

Step3- Variable shortlisting and running the first round of imputations: In the third step, I ran MICE in *STATA 16* for all variables. Out of 64 variables, chained imputations did not work for three variables (multipoverty index, multipoverty intensity, agricultural machinery).[7] Hence I excluded them from the analysis. Then I run a first successful round of imputations (m=20) followed by descriptive analyses of all these 61 variables. Out of these variables, I dropped off another 14 variables because the results

[7] The system gave the error message that "the posterior distribution from which MI drew the imputations for these variables is not proper when the VCE estimated from the observed data is not positive definite." This essentially means that there is collinearity. Since these variables have more than 97% missing values, therefore, to deal with the reported error I dropped off these variables from the analysis.

were not of sufficient reliability. They had a considerable fraction of missing information (FMI),[8] or their descriptive statistics were very different from the observed (incomplete) dataset, and they varied a lot in successful imputations. Thus, the list of variables was reduced to 47.

Step 4- Running the second round of imputations on shortlisted variables: In the fourth step, I did a second round of PMM imputations for the truncated list of 47 variables together. I included data on complete variables of time and country identifiers (year and country) and auxiliary variables (GDP per capita, technical cooperation grant, total population, gross capital formation, net ODA and official aid assistance, number of international tourist arrivals receipts, merchandise import from high-income economies as percentage of total merchandize imports, current health expenditure) following the recommendations of the multiple imputation literature. The inclusion of complete identifiers and other auxiliary variables increases the precision of the imputation results for variables exhibiting high missingness and makes the MAR assumption more plausible (Hardt, Herke, and Leonhart 2012). To obtain a high-efficiency level in parameter results, I set m = 50, i.e., fifty complete datasets (copies of original dataset) were estimated for all 47 variables.[9] Subsequent econometric analyses are performed separately on each dataset

[8] Generally, these variables reported FMI higher than 60%. FMI is the proportion of the total sampling variance that is due to missing data. It is calculated based on the percentage missing for a specific variable and how correlated this variable is with other variables in the imputation model (Pan & Wei, 2018). A high FMI shows a problematic variable.

[9] Traditionally researchers set *m* = 5 or 10. New research indicates that *m* should be high to achieve accurate standard errors and point estimates (von Hippel, 2020). With large *m*, variance estimates stabilize, and standard errors become more accurate. In essence, by returning accurate standard errors, large m models the uncertainty within imputations (missing values are uncertain) with more certainty. In addition, large *m* is particularly recommended if FMI is high for variables. Similarly, large *m* increases the relative efficiency of parameters (point estimates). i.e., how well the true population parameters are estimated. Generally, when

(50 analyses because m= 50). Then, the results from each analysis are pooled according to Rubin's rules. Here, I randomly pick results from imputation # 25 for descriptive statistics and illustration purposes. This dataset contains 47 variables for 1,230 observations (82 countries for the period 2005-2019).

Step 5- Quality check: Finally, I thoroughly investigated the variables to analyze the imputed values' quality. This investigation informs the extent to which the new complete dataset may be regarded as reliable. I did a visual inspection of kernel density graphs of imputed values, completed values, and original values for all the variables in this investigation. Similarly, I checked descriptive statistics of observed and imputed values. This quality check is discussed fully in the next section. This check results suggest that multiple imputations with PMM have been successful for the truncated list of variables.

In brief, following the above steps, the final version of the MSK database is constructed and made available. The dataset consists of 47 variables for 82 IDA-eligible countries spanning over 15 years (1,230 country-years observations). In contrast, the remaining 17 variables were rejected and not included in the database because either the system could not impute them or returned unreliable imputed values of poor quality.

6. Descriptive analysis of the MSK dataset

To empirically illustrate the usefulness of the MSK dataset and how it can be used to study absorptive capacity systems across countries, detailed analysis will follow in Chapter 3. A brief descriptive analysis of the MSK dataset is conducted here. This analysis

the amount of missing information is high, more imputations (high *m*) are needed to attain adequate efficiency for point estimates (Pan & Wei, 2018; von Hippel, 2020).

offers insights into the trends in capacities constituting NACS in LMICs and how they evolve over time. Three brief analyses are conducted: distribution (kernel density) of select few variables of interest within each capacity at the start, middle, and the end of the study period (i.e., 2005, 2010, and 2019); time trends (2005-2019) of the variables of interest for select countries (six countries, one from each region in our countries of study); and comparative ranking of countries based on composite capacity indices.

i) Distribution (kernel density) of select few variables of interest within each capacity at different periods (i.e., 2005, 2010, and 2019):

The distribution patterns (Appendix D) are drawn for a select set of variables from each capacity for three years (2005, 2010, and 2019). Distributions for technological capacity by and large show that LMICs have not significantly improved their technological base. A rightward shift in distributions for infrastructure capacity indicates that LMICs overall have experienced an improvement in their infrastructure base. However, we see a leftward shift in the distributions for social capacity, meaning that LMICs eligible for IDA support are moving backward in their social capacity. For the remaining three capacities (human, financial, and public policy), cross-country distributions' evolution is not very evident. Their pattern depends on the specific variable under discussion. For example, distributions for human capacity show that employment in the service sector has improved over time. On the contrary, expenditure on education has not increased.

ii) ***Time trends (2005-2019) of the variables of interest for select countries (six countries, one from each region in our countries of study):***

Next, time trends of the select variables from each capacity are observed for six countries (Appendix E). The trends in technological capacity variables vary over time for most countries. In Pakistan, while most trends in such variables are either uniform or erratic, the trends in s*cientific articles* and *ECI scores* rise. Similar trends (uniform in some cases and unpredictable in others) are observed for financial capacity variables. Myanmar and Nicaragua experience a rising trend in domestic credit availability, while other countries have experienced an oscillating trend (increasing and then decreasing). In the case of human capacity and infrastructure capacity, trends for some variables (primary completion, expenditure on education, LPI score) have experienced erratic movements; however, most countries are improving in other variables (service and technological sector employment, mobile and internet penetration) of these capacities. This may allude to the fact that these countries are perhaps catching up with advanced economies in terms of these indicators. Finally, it is hard to identify a clear winner for the last two capacities (public policy and social capacity); most trends are either uniform or erratic. However, the statistical score index is strikingly improving for Djibouti and Myanmar. These results largely corroborate the abovementioned distribution analysis. The crux is that countries show varying progress (clearly visible in some cases and diffused in other cases) over time for all these variables.

iii) Comparative ranking of countries:

Lastly, comparative ranking of countries was conducted for recent data in 2019 (see Appendix F). For this, I first calculated six composite indices (Technology, Finance, Human Capital, Infrastructure, Public Policy, and Social Capacity) and then aggregated them into a composite Absorptive Capacity Index. Vietnam tops the list of the countries whereas, South Sudan scored the least. This ranking can be conducted for all years, which would show longitudinal changes in absorptive capacity systems of countries.

While not an exhaustive list of the uses of the dataset, these analyses provided a flavor of how this dataset might be used in comparative analyses of National Absorptive Capacity Systems. These analyses can be extended and conducted in a number of ways in future research. This section's purpose was to give a brief demonstration of how one might get started on subsequent empirical analyses.

7. Quality check of the estimated MSK dataset

A quality check is conducted to determine the usefulness and vitality of this dataset.

As mentioned in section 5, I collected 64 variables to measure countries' capacities to construct the database. After carrying out imputations and evaluation, I shortlisted 47 variables to be included in the dataset for an entire range of 1,230 country-year observations (15 years for 82 countries). The remaining 17 variables were rejected either because the system could not impute them (three variables) or the results produced (14 variables) were not of good quality.

In order to assess the imputation procedure and the reliability of the variables included in the MSK dataset, this chapter conducts a four-way quality check: first descriptive statistics of the two datasets (complete and observed) is conducted; secondly, distributions of completed and observed datasets are observed; thirdly, correlation tables of the observed and complete variables are compared; and fourthly, trends within imputations and convergence pattern are observed.

i) Descriptive statistics of two datasets:

I looked into means, maximum, minimum, and standard deviation for complete and observed datasets. Table 1 reports a comparison of such descriptive statistics for both datasets. First, the table indicates that means (averages) and standard deviations (variability) for all 47 variables are almost identical. Imputing at the mean might reduce variability in some variables, though (as evident in lower standard deviation values). Secondly, we can see that the complete dataset has the same maxima and minima, and the values are meaningful (no negative numbers on researchers, for instance). Moreover, I inspected relative efficiency values for only imputed variables. This glance of relative efficiency values (above 98% for all variables with m=50) suggested highly efficient point estimates. All this shows that the complete dataset's imputed values are roughly the best approximation of the original sources' missing data.

ii) Distribution of compete and observed dataset:

A detailed distribution assessment is conducted for the two datasets. This is accomplished via visual inspection of kernel densities for all 47 variables in the observed (incomplete) and complete (MSK) datasets.

The logic behind comparing the two datasets statistical distributions is to see how best the complete dataset is an extension of the observed dataset. If the two distributions are roughly similar, we can claim the reliability of the imputed values. But, if the two distributions differ, the imputation results may not be reliable.

Visual inspection of kernel densities provides an interesting quality check (See Appendix G). For almost all the variables within capacities, variables' distributions in the MSK dataset are similar to those in the incomplete data in various imputations.[10] Even for those variables that report missingness higher than 80% (R & D, Researchers, Technicians, Account ownership, HCI scale), the approximation level (similarity), while relatively lower, is still very close to the original distributions. This means that the PMM imputation has successfully estimated missing information with high accuracy. Thus, this visual inspection of kernel density distributions grants substantial reliability status to the MSK dataset.

iii) Correlation tables of the original and complete:

Lastly, pairwise correlation coefficients are calculated and compared in the original dataset and complete dataset.[11] The tables, shown in Appendix H, report such correlation coefficients for each capacity within both datasets. The correlation coefficients for the observed dataset are reported above the pairwise correlations for the complete dataset.

The rationale behind this correlation comparison is if the two correlations are similar, then statistical distributions between the two will likely match. This will indicate the reliability of the imputation results. However, if the two coefficients are not comparable, this would mean unreliability and bias in the imputation results produced

[10] I looked into kernel density distributions at different imputations (randomly chosen) for all capacities.
[11] Correlations were compared of original (m=0) and complete dataset (at imputation m=25).

through the imputation procedure. The bias and unreliability will subsequently affect post-imputation analysis on the complete dataset.

A close inspection of the correlation tables suggests that correlation coefficients are very similar across the variables in both datasets. Not only the magnitudes of coefficients are roughly similar, but also the signs of the coefficients are maintained in the complete dataset following the multiple imputation exercise. Some coefficients (for example, R & D, Number of technicians, Domestic credit, among others) change in size; however, these changes are not substantial. Overall, this check suggests that PMM imputation has preserved the correlation structure among the variables. Thus, it can be concluded that the MSK dataset is sufficiently reliable.

iv) Trends within imputations and convergence pattern:

Similarly, I inspected the trends in imputed variables' values across imputations (at m=1, m=10, m=25, m=40, m=50). I noticed that values across imputations were highly similar, suggesting that the imputation exercise was successful. Also, since the dataset was obtained through chained imputations involving iterations, the reliability of the imputation process must be established. Therefore, to establish the reliability of the imputation process, I checked for convergence among iterations for imputed variables. Convergence can be checked in a few ways. One way is to plot the mean and variance of the imputed values of different missing variables against the iteration number (Zahid et al. 2021). For healthy convergence, these plots for *m* imputed datasets should freely intermingle, and there should not be any definite trends (Zahid et al. 2021; Stef 2018). Another way is to examine between and within sequence variance (Zahid et al. 2021; Stef 2018). On healthy convergence, the variance between sequences is no larger than the variance within each sequence (Zahid et al. 2021; Buuren 2018; Heymans and Eekhout 2019). Since the plots for imputed datasets freely intermingled with no definite trend, the convergence pattern of the iterations through which the dataset was generated showed a healthy convergence (Appendix I). All this shows that the MSK dataset is of good quality.

8. Conclusion and Implications

Comparative country analyses on absorptive capacity and economic development in LMICs lack because of the lack of complete data availability. To address this problem, this chapter employed Rubin's Multiple Imputation to impute missing values in variables. Specifically, it used Multiple Imputation by Chained Equations with Predictive Mean Matching approach to estimate the MSK panel dataset. The dataset consisted of six country-related capacities. A total of 47 continuous variables measured these capacities. This dataset was estimated from an observed dataset containing a lot of missing values. The complete dataset contained 82 countries for the period 2005-2019, for 1,230 country-year observations.

The MSK dataset provides a rich panel (across countries and over time) of statistical content that can be used in several ways. For instance, this dataset can be used to estimate the impact of absorptive capacities on economic growth in LMICs. Similarly, the capacities can be aggregated for different LMICs to find the relative standing of one economy viz-a-viz other economies. Further, such an exercise can be used to investigate the factors of development within leading and lagging LMICs. Finding leading and lagging economies within LMICs at the same level of development offer lessons to lagging economies on how they can catch up. Here, I demonstrated how a simple descriptive analysis of capacities within the complete dataset could be used to gain insights into the dynamic evolution of such capacities in different countries.

On the methodological front, MICE PMM for estimating dataset for the comparative analyses of capacities and economic growth in LMICs is powerful compared to other solutions such as mean imputation or deletion. MICE PMM is powerful because it retains variability in data as the imputed value is randomly taken from the suitable donor pool. Moreover, PMM is a good technique because it reduces bias by keeping information on all variables (variables for which partial data is available are imputed rather than deleted). Similarly, the technique preserves representation (by keeping all economies even if they have partial data rather than dropping them of analysis), returns accurate or realistic data (imputed data is taken from neighboring data pool), and captures dynamic evolution for all economies (which is compromised by using other imputation techniques).

However, MI returns multiple datasets, which indicates the uncertainty underlying missing data values. Thus, no matter how rigorous MI is, no imputation can claim with 100 percent certainty the accuracy of imputed values. Therefore, the dataset generated through MI must be used carefully in any analysis. The results of such analysis must make a disclaimer about the process through which the dataset was obtained. The reliability or quality check must be performed on the newly generated dataset, just as conducted for the MSK dataset. The MSK dataset generated here passed the quality check as the observed and complete dataset exhibited almost similar distributions, descriptive statistics, and correlation coefficients, and the process through which the dataset was imputed returned a healthy convergence among iterations.

As the MI-generated dataset is reliable, such a dataset can be valuable for hypothesis generation in LMICs suffering from poor data environments. Results based on original datasets for countries (and LMICs) with reasonably complete datasets can be compared with those based on imputed datasets. Such a comparison will offer interesting insights into what drives economic development in various countries. Besides refining the absorptive capacity framework, the next chapter uses the MI-generated dataset to test the framework.

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Appendix A

Table 2.2. Handling Missing Data Strategies, Assumptions, Advantages, and Disadvantages

Strategies	**Definition**	**Assumption**	**Advantage**	**Disadvantage**
Listwise deletion	Complete-case analysis). It removes all data for a case that has any missing values (Kang 2013; Donner 1982)	MCAR	-Generally used if the researcher is performing a treatment study and wishes to compare a completers analysis (listwise deletion) vs. an intent-to-treat analysis (includes cases with missing data imputed or considered in a treatment design) - Can be applied to any statistical model (structural equation modeling, multi-level regression, etc.) - In the instance of MAR among independent variables (i.e., they do not depend on the values of dependent variables), listwise deletion parameter estimates can be unbiased. (Little 1992)	- MCAR assumptions are generally rare to support - Produce bias parameters and the estimates
Pairwise deletion	Available-case analysis aims to reduce the loss that occurs in listwise deletion. Pairwise maximizes all data available through checking into the correlation matrix between variables (Kang	MCAR	-It increases statistical power in analyses - Could be used in linear models such as linear regression, factor analysis, or SEM.	- Produce under- or overestimated standard of errors - If the data mechanism is MAR, pairwise will return biased estimates.

Strategies	Definition	Assumption	Advantage	Disadvantage
	2013; J.-O. Kim and Curry 1977)			
Mean substitution	This method substitutes the mean value of a variable for missing value (Kang 2013; Zhang 2016a). Also called unconditional mean substitution	NA	-Simple to execute	- Does not preserve the relationships among variables - Leads to underestimated standard errors
Regression imputation	Called as conditional mean imputation, here missing value is based (regressed) on other variables (Zhang 2016a)	-MCAR or MAR	-Maintain the relationship with other variables - If the data are MCAR, least-squares coefficients estimates will be consistent and unbiased in large samples (Gourieroux and Monfort 1981)	- No variability left -Treated data as if they were collected - Leads to underestimated standard errors & overestimated test statistics
Cold deck imputation	Cold Deck picks value from a case that has similar values on other variables (Haukoos & Newgard 2007)	MAR	-Easy to execute	-Removes the desired random variation
Maximum likelihood (ML)	It models the missing data based on observed data. This procedure considers available data as part of some distribution. Subsequently, parameters are estimated that	-MAR and Monotonic (meaning, that if an obs. is missing on one variable, then the	- Consistent -Asymptotically efficient (becomes efficient for large sample) -Asymptotically normal	- ML can usually handle linear models, log-linear models. However, beyond that, ML still is lacking in theory and

Strategies	Definition	Assumption	Advantage	Disadvantage
	maximize the chance of observing the observed data (Enders 2001)	following variables of that obs. have also missing data		software implementation
Expectation-Maximization Algorithm	Similar to ML, but it is an iterative process. In the Expectation stage, data is imputed from observed data. In the second stage, the values are checked if they are the most likely. If not, it imputes again a more likely value (Enders 2001)	MAR	- Easy to use - Preserves the relationship with other variables	- Standard errors of the coefficients are incorrect (biased usually downward - underestimate) -Models with overidentification, the estimates will not be efficient
Multiple imputation (many ways to execute MI) **-Multivariate Normal MI** **-Chained MI - (Predictive Mean Matching, Regression, Logistic)**	MI replaces missing values with a set of imputed values. Analyses are subsequently performed on all the imputed values, and results are pooled (Rubin 1987)	MAR	-Consistent -Asymptotically efficient -Asymptotically normal - MI can be applied to any model, unlike ML, which can be applied only to limited models	- MI delivers a little different result in various runs. Seeding can evade the problem. - Some MI methods may cause unlikely values (e.g., negative values) - Not all MI methods can handle heteroskedastic data

Appendix B

Table 2.3. List of all 64 Variables, their Definitions, Sources, Missingness Amount in Observed Variables, and Acceptance/Rejection Status for the MSK Dataset

		Definition and source of the variables included in the MSK Database			
Capacity	**Variable code**	**Definition**	**Source**	**%Missing**	**Accept/ Reject**
Technology Capacity	tippay	**Charges for the use of intellectual property, payments (BoP, current US$)**. Payment or charges per authorized use of intangible, non-produced, non-financial assets and proprietary rights (such as patents, trademarks, copyrights, industrial processes and designs including trade secrets, and franchises) and for the use, through licensing agreements, of produced originals of prototypes. Data are in current US dollars	IMF, World Bank	33.50%	Accepted
	tinddesapprebyco	**Industrial design applications, resident, by count**	WIPO	75.12%	Rejected
	tscitjar	**Scientific and technical journal articles.** Number of scientific and engineering articles published in the following fields: physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering and technology, and earth and space sciences, per million people.	World Bank	6.67%	Accepted
	trandd	**Research and development expenditure (% of GDP)**	UNESCO	81.71%	Accepted
	tresinrandd	**Researchers in R&D (per million people)**	UNESCO	87.97%	Accepted
	ttechinrandd	**Technicians in R&D (per million people)**	UNESCO	88.29%	Accepted
	tpatappre	**Patent applications, residents**	WIPO	60%	Rejected
	ttradappresbyco	**Trademark applications, resident, by count**	WIPO	70.89%	Rejected
	thigexperofmanex	**High-technology exports (% of manufactured exports).** High-technology exports are products with high R&D intensity, such as in aerospace, computers, pharmaceuticals, scientific instruments, and electrical machinery.	UN, COMTRADE	55.53%	Accepted
	tsecedvoc	**Secondary education, vocational pupils.** Secondary students enrolled in technical and vocational education programs, including teacher training.	UNESCO	53.58%	Accepted

	teciscore	**ECI Score.** Measure of economic complexity containing information about both the diversity of a country's export and their sophistication. High ECI Score shows that an economy exports many goods that are of low ubiquity and that are produced by highly diversified countries. In other words, diverse and sophisticated economies have high scores.	OEC, MIT	27.48%	Accepted
Capacity	**Variable code**	**Definition**	**Source**	**%Missing**	**Accept/ Reject**
Financial Capacity	fdaystoenfctt	**Time required to enforce a contract (days).** Days required to enforce a contract, whereas the days are counted from the day a plaintiff files the lawsuit in court until payment. Low values indicate high competitiveness and vice verca.	World Bank, Doing Business Project	6.18%	Accepted
	fdomcrprsecbybkpergdp	**Domestic Credit by Banking Sector.** This includes all credit to various sectors (monetary authorities, banks, financial corporations) on a gross basis, with the exception of credit to the central government, which is net, as a % of GDP.	IMF, World Bank	10.57%	Accepted
	fopenind	**Openness Indicator.** (Import + Export)/GDP. Constant US 2010.	World Bank	31.14%	Accepted
	fdepcombkp1k	**Depositors with commercial banks (per 1,000 adults)**	IMF, World Bank	47.32%	Rejected
	fdaystoregpro	**Time required to register property (days).** The number of calendar days needed for businesses to secure rights to property.	World Bank, Doing Business Project	10.24%	Accepted
	fcosbstpropergni	**Cost of business start-up procedures (% of GNI per capita)**	World Bank	6.18%	Accepted
	ftaxrpergdp	**Tax revenue (% of GDP).** Tax revenue means compulsory transfers to the government for public purposes.	IMF, World Bank	52.60%	Accepted
	fcombkbr1k	**Commercial bank branches (per 100,000 adults)**	IMF, World Bank	10.65%	Accepted
	fdaystoobtelecconn	**Time to obtain electrical connection (Days).** Days to obtain electrical connection. Days experienced to obtain an electrical connection from the day an establishment applies for it to the day it receives the service.	World Bank, Enterprise Survey	87.56%	Accepted
	ftdaystobusi	**Time required to start a business (Days).** The number of days needed to complete the procedures to legally operate a business.	World Bank, Doing Business Project	6.18%	Accepted

	faccownperofpop15p	**Account ownership at a financial institution or with a mobile-money-service provider (% of pop ages 15+).** Account denotes the percentage of respondents who report having an account (by themselves or together with someone else) at a bank or another type of financial institution or report personally using a mobile money service in the past 12 months (% age 15+).	Demirguc-Kunt et al., 2018, Global Financial Inclusion Database, World Bank.	86.99%	Accepted
	fnewbusdenper1k	**New business density (new registrations per 1,000 people ages 15-64)**. New businesses registered are the number of new limited liability corporations registered in the calendar year.	World Bank, Enterprise Survey	52.60%	Accepted
Capacity	**Variable code**	**Definition**	**Source**	**%Missing**	**Accept/ Reject**
Human Capacity	hprimenrollpergross	**School enrollment, primary (% gross).** Ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the primary level.	UNESCO	25.93%	Accepted
	hsecenrollpergross	**School enrollment, secondary (% gross).** Ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the secondary level.	UNESCO	42.20%	Accepted
	hcompeduyears	**Compulsory education, duration (years).** No. of years that children are legally obliged to attend school.	UNESCO	16.42%	Accepted
	hgvtexpedupergdp	**Government expenditure on education (% of GDP).** General government expenditure on education (current, capital, and transfers) is expressed as a percentage of GDP.	UNESCO	50%	Accepted
	hpupteapriratio	**Primary pupil-teacher ratio**. Ratio (number of pupils enrolled in primary school) / (number of primary school teachers)	UNESCO	38.94%	Accepted
	hempinduspertotem	**Employment in industry (% of total employment).** Employment is defined as persons of working age who were engaged in any activity to produce goods or provide services for pay or profit, whether at work during the reference period or not at work due to temporary absence from a job, or to working-time arrangement. The industry sector consists of mining and quarrying, manufacturing, construction, and public utilities (electricity, gas, and water), in accordance with divisions 2-5 (ISIC 2) or categories C-F (ISIC 3) or categories B-F (ISIC 4).	ILO, World Bank	8.54%	Accepted
	hempserpertotem	**Employment in services (% of total employment).** Employment is defined as persons of working age who were engaged in any activity to produce goods or provide services for pay or profit, whether at work during the reference period or not at work due to temporary absence from a job, or to working-time arrangement. The services sector consists of wholesale and retail trade and restaurants and hotels; transport, storage, and communications; financing, insurance, real estate, and business services;	ILO, World Bank	8.54%	Accepted

		and community, social, and personal services, in accordance with divisions 6-9 (ISIC 2) or categories G-Q (ISIC 3) or categories G-U (ISIC 4).			
	hprimcompra	**Primary completion rate, total (% of relevant age group)**	UNESCO	40.24%	Accepted
	hhciscale0to1	**Human capital index (HCI) (scale 0-1).** The HCI calculates the contributions of health and education to worker productivity. The final index score ranges from zero to one and measures the productivity as a future worker of child born today relative to the benchmark of full health and complete education.	World Bank	87.48%	Accepted
	hlfwithadedu	**Labor force with advanced education (% of total working-age population with advanced education)**	ILO, World Bank	78.46%	Accepted
	hlfwithbasiced	**Labor force with basic education (% of total working-age population with basic education)**	ILO, World Bank	78.13%	Rejected
	hlfwithintermeded	**Labor force with intermediate education (% of total working-age population with basic education)**	ILO, World Bank	78.13%	Rejected
Capacity	**Variable code**	**Definition**	**Source**	**%Missing**	**Accept/ Reject**
Infrastructural Capacity	ielecconkwhpercapita	**Electric power consumption (kWh per capita).** Production of power plants and combined heat and power plants less transmission, distribution, and transformation losses and own use by heat and power plants.	IEA, World Bank	66.42%	Rejected
	icarrierdepwdwide	**Air transport, registered carrier departures worldwide**. Registered carrier departures worldwide are domestic takeoffs and takeoffs abroad of air carriers registered in the country	World Bank	37.40%	Rejected
	imobsubper100	**Mobile cellular subscriptions (per 100 people).**	International Telecom Union, World Bank	0.89%	Accepted
	itelesubper100	**Fixed telephone subscriptions (per 100 people)**	International Telecom Union, World Bank	0.98%	Accepted

	ibdbandsubper100	**Fixed broadband subscriptions (per 100 people)**	International Telecom Union, World Bank	9.43%	Accepted
	iaccesselecperpop	**Access to electricity (% of population).** The percentage of population with access to electricity.	World Bank, Sustainable Energy for All	7.72%	Accepted
	ienergyusepercap	**Energy use (kg of oil equivalent per capita).** The use of primary energy before transformation to other end-use fuels, which is equal to indigenous production plus imports and stock changes, minus exports and fuels supplied to ships and aircraft engaged in international transport.	IEA, World Bank	61.71%	Accepted
	ieletanddislossesperoutput	**Electric power transmission and distribution losses (% of output)**	IEA, World Bank	67.32%	Rejected
	imachtpeqpervaladdmanu	**Machinery and transport equipment (% of value added in manufacturing).** Value added in manufacturing is the sum of gross output less the value of intermediate inputs used in production for industries classified in ISIC major division D. Machinery and transport equipment correspond to ISIC divisions 29, 30, 32, 34, and 35.	UNIDO, World Bank	75.28%	Rejected
	iindintperpop	**Individuals using the internet (% of population).** Internet users are individuals who have used the Internet (from any location) in the last 3 months. The Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV etc.	International Telecom Union, World Bank	1.71%	Accepted
	iraillinestotalkm	**Rail lines (total route km).** Railway route in km for train service, irrespective of the number of parallel tracks.	International Union of Railway	78.05%	Rejected
	isecinterserper1mill	**Secure internet servers per 1 million people**	World Bank	35.93%	Rejected
	iagmachtracper100sqkm	**Agricultural machinery, tractors per 100 sq. km of arable land**	FAO, World Bank	98.05%	Rejected
	ilpiquoftratraninfr	**Logistics performance index: Quality of trade and transport-related infrastructure (1=low to 5=high)**. Logistics professionals' perception of country's quality of trade and transport related infrastructure (e.g. ports, railroads, roads, information technology), on a rating ranging from 1 (very low) to 5 (very high). Scores are averaged across all respondents.	World Bank	69.76%	Accepted

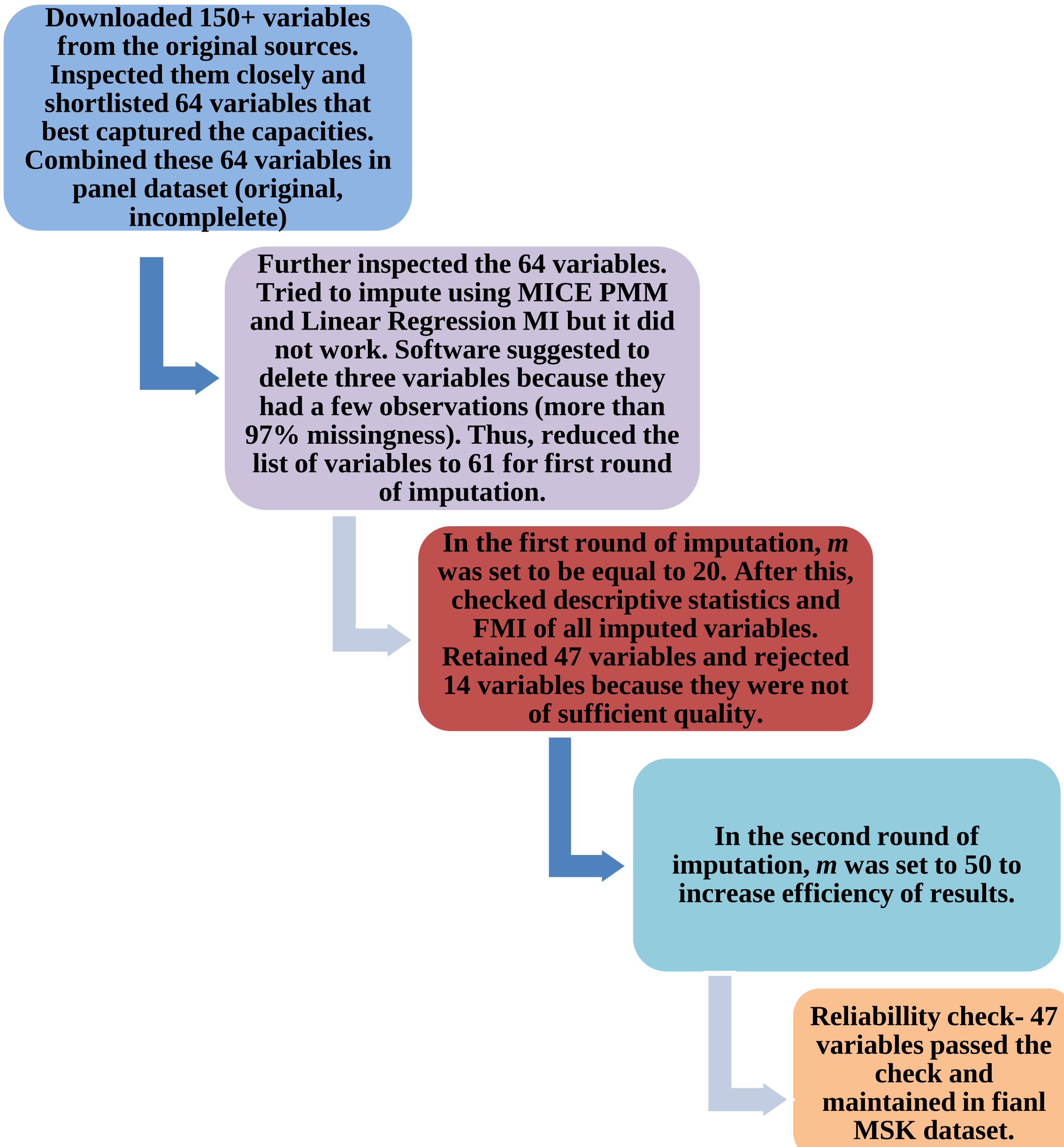
Capacity	Variable code	Definition	Source	%Missing	Accept/ Reject
Public Policy Capacity	pcpiapsmgandinscl1to6	**CPIA public sector management and institutions cluster average (1=low to 6=high).** The public sector management and institutions cluster includes property rights and rule-based governance, quality of budgetary and financial management, efficiency of revenue mobilization, quality of public administration, and transparency, accountability, and corruption in the public sector.	World Bank, CPIA Database	7.97%	Accepted
	pcpiastpolclavg1to6	**CPIA structural policies cluster average (1=low to 6=high).** The structural policies cluster includes trade, financial sector, and business regulatory environment	World Bank, CPIA Database	7.97%	Accepted
	pstrengthoflegalright	**Strength of legal rights index (0=weak to 12=strong).** Strength of legal rights index measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders and thus facilitate lending. The index ranges from 0 to 12, with higher scores indicating that these laws are better designed to expand access to credit.	World Bank, Doing Buisness Project	54.07%	Accepted
	iscapscoravg	**Overall level of statistical capacity (scale 0 - 100).** A composite score (on a scale of 0-100) which assesses the capacity of a country's statistical system in three areas (25 criteria): methodology; data sources; and periodicity and timeliness.	World Bank	1.95%	Accepted
	pcpiaeconmgtcl1to6	**CPIA economic management cluster average (1=low to 6=high).** The economic management cluster includes macroeconomic management, fiscal policy, and debt policy.	World Bank, CPIA Database	7.97%	Accepted

Capacity	Variable code	Definition	Source	%Missing	Accept/ Reject
	scpiabdhumanres1to6	**CPIA building human resources rating (1=low to 6=high).** Building human resources assesses the national policies and public and private sector service delivery that affect the access to and quality of health and education services, including prevention and treatment of HIV/AIDS, tuberculosis, and malaria.	World Bank, CPIA Database	7.97%	Accepted
Social Capacity	scpiaeqofpbresuse1to6	**CPIA equity of public resource use rating (1=low to 6=high).** Equity of public resource use assesses the extent to which the pattern of public expenditures and revenue collection affects the poor and is consistent with national poverty reduction priorities	World Bank, CPIA Database	7.97%	Accepted
	scpiasocprorat1to6	**CPIA social protection rating (1=low to 6=high).** Social protection and labor assess government policies in social protection and labor market regulations that reduce the risk of becoming poor, assist those who are poor to better manage further risks, and ensure a minimal level of welfare to all people.	World Bank, CPIA Database	8.29%	Accepted

	scpiapolsocinclcl1to6	**CPIA policies for social inclusion/equity cluster average (1=low to 6=high).** The policies for social inclusion and equity cluster includes gender equality, equity of public resource use, building human resources, social protection and labor, and policies and institutions for environmental sustainability	World Bank, CPIA Database	8.29%	Accepted
	scovofsocprolbrpro	**Coverage of social protection and labor programs (% of population).** Coverage of social protection and labor programs (SPL) shows the percentage of population participating in social insurance, social safety net, and unemployment benefits and active labor market programs	World Bank	87.48%	Rejected
	sginiinedxwbest	**GINI index (World Bank estimate).** Measures income inequality. A Gini index of 0 represents perfect equality, while an index of 100 implies perfect inequality.	World Bank	80.16%	Rejected
	spovheadcnational	**Poverty headcount ratio at national poverty lines (% of population).** National poverty headcount ratio is the percentage of the population living below the national poverty line(s)	World Bank	80.98%	Accepted
	smultipovertyintensity	**The average share of weighted deprivations (intensity).**	World Bank	97.97%	Rejected
	ssocialconperofrev	**Social contributions (% of revenue).** Social contributions include social security contributions by employees, employers, and self-employed individuals, and other contributions whose source cannot be determined. They also include actual or imputed contributions to social insurance schemes operated by governments	IMF, World Bank	53.74%	Accepted
	smultipoverindex	**Multidimensional poverty index (scale 0-1).** Proportion of the population that is multidimensionally poor adjusted by the intensity of the deprivations	World Bank	98.78%	Rejected

Appendix C

Figure 2.3. Construction of the MSK Dataset



Appendix D

Figures 2.4. Kernel Densities for Select variables of Interest at Different Points.

Kernel densities are observed to examine the distribution pattern of select variables under each capacity at three periods (2005, 2010, and 2019). Overall technological capacity does not show any change in distribution, whereas infrastructure and social capacity show a rightward and leftward shift, respectively. The remaining three financial, human, and public policy capacities do not display any clear cross-country distributions' evolution.

Figure 2.4.1. Technology Capacity:

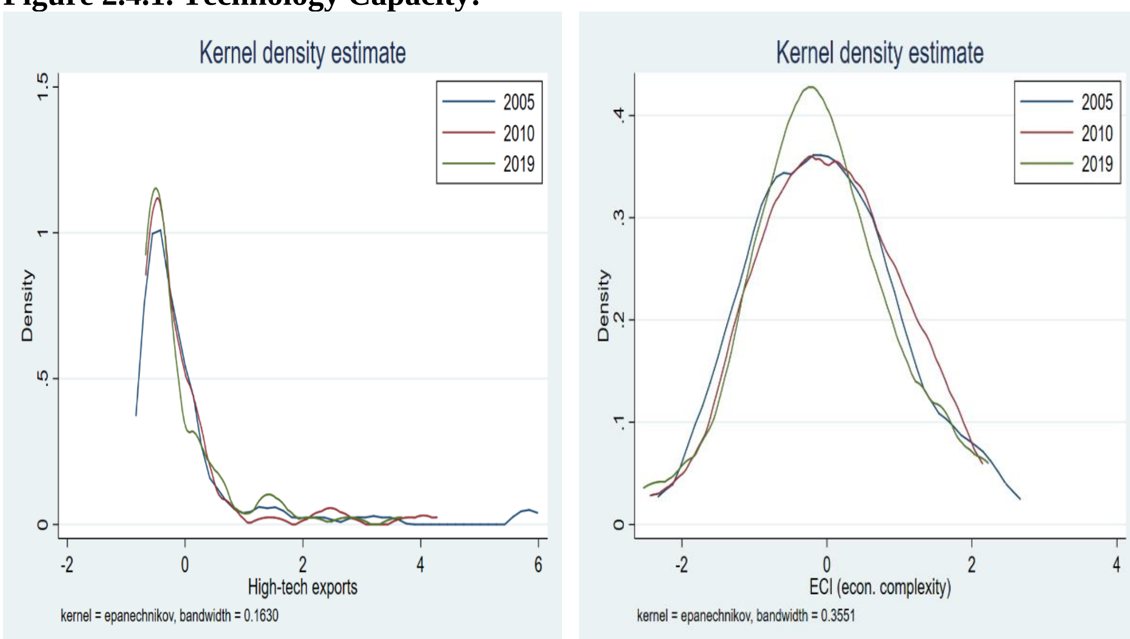


Figure 2.4.1. Technology Capacity (continued)

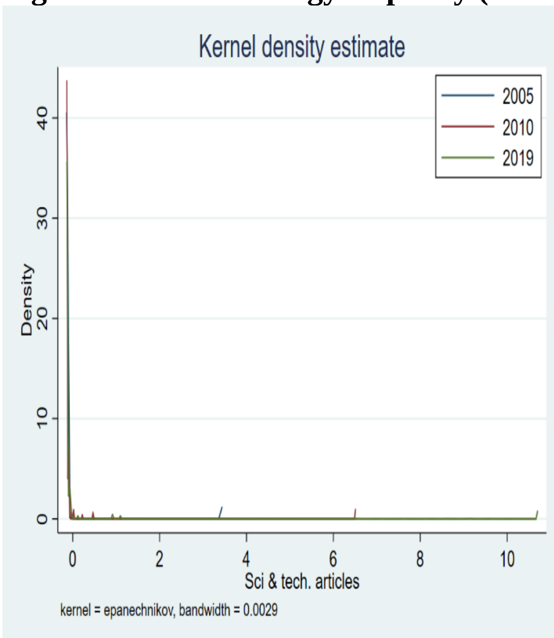


Figure 2.4.2: Financial Capacity

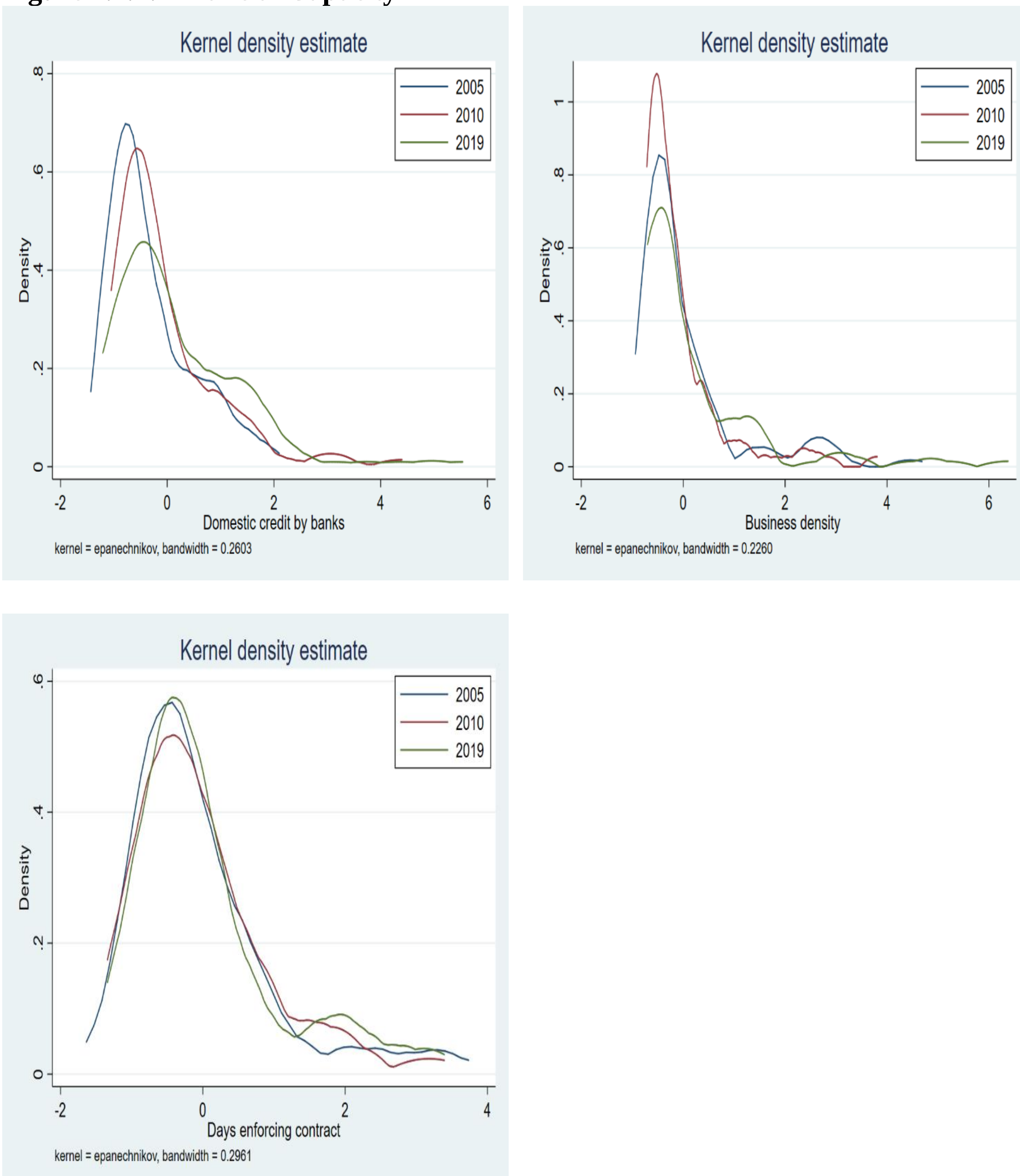


Figure 2.4.3: Human Capacity

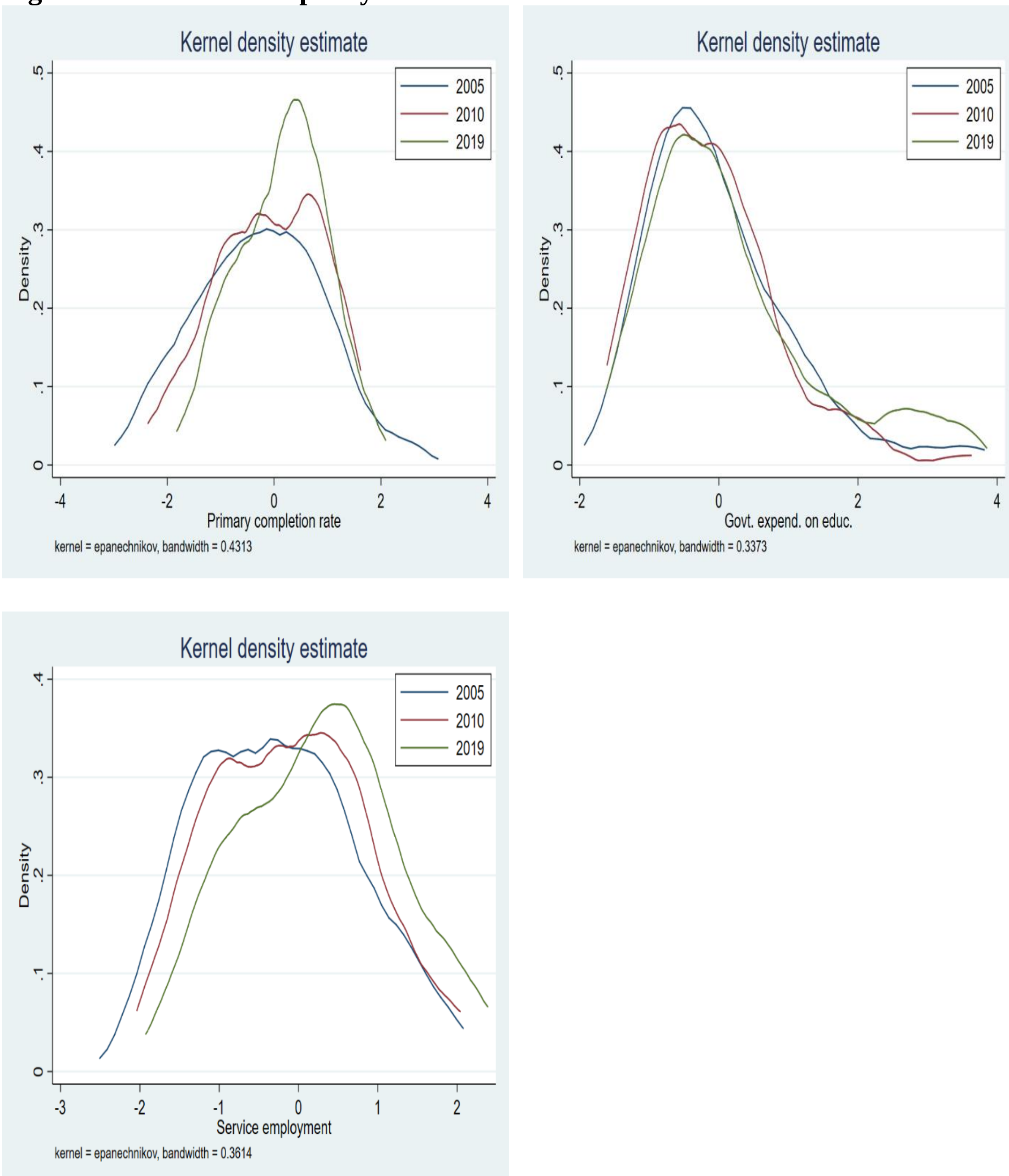


Figure 2.4.4: Infrastructure Capacity

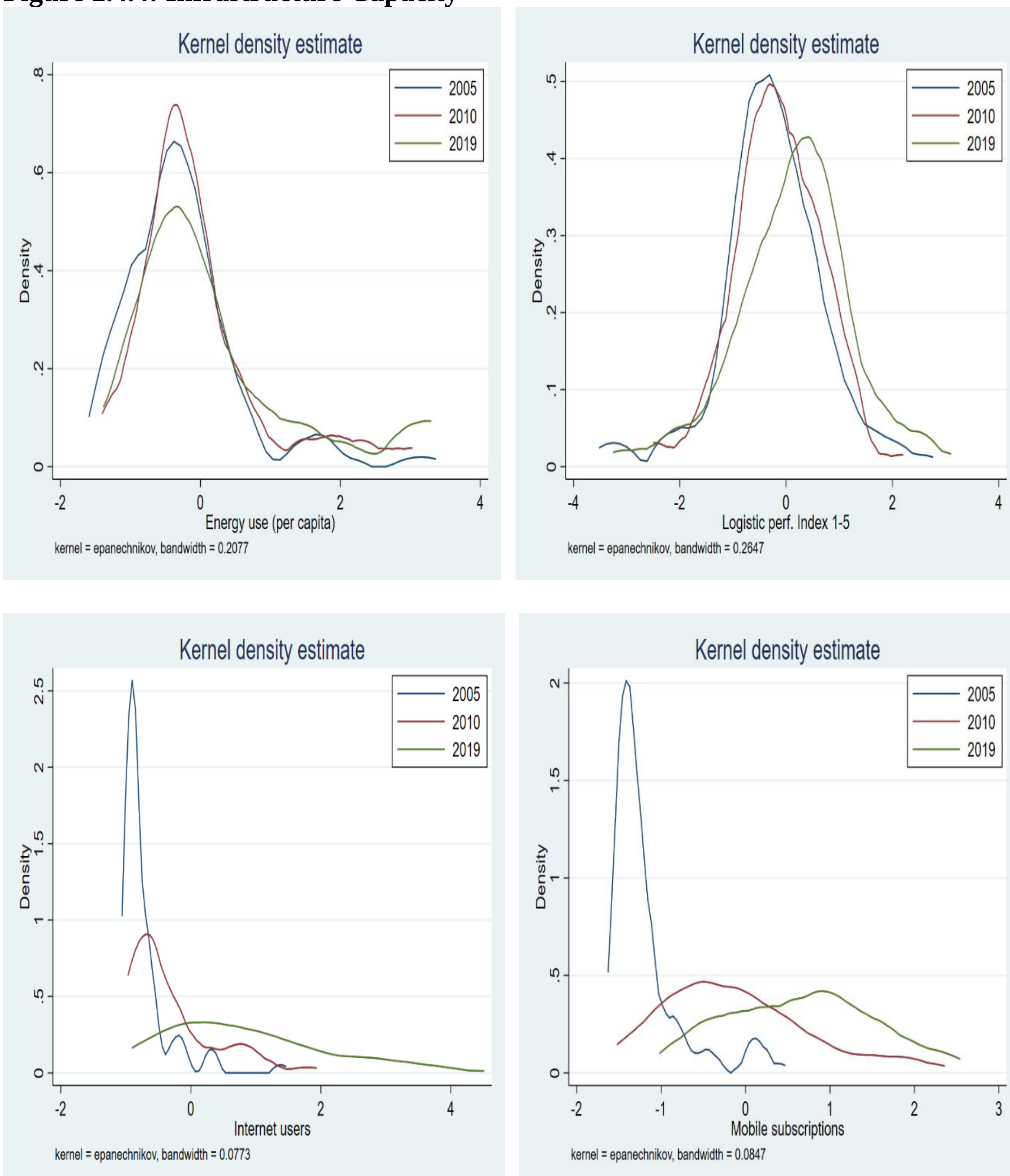


Figure 2.4.5: Public Policy Capacity

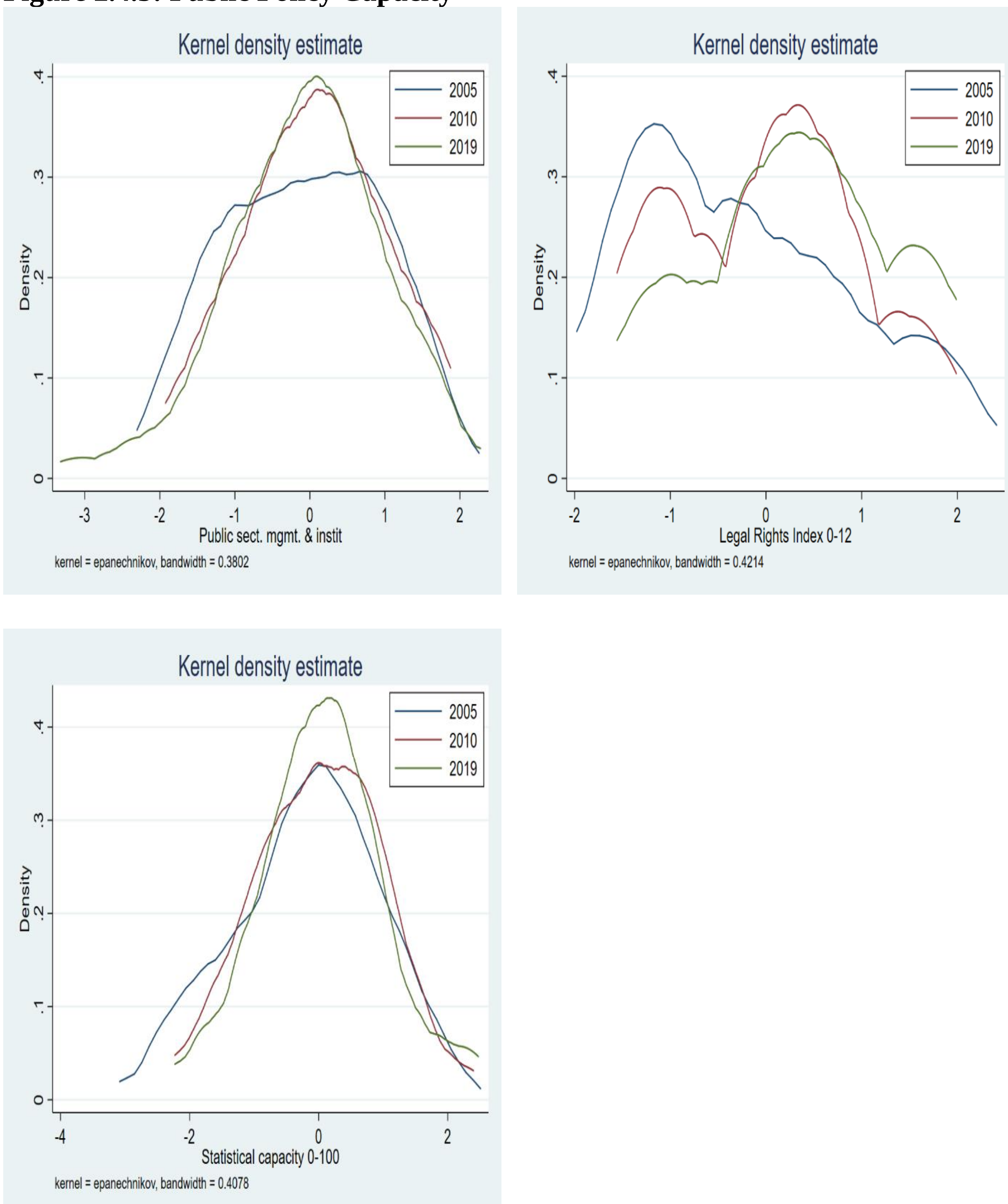
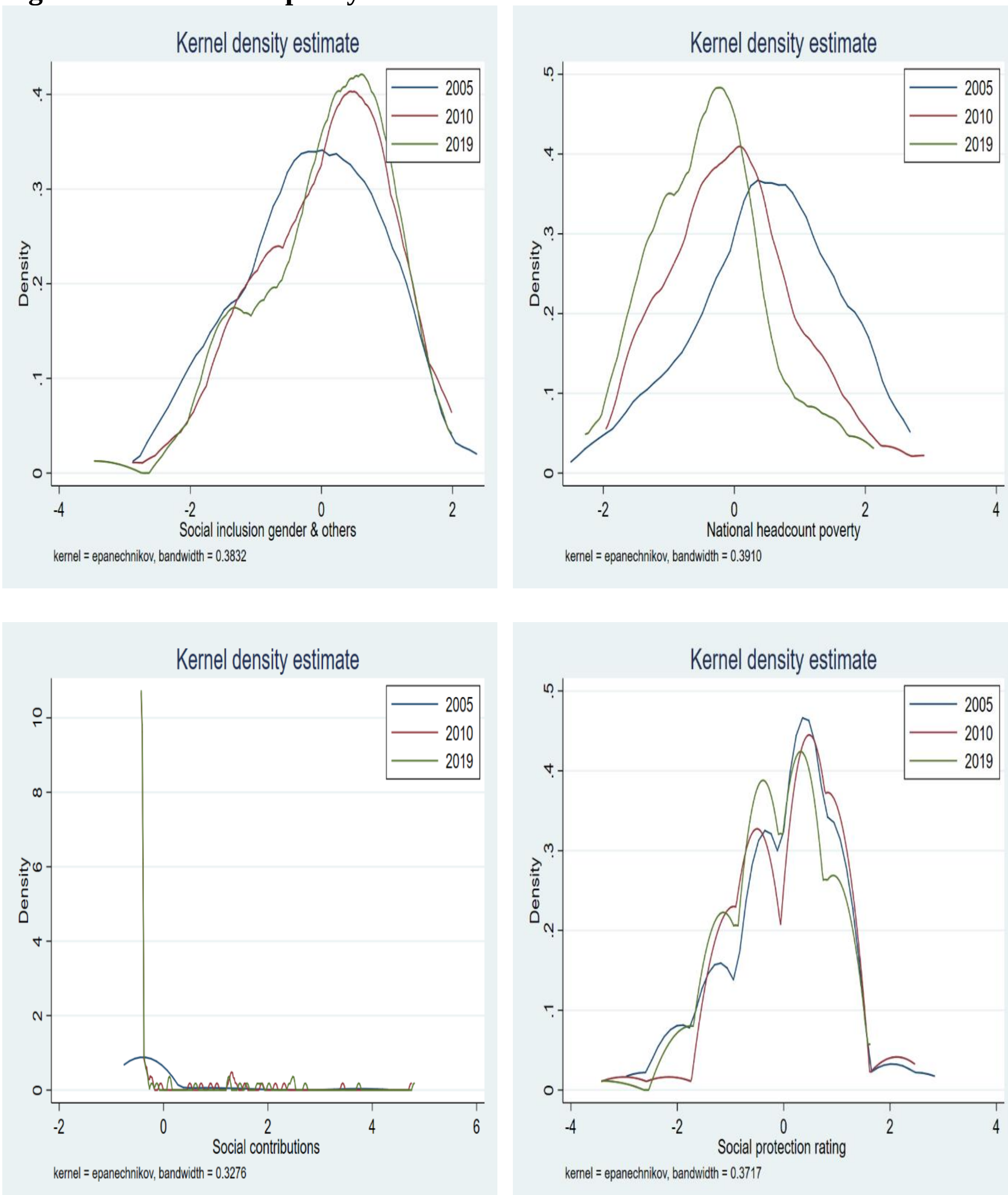


Figure 2.4.6: Social Capacity

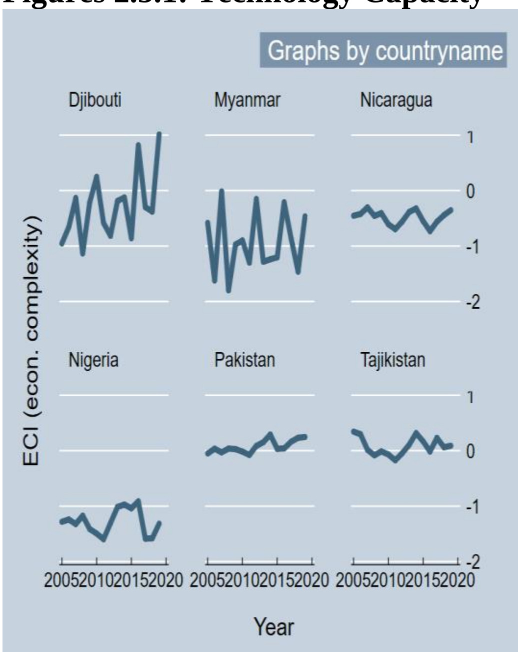


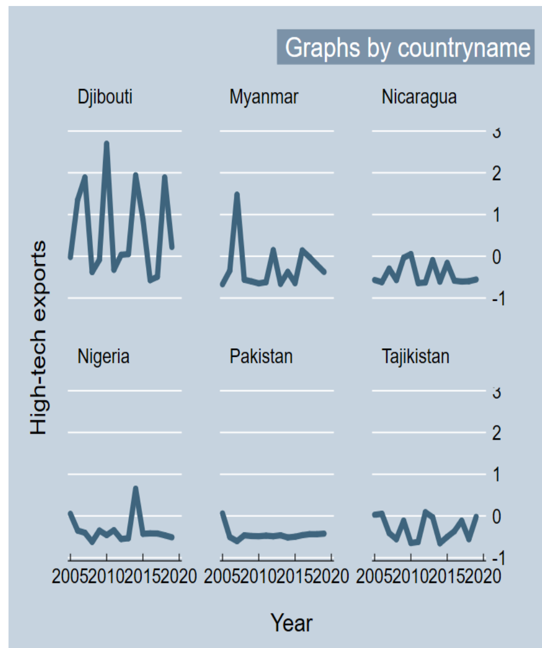
Appendix E

Figures 2.5. Time Trends for Select Countries for Select Variables.

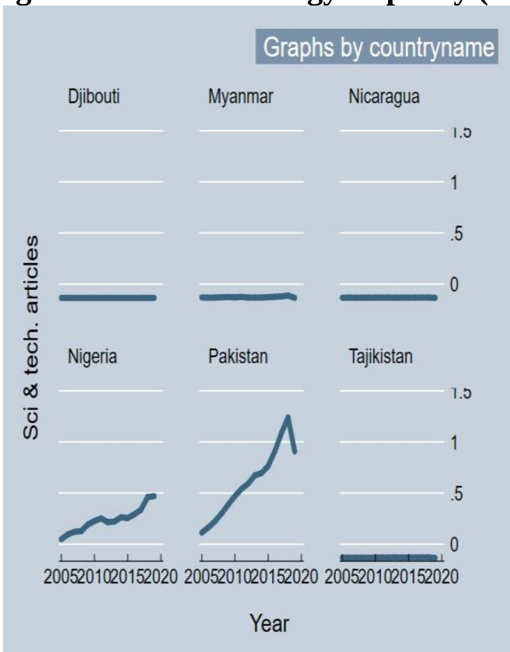
Trends of select variables under each capacity for select countries are given below. While some variables return a uniform trend, others indicate completely erratic or rising trends. The x-axis indicates the period from 2005 to 2019, whereas the y-axis shows the name of the variables.

Figures 2.5.1: Technology Capacity

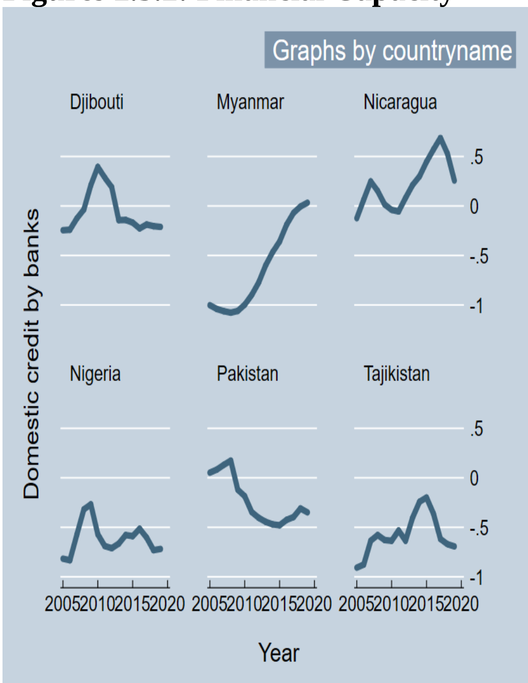


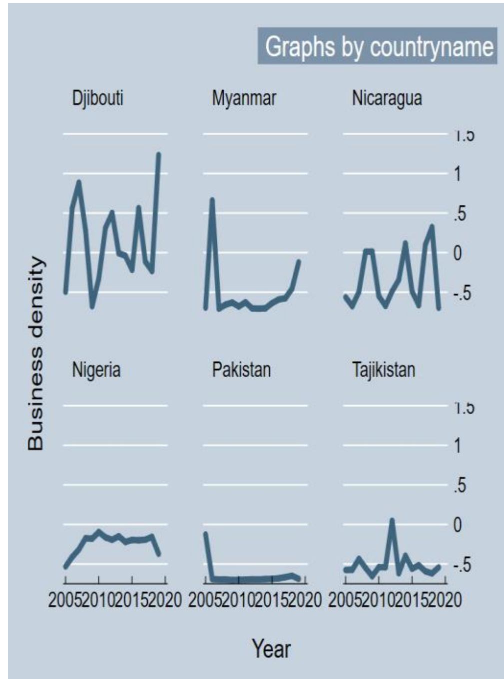


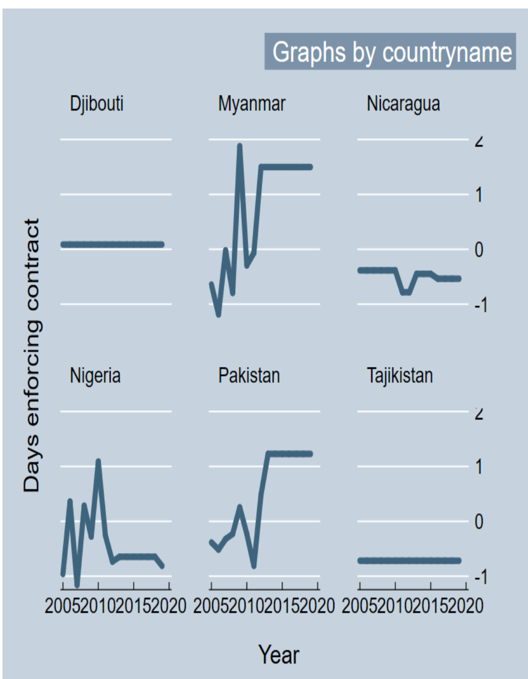
Figures 2.5.1: Technology Capacity (continued)



Figures 2.5.2: Financial Capacity







Figures 2.5.3: Human Capacity

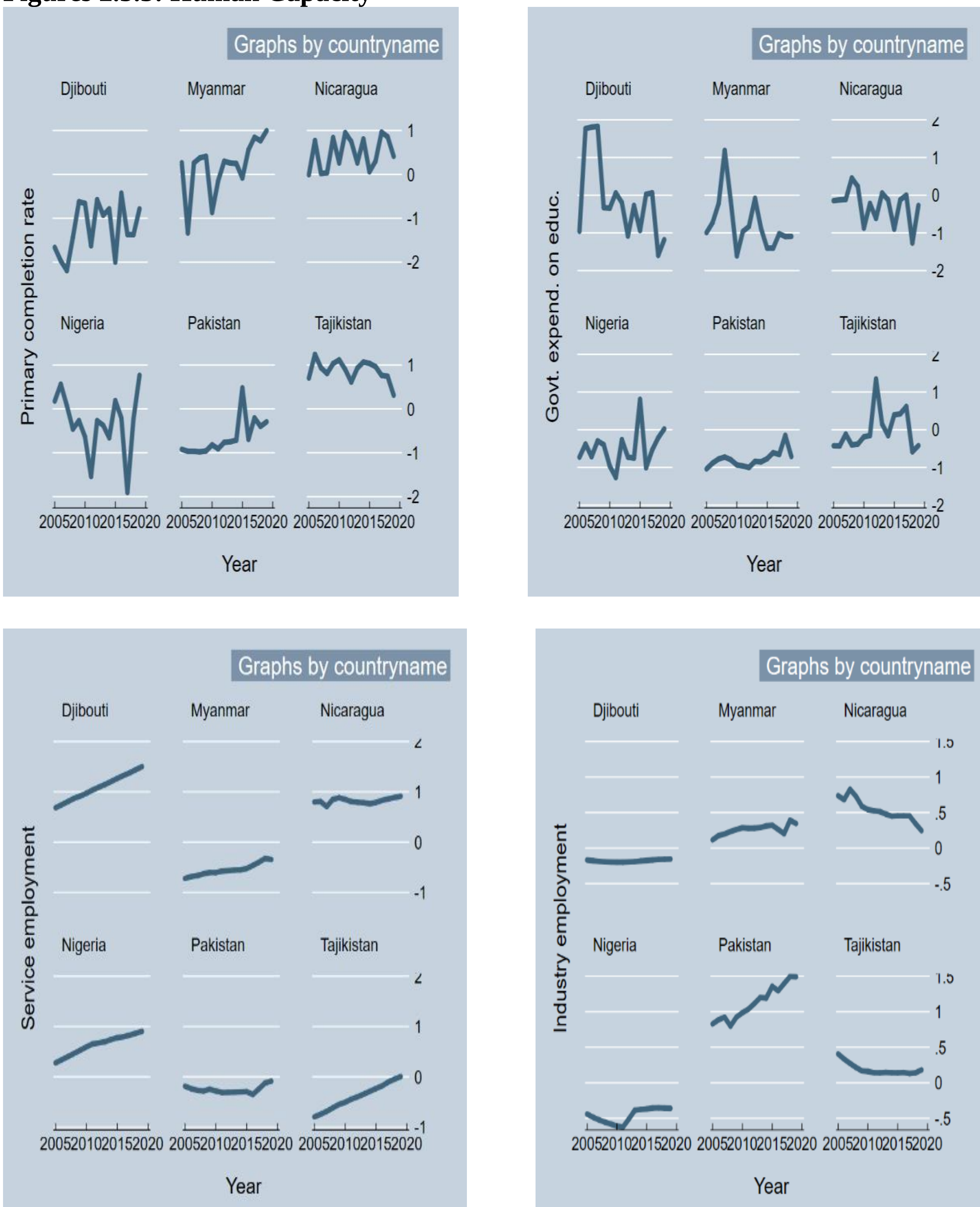


Figure 2.5.4: Infrastructure Capacity

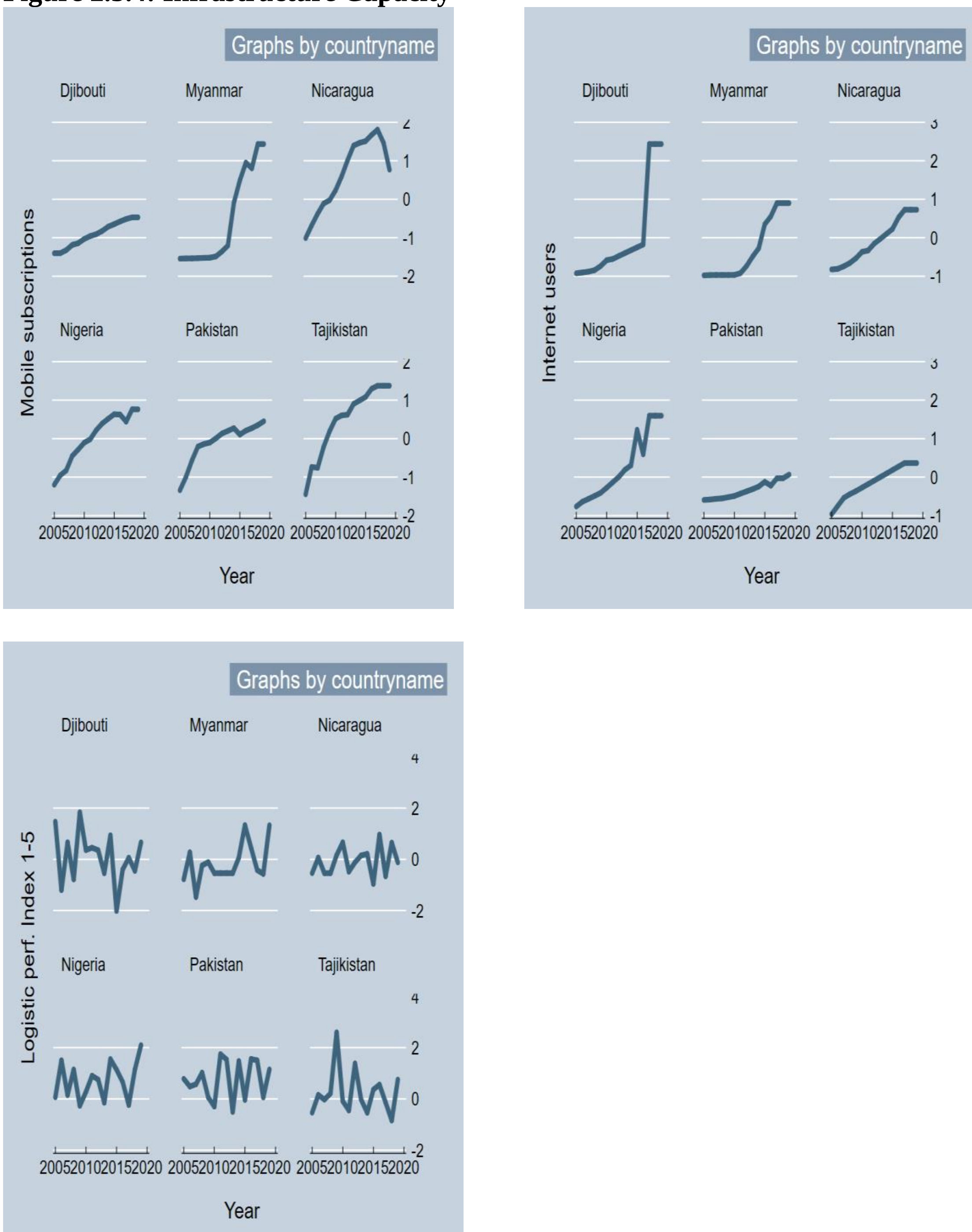
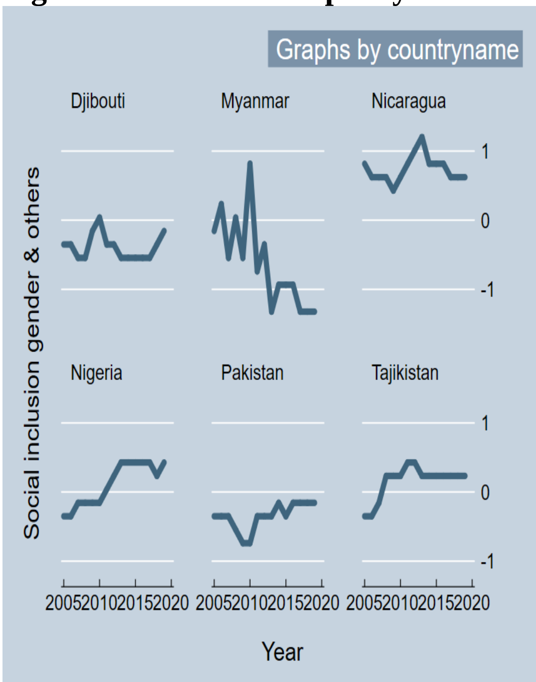
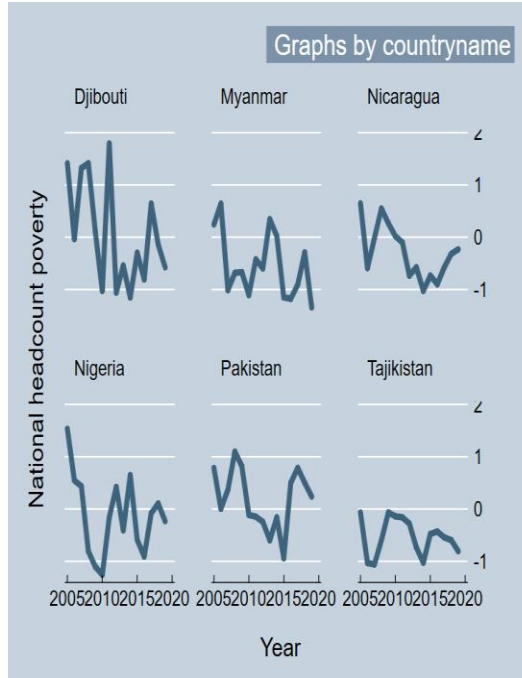
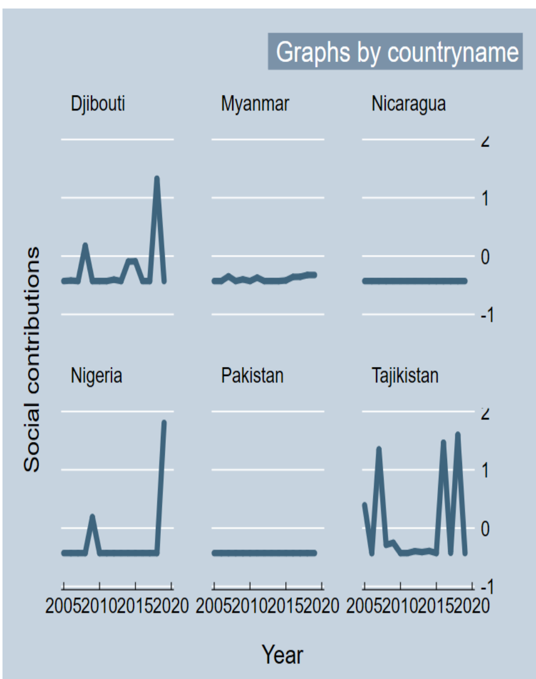


Figure 2.5.5: Public Policy Capacity

Figures 2.5.6: Social Capacity







Appendix F.

Table 2.4. Comparative Ranking of Countries Per Absorptive Capacity Index (2019)

Rank	Country	Tech_Index	Finance _Index	Infrastructure _Index	HumanCapacity _Index	PublicPolicy _Index	SocialCapacity _Index	AbsorptiveCapacity _Index
1	Vietnam	1.835127	1.823812	1.932174	0.765487	1.076316	0.504371	1.322881
2	India	4.306017	0.982093	0.825784	0.428893	-0.11115	0.561976	1.165602
3	Bosnia and Herzegovina	0.230912	0.842245	2.37799	1.014441	0.332861	1.059924	0.976395
4	Kosovo	1.237119	0.593937	1.921194	0.621909	0.626732	0.436277	0.906195
5	Moldova	0.387072	0.462939	2.018654	0.425024	1.032233	1.019524	0.890908
6	Georgia	0.378321	0.507115	2.306922	0.393636	1.286522	0.438898	0.885235
7	Mongolia	1.928538	0.183368	0.108906	1.180915	0.670887	0.814918	0.814589
8	Uzbekistan	0.811956	-0.2022	1.691056	0.950817	0.510404	0.976198	0.789705
9	Bolivia	0.293038	0.894145	1.058183	1.012945	0.155349	1.158961	0.762103
10	St. Vincent and the Grenadines	1.053247	0.208629	1.541172	0.660106	0.48422	0.26156	0.701489
11	Grenada	0.3357	0.14374	2.150201	0.598516	0.417394	0.514369	0.69332
12	Armenia	0.128657	0.107966	1.320656	0.568944	1.224323	0.48454	0.639181
13	St. Lucia	0.461946	0.093167	1.815016	0.638062	0.351249	0.457002	0.636074
14	Dominica	0.132727	1.010012	1.471019	0.758585	0.462641	-0.14163	0.61556
15	Kyrgyz Republic	0.42882	-0.21069	0.918591	0.663019	0.973312	0.717389	0.581741
16	Cabo Verde	-0.23006	0.358551	0.900362	0.568667	0.370873	1.104725	0.512186
17	Samoa	-0.37554	0.426603	0.845797	0.439965	1.087011	0.596361	0.503366
18	Kenya	0.820638	0.242582	0.088082	0.345713	0.817826	0.390348	0.450865
19	Nepal	0.123604	0.321283	0.715523	0.39143	0.584091	0.486709	0.437107
20	Bhutan	-0.23118	0.578921	0.435955	0.466053	0.606513	0.527948	0.397369
21	Honduras	0.254915	0.323002	0.605793	0.342447	0.229982	0.594319	0.391743
22	Cambodia	0.074192	0.763915	0.704527	0.409797	0.388614	-0.11648	0.370761
23	Sri Lanka	-0.19002	0.233907	0.967374	0.555663	0.282689	0.148645	0.333043
24	Rwanda	0.327286	-0.46087	0.051823	-0.06512	1.26666	0.750217	0.311665
25	Nigeria	0.4944	-0.31568	0.777391	0.117993	-0.00503	0.630286	0.283226
26	Maldives	-0.45821	0.245947	1.475443	0.492052	-0.15242	0.00429	0.267849
27	Lao PDR	0.143695	0.577372	0.567417	0.261909	-0.24236	0.269928	0.262993

Rank	Country	Tech_Index	Finance _Index	Infrastructure _Index	HumanCapacity _Index	PublicPolicy _Index	SocialCapacity _Index	AbsorptiveCapacity _Index
28	Senegal	-0.0125	-0.25093	0.39761	-0.24882	0.847148	0.458069	0.198429
29	Tonga	-0.41569	-0.09632	0.519016	0.309611	0.603783	0.101094	0.170249
30	Ghana	-0.37397	-0.55224	0.604351	0.353584	0.650955	0.182034	0.144118
31	Tanzania	0.026761	-0.09467	0.203206	-0.48162	0.207781	0.796058	0.109586
32	Cote d'Ivoire	-0.07358	-0.22658	0.366575	-0.01271	0.480156	0.108809	0.107113
33	Ethiopia	0.577417	-0.20974	-0.22005	-0.11129	0.017556	0.565574	0.103244
34	Djibouti	0.225756	-0.15364	0.400645	-0.04848	0.154949	-0.04464	0.089098
35	Lesotho	0.303178	0.38123	0.19675	-0.11242	0.142388	-0.403	0.084688
36	Togo	-0.03731	-0.28685	-0.00302	0.256051	0.283281	0.29095	0.083851
37	Bangladesh	-0.10129	0.4261	0.06743	0.329799	-0.23315	-0.04416	0.074122
38	Guyana	-0.3607	-0.37911	1.019161	0.422247	-0.21172	-0.0783	0.068595
39	Pakistan	0.062532	-0.09652	0.137691	0.111673	0.095186	0.099132	0.068282
40	Kiribati	0.019126	0.386583	0.227063	0.653179	-0.60597	-0.39131	0.048111
41	Vanuatu	-0.19003	-0.04284	0.385256	0.219316	0.447211	-0.55403	0.044149
42	Burkina Faso	0.135966	-0.13823	-0.15245	0.123046	0.317112	-0.04392	0.040255
43	Benin	-0.16928	-0.15866	-0.3173	-0.00672	0.570117	0.148464	0.011105
44	Malawi	-0.1415	-0.29775	-0.33264	0.1113	0.405855	0.154537	-0.0167
45	Nicaragua	-0.31277	-0.23147	0.232112	0.103423	-0.19638	0.281213	-0.02065
46	Tajikistan	0.032905	-0.56481	0.298435	-0.04933	0.286401	-0.15013	-0.02442
47	Tuvalu	0.150786	0.103685	0.691382	0.070817	-0.58147	-0.61998	-0.0308
48	Uganda	-0.15365	-0.37509	-0.4356	-0.30694	0.581907	0.363349	-0.05434
49	Gambia, The	-0.45538	-0.08629	0.017895	0.129778	-0.15273	-0.02504	-0.0953
50	Mali	-0.21218	-0.23106	-0.18255	-0.29749	0.386897	-0.04213	-0.09642
51	Micronesia, Fed. Sts.	-0.02808	0.044986	0.069799	0.316725	-0.40417	-0.66775	-0.11141
52	Zambia	-0.01398	-0.35426	-0.04731	-0.07948	0.303056	-0.55552	-0.12458
53	Sao Tome and Principe	-0.06513	0.416852	-0.05536	-0.01201	-0.52065	-0.6106	-0.14115
54	Mauritania	-0.31342	-0.27998	-0.04341	-0.21894	-0.17649	0.098707	-0.15559
55	Sierra Leone	-0.04923	-0.3396	-0.49023	0.11846	-0.16617	-0.20295	-0.18829
56	Cameroon	-0.33608	-0.41874	0.10723	-0.1589	0.101027	-0.43662	-0.19035
57	Timor-Leste	-0.37282	-0.21221	0.086283	0.432846	-0.67408	-0.46295	-0.20049

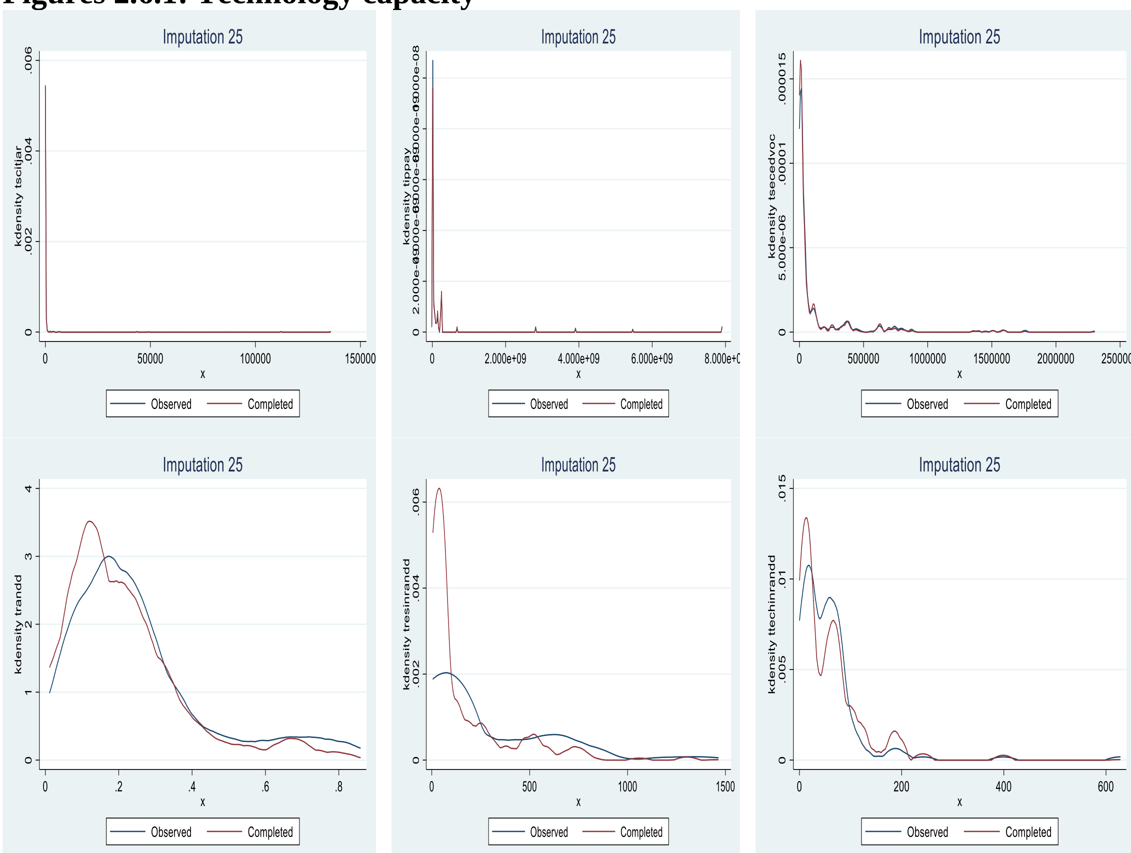
Rank	Country	Tech_Index	Finance _Index	Infrastructure _Index	HumanCapacity _Index	PublicPolicy _Index	SocialCapacity _Index	AbsorptiveCapacity _Index
58	Zimbabwe	-0.16584	-0.13868	-0.16432	-0.48678	-0.46139	0.211109	-0.20098
59	Myanmar	-0.29059	0.075565	0.457526	-0.17931	-0.12093	-1.15453	-0.20205
60	Liberia	-0.47768	-0.14699	-0.19402	-0.23901	-0.16844	-0.24811	-0.24571
61	Marshall Islands	0.127603	-0.10766	0.089237	0.330901	-0.69479	-1.23307	-0.24796
62	Niger	-0.2654	-0.63205	-0.42542	-0.7227	0.338601	0.190373	-0.25276
63	Afghanistan	-0.2297	0.081822	-0.54753	-0.00905	-0.39105	-0.56674	-0.27704
64	Mozambique	-0.07728	0.071048	-0.54299	-0.6898	-0.31835	-0.26513	-0.30375
65	Guinea	-0.53699	-0.69755	-0.02544	-0.66646	-0.01886	0.105032	-0.30671
66	Solomon Islands	-0.02331	-0.19956	-0.35161	-0.35527	-0.07189	-0.84626	-0.30798
67	Papua New Guinea	-0.42733	-0.20056	-0.31732	-0.26572	-0.01698	-0.69641	-0.32072
68	Madagascar	-0.24931	-0.22504	-0.53249	-0.32918	-0.29181	-0.31105	-0.32314
69	Haiti	-0.27428	0.586672	-0.24086	-0.31125	-0.82586	-0.91451	-0.33001
70	Burundi	-0.29326	-0.5261	-0.58438	-0.50933	-0.63882	0.326913	-0.37083
71	Congo, Rep.	-0.42095	-0.33139	-0.21451	-0.03004	-0.70382	-0.61605	-0.38613
72	Angola	-0.53496	-0.03026	-0.15295	-0.56374	-0.83363	-0.69364	-0.4682
73	Central African Republic	-0.0446	-0.32443	-0.57165	-0.08778	-0.92302	-1.06998	-0.50358
74	Guinea-Bissau	-0.5636	-0.06699	-0.4075	-0.51317	-0.75815	-0.81315	-0.52043
75	Comoros	-0.57087	-0.51273	-0.33662	-0.39159	-0.58277	-0.744	-0.5231
76	Chad	-0.40747	-0.30302	-0.84945	-0.83105	-0.62751	-0.23418	-0.54211
77	Congo, Dem. Rep.	-0.41142	-0.67921	-0.73101	-0.87923	-0.57574	0.008977	-0.54461
78	Sudan	-0.42613	-0.42575	0.009877	-0.7036	-1.09683	-0.84189	-0.58072
79	Eritrea	-0.15135	0.052468	-0.34355	0.024908	-2.30063	-0.84071	-0.59314
80	Yemen, Rep.	0.161517	-0.35635	0.024481	-0.53569	-2.06751	-1.01354	-0.63118
81	Somalia	-0.51377	-0.10877	-0.76224	-0.49105	-2.24777	-0.80263	-0.82104
82	South Sudan	-0.66031	-0.50391	-0.86225	-0.32214	-2.27191	-1.80079	-1.07022

Appendix G

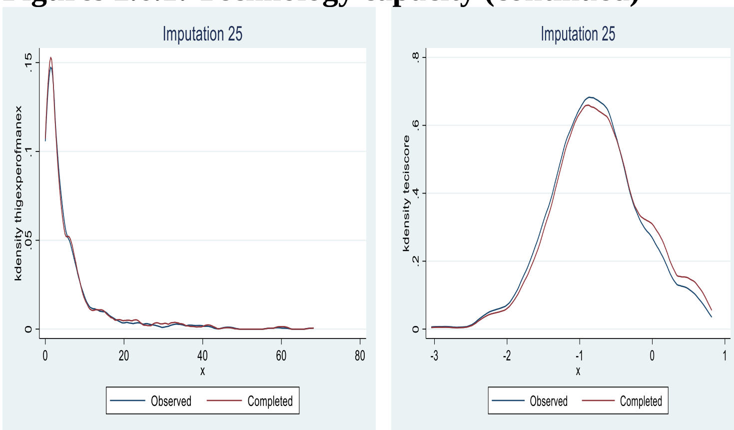
Figures 2.6. Kernel Densities of the Observed and Complete Dataset.

Statistical distributions of observed and complete datasets are compared to examine how best the complete dataset represents the observed dataset. Distributions overall match, indicating the accuracy and reliability of imputation.

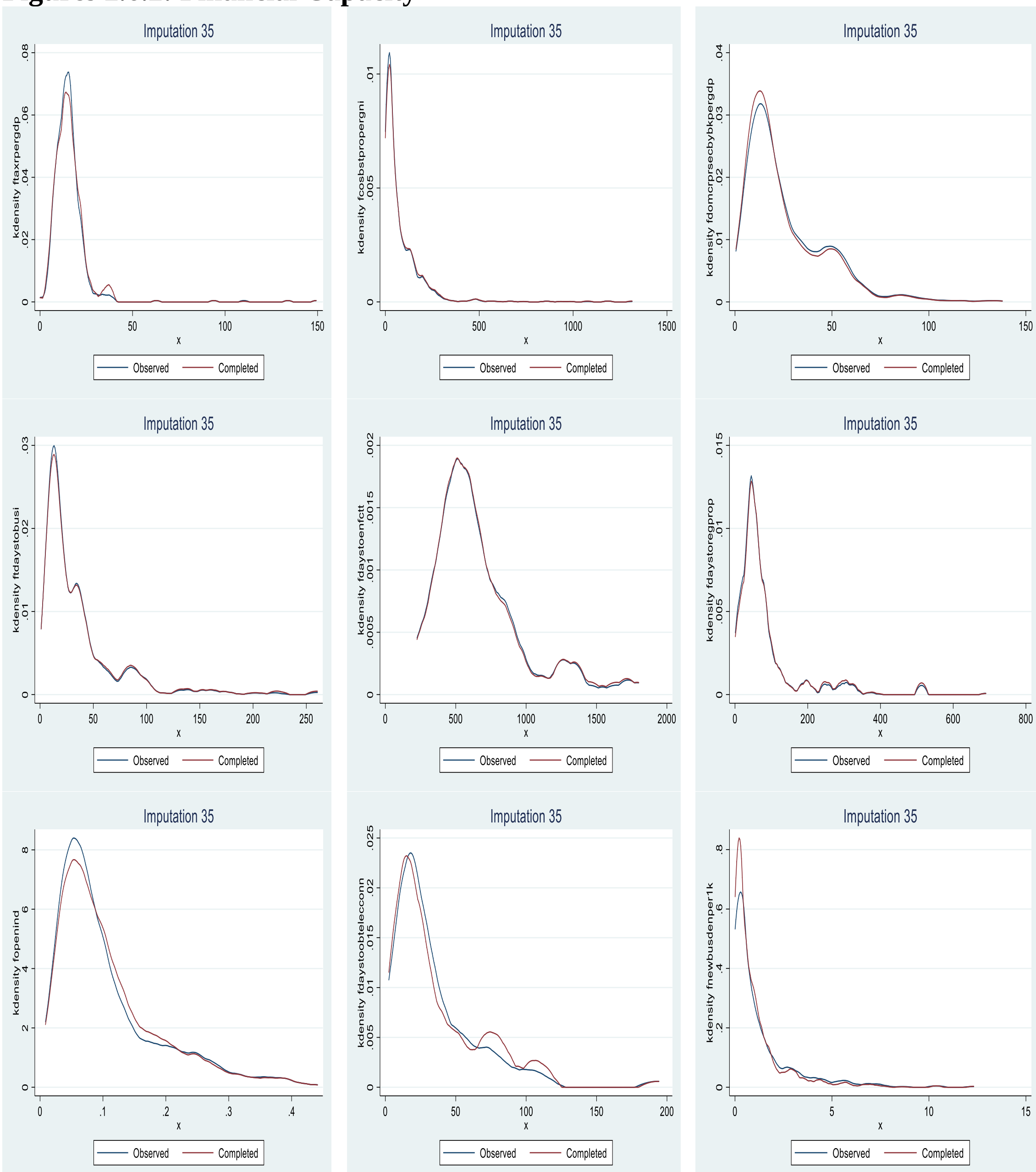
Figures 2.6.1: Technology capacity



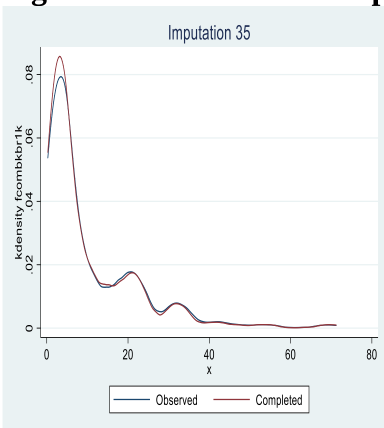
Figures 2.6.1: Technology capacity (continued)



Figures 2.6.2: Financial Capacity



Figures 2.6.2: Financial Capacity (continued)



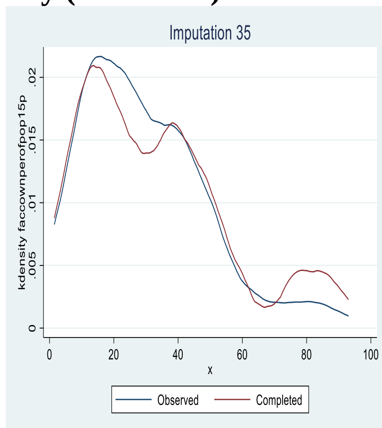


Figure 2.6.3: Human Capacity

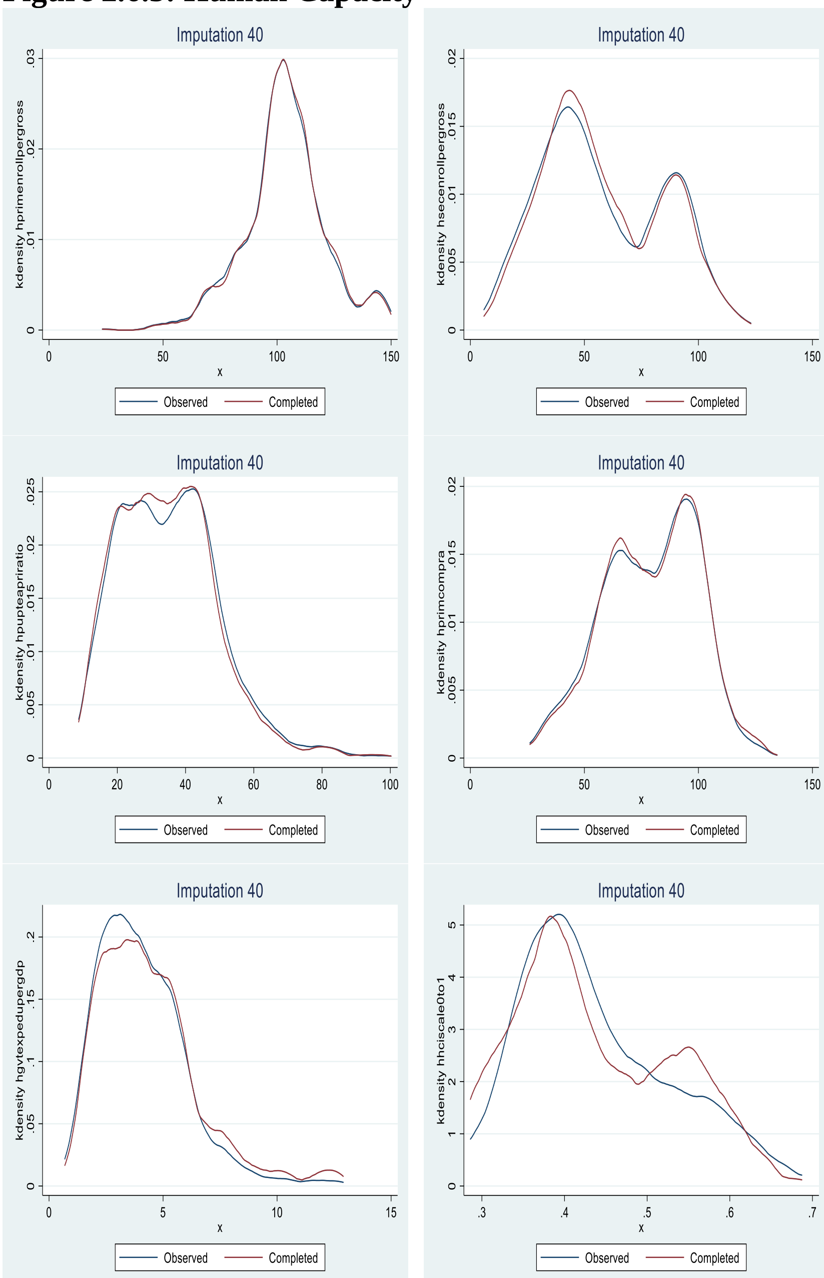
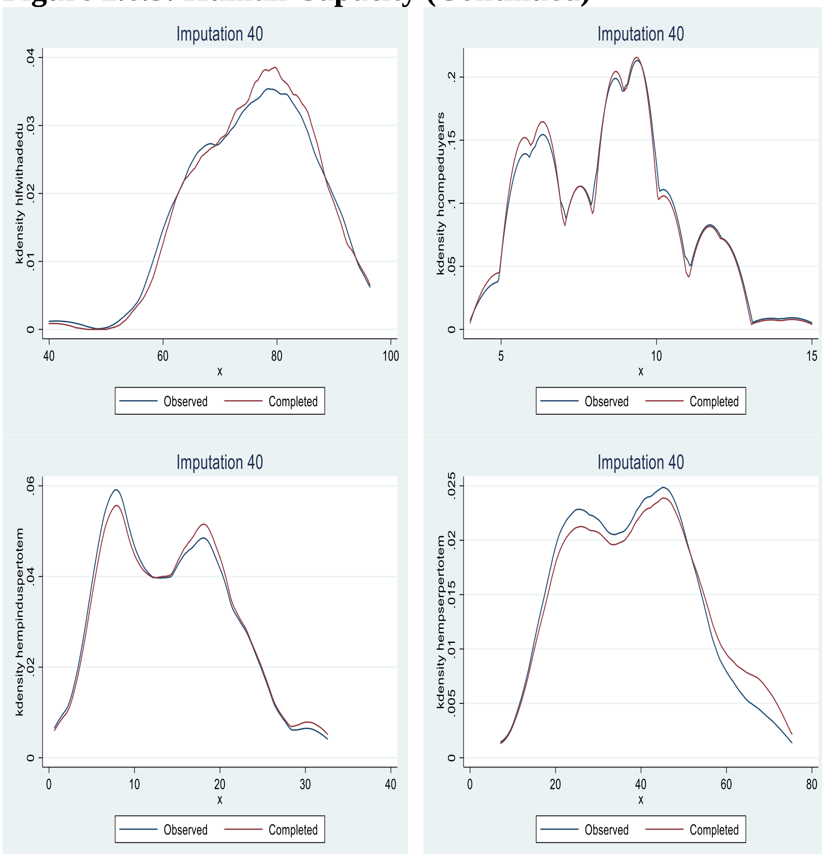
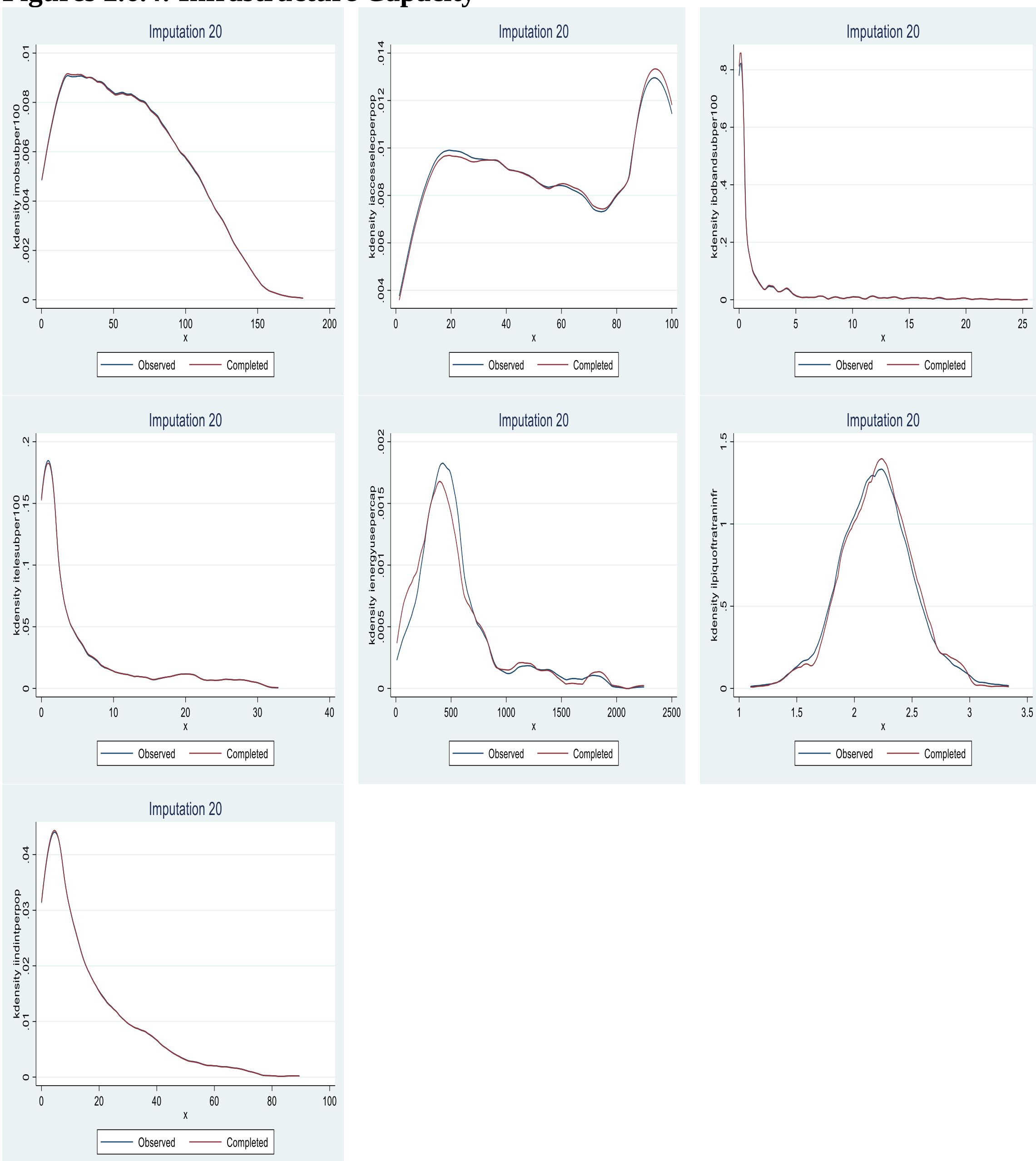


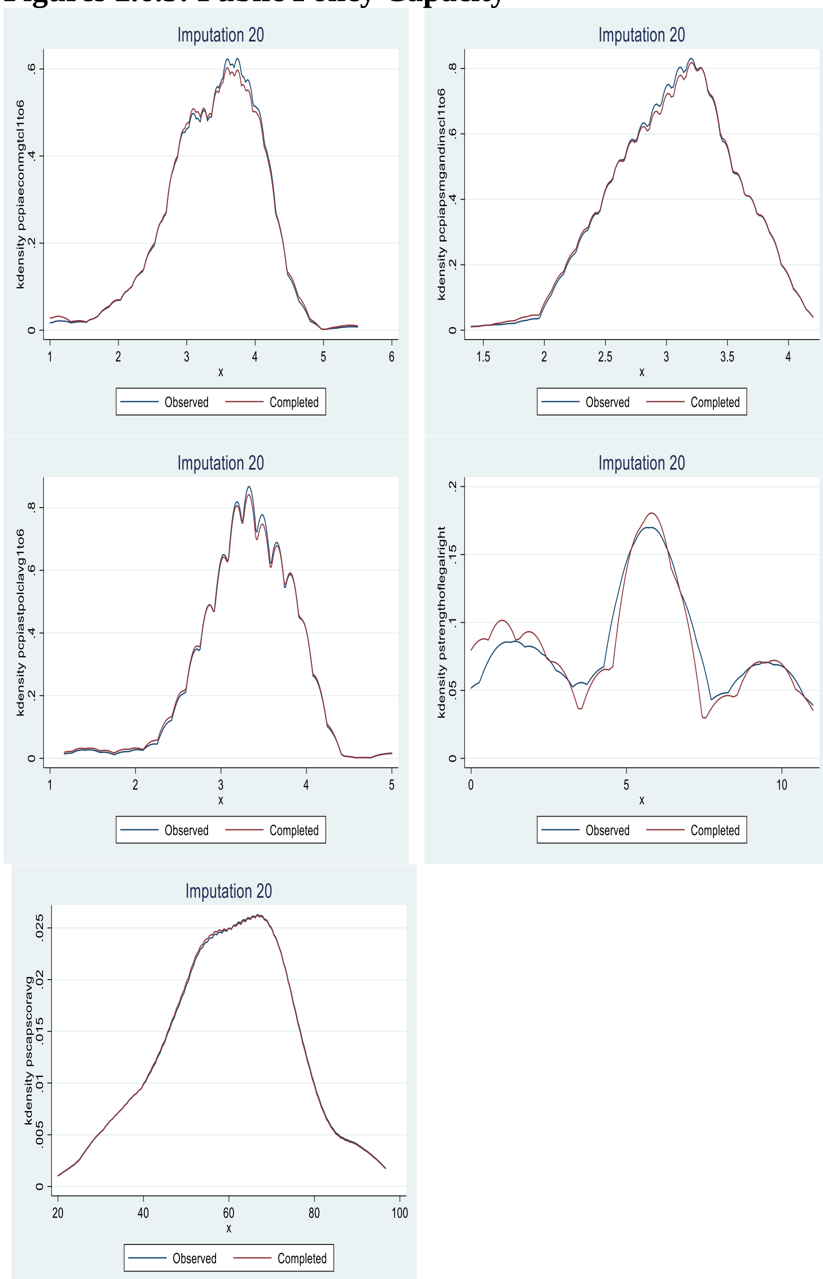
Figure 2.6.3: Human Capacity (Continued)



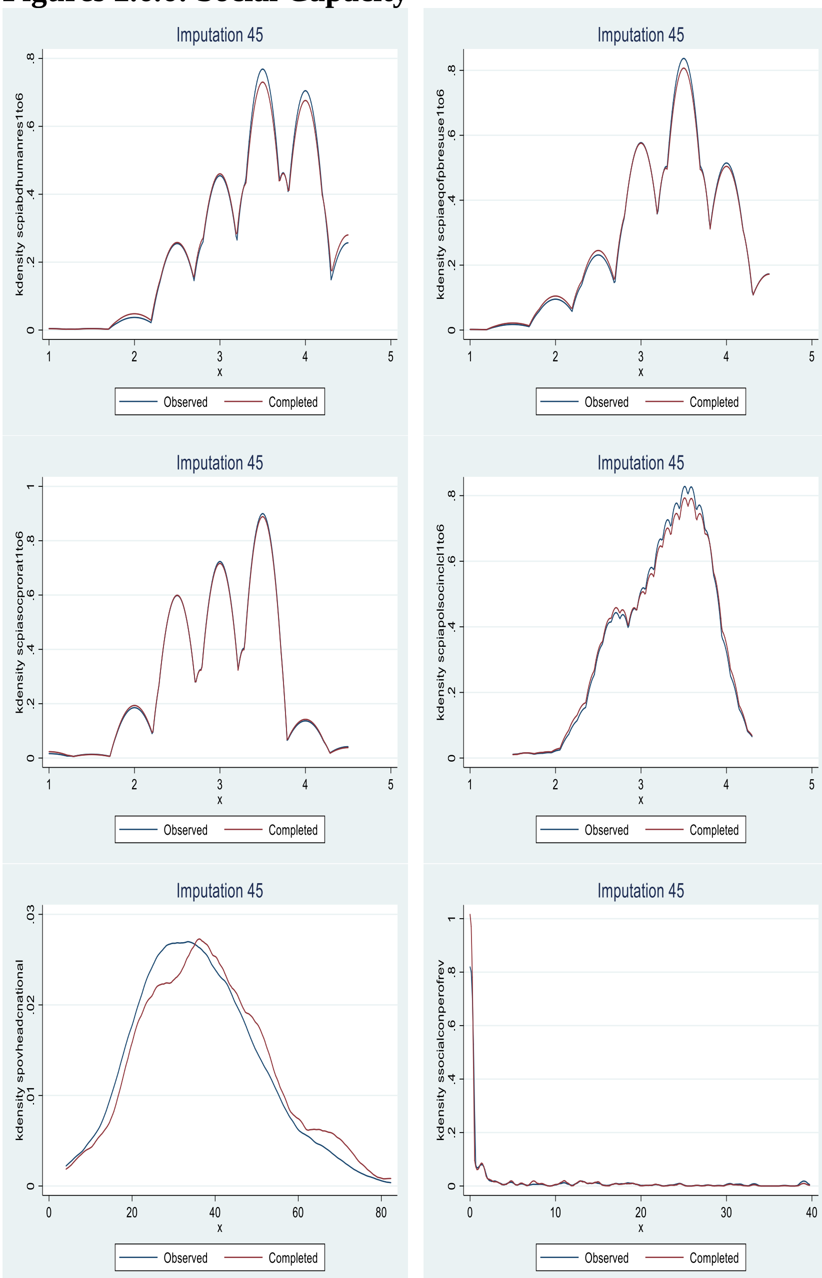
Figures 2.6.4: Infrastructure Capacity



Figures 2.6.5: Public Policy Capacity



Figures 2.6.6: Social Capacity



Appendix H

Tables 2.5. Pairwise Correlations for Incomplete (m=0) and Complete Datasets (at imputation m=25).

Overall, the correlations for incomplete and complete datasets are similar, suggesting the reliability of the imputation results.

Tables 2.5.1 Technology capacity pairwise correlations

Pairwise correlation for the incomplete dataset is above, whereas it is listed below for complete.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Sci & tech. articles	1.000							
(2) Intellectual payments (mil)	0.981	1.000						
(3) Voc. & tech. students (mil)	0.621	0.653	1.000					
(4) R&D expend. % of GDP	0.605	0.549	0.385	1.000				
(5) R&D researchers (per mil)	-0.015	-0.020	0.064	0.187	1.000			
(6) R&D technicians (per mil)	0.074	0.071	0.050	0.244	0.439	1.000		
(7) High-tech exports (mil)	0.041	0.061	-0.034	0.170	0.183	0.013	1.000	
(8) ECI (econ. complexity)	0.244	0.268	0.096	0.338	0.545	0.323	0.080	1.000

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Sci & tech. articles	1.000							
(2) Intellectual payments (mil)	0.968	1.000						
(3) Voc. & tech. students (mil)	0.527	0.487	1.000					
(4) R&D expend. % of GDP	0.346	0.307	0.264	1.000				
(5) R&D researchers (per mil)	-0.005	-0.004	0.072	0.122	1.000			
(6) R&D technicians (per mil)	0.148	0.115	0.046	0.258	0.097	1.000		
(7) High-tech exports (mil)	0.024	0.033	-0.049	0.169	0.052	0.123	1.000	
(8) ECI (econ. complexity)	0.193	0.176	0.040	0.085	0.409	0.244	0.066	1.000

Tables 2.5.2: Financial capacity pairwise correlations

Pairwise correlation for the incomplete dataset is above, whereas it is listed below for complete.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Tax revenue (% of GDP)	1.000										
(2) Business startup cost	-0.207	1.000									
(3) Domestic credit by banks	0.072	-0.333	1.000								
(4) Days to start business	0.127	0.382	-0.134	1.000							
(5) Days enforcing contract	0.025	0.055	-0.132	0.165	1.000						
(6) Days to register property	-0.045	0.193	-0.166	0.250	0.199	1.000					
(7) Openness measure	-0.006	0.077	0.518	0.552	-0.426	0.071	1.000				
(8) Days to electric meter	-0.200	0.034	-0.140	-0.078	0.129	0.137	-0.138	1.000			
(9) Business density	0.278	-0.193	0.390	-0.119	-0.155	-0.306	0.186	-0.123	1.000		
(10) Financial accountholders	0.171	-0.224	0.400	-0.052	0.020	-0.141	0.134	-0.116	0.475	1.000	
(11) Commercial banks	0.086	-0.319	0.526	-0.183	-0.237	-0.202	0.220	-0.096	0.553	0.531	1.000

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Tax revenue (% of GDP)	1.000										
(2) Business startup cost	-0.068	1.000									
(3) Domestic credit by banks	0.167	-0.270	1.000								
(4) Days to start business	0.290	0.419	-0.126	1.000							
(5) Days enforcing contract	0.175	0.060	-0.068	0.169	1.000						
(6) Days to register property	0.074	0.189	-0.173	0.235	0.197	1.000					
(7) Openness measure	0.153	0.095	0.476	0.537	-0.380	0.009	1.000				
(8) Days to electric meter	-0.131	-0.104	0.082	-0.122	0.081	0.038	-0.081	1.000			
(9) Business density	0.273	-0.145	0.339	-0.125	-0.119	-0.201	0.138	0.026	1.000		
(10) Financial accountholders	0.199	-0.231	0.451	-0.068	0.053	-0.138	0.111	0.094	0.401	1.000	
(11) Commercial banks	0.043	-0.260	0.501	-0.175	-0.216	-0.123	0.218	-0.006	0.455	0.533	1.000

Tables 2.5.3: Human capacity pairwise correlations

Pairwise correlation for the incomplete dataset is above, whereas it is listed below for complete.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Primary enrollment (gross)	1.000									
(2) Sec. enrollment (gross)	0.178	1.000								
(3) Primary pupil-teacher ratio	0.064	-0.787	1.000							
(4) Primary completion rate	0.370	0.867	-0.694	1.000						
(5) Govt. expend. on educ.	0.140	0.240	-0.261	0.252	1.000					
(6) Human Capital Index 0-1	0.052	0.908	-0.717	0.792	0.164	1.000				
(7) Advanced educ. labor	0.171	-0.005	0.005	0.001	-0.143	0.251	1.000			
(8) Compulsory educ. (years)	-0.288	0.338	-0.260	0.171	0.234	0.364	-0.126	1.000		
(9) Industry employment	-0.044	0.637	-0.546	0.538	0.060	0.534	0.001	0.306	1.000	
(10) Service employment	-0.162	0.620	-0.648	0.449	0.222	0.372	-0.109	0.268	0.559	1.000

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Primary enrollment (gross)	1.000									
(2) Sec. enrollment (gross)	0.174	1.000								
(3) Primary pupil-teacher ratio	0.020	-0.708	1.000							
(4) Primary completion rate	0.372	0.815	-0.646	1.000						
(5) Govt. expend. on educ.	0.107	0.325	-0.284	0.346	1.000					
(6) Human Capital Index 0-1	0.187	0.796	-0.619	0.723	0.204	1.000				
(7) Advanced educ. labor	0.011	-0.129	0.181	-0.144	-0.067	-0.034	1.000			
(8) Compulsory educ. (years)	-0.306	0.335	-0.211	0.178	0.176	0.308	-0.076	1.000		
(9) Industry employment	-0.024	0.633	-0.529	0.514	0.147	0.494	-0.174	0.345	1.000	
(10) Service employment	-0.105	0.623	-0.641	0.446	0.263	0.472	-0.163	0.313	0.565	1.000

Tables 2.5.4: Infrastructure capacity pairwise correlations

Pairwise correlation for the incomplete dataset is above, whereas it is listed below for complete.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Mobile subscriptions	1.000						
(2) Access to electricity	0.514	1.000					
(3) Broadband subscriptions	0.490	0.519	1.000				
(4) Telephone subscriptions	0.343	0.682	0.694	1.000			
(5) Energy use (per capita)	0.371	0.567	0.573	0.556	1.000		
(6) Logistic perf. Index 1-5	0.344	0.250	0.244	0.160	0.154	1.000	
(7) Internet users	0.680	0.651	0.733	0.579	0.580	0.343	1.000

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Mobile subscriptions	1.000						
(2) Access to electricity	0.509	1.000					
(3) Broadband subscriptions	0.471	0.496	1.000				
(4) Telephone subscriptions	0.342	0.664	0.684	1.000			
(5) Energy use (per capita)	0.363	0.559	0.702	0.585	1.000		
(6) Logistic perf. Index 1-5	0.238	0.261	0.100	0.092	0.115	1.000	
(7) Internet users	0.669	0.643	0.732	0.571	0.592	0.240	1.000

Tables 2.5.5: Public Policy capacity pairwise correlations

Pairwise correlation for the incomplete dataset is above, whereas it is listed below for complete.

Variables	(1)	(2)	(3)	(4)	(5)
(1) CPIA econ. mgmt.	1.000				
(2) Public sect. mgmt. & instit	0.612	1.000			
(3) Structural policies	0.649	0.740	1.000		
(4) Statistical capacity 0-100	0.498	0.437	0.527	1.000	
(5) Legal Rights Index 0-12	0.218	0.189	0.293	0.067	1.000

Variables	(1)	(2)	(3)	(4)	(5)
(1) CPIA econ. mgmt.	1.000				
(2) Public sect. mgmt. & instit	0.625	1.000			
(3) Structural policies	0.641	0.740	1.000		
(4) Statistical capacity 0-100	0.518	0.493	0.558	1.000	
(5) Legal Rights Index 0-12	0.182	0.274	0.337	0.160	1.000

Tables 2.5.6: Social capacity pairwise correlations

Pairwise correlation for incomplete dataset is above whereas for complete it is listed below.

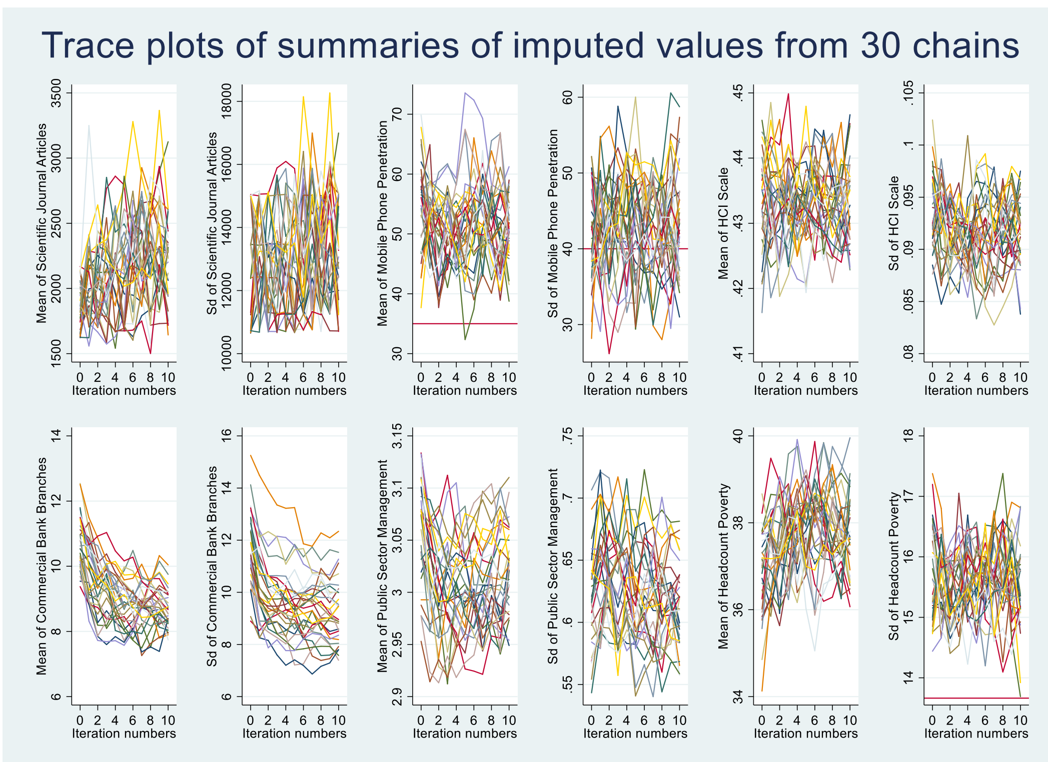
Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Human resources rating	1.000					
(2) Equity of public resc use	0.620	1.000				
(3) Social protection rating	0.627	0.655	1.000			
(4) Social inclusion o..	0.852	0.827	0.815	1.000		
(5) National headcount poverty	-0.387	-0.244	-0.374	-0.410	1.000	
(6) Social contributions	0.213	0.169	0.326	0.338	-0.187	1.000

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Human resources rating	1.000					
(2) Equity of public resc use	0.640	1.000				
(3) Social protection rating	0.644	0.658	1.000			
(4) Social inclusion o..	0.865	0.832	0.819	1.000		
(5) National headcount poverty	-0.395	-0.225	-0.303	-0.364	1.000	
(6) Social contributions	0.217	0.131	0.290	0.305	-0.156	1.000

Appendix I

Figure 2.7. Checking for Convergence through Trace Plots.

Trace plots show the convergence pattern of iterations involved in the imputation process. In this case, we see a healthy convergence. In other words, after plotting the mean and variance of the imputed values of different missing variables against the iteration number, the plots for imputed datasets freely intermingle without showing any definite trend. This suggests that the imputed dataset is of good quality.



CHAPTER THREE: ABSORPTIVE CAPACITIES AND ECONOMIC GROWTH IN LOW- AND MIDDLE-INCOME ECONOMIES

Abstract: I extend the firm-level concept of absorptive capacity to a framework applicable to the national level in low- and middle-income- economies (LMICs). Employing confirmatory factor analyses on 47 variables, I build 13 composite factors crucial to measuring six national level capacities: technological capacity, financial capacity, human capacity, infrastructural capacity, public policy capacity, and social capacity. Data cover most LMICs, eligible for the World Bank's International Development Association (IDA) support between 2005 and 2019. I then analyze the relationship between the estimated capacity factors and economic growth, controlling for potential confounders. My results indicate enhancing infrastructure, finance, business environment, specialized human capital, and public policy capacities improve economic growth. Finally, by ranking empirically important capacities for economic growth, I offer suggestions to cash-strapped governments and international organizations such as the World Bank, the UN, and the USAID to make effective investments to achieve sustainable development goals and boost shared prosperity.

1. Introduction

Economic growth across the world and, in particular, within the low- and middle-income economies (LMICs) is uneven because of multiple factors, including the quality of institutions, the strength of policies, unequal access to larger markets, and human capital allocation to innovation (Burgess and Barbier 2001; Kaplinsky and Kraemer-Mbula 2022).

A closer look at GDP per capita data[12] suggests that while some LMICs have relatively advanced such as Georgia and Moldova (per capita GDP < $4,500), and few like Tajikistan and Pakistan, are lingering in the middle (per capita GDP < $1,200), many have yet to escape the deep trench (e.g., Afghanistan and Sudan with per capita GDP < $550).

[12] This classification is tentative based on GDP per capita data in 2020 from the World Bank. https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?name_desc=true

Why is it that some of those economies have higher economic growth than others? This intriguing and essential but complicated question of economic growth differential has been a subject of debate within the realm of conventional economics for decades (Solow 1956; Romer 1994; Freeman 1995; Burgess and Barbier 2001; Jones 2005; Meissner 2014; Barro 1999; Kaplinsky and Kraemer-Mbula 2022; Stokey 2015; Gründler and Potrafke 2019; Hu and Yao 2021; Acemoglu and Robinson 2012).

Most of these mainstream studies explain economic growth as an outcome of multiple factors. The observed growth left unexplained is captured by *Total Factor Productivity* (TFP) or, in technical terms, "*productive efficiency*," expressed as the capacity of a system to combine growth factors efficiently. For some researchers, technological adoption (Romer 1994) and institutional strength (Acemoglu and Robinson 2012) affect TFP. However, it is not clear how TFP is determined (Kataryniuk and Martínez-Martín 2018). Even if technological adoption is considered a prime determinant impacting TFP and hence growth, it is uncertain what drives the pace of technological adoption in poor economies. Is it the only factor influencing development in poorer countries? Similarly, studies linking institutional strength with economic growth generally face the econometric challenge of simultaneity. In other words, what comes first: the institutional quality or economic growth? While these studies contribute immensely to the question of differences in growth performance, much still needs to be uncovered when considering growth dynamics in poor countries. Inspired by these contributions, as well as strides made in strategic management and innovation studies paradigms, I further explore a more relevant and comprehensive list of dimensions that influence development in LMICs. Deeming

LMICs as "learning economies" (Viotti 2002), this work complements the existing studies using a more comprehensive dataset in an empirically rigorous manner.

It is well-known that LMICs lag in growth (Irshad, Mehr-un-Nisa, and Ghafoor 2022). However, since it is unclear how the dimensions of growth come to exist and are deployed, it requires a thorough investigation. Building technology or skilled resources is not a free lunch; a country will likely make a conscious choice and effort to build those dimensions, referred to as "national capacities" in this chapter. The concepts such as "national innovation system" (Freeman 1995) and a firm's "absorptive capacity" (Cohen and Levinthal 1990) provide a foundation to *national capacity* and *knowledge absorption ideas*. I argue these notions are at the forefront of economic growth analysis in LMICs. However, perhaps two reasons are downplaying the significance of knowledge absorption and capacities in economic growth studies.

First, many studies (such as Heath 2001) argue that knowledge absorption and exploitation are individual rather than national attributes, as illustrated in research (Fagerberg and Srholec 2017). Because of this notion, these processes are not viewed as impacting economic development on the national scale. However, other studies claim these are national attributes shaped and influenced by institutions and their interactions, impacting economic development (Lewis 2021; Nelson 1993; Fagerberg and Srholec 2017). Despite their importance, these attributes lack due prominence because it is challenging to aggregate measures of complex concepts. While some indices, such as the "competitiveness index" (WEF 2020) and the "global entrepreneurship index" (Acs, Szerb, and Autio 2017), draw media attention, these measures do not often engage theory comprehensively (Im and Choi 2018; Erkkilä 2020).

The second reason that capacities and knowledge are not fully deciphered in comparative economic growth analyses pertains to how the growth accounting framework is set up by employing aggregate production function and TFP. While the framework includes many easily measurable indicators of the capacities (such as capital accumulation) in the aggregate production function, it situates immaterial and non-directly quantifiable indicators such as knowledge (Romer 1990; Barro 1999) and the underlying technology (Balk 2021) in the TFP. As the framework offers an indirect measure of TFP as residual growth, TFP is not well-understood (Kataryniuk and Martínez-Martín 2018). Some studies even question the theoretical notion of TFP as acquired from the employment of an aggregate production function to macroeconomic data (Felipe and McCombie 2004; Felipe and Fisher 2003). The authors of these studies assert that TFP measurement in the growth accounting framework is problematic because such measurement is based on aggregate production functions, which theoretically do not exist in the first place.

These concerns persist secularly in the economic literature worldwide. However, the global south, especially the poorest, further faces underrepresentation in the economic growth literature. Part of the problem is the relevance of the existing frameworks and concepts that render them not fully applicable to social and political realities within the poorest economies. This is so because the existing frameworks and ideas are conceived mainly in High-Income Countries (HICs). Another fundamental issue for the lack of reasonable literature representation from the low-income economies stems from the lack of data. With missing data, low-income economies are excluded from the analysis. Consequently, results are not representative of the entire world economies.

Against this backdrop, I argue for a holistic approach to study what causes growth differentials in LMICs, also earlier pleaded by Fagerberg and Srholec (2017). In concurrence with Fagerberg and Srholec (2017), my approach calls an economy (an LMIC for this analysis) a warehouse of knowledge, skills, institutions, resources, finance, and infrastructure, in other words, capacities. An essential difference in my approach is comparing a complete list of capacities *among LMICs*, primarily those supported by the World Bank International Development Association (IDA), and not with those in wealthier countries. Such capacities, I theorize, are fundamental tools to the generation of economic value in LMICs.

I define capacities as part of my proposed framework of the National Absorptive Capacity System (NACS). The capacities include business environment and finance, infrastructure (ICT, energy, and trade- and transport-related infrastructure), technology and innovation, human capital, public policy (including indicators from the World Bank's Country Policy and Institutional Assessment (CPIA) clusters and other indicators of legal strength, statistical capacity, and environmental sustainability policies), and social capacity interventions (including indicators on welfare, inclusion, and equity).

For the last three decades, capacities are established as firm-level phenomena in management and innovation literature (Cohen and Levinthal 1990; Zahra and George 2002; Müller, Buliga, and Voigt 2021; Duan, Wang, and Zhou 2020; Kale, Aknar, and Başar 2019). However, since both firms and nations (LMICs) are, in essence, collectives, capacities can be defined at the national LMIC level too. Therefore, in spite of visible differences between firms and nations and them being not similar in many ways (e.g., a firm operates in a regulated manner with the outer space whereas a nation may freely interact with the rest of the world), a researcher can still apply the ideas from firm-level literature to understand and appreciate capacities in the national LMIC context (Fagerberg and Srholec 2017). Moreover, many parallels between these entities underpin this idea. For instance, both firms and countries comprise people with varying skills and resources, interacting with each other and creating economic value (Fagerberg and Srholec 2017). Additionally, both firms and nations are overseen by management and governance that incentivize people's performance, invest in their skills acquisition, and stimulate the creation and distribution of economic value. Therefore, utilizing firm-level concepts on a national level to advance an understanding of economic growth in LMICs presents interesting insights.

I postulate that national capacities positively and significantly impact economic growth in LMICs while controlling for potentially important confounders. Keeping in view data-poor environments within LMICs, in Chapter 2, I have developed and validated a dataset for this current study (MSK dataset) from an extensive set of variables (47 variables) for 82 LMICs between 2005 and 2019. In doing so, I supplement the existing data from the World Bank Group (World Development Indicators) and other sources with estimated data imputed for LMICs using cutting-edge statistical, multiple imputation, and machine learning techniques.

By employing factor analysis for dimension reduction and then conducting panel analysis to estimate the impact of capacities on economic growth, my research combines the strengths of these methodologies. Results indicate that improving infrastructure, finance, and public policy capacities enhances LMICs' economic growth. Similarly, I find skilled human capital boosts economic growth. On the other hand, technology and R&D spending—as enshrined in general human capital—does not affect economic growth. Lastly, I find that infrastructure capacity (particularly ICT and energy), followed by public policy capacity, and specialized human capital (including service and industry sector employment and government expenditure on education, among other things) offer the biggest bang for the buck in LMICs.

Performing analyses on the multiply imputed complete dataset, my study caters to the various problems of biasedness, face validity, missing confounders, and, most importantly, missing data, thus contributing to the body of literature. Similarly, the notions of firm-level capacities at the LMIC level are a valuable and novel contribution to studying economic growth differential within LMICs. Alongside engaging a thorough list of capacities, another unique contribution to the literature is operationalizing the capacities that suit the LMICs' context.

By offering a ranking of which capacity is empirically more critical for economic growth among LMICs, I propose finance and planning ministries with tight budgets to make effective investments. For instance, I suggest they prioritize investment in infrastructure, public policy, specialized skills, and finance infrastructure and business environment capacities. Similarly, I advise international organizations implementing programs in LMICs like the World Bank, the United Nations, and the USAID to integrate such essential capacities in designing growth diagnostic and country partnership frameworks to achieve sustainable development goals and boost shared prosperity.

The rest of the chapter is structured as follows. In Section 2, I discuss the literature on the relationship between capacities and economic growth; in Section 3, I model this relationship in a novel framework. In Section 4, I derive hypotheses from this theory, and Section 5 briefly discusses the data. Section 6 addresses capacities measurement, particularly how I have employed factor analysis on a full set of variables to derive composite factors to measure national capacities. The following two sections explore the longitudinal impact of the national capacities on economic growth before conducting sensitivity analyses of the results. Section 9 and 10 present this study's conclusions and implications, respectively. Lastly, Section 11 makes suggestions for future research.

2. Capacities and Economic Growth Literature

My research focuses on the role of capacities in economic growth in LMICs eligible for the World Bank's IDA support. Many researchers have studied economic growth differential across countries. From Solow's (1956) view of differences in the amount of accumulated capital per worker to Gerschenkron's (1962) idea of technological differences, and then later on the same notion by "new growth theory" pioneers (Romer 1994; Lucas 2004) ascribing growth differences to variation in the degree of technology adoption and human capital accumulation, there exists a range of perspectives. While these are great works, they are inadequate to capture and explain all the development dimensions that policymakers want to know. For instance, Solow's view cannot account for the entirety of growth. Much of the unexplained observed growth is left in the TFP, a catch-all term denoting the efficiency with which an economy uses its resources (Barro 1999). Its measure is obtained only indirectly as Solow's residual. Solow did not explain what dimensions determine TFP. Similarly, Gerschenkron's work provides a solid alternative for growth differences in advanced economies, yet it fails to offer a convincing explanation for growth differences in LMICs. Development is more than technological differences, particularly in LMICs, where technology accumulation may come later in their priority list.

New growth theory is promising as it aims to explain TFP. Technology adoption is regarded as the key to differences in TFP. Similarly, the theory considers human capital and R&D investment as engines of TFP and growth through innovation (Mastromarco and Zago 2012; Romer 1990). However, the theory does not explain what drives the pace of technological adoption or human capital and R&D investments in LMICs. Poor economies can have higher crime rates, corrupt institutions, inefficient bureaucracy, and controlled markets, all causing inefficient resource allocation. The new growth theory seems to ignore these factors. Overall, this approach adds little to how institutions and public policy impact accumulation or efficiency.

Some later works extensively discuss the role of institutions and how they may impact TFP differences (Acemoglu, Johnson, and Robinson 2001; Hall and Jones 1999). For instance, Hall and Jones (1999) coined social infrastructure to describe the social institutions that affect incentives to produce and invest, concluding that institutions are critical determinants of TFP and factor accumulation. One fundamental problem these studies face is endogeneity. Do countries get prosperous because they have strong institutions, or do countries have strong institutions because they are prosperous? The problem of endogeneity is even more earnest when alternative paradigms, namely *demand-led growth,* are considered. Such paradigms see the growth of factors as the effect rather than the cause of economic growth (Fazzari, Ferri, and Variato 2020; Barbosa-Filho 2000; Smith 2012). In other words, economic growth improves the strength of factors. A careful analysis of growth, accounting for endogeneity, is therefore warranted.

All these theories offer a very enriching background; however, because of distinct LMICs' circumstances, the theories are not entirely equipped to explain the development processes in LMICs. Thus, I approach the question from a management science and innovation studies perspective by untangling the TFP and explaining what relevant dimensions may impact economic development in LMICs, which are generally ignored in the literature.

Earlier empirical works on the industrialization processes in Asian and Latin American countries demonstrate an active government and institutional role in developing "capabilities" (here termed as capacities to indicate my use of the term as inspired by firm-level management literature) required to catch up (Kim 1980; Fransman 1982; Lall 1992; Dahlman and Nelson 1995). In that period, "technological capability" (Kim 1980) and "social capability" concepts (Abramovitz 1986) emerged to explain development. Since these concepts provide foundations for many works linking capacities and economic development, it is important to illustrate them briefly.

Kim (1997) defines technological capability as "the ability to make effective use of technological knowledge in efforts to assimilate, use, adapt and change existing technologies." Further, he asserts that technological capability has three aspects: innovation, production, and investment. Hence, Kim's concept includes both planned R&D—which presumably is a minute activity in many LMICs—and the capacities necessary to exploit technology commercially. On the other hand, social capability encompasses collective capacities regarding what organizations can do and how this is aided (or impeded) by broader social and cultural factors. Among the aspects of social capability that Abramovitz (1986) highlights include technical skills, experience in organizing and managing large-scale enterprises, working financial institutions, markets mobilizing capital, honesty and trust, and governments' stability and ability to make and enforce rules and support economic growth. While these concepts are a useful characterization of important ideas, they typically lack a rigorous operationalization, which is key to testing theories of their impact on economic growth and relative importance.

Around the same time, a more interactive approach in the form of a "national innovation system" (NIS) surfaced, focusing on systems, activities, institutions, and their interactions as the driving force of growth and development (Castellacci and Natera 2011; Nelson 1993; Edquist 1997; 2006). The NIS literature also utilized the concepts of technological and social capacities (Castellacci and Natera 2011). Most of the initial theoretical and empirical work on NIS focused mainly on prosperous economies (Nelson 1993; Edquist 2001); however, later theoretical NIS research became more inclusive by emphasizing "diffusion," "imitation," and "learning" processes in developing economies (Viotti 2002; Lundvall et al. 2009; Casadella and Uzunidis 2017). This literature termed developing LMICs as "national economic learning" entities and "imitation centers (Viotti

2002; Lundvall et al. 2009; Fagerberg and Verspagen 2002; Casadella and Uzunidis 2017). Despite this emphasis on diffusion and learning, this NIS literature has not fully explained absorption and learning processes and how they might happen in the political and social context of LMICs.

Meanwhile, Cohen and Levinthal (1990) developed the idea of "absorptive capacity" to explain how learning is consolidated at the firm level and how it impacts a firm's growth. They define absorptive capacity as "the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends." Other researchers termed this concept a multifaceted and *complex construct* (Minbaeva et al. 2014; Fagerberg and Srholec 2008). Over the past three decades, it gained considerable traction in many fields, including strategic management, international business, and organizational sciences (for example, see bibliometric analysis of Absorptive capacity by Apriliyanti and Alon 2017; Camisón and Forés 2010; Kale, Aknar, and Başar 2019; Müller, Buliga, and Voigt 2021). Most of these works included *acquisition, assimilation, transformation,* and *exploitation* as elements of absorptive capacity, which they envisioned and operationalized in various interesting ways.

Some of the firm-level studies proxied absorptive capacity in terms of a firm's R&D investment; such studies argue that through its R&D activities, a firm develops knowledge about markets, science, and technology (Aldieri, Sena, and Vinci 2018; Omidvar, Edler, and Malik 2017; Brinkerink 2018). Subsequently, the firm then employs the knowledge gained in designing and developing its products and services, eventually increasing its economic value (Brinkerink 2018). However, the R&D indicators at firm-level are only great in richer economies; they are weak indicators of firms' performances in LMICs as those firms rarely have any R&D budgets.

In the early 2000s, Narula (2004) and Criscuolo and Narula (2008) extended the firm-level concept to a national level. They developed a theoretical framework for aggregating national absorptive capacities upwards from the firm level. Aggregating individual firms' absorptive capacities to understand national-level processes seems a workable idea. However simple as it sounds, it is insufficient to aggregate individual firms' absorptive capacities for two reasons. Firstly, while firms have regulated interactions with outer space, nations experience exchanges (knowledge, technologies, and aid, for instance) with the rest of the world. Since such exchanges influence national absorptive capacity processes, they must be considered. Secondly, aggregation from the firm level also simply may not capture national-level processes. For instance, the firm-level aggregation completely misses the national regulatory environment, government's capacity, national fiscal and financial management, legal system, infrastructure, and business enabling environment, among other things. Since these things are not even firm characteristics, no such aggregation would capture them.

Other recent empirical studies applied the idea in a national setting (Fagerberg and Srholec 2008 and 2017), using different capacities earlier applied in the NIS literature (such as technological and social capacities) as proxies or measures for absorptive capacity. For example, after conducting factor analysis on 25 indicators and 115 countries from the 1992-2004 period, Fagerberg and Srholec (2008) identified four capacities: the development of the innovation system, the quality of governance, the type of political system, and the openness of an economy. The authors concluded that innovation systems and governance were particularly crucial for economic development. Similarly, in another analysis, the authors included 11 indicators covering 114 countries on different levels of development for the period 1995-2013 (Fagerberg and Srholec 2017). After factor analysis, they grouped the indicators into three capacities: *technology*, *education*, and *governance*. They found technology and governance as significant for economic development.

While these studies provide a starting point, their indicators do not have strong measurement validity, especially when the countries under study are the poor LMICs. For example, using R&D investment and journal articles for technology and innovation may not fully capture innovation as innovation does not entirely manifest itself in R&D investment or journal articles in poor economies. R&D proxies are also not suitable because R&D expenditures and allocations are seldom paid attention to in poor economies. Moreover, these economies may be allocating just sufficient R&D, but they do not know how to utilize R&D for beneficial activities because of the lack of an enabling environment. Similarly, S&T articles do not capture absorptive capacity in poor economies because most of these articles do not translate into any significant value for many reasons. A prime reason is that producers and innovators in these economies hardly utilize the results of scientific research directly to produce economic value. Likewise, Law and Order and (lack of) corruption produce a limited measure of governance that ignores important governance characteristics; there are better ways of measuring it.

Second, these studies did not consider vital indicators that could correlate with both capacities and growth. For example, they omitted important confounders such as incoming flows from abroad (foreign aid, technical and cooperation grants, among others), committing omitted variable bias. In the presence of such a bias, some capacities seem to matter more or less than they do.[13]

Third, while they have included countries with varying levels of development, the estimates are not representative of all the nations because their analyses excluded many low-income economies due to missing data. Fourth, such studies are not very comprehensive as they do not consider financial, bureaucratic and economic environment, trade and transport infrastructure, manufacturing and service sector employment, and information and communications technology (ICT) infrastructure and multiple institutional factors, which can be crucial for a developing country's absorptive capacity and subsequent development.

All these firm-based and NIS approaches, at best, only capture part of reality, the country's absorptive capacities. A more comprehensive framework is needed to capture accurately and comprehensively elements of absorptive capacity at the national level in LMICs.

Another big shortcoming of the current national-level empirical studies lies in methodological challenges. Empirical studies of capacities and development have used

[13] For instance, Fagerberg and Srholec (2017) only include three dimensions of Governance: government effectiveness, (lack of) corruption, and law and order. The estimated coefficient size for the impact of governance on GDP per capita is 29%. This seems most likely an overestimation because governance includes many other important indicators on institutions and public sector management, which they do not have in their analysis. Similarly, they include tertiary, secondary, and primary attainment as measures for Education capacity. The estimated coefficient size on overall education is 0, which is likely an underestimation because education capacities include many other indicators, which they overlook. Perhaps, because of the exclusion of many important variables, their models also lack overall explanatory power: the best model only explain about 43% of variation (R-squared value = 0.43).

mainly two methodologies: panel regression analyses (Teixeira and Queirós 2016) and composite indicator analyses (Fagerberg and Srholec 2017). While these analyses can handle many variables, countries, and periods, data availability imposes severe limitations.

Panel regression analyses account for a few key variables that supposedly measure countries' differences in their different capacities. Subsequently, these studies examine the empirical relationship between these variables and comparative national differences in GDP per capita growth (Castellacci, 2004, 2008 and 2011; Teixeira and Queirós 2016; Ali, Egbetokun, and Memon 2018). While powerful as they consider the dynamic nature of capacities, such panel studies particularly ignore many low-income economies because longitudinal data for many variables are missing in these countries. These analyses drop off the countries for which there are missing data for variables through listwise deletion. As a result, the coefficients of interest obtained through panel analyses do not provide information about the poorest economies. The estimates obtained through such studies may exhibit an upward bias by overestimating the effect of *capacities* on *economic growth*.

On the other hand, composite indicator analyses build aggregate indicators and conduct descriptive analyses. Such studies use many variables, denoting various dimensions of technological and social capacities. The variables are then systematically combined into a single composite indicator through factor and cluster statistical tools (Fagerberg and Srholec 2008; 2015; 2017). As opposed to panel analyses, the composite analyses consider many countries, including some low-income economies. But since low-income countries have limited data available, such studies are usually static (one-year study), ignoring system-level evolution in the countries analyzed. Additionally, not all low-income economies have data on all the variables of interest available for one particular year. Therefore, even composite analyses cannot possibly include all low-income countries.

Keeping in mind the issues of conceptual relevance and data and methodology challenges, my research establishes a renewed relationship between conceptual and empirical work. For conceptual understanding, Fagerberg and others consulted the literature on "technological" and "social" capacities instead of employing the framework of absorptive capacity from the strategic management (and business) literature. It seems like their understanding was driven primarily by choice of their methodological approach and data availability. My research, on the contrary, develops a framework for absorptive capacity in LMICs informed by strategic management literature in conjunction with the national-level capacities and NIS literature. This framework illuminates how capacities impact economic growth across LMICs. The framework also measures various elements of the concept of absorptive capacity. In order to test the framework and settle data issues, in Chapter 2, I construct a fresh, relatively recent, and full dataset of 82 LMICs, utilizing an expanded set of variables and employing a more thorough list of capacities, their structure, and conception. In contrast to previous studies, my research also considers key controls (incoming flows) when analyzing the impact of absorptive capacities on economic growth. In summary, offering a novel framework, building a rigorous dataset, and engaging established quantitative approaches and tools, my study tests more thoroughly whether absorptive capacity influences economic growth outcomes after controlling for controls, including incoming flows in LMICs.

3. The National Absorptive Capacity System (NACS) Framework

3.1 *A Brief Introduction of the Framework and its Theoretical Foundation*

A rich analytical framework is needed to capture capacities and their impact on economic growth, befitting the data deficient environments of the LMICs. I call the proposed framework *National Absorptive Capacity System (NACS)***.** The framework for National Absorptive Capacity System (NACS) situates a developing nation as an "economic learning" entity, constantly absorbing, exploiting, and using knowledge, skills, and learning and converting the gains into economic value proportionate to the strength of its "local" capacities. I develop NACS based on the firm-level concept of "absorptive capacity" found in the strategic management literature (Cohen and Levinthal 1990; Zahra and George 2002).[14] From the firm-level literature, I consider a nation an analogous entity where individuals and institutions interact, learn, create, and distribute economic value according to some set rules. Further, the National Innovation System (NIS) literature also inspires this NACS framework. The NIS literature, particularly its later literature on emerging economies, informs that a developing nation, as an active learning entity, absorbs and utilizes knowledge and improvises on the existing knowledge (Casadella and Uzunidis 2017; Juma et al. 2001).

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[14] The adjective 'absorptive' implies that an LMIC absorbs 'knowledge from abroad' and then utilizes the knowledge to create (economic) value subject to the strength of its local conditions (capacities). In a way, absorptive capacity includes both incoming flows (knowledge and technology, for example) and existing on-the-ground conditions (capacities). Suppose an LMICs' capacities are not strong enough. In that case, it won't absorb (or improvise on) that incoming knowledge and technology and hence not covert the incoming learning into economic value.

While they jointly provide foundation and legitimacy to the framework I propose, the firm-level absorptive capacity and traditional NIS concepts are by themselves insufficient and inappropriate to fully and accurately capture absorption processes and their subsequent impact on economic growth in developing LMICs, as illustrated in the literature review section. The proposed NACS framework thoroughly envisions capacities and absorption processes in LMICs and rigorously operationalizes the capacities, employing concepts from firm-level and national-level NIS literature. The following subsection describes the development of the NACS framework.

3.2 *Developing the Framework for Absorptive capacity: From Firm to Nation*

My NACS framework consists of three main elements. The first central element is "absorptive capacities," which this research examines. The second element is "outcome processes," which are hypothesized to be impacted by capacities. Finally, the third element is "control inputs," which may influence the relationship between the first and second elements. Figure 1 below depicts this framework:

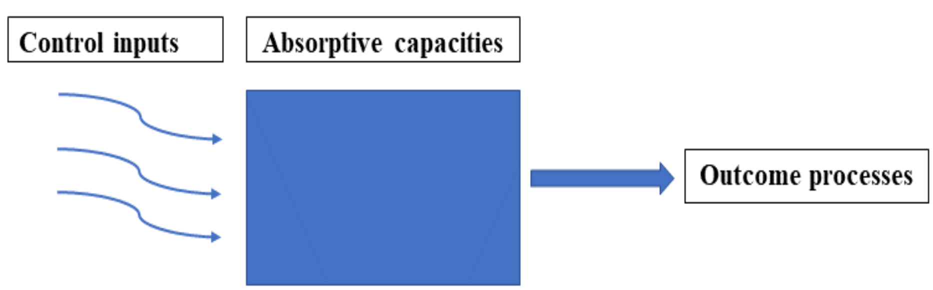

Figure 3.1: National Absorptive Capacity System—a framework showing how absorptive capacities influence outcome processes while controlling for confounders or controls (control inputs).

More formally, I illustrate this figure in the form of the following equation (or model):

$$\boldsymbol{Log(Y) = \Sigma\, \alpha_n C_n \ + \ \Sigma\, \beta_n Z_n \ + \ \varepsilon} \qquad \textbf{(1)}$$

A more accurate equation (or model) incorporating interaction effects will be:

$$\boldsymbol{Log(Y) = \Sigma\, \alpha_n C_n \ + \ \Sigma\, \beta_n Z_n \ + \ \Sigma \Upsilon_n C_n Z_n \ + \ \varepsilon} \qquad \textbf{(2)}$$

In equations (1) and (2), Y shows outcome processes, $\boldsymbol{C_n}$ indicates all absorptive capacities, $\boldsymbol{Z_n}$ shows confounders or control variables (including incoming flows), and the symbol $\boldsymbol{\varepsilon}$ shows the error term. Vector coefficients $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ measure the impact of capacities and confounders on outcome processes, respectively. Finally, vector coefficient Υ indicates the effect of capacities on outcome processes depends on the value of control inputs.

To define these elements of national absorptive capacity, I employ firm-level elements of absorptive capacity: knowledge and skills *acquisition*, *assimilation*, *transformation*, and *exploitation*. These elements translate into related yet quite different things when applied to the national level in LMICs.

Let us define the firm-level elements and respective national (LMIC) level dimensions that I derive from these elements:[15]

I. Control inputs—Acquisition and Assimilation

On a firm level, the *acquisition* is a company's ability to capture external knowledge based on its efforts (Cohen and Levinthal, 1991). Similarly, *assimilation* is the

[15] Please note I derive the national elements from my understanding of firm-level elements. This derivation is by no means complete or perfect. Since these firm-level elements are themselves defined in many ways, someone may come up with a different derivation, which may be fine too.

absorption (internalization and diffusion) of *acquired* external knowledge (Zahra and George 2002). The pioneer literature asserts that the rate of acquisition and assimilation corresponds to a firm's prior knowledge, among other things (Zahra and George 2002). Meaning a firm's current knowledge (perhaps through R&D expenditure and training) attracts *external* flows.

On a national (LMIC) level, I theorize them as control inputs. I see them as the ability of a nation to make a deliberate effort in capturing and assimilating external knowledge (learning, training, technology, and skills), practices, and resources. While it is hard to measure the extent or magnitude of such inputs, the size of *incoming* flows indirectly informs about their strength. Similarly, other controls (current circumstances), such as country geographical status (landlocked vs. coastal), natural resources, and population density, influence the rate of acquisition and assimilation. Thus, this formal model includes incoming flows and other controls to indicate acquisition and assimilation on a national (LMIC) level. Relevant variables to measure the two may consist of population size, geography, resources, brain flow, linkages, and information flow.

The framework here includes control inputs such as population size, capital formation, technological cooperation grants that LMICs receive from developed countries and donors, international tourist arrivals, merchandize import from the high-income economies, and net Official Development Assistance (ODA) received from abroad.

II. Absorptive capacities—Transformation

Transformation on a firm-level refers to the combination and recombination of old and new knowledge in the pursuit of adding value (Vasconcelos et al. 2019; Müller, Buliga, and Voigt 2021). Transformation is proportional to a firm's competencies and resources (Müller, Buliga, and Voigt 2021). Extending the concept of transformation to a national (LMIC) level would translate into *capacities*, causing knowledge absorption, improvisation, and realization of economic value. Such capacities help construct new routines, products, and processes once the new knowledge is *assimilated* and spread in a country. The NIS literature provides valuable insights here. This literature considers technology, governance, human capital, and infrastructure, among others, as prime capacities. My framework in this chapter includes six capacities drawn from the literature: 1) Technological capacity, 2) Financial capacity, 3) Human capacity, 4) Infrastructural capacity, 5) Public Policy capacity, and 6) Social capacity. Figure 3.2 refers to these capacities while also acknowledging the incoming flows held constant in this framework.

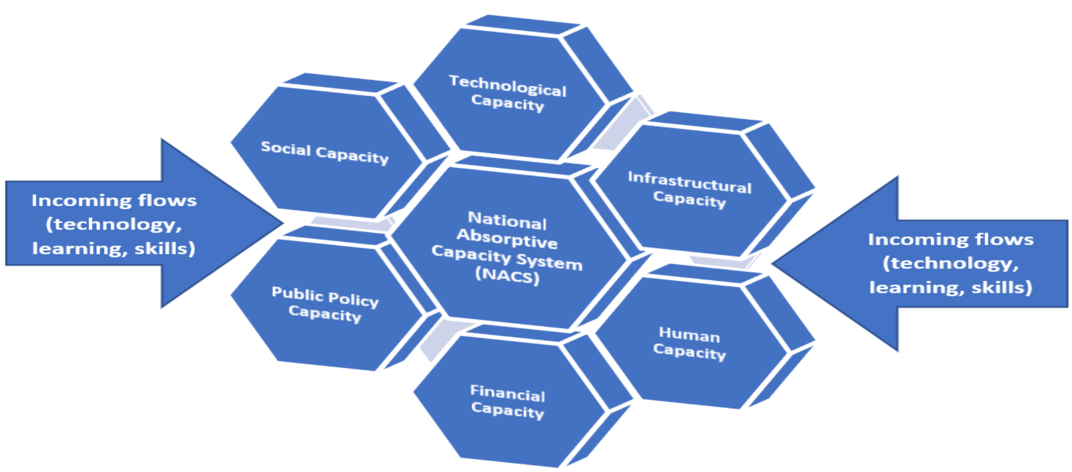

Figure 3.2: National Absorptive Capacity System (NACS). These six capacities constitute the bulk within the framework for NACS. Incoming flows are also shown.

III. Outcome processes—Exploitation

After a firm *acquires, assimilates, and transforms* knowledge, the firm moves towards knowledge application (Solís-Molina, Hernández-Espallardo, and Rodríguez-Orejuela 2018; Seo, Chae, and Lee 2015). Exploitation or knowledge application on a firm-level entails creating new products or services using competencies or improving competencies (Cohen and Levinthal 1990). Gebauer and Colleagues (2012) measure it by employing the commercial application of the acquired knowledge. Similarly, César and Colleagues (2010) consider exploitation as activities related to product and process changes and improvements. On a national (LMIC) level, this step indicates achieving a country's economic outcomes by engaging the capacities. Economists usually measure economic outcomes in terms of economic growth. Thus, exploitation can be indicated by many of the outcome processes, including economic growth (GDP growth), per capita GDP, value-added industry growth, product, process, marketing, or organizational innovations. I consider countries' GDP per capita (and GDP per capita growth) as an outcome for pragmatic concerns.

To sum it up, the NACS framework illustrated here (and shown in Figure 3.1) combines the firm-level *acquisition* and *assimilation* into confounders or control inputs, whereas firm-level *exploitation* signifies national outcome processes. Finally, the firm-level *transformation* is a black box on a national (LMIC) level that includes national capacities influencing outcome processes.

Based on this framework, I test the following hypotheses in the context of LMICs.

4. Hypothesis:

The literature so far suggests that various factors (dimensions) within capacities positively impact economic growth. For instance, science and technology indicators (within technological and human capital capacities) have proven to positively impact economic growth (Çalışkan 2015; Wu, Zhao, and Wu 2019; Pinto and Teixeira 2020; Baneliene and Melnikas 2020; Bhalla and Fluitman 1985; Laverde-Rojas and Correa 2019). The growth improves because scientific and technological progress causes an efficient and quality production of goods and services on a mass scale (Nelson and Romer 1996). However, as per the demand-led growth, the reverse also may be true. Only rich nations will invest in and grow their science and technology indicators as they can afford, and they would like to stay as technological leaders.

Similarly, in developing economies, functioning financial markets catering to citizens and businesses and financial inclusion also improve economic growth (Durusu-Ciftci, Ispir, and Yetkiner 2017; Asteriou and Spanos 2019; Ibrahim and Alagidede 2018; Kim, Yu, and Hassan 2018). With functioning financial markets, most citizens have access to bank accounts, credit, and access to world markets, which removes business hurdles and facilitates efficient channeling of investment in the economy, leading to better economic outcomes (Popov 2018). However, reverse causality may also be likely that growth enhancement strengthens financial markets and inclusion. While the direction is uncertain, poor economies may have relatively more incentives to build their financial base perceiving enormous marginal gains in development from financial capacity.

Furthermore, developing countries need robust ICT infrastructure, energy access, and transport-related infrastructure to have strong economic growth (Bahrini and Qaffas 2019; Munim and Schramm 2018; Saidi, Shahbaz, and Akhtar 2018; Mohmand, Wang, and Saeed 2017). By ensuring easy movement of raw materials, trade and transport infrastructure reduce inefficiencies, contributing to economic development. Similarly, ICT infrastructure and affordable energy access reduce inefficiencies and support production activities, improving economic development. A reverse direction is possible, too, where economic growth will cause an economy to invest in infrastructure.

In addition, social capacity (including redistribution and income equality) across the world has been found to improve economic growth (Kennedy et al. 2017; Berg et al. 2018). When people take care of each other, and the government supports the poor through social programs that are ‘productivist,’ people participate in economic activities, leading to higher economic outcomes (Dearmon and Grier 2009; Midgley 1999). The converse may also be true: economic growth strengthens social welfare, social cohesion, and general social wellbeing in an economy.

Lastly, public policies in terms of fiscal management, financial management, bureaucratic management, strong institutions have been affecting economic growth across the world (Hussain et al. 2021; Urbano, Aparicio, and Audretsch 2019; Williams 2019; Acemoglu and Robinson 2019; Alexiou, Vogiazas, and Solovev 2020; Acemoglu, Johnson, and Robinson 2005; Asghar, Qureshi, and Nadeem 2020). Sound and strong public policies and institutions give the right signals to produce and invest, leading to economic growth (Hall and Jones 1999). However, as discussed earlier (in the literature review), the reverse direction is also possible. Rich countries perhaps would have significant incentives to make solid policies and institutions that promote productive efficiency. Otherwise, they would have to lose a lot if their markets stopped functioning. On the other hand, such incentives are weaker in poorer countries.

Furthermore, capacities are not the only factors influencing the economic growth of a developing country. In this globalized world where a nation does not operate in isolation, incoming flows such as technical cooperation grants, foreign aid, and merchandise import from high-income economies and other controls such as a country's population density and capital stock also may influence economic value (Galiani et al. 2017; Asongu and Ezeaku 2020.; Kugler 2006; Uneze 2013; Bal, Dash, and Subhasish 2016). For instance, one such inflow of technical cooperation grants[16] was found to positively (and jointly with loan aids) influence economic growth in Sub-Saharan Africa (Asongu and Ezeaku, 2020).

Based on this literature and in light of the NACS framework, my hypothesis is:

H: *Capacities (defined within the transformation stage of NACS) positively influence economic growth in LMICs after controlling for confounders (including incoming flows).*

While economic growth is captured by the natural log of GDP per capita (outcome variable), the capacities (used as independent variables) must be measured and

[16] Technical cooperation grants comprise of: (i) free-standing technical cooperation grants projected for financing the transfer of technical as well as managerial skills or of technology to build-up general national capacity without reference to any explicit investment projects; and (ii) investment related technical cooperation grants, which are made available to strengthen the capacity to carry out specific investment projects ("Technical Cooperation Grants (BoP, Current US$) | Data Catalog" https://data.worldbank.org/indicator/BX.GRT.TECH.CD.WD).

operationalized (more on capacities and conception in Section 6). Before explaining the process of measuring capacities, let us briefly describe the data at hand.

5. Data Description

In this chapter, I use the dataset constructed in Chapter 2. It is worth mentioning again that the dataset is constructed for data-poor 82 LMICs between 2005 and 2019 based on the assumption that LMICs exhibit a data pattern that is termed as *missing at random (MAR)*. The pattern, by definition, implies that the *missingness* pattern in data is conditional on *observed* variables (Afghari et al., 2019). In other words, missingness can be predicted by the observed data. LMICs can have missing data for many reasons, ranging from poor data infrastructures and meager resources to frequent natural disasters and severe civil conflicts. However, despite missingness in many variables of significance, such countries offer rich information on poverty indicators, economic development, literacy rates, and demographics. I argue that this rich corpus of data can be employed to explain and predict the missingness pattern for data on other variables, thus justifying the MAR assumption. In other words, missing values of variables in those countries are conditional on the data I observe.

Relying on this MAR pattern of data in the LMICs, I use a *multiple imputed* MSK Panel dataset obtained after applying Rubin's Multiple Imputation by Chained Equations (MICE), specifically MICE predictive mean matching (Akmam et al., 2019). While respecting the structure of multivariate continuous panel data at the country level, this technique generated a dataset with no missing values.

As explained in Chapter 2, for the data structure, Castellaci and Natera (2011) inspired my work (CANA dataset). They estimated a dataset for 134 countries between 1980 and 2008 using a Multiple Imputation (MI) algorithm developed by Honaker and King (2010). I also applied Rubin's novel M1 techniques (Rubin 1996 and 1987) to estimate the MSK panel dataset for this study. However, despite a similar data structure, there are functional and operational differences between MSK and CANA datasets, as highlighted in Chapter 2.

The 47 variables included in the dataset were collected from publicly available databases (see Appendix Table 3.4 for variables' definitions and their sources). Table 3.4 also details a set of control variables and the outcome variable. A summary description of all the variables is available in Appendix Table 3.5. The variables included in the dataset are crucial for measuring six capacities alongside incoming factors (Figure 3.2) included in the National Absorptive Capacity System (NACS).

The variables included are a mix of *continuous* variables and indices, measured in many ways. For instance, the outcome variable of GDP per capita is a continuous variable, constant in 2010 US dollars. Public Policy and social capacity variables are generally clustered averages and composite indicators, with low values or scores indicating lower magnitude or strength of the variables (e.g., economic management cluster ranging from 1 to 5.5, with 1 showing the low score and 5.5 meaning high score).[17] Some variables in the

[17] The composite indicators may present some problems, primarily the problems of weighting and aggregation due to human and value judgments (as discussed in (Greco et al., 2019). Still, we use them as the available ones, collected by reputed organizations like the World Bank and IMF, which should lend some credence to their construction. Another thing that should be further assured is that I am using pooled data from diverse sources, reducing this concern.

financial capacity are continuous, measured in days (e.g., days to enforce a contract). Additionally, some continuous variables in technological capacity are measured per 1 million people (e.g., number of researchers or technicians in R&D). Lastly, some continuous variables in infrastructure capacity are measured per 100 people (e.g., telephone and mobile phone subscriptions).

The following section shows how I use these variables to construct capacities factors.

6. Measuring National Capacities in the Framework for NACS

I measure national capacities by constructing composite factors. To build the factors, I employ a set of relevant variables. The variables capture phenomena of interest—latent factors to be discovered in this case and, by extension, the proposed capacities in the NACS framework. I use factor analysis to generate a small number of factors from a set of many variables (Stephenson 1935; Yong and Pearce 2013). The core assumption is that variables relating to the same dimension of reality strongly correlate (Bandalos and Finney 2018). Most variables are correlated from a higher to a moderate level in the current dataset, suggesting a piece of crude diagnostic evidence for factor analysis.[18] Readers interested in details about factor analysis can consult practical resources (Bandalos and Finney 2018; Yong and Pearce 2013; Goretzko, Pham, and Bühner 2019), but overall, bear in mind that correlation matrices guide this analysis.

[18] After conducting pairwise correlations, I find some correlations are higher than others. Overall, most correlations were significant at p=0.05

Generally, factor analysis is conducted in one of two ways: 1) exploratory factor analysis and 2) confirmatory factor analysis. While exploratory factor analysis is an unsupervised analysis and does not require a priori input from theory or hypotheses, confirmatory factor analysis is a supervised method that incorporates prior information from theory (Bandalos and Finney 2018). Since the extant literature informs what variables might constitute different capacities, I first conduct confirmatory factor analysis. Based on my understanding of theory and literature, I assign the variables under each capacity and then employ factor analysis to reduce the variables in latent factors. For robustness, I also conduct exploratory factor analysis without any assignment of variables.[19] Both analyses, by and large, produce similar results. I execute these analyses using *STATA* (version SE 15.1).

To explain confirmatory factor analysis more, in the first step, the literature informs to assign the variables in the MSK dataset to one of the appropriate six capacities. After assigning all variables to the capacities, I program the software to perform a total of six confirmatory factor analyses, one for each capacity, using the principal-components factors with the orthogonal varimax rotation (Chavent, Kuentz-Simonet, and Saracco 2012). The analyses return factor loadings and factors. Factor loadings indicate how each variable is related to each latent factor (see Appendix B. Tables 3.6.1-3.6.6 for factor loadings of the six capacities). Based on the factor loadings, I designate variables (within each capacity) to an appropriate capacity factor. Per the literature recommendation, I employ an

[19] Factor analyses, by definition, produce orthogonal factors independent of each other. Since I conduct six confirmatory factor analyses, one for each capacity, factors within a capacity will be orthogonal, but capacities may be related. However, the fact that the single exploratory analysis generates almost the same kind of factors mitigates this concern.

eigenvalue[20] higher than one as a criterion to retain a factor (Goretzko, Pham, and Bühner 2019). I also observe *Scree plots* to assess the number of extracted factors (see Appendix C. Figures 3.3.1-3.3.6).[21]

The confirmatory factor analyses lead to the generation of 13 factors.[22] I name them such that they capture the essence of underlying variables. Later, I run post-estimation tests, finding strong evidence for uncorrelation among the factors.[23] In other words, factor analysis returns distinct latent constructs. Table 3.1 below shows these 13 factors, their respective capacities, and the specific variables (a set of 47 variables) from which the factors are extracted. The table also shows a descriptive summary of the factors. The factors are standardized,[24] and their ranges vary, with technology capacity factors exhibiting the highest range.

[20] An eigenvalue is the amount of variance in the sample, which is explained by each factor. The eigenvalue is calculated by summing the squared factor loadings for that factor.

[21] Scree plot is a powerful visual tool for determining the number of factors to be retained. It is basically a plot of the eigenvalues shown in decreasing order.

[22] I perform a post-estimation Kaiser-Mayer-Olkin (KMO) test to check the appropriateness of factor analysis to these data (Kaiser 1974). KMO values range between 0 and 1, with small values indicating that the variables have not much in common to warrant factor analysis. Here, by including all variables, the KMO test return a value of about 0.80, suggesting factor analysis is appropriately applied (Watson, 2017).

[23] A post-estimation *estat common* displays correlation matrix. Since the factors are orthogonally loaded, the common factors obtained are uncorrelated, as evidenced by identity matrix (STATA Manual).

[24] By definition, the standardized factors have mean values of zero and SD (and variance) of 1.

Table 3.1: Capacities (6), Capacity Factors obtained through CFA (13), their Variables (47), and Descriptive Statistics

Capacity and Capacity Factors	**Variables**	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Technological Capacity						
1. Base sci & tech	Sci & tech. articles Intellectual property payments (mil) Voc. & tech. students (mil)	1230	0	1	-.87	13.5
2. Medium sci & tech	R&D researchers (per mil) ECI (economic complexity)	1230	0	1	-2.47	4.54
3. High sci & tech	R&D expenditure % of GDP R&D technicians (per mil) High-tech exports (mil)	1230	0	1	-1.65	6.65
Financial Capacity						
4. Financial infrastructure	Domestic credit by banks Business density Financial accountholders Commercial banks	1230	0	1	-2.68	4.86
5. Financial (business) environment	Business startup cost Days to start a business Openness measure	1230	0	1	-1.29	6.69
6. Strength of financial regulation	Tax revenue (% of GDP) (tax capacity) Days enforcing a contract Days to register property	1230	0	1	-2.07	7.55

Capacity and Capacity Factors	Variables	Obs.	Mean	Std. Dev.	Min	Max
7. Enabling financial environment	Days to obtain electric meter Days to register property (also loads moderately on this variable)	1230	0	1	-4.23	4.85
Human Capacity						
8. Specialized skills	Human Capital Index 0-1 Industry employment Service employment Govt. expend. on educ. (loads moderately) Compulsory educ. (years) (loads moderately) Secondary enrollment (gross) Primary completion rate	1230	0	1	-2.43	2.58
9. Generalized skills	Primary enrollment Primary pupil-teacher ratio Advanced education labor (loads very low, though)	1230	0	1	-3.48	3.01
Infrastructure Capacity						
10. Infrastructure (ICT & energy)	Mobile subscriptions Access to electricity Broadband subscriptions Telephone subscriptions Energy use Internet users	1230	0	1	-1.31	4.23

Capacity and Capacity Factors	Variables	Obs.	Mean	Std. Dev.	Min	Max
11. Logistic Per. Index (trade & transp. i~)	Logistic perf. Index 1-5	1230	0	1	-3.36	3.45
Public Policy Capacity						
12. Public policy factor (inc. fiscal, monetary, structural policies…)	Statistical capacity 0-100 CPIA economic management Public sector management & institutions Structural policies Legal Rights Index 0-12	1230	0	1	-3.78	2.9
Social Capacity						
13. Social capacity factor (inc. equity, inclusion…)	Human resources rating Equity of public resource use Social protection rating Social inclusion National headcount poverty (loads low though) Social contributions (loads moderately)	1230	0	1	-3.83	2.2

For the complete detail about the variables, their units, and sources, please refer to Table A.1 in the Appendix. As shown in Table 1 here, in the case of technology capacity, the variables considered are grouped into three factors: *base science and technology* (as reflected in journal articles, payments for intellectual use and secondary education pupils enrolled in technical and vocational education programs), *medium science and technology* (as indicated by economic complexity score calculated by Harvard's Center for International Development and researchers in R & D and R & D researchers), and *high science and technology* (high technology exports, R & D expenditure, and technicians in R & D). While the first factor indicates a general research culture, the latter two factors generally portray innovation and invention, and they may approximate Kim's concept of "innovation capability."

In the case of financial capacity, factor analysis creates four important factors. The first factor I name is *financial infrastructure* as indicated by account ownership, commercial bank branches, new business density, and domestic credit by the banking sector. The second factor I call is *financial (business) environment* as reflected in the days required to start a business, economy openness, and cost of business startup procedures. The third factor is the *strength of the financial regulations* as measured by days to enforce contracts, the ability to collect tax revenue, and the days required to register a property. In contrast, the fourth factor is *an enabling financial environment*, as indicated by days to obtain an electric connection and days to register a property to a moderate extent.

Regarding human capacity, the analysis generates two broad factors; the first is the *generalized skill level of the population* as reflected in primary enrollment, primary pupil-teacher ratio, alongside the variable labor force with advanced education albeit the factor's low loading on this variable. A second factor refers to the *specialized skill level of a population* as shown by the World Bank's Human Capital Index score, employment in industry and service sectors, secondary enrollment, primary completion rate, government expenditure on education, and compulsory education duration. While the factor loads highly on many variables, it loads moderately on the last two variables.

Similarly, the chapter extracts two factors for infrastructural/infrastructure capacity. I call *general infrastructure* the first factor, as captured by ICT infrastructure, including broadband subscribers, telephone subscribers, mobile cell subscribers, internet users, and energy infrastructure proxied by per capita energy use and access to electricity. The second factor indicates the *quality of trade and transport-related infrastructure*, including ports, roads, and railways (as proxied by logistic performance index score calculated by the World Bank). In essence, the two factors might be equivalent to Kim's "production" capability coined in the context of firms. Thus, ICT penetration, energy provision, and transport-related infrastructure are crucial for a country's economic progression as they are for firms' ability to produce and market goods and services and compete in international markets.

In light of my confirmatory-led information, the analysis groups variables into two factors based on factor loadings for the last two capacities. Since I conceptualized these two capacities more uniquely, they merit more attention. First, I capture the public policy capacity by a *public policy factor,* which loads highly on variables about public sector management and institutions, economic management, structural policies, the strength of legal rights, and statistical capacity scores of countries. All of these are composite indicators that the World Bank Group constructed based on the data they collected. For instance, *public sector management and institutions* are composite measures, indicating property rights and rule-based governance, quality of budgetary and financial management, the efficiency of revenue mobilization, quality of public administration, transparency, accountability, and corruption in the public sector. Similarly, *structural policies* indicator includes trade and business regulatory environment. On the other hand, the *economic management* indicator measures macroeconomic management, fiscal policy, and debt policy. Furthermore, the *legal rights* index measures the extent to which laws protect the rights of borrowers and lenders. Finally, all these policies require a solid statistical capacity (as measured in the statistical capacity score) in a country to report the findings timely and periodically for policy formulation, coordination, and implementation.

By incorporating all the traditional governance measures (corruption, the rule of law, and accountability in the public sector, business regulatory environment) and other broader measures for governance (fiscal policy, monetary policy, debt policy, macroeconomic management) alongside new measures (statistical capacity and legal rights), the public policy factor is very encompassing. In a way, this factor is a good fusion of neoclassical and traditional capacities approaches: while the most conventional measures included in this factor approximate Abramovitz’s social capacity (1986), the broader measures are neoclassical.

Lastly, the analysis captures dimensions of social capacity by a *social capacity factor*. This factor loads highly on policies for social inclusion, human resource rating, social protection rating, equity of public resource use, poverty headcount ratio, and social contributions. Again, some of these are composite indicators constructed by the World Bank. For instance, the social inclusion indicator includes gender equality and policies and institutions for environmental sustainability, among other things. Similarly, social protection rating assesses government policies in social protection and labor market regulations that reduce the risk of becoming poor. Equity of public resource use, on the other hand, evaluates the degree to which public expenditures and revenue collection affects the poor and is consistent with national poverty reduction. Finally, poverty headcount indicates poverty, whereas social contributions are contributions by employees to social insurance schemes operated by the government. At the heart of this capacity is how societal members benefit each other and whether and how the government creates an enabling environment in terms of regulations and social policies to cater to the vulnerable and poor in society. Further information on definitions and sources of all the six capacities variables can be found in Appendix Table A.1.

7. Results and Discussion

Here I report results and discuss key findings. In doing so, I explain the rationale behind the technical methods and models that I employ in this chapter. Some readers familiar with them may skip the details and focus on results. However, briefly illustrating why I choose one model or method will benefit readers in general.

To recap, in this chapter, I estimate the impact of all capacities (as framed in the NACS) on per capita GDP (outcome) using the MSK panel dataset. As illustrated, based on the six capacities, confirmatory factor analyses returned a total of thirteen factors (Table 3.1). These 13 factors serve as independent variables. My empirical estimation controls confounders that can possibly influence the relationship between economic growth and estimated capacity factors to find the true effect size.[25]

The initial equation (1) mentioned in section 4 bears repeating here.

$$\boldsymbol{Log\, Y = \Sigma\, \alpha_n C_n \,+\, \Sigma\, \beta_n Z_n \,+\, \varepsilon} \qquad (1)$$

Log Y is the natural logarithm of GDP per capita, C_n is composed of absorptive capacities factors, Z_n is composed of controls, α_n is a vector of parameters that capture the effects of capacities factors on the log of GDP per capita, and β_n is a vector of parameters that capture the effects of controls on the log of GDP per capita.

As mentioned, the absorptive capacities factors are independent variables—13 factors (from Table 3.1). The controls, on the other hand, include *incoming dimensions* (such as technological cooperation grants, international tourist arrivals, merchandize import from high-income countries, net ODA and official assistance received) and other variables (health expenditure as a percentage of GDP, employers' percentage in total employment, total population, and gross capital formation). Since my independent

[25] While Fixed Effects take care of many time-invariant country-specific characteristics, I have included incoming flows as confounders. I have also run some models with interactions between incoming flows and capacity factors (equation 2) in Appendix F. However, data limitations prevent from doing a good analysis that includes interactions, because of too many possible interactions, relatively too few observations, and a good degree of multicollinearity which interactions only exacerbate.

variables are standardized factors, I standardize all the control variables as well; all controls have a mean of zero and SD of 1.

As a preliminary analysis, I estimate a simple pooled OLS regression—an OLS estimation run on panel data (Collischon and Eberl 2020). Pooled OLS returns all statistically significant results, including a positive and significant relationship for public policy factor (see Table 2 below). However, Pooled OLS does not serve our purpose here for two reasons. One Pooled OLS is most suitable when a researcher selects a different sample for each year in the data (Wooldridge 2010). However, here the same sample of countries is observed across different years, warranting a different model. Secondly, applying OLS on panel data is tantamount to ignoring all country-specific effects. This omission leads to a violation of many basic assumptions, including independence of the error term.

To systematically determine the extent to which the data are *poolable* and, subsequently, if Pooled OLS is the correct estimation for these data, I conduct the Breusch-Pagan Lagrange multiplier test (Onali, Ginesti, and Vasilakis 2017).[26] A significant test result confirms unobserved effects (country-specific) across countries, which must be accounted for. The test diagnostic further indicated that Pooled OLS is not appropriate for these data.

To cater to the problems posed by Pooled OLS modeling, I use *Random* and *Fixed Effects* Models. Such models are employed when the same sample of countries is observed

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[26] The null hypothesis for this test is that the variance of the unobserved Fixed Effects is zero. A highly significant test results (chisq=4647 and p=0.0001) suggests rejecting the null hypothesis (var=zero for countries). This indicates that Pooled OLS is not an appropriate model for this data.

longitudinally (Onali, Ginesti, and Vasilakis 2017).[27] Random Effects Models assume that the country-specific effects (if any) are independent of the other variables in the model. Thus, such models estimate the effects of time-invariant variables by including them in the model (Bell, Fairbrother, and Jones 2019). On the other hand, Fixed Effects Models assume the country-specific effects are correlated with other variables (and therefore, such models can deal with the omitted variable bias, as long as these omitted variables are time-invariant). The time-invariant variables are then held constant or "*fixed*" in the Fixed Effects models (Collischon and Eberl 2020; Kropko and Kubinec 2020).[28]

Here, I focus on results from Fixed Effects modeling because Fixed Effects are more meaningful for a few reasons. First, Fixed Effects control for time-invariant characteristics of LMICs, which are otherwise hard to incorporate. Secondly, it is impossible to include all the variables that impact economic growth because the countries in this sample have poor data environments. Thirdly, these omitted variables can be correlated with the explanatory variables (capacity factors), leading to biased estimates. Fixed Effects models alleviate these problems. In terms of technical diagnosis, a significant Hausman test also rules in favor of Fixed Effects modeling.[29]

[27] Fixed Effects models capture *within* variability, whereas Random Effects models capture both *within* and *between* variability. Both models have pros and cons. In general, Random Effects models more often have smaller *standard errors,* but they more likely produce *biased* estimates. On the other hand, Fixed Effects models may produce larger standard errors but more likely unbiased estimates

[28] Fixed Effects models hold the effects of time-invariant variables (whose values do not change with time, for instance, gender) constant. This means that whatever effects omitted variables have on the subject at one time, they have the same effect on the later time; hence their effect is "constant" or "fixed."

[29] After conducting Hausman test, I reject null hypothesis that difference in coefficients under the two modeling is not systematic (chi2= 163 and p-value=0.0001). This indicates to conduct Fixed Effects modeling.

Furthermore, as per the literature recommendation (Wooldridge 2010), I have included dummy variables for years (time effects) in all the models in this chapter. Similarly, I have incorporated robust standard errors.[30] The inclusion of time dummies and robust errors account for heteroskedasticity and other inertial effects (Stock and Watson 2008).[31]

Table 3.2 reports the results of the models discussed above. A complete table including estimates for control variables and year effects is available in Appendix D. Here, I have excluded them for brevity.

[30] I conduct all the regressions reported here in the chapter with normal standard errors as well (details in sensitivity analysis). Significances of the factors do not alter; however, standard errors are lower than the robust errors.

[31] Heteroskedasticity is the variance of the error term in a regression model in an explanatory variable, which violates model assumptions. It needs to be diagnosed and corrected. I have used Brusch Pagan (null hypothesis= constant variance) and White tests (null hypothesis= homoskedascity) to detect heteroskedascity. BP returns significant results (chi2= 18 and p=0.0001), suggesting hetroskedasity. Similarly, White test returns significant results (chi2=892 and p=0.0001), again suggesting heteroskedascity.

Table 3.2: Main Regressions Results. Dependent Variable, Log of GDP Per Capita.

VARIABLES	Pooled OLS	Random Effects	Fixed Effects
Public policy (inc. fiscal, monetary, structural…)	0.098***	0.077***	0.087***
	(0.022)	(0.025)	(0.027)
(General) Infrastructure (ICT & energy)	0.371***	0.134***	0.095***
	(0.026)	(0.024)	(0.028)
Logistic Per. Index (trade & transport infrast.)	0.100***	0.037***	0.029***
	(0.016)	(0.009)	(0.009)
Specialized skills	0.240***	0.111***	0.061***
	(0.024)	(0.018)	(0.018)
Generalized skills	-0.081***	-0.030**	-0.018
	(0.012)	(0.015)	(0.014)
Financial infrastructure	0.109***	0.037***	0.025**
	(0.017)	(0.013)	(0.012)
Financial (business) environment	0.047***	0.023**	0.025**
	(0.015)	(0.010)	(0.010)
Strength of financial regulations	-0.045***	0.010	0.010
	(0.014)	(0.018)	(0.018)
Enabling financial environment	0.036***	0.003	0.002
	(0.011)	(0.005)	(0.005)
Base sci & tech	-0.179***	-0.023	-0.028
	(0.034)	(0.023)	(0.025)
Medium sci & tech	-0.127***	-0.001	0.002
	(0.017)	(0.013)	(0.013)
High sci & tech	-0.061***	-0.002	0.001
	(0.014)	(0.006)	(0.006)
Social capacity (incl. equity, inclusion, etc.)	-0.128***	0.004	-0.001
	(0.023)	(0.019)	(0.018)
Constant	7.329***	7.181***	7.149***

VARIABLES	Pooled OLS	Random Effects	Fixed Effects
	(0.051)	(0.068)	(0.032)
Observations	1,230	1,230	1,230
R-squared	0.799	0.727	0.468
Control Variables	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Country Fixed Effects	NO	NO	YES
Robust Standard Errors	YES	YES	YES
Number of countries	82	82	82

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The Fixed Effects estimates return six capacities factors to be statistically significant. The public policy capacity factor appears to be significant throughout the models, indicating public policy capacity impacts GDP per capita growth (hereafter, *economic growth*) in LMICs. A one-point standard deviation (SD) increase in the public policy capacity leads to about an 8.7 percent increase in economic growth, holding other factors constant.[32] While the particular magnitude coefficient size for this factor ranged from about 8.7 in the Fixed Effects specification to 9.8 percent in the Pooled OLS model, this is significant across different specifications, including robust errors, Pooled OLS, Random Effects, and Standard Error models (see Appendix J for further details).

[32] Factors obtained through factor analysis are standardized with a mean of zero and a standard deviation of 1. Therefore, all interpretations in this chapter capture the impact of 1 standard deviation change on economic growth. Also, since the dependent variable is the log of GDP per capita, a 1 standard deviation change in any independent variable causes X percent change in the dependent variable.

Similarly, the two infrastructure capacity factors exhibit a positive and significant impact on economic growth throughout. The estimated coefficient magnitude of the first infrastructure capacity factor (general) infrastructure (includes ICT and energy infrastructure) ranges from about 9.5 percent in the Fixed Effects model to 37 percent in the Pooled OLS model. For the LPI factor (transport and trade-related infrastructure), the estimated coefficient size ranges from about 2.9 percent to 10 percent. Thus, interpreting the former factor in the Fixed Effects specification means that increasing ICT and energy infrastructure by 1 standard deviation in LMICs increases economic growth by about 9.5 percent, holding other factors constant. Similarly, increasing transport and trade-related infrastructure by 1 standard deviation in LMICs improve economic growth by 2.9 percent, holding other factors constant.

While the generalized skills factor is insignificant in the Fixed Effects specification within the human capital capacity, specialized skills positively and significantly impact economic growth in LMICs. The estimated coefficient size of this particular factor ranges from 6 percent (Fixed Effect) to 24 percent (Pooled OLS). A 6 percent estimated coefficient means that increasing 1 SD of specialized skills factor (which includes HCI, service, and industry sector employment, among other things) in a country increases GDP per capita by 6 percent while holding all other factors constant.

Finally, within financial capacity, I observe two factors of financial infrastructure (including banks, credit, businesses, among others) and environment (including the cost of business start-up procedures, economy openness, and days required to set up a business) as significant. The estimated coefficient size for both these factors is the same, meaning both are equally important. By improving 1 SD of financial infrastructure or 1 SD of the financial (business) environment, GDP per capita in a particular country increases by 2.5 percent.

Additionally, to ascertain the role of controls, I perform this analysis with and without controls (see Appendix E). While the directions and significances do not change in most cases, some earlier significant capacity factors become insignificant and even flip signs.[33] Moreover, estimates sizes in some instances drop considerably with the addition of controls,[34] suggesting that controls should be included in the regression analyses. The change in results (decline in magnitude or significance) with the addition of controls underpins one of my research premises that control variables may influence the relationship.

To further probe the role of controls, I perform the model with interactions between incoming confounders (controls) and capacity factors (equation 2). For instance, first, I perform multiple interactions between incoming confounders (Technical cooperation grants) and all the capacity factors (Appendix F). These results are consistent with the primary results in Table 3.2 for the coefficients on capacity factors; however, coefficients on interactions for all those factors are not significant. The insignificant results for interaction coefficients are likely because of data limitations, which prevent from doing a good analysis that incorporates interactions, because of relatively too many possible

[33] *Base sci & tech* has coefficient estimate of 3.7 percent without controls. After controls are included, it becomes insignificant and size drops to -2.9 percent.
[34] For instance, *social capacity factor* estimate drops from 0.019 to 0.007. Similarly, *strength of financial regulations* coefficient estimate drops from 0.032 to 0.019.

interactions, rather too few observations, and a good degree of multicollinearity, which multiple interactions only exacerbate. Then I perform single interactions between three capacity factors (Infrastructure, Trade and Transport Infrastructure, Specialized skills) and two incoming confounders (Technical cooperation grants and Aid received) in three single interaction models (Appendix F). Again, these results are mostly consistent with previous results, and the interaction coefficients are also significant. Considering this interaction analysis in conjunction with the control variables analysis, there is an indication that incoming confounders most likely influence the relationship between local capacities and economic growth in LMICs.

Finally, I empirically examine the issue of reverse causality as discussed in the literature review and hypotheses sections. There is a possibility that the relationship between capacities and economic growth may suffer from the reverse causality issue. To address this issue, the literature suggests performing instrumental variable regression by taking lags of endogenous variables, among other ways (Góes 2016; Lillo and Torrecillas 2018; Leszczensky and Wolbring 2019). The idea is that the value of the current outcome will not impact the values of endogenous variables in previous years. Thus, I employ the instrument of 1-year and 5-year lags of endogenous capacity factors and incorporate them in the model, keeping in mind that the per capita GDP of the current year will not affect endogenous capacity factors from the previous years (Appendix G). Results by and large did not change, lending further credence to my hypotheses.

Generally, trends (directions) in results are very consistent across various specifications in conveying the role of capacities in economic growth. However, magnitudes of effects vary in the three specifications, with Pooled OLS returning higher magnitudes than Random and Fixed Effects. This reflects that the Pooled OLS models omitted variable bias, which is corrected for in Random and the more conservative Fixed Effects estimates.

Overall, improving public policy capacity and infrastructure capacity factors have positive and significant effects in all cases. However, the results for the financial capacity and human capital capacity factors are more mixed, suggesting that some factors within these capacities are more important than others in LMICs. Specifically, the factor of specialized skills (within human capital capacity), which reflects secondary and vocational school attainment and industry and service sector employment, among other things, is significant and positive throughout. Similarly, financial infrastructure (indicating bank accounts ownership, commercial bank branches, new business density, and domestic credit by banking sector) and financial business environment (measuring days required to start a business, economy openness, and cost of business startup procedures), which appears consistently in the literature, are positive and significant for economic growth in developing economies. All these results corroborate the findings of the existing capacities literature. For instance, in one previous study, the size of the effect of Governance capacity (government effectiveness, corruption, law and order) ranges from 13 percent to 29 percent, whereas the magnitude of Education capacity (primary, secondary, and tertiary attainment) varies from -2 percent to 12 percent (Fagerberg and Serholic 2017). In my study, although the sizes are different, for obvious reasons, because I included an extended set of variables, trends and significances are the same.

On the other hand, in my study, technology, and social capacities, on average, are not significant for economic growth within LMICs. As a matter of fact, the LMICs have not been paying any special attention to these capacities and perhaps rightly so, as these capacities in poor economies by themselves may depend on other capacities, such as foundational public policy, finance, and infrastructure. For example, suppose a poor economy does not have enough fiscal space, strong fiscal management, statistical capacity, and tax capacity as reflected in public policy and financial capacities. In that case, it might not roll out successful social capacity interventions. Similarly, if a developing country's infrastructure (trade infrastructure, electricity provision, and internet communication) is weak, investments in science and technology may hardly lead to any significant economic value. Therefore, while very important for explaining economic growth in High-Income economies, technology, and social capacities are seldom priorities of LMICs. Such results are different for LMICs than the existing literature. For example, in the case of technology, compared to insignificant effects in my study, one previous research records large effect sizes ranging from 18 percent to 28 percent for a mix of economies, including higher-income economies (Fagerberg and Srholec 2017). The sizes are likely large because their technology capacity is very narrow: this capacity includes S&T journal articles, R&D expenditures, and USPTO patent applications. Perhaps, their technology capacity is overestimating the impact on economic growth. Regardless of the reason, in my study, economic growth variation is not explained by technology capacity. This finding suggests that in LMICs, technology capacity (including narrow technology indicators of S&T articles, R&D expenditures, Researchers, among others) is not as important.

Different effects sizes from Fixed Effects illustrate that some capacities matter more than others for economic growth in LMICs. For instance, general infrastructure (ICT and energy infrastructure) with an effect size of 9.5 percent tops the list. This factor is followed by the public policy capacity factor with an effect size of 8.7 percent and then the specialized skills capacity factor with an effect size of 6.5 percent. Similarly, the fourth place goes to trade and transport-related infrastructure (effect size 2.9 percent). Finally, the fifth place is captured by financial infrastructure and financial environment, both with an effect size of 2.5 percent. This result about factors' relative importance or ranking is particularly crucial for tight-budget LMICs when prioritizing their investments.

8. Sensitivity Analysis

Here I conduct sensitivity analysis of average treatment effects to examine their robustness. As a first sensitivity analysis, I conduct an exploratory factor analysis (EFA) and then include EFA factors in the same regression models as I show in Table 3.2, comprising factors from confirmatory factor analyses (CFAs). Regressions incorporating EFA factors substantiate the results from regressions, including CFAs factors as predictors. The EFA provides 12 factors (see factor loadings in Appendix H). I retain the factors using the same Eigenvalue criteria I have for CFAs. Then, I include the retained factors in a separate set of regressions using the exact specifications of Pooled OLS, Random Effects, and Fixed Effects. Results from the EFA and subsequent regressions are included in Appendix I. By looking at the results from the Fixed Effects specification, the same six factors appear to be significant. Also, the sizes and directions are comparable. For instance, the public policy factor (although now merged with the social capacity factor) obtained from the EFA is significant in all the regressions. The estimated coefficient size of the public policy factor ranges from a comparable 7.6 percent (Pooled OLS) to 11.5 percent (Random). For a Fixed Effects specification, its size is 9.8 percent, which is almost similar to what I observe in the accordingly similar Fixed Effects specification conducted above after including factors from the CFAs.

I conduct a similar analysis with different specifications for an additional sensitivity analysis. For instance, I run all the above regressions (from Table 3.2) with standard errors (see Appendix J) while admitting that robust errors are superior and suitable for these models. My main results (estimates size, direction, and significance) do not alter. Similarly, I perform backward and forward regression analyses with and without time effects (see Appendix E). Again, my main results (directions and their significance) do not alter despite a drop in estimate sizes. The reduction in coefficient sizes suggests that the use of time effects (in Table 3.2) is accurate. Lastly, I average the entire data over five years (2005-10, 2010-15, 2015-19) and then conduct the same analyses (see Appendix K). My main results, by and large, remain the same.

9. Conclusions

By extending firm-level capacities to a nation (LMIC), I argue that capacities play a role in the economic development of LMICs. Just like other countries, LMICs are reservoirs of capacities in the form of skills, policies, institutions, resources, and humans, whereby these capacities engage to generate economic value. Therefore, capacities should be integrated into LMICs' economic growth and policy frameworks.

In this chapter, I develop a framework called National Absorptive Capacity System (NACS). The framework extends the two social and technological capacities in the extant literature by adding four more capacities to and considering important confounders such as incoming flows. Such new capacities were generated by utilizing extensively updated data containing a comprehensive set of variables.

In line with previous research, I find that infrastructure, public policy, finance, business environment, and specialized skills, including service and industry-level employment, are fundamental in explaining economic growth within LMICs. On the other hand, in contrast to existing research for developed countries, I observe technological and social capacity are not significant within LMICs. In the future, these capacities could add economic value once LMICs develop a base level of policy, infrastructure, and finance.

In terms of technology capacity, the insignificant result may also suggest that instead of unchecked spending on building technological base, LMICs, particularly the poorest economies, can be more strategic by learning from other richer countries. As they rise further on the development ladder, they may start improvising and building their own technological capacities. Thus, I propose richer countries facilitate technology transfer to poorer economies to boost shared prosperity.

As far as infrastructure capacity goes, I find that ICT infrastructure and energy provision and infrastructure stand out as the most crucial capacities for economic growth in LMICs. Similarly, public policy capacity, which indicates fiscal and financial management, quality of institutions, and other bureaucratic reforms, are also extremely important in LMICs. Moreover, these capacities are crucial, as they may have spillover effects on other capacities. That is to say, if an LMIC has strong infrastructure and public policy capacities, it probably will ensure an enabling environment for various other capacities, thus leading to higher economic value.

10. Implications

LMICs lack the representation they deserve in empirical economic and innovation literature partly because of "imported" frameworks conceived in HICs, as they fail to capture political and social realities and contexts in LMICs. Moreover, the missing data for LMICs further push their analysis to the peripheries in the literature. This study attempts to address these issues using insights from innovation systems, development economics, and strategic management. It does so by employing a novel panel dataset collected and validated previously in Chapter 2 and establishing a rich capacities framework to explain economic growth in LMICs. One successful outcome of the study is a thorough list of capacities befitting the LMICs' context. Another related outcome is ranking crucial capacities for growth in tight-budget economies.

The table below shows the ranking and magnitude of the crucial significant capacities' impact:

Table 3.3: Significant Capacities, Factors, their Rankings and Impact Size

Ranking	Capacity Name	Capacity Factor	Percent Size of Impact (Coefficient Size)
1	**Infrastructure Capacity**	Infrastructure (ICT & energy)	9.5% (0.095)
2	**Public Policy Capacity**	Public policy factor (inc. fiscal, monetary, structural policies…)	8.7% (0.087)
3	**Human Capacity**	Specialized skills	6.1% (0.061)
4	**Infrastructure Capacity**	Logistic Per. Index (trade & transp. infrastructure)	2.9% (0.029)
5	**Financial Capacity**	Financial infrastructure	2.5% (0.025)
6	**Financial Capacity**	Financial (business) environment	2.5% (0.025)

As it is evident from Table 3.3 in LMICs, infrastructure capacity related to ICT and energy ranks first, followed by public policy, specialized skills human capacity, infrastructure in trade and transport, and financial capacity (infrastructure and business environment). LMICs must invest in those capacities to achieve economic development. It is hard to imagine economic growth without essential communications, energy, trade, and transport infrastructure. Similarly, stable structural, monetary, and fiscal policies, as well as the quality of institutions, offer considerable gains in development in LMICs. Likewise, economic growth won't be long-lasting without specialized and skilled human resources. Finally, financial infrastructure for individuals and businesses as simple as transaction accounts for every eligible individual, lower business costs, and accessibility to the world markets are crucial for growth in tight budget economies.

The knowledge of capacities as well as the extent to which those capacities drive economic growth offer valuable lessons for consideration and subsequent implementation in LMICs. Policymakers in LMICs in the planning, finance, and science and technology ministries can apply these insights when devising national growth frameworks. Similarly, other stakeholders and international organizations, such as the World Bank Group, the IMF, USAID, and the United Nations, can devise informed strategies in building country-wide growth diagnostic tools and growth partnership frameworks for LMICs. Overall, in the long run, the results will help achieve sustainable development goals and economic prosperity for the LMICs, which are prime candidates for development.

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Appendix A

Table 3.4. Variables Included in NACS Framework, Definitions, and Sources.

Capacity	Variable code	Definition	Source
Technology Capacity	tippay	**Charges for the use of intellectual property, payments (BoP, current US$)**. Payment or charges per authorized use of patents, trademarks, copyrights, industrial processes and designs including trade secrets, and franchises and for the use, through licensing agreements, of produced originals of prototypes. Data are in current US dollars.	IMF, World Bank
	tscitjar	**Scientific and technical journal articles.** Number of scientific and engineering articles published in physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering and technology, and earth and space sciences, per million people.	World Bank
	trandd	**Research and development expenditure (% of GDP)**	UNESCO
	tresinrandd	**Researchers in R&D (per million people)**	UNESCO
	ttechinrandd	**Technicians in R&D (per million people)**	UNESCO
	thigexperofmanex	**High-technology exports (% of manufactured exports).** High-technology exports are products with high R&D intensity, such as in aerospace, computers, pharmaceuticals, scientific instruments, and electrical machinery.	UN, COMTRADE
	tsecedvoc	**Secondary education, vocational pupils.** Secondary students enrolled in technical and vocational education programs, including teacher training.	UNESCO
	teciscore	**ECI Score.** Measure of economic complexity containing information about both the diversity of a country's export and their sophistication. High ECI Score shows that an economy exports many goods that are of low ubiquity and that are produced by highly diversified countries. Diverse and sophisticated economies have high scores.	OEC, MIT
Capacity	**Variable code**	**Definition**	**Source**
Financial Capacity	fdaystoenfctt	**Time required to enforce a contract (days).** Days required to enforce a contract, whereas the days are counted from the day a plaintiff files the lawsuit in court until payment. Low values indicate high competitiveness and vice verca.	World Bank, Doing Business Project
	fdomcrprsecbybkpergdp	**Domestic Credit by Banking Sector.** This includes all credit to various sectors (monetary authorities, banks, financial corporations) on a gross basis, with the exception of credit to the central government, which is net, as a percentage of GDP.	IMF, World Bank

	fopenind	**Openness Indicator.** (Import + Export)/GDP. Constant US 2010.	World Bank
	fdaystoregpro	**Time required to register property (days).** The number of calendar days needed for businesses to secure rights to property.	World Bank, Doing Business Project
	fcosbstpropergni	**Cost of business start-up procedures (% of GNI per capita)**	
	ftaxrpergdp	**Tax revenue (% of GDP).** Tax revenue means compulsory transfers to the government for public purposes.	IMF, WBG
	fcombkbr1k	**Commercial bank branches (per 100,000 adults)**	IMF, World Bank
	fdaystoobtelecconn	**Time to obtain electrical connection (Days).** Days to obtain electrical connection. Days from application to getting the connection.	World Bank, Enterprise Survey
	ftdaystobusi	**Time required to start a business (Days).** The number of days needed to complete the procedures to legally operate a business.	World Bank, Doing Business Project
	faccownperofpop15p	**Account ownership at a financial institution or with a mobile-money-service provider (% of pop ages 15+).** Account denotes the percentage of respondents who report having an account at a bank or another type of financial institution or report personally using a mobile money service in the past 12 months (% age 15+).	Demirguc-Kunt et al., 2018, Global Financial Inclusion Database, World Bank.
	fnewbusdenper1k	**New business density (new registrations per 1,000 people ages 15-64)**. New businesses registered are the number of new limited liability corporations registered in the calendar year.	World Bank, Enterprise Survey
Capacity	**Variable code**	**Definition**	**Source**
Human Capacity	hprimenrollpergross	**School enrollment, primary (% gross).** Ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the primary level.	UNESCO
	hsecenrollpergross	**School enrollment, secondary (% gross).** Ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the secondary level.	UNESCO
	hcompeduyears	**Compulsory education, duration (years).** Duration of compulsory education is the number of years that children are legally obliged to attend school.	UNESCO
	hgvtexpedupergdp	**Government expenditure on education (% of GDP).** General government expenditure on education (current, capital, and transfers) is expressed as a percentage of GDP.	UNESCO
	hpupteapriratio	**Primary pupil-teacher ratio**. Ratio (number of pupils enrolled in primary school) / (number of primary school teachers)	UNESCO

	hempinduspertotem	**Employment in industry (% of total employment).** Industry sector comprise mining and quarrying, manufacturing, construction, & public utilities (electricity, gas, & water),	ILO, World Bank
	hempserpertotem	**Employment in services (% of total employment).** The services sector consists of wholesale and retail trade and restaurants and hotels; transport, storage, and communications; financing, insurance, real estate, and business services; and community, social, and personal services.	ILO, World Bank
	hprimcompra	**Primary completion rate, total (% of relevant age group)**	UNESCO
	hhciscale0to1	**Human capital index (HCI) (scale 0-1).** The HCI calculates the contributions of health and education to worker productivity. The final index score ranges from zero to one and measures the productivity as a future worker of child born today relative to the benchmark of full health and complete education.	World Bank
	hlfwithadedu	**Labor force with advanced education (% of total working-age population with advanced education)**	ILO, World Bank
Capacity	**Variable code**	**Definition**	**Source**
Infrastructure Capacity	imobsubper100	**Mobile cellular subscriptions (per 100 people).**	International Telecom Union, World Bank
	itelesubper100	**Fixed telephone subscriptions (per 100 people)**	International Telecom Union, World Bank
	ibdbandsubper100	**Fixed broadband subscriptions (per 100 people)**	International Telecom Union, World Bank
	iaccesselecperpop	**Access to electricity (% of population).** The percentage of population with access to electricity.	World Bank, Sustainable Energy for All
	ienergyusepercap	**Energy use (kg of oil equivalent per capita).** The use of primary energy before transformation to other end-use fuels, which is equal to indigenous production plus imports and stock changes, minus exports and fuels supplied to ships and aircraft engaged in international transport.	IEA, World Bank
	iindintperpop	**Individuals using the internet (% of population).** Internet users are individuals who have used the Internet (from any location) in the last 3 months.	International Telecom Union, World Bank
	ilpiquoftratraninfr	**Logistics performance index: Quality of trade and transport-related infrastructure (1=low to 5=high)**. Logistics professionals' perception of country's quality of trade and	World Bank

Capacity	Variable code	Definition	Source
		transport related infrastructure (e.g. ports, railroads, roads, information technology), on a rating ranging from 1 (very low) to 5 (very high). Scores are averaged across all respondents.	
Capacity	**Variable code**	**Definition**	**Source**
	pcpiapsmgandinscl1to6	**CPIA public sector management and institutions cluster average (1=low to 6=high).** The public sector management and institutions cluster includes property rights and rule-based governance, quality of budgetary and financial management, efficiency of revenue mobilization, quality of public administration, and transparency, accountability, and corruption in the public sector.	World Bank, CPIA Database
Public Policy Capacity	pcpiastpolclavg1to6	**CPIA structural policies cluster average (1=low to 6=high).** The structural policies cluster includes trade, financial sector, and business regulatory environment	World Bank, CPIA Database
	pstrengthoflegalright	**Strength of legal rights index (0=weak to 12=strong).** Strength of legal rights index measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders and thus facilitate lending. The index ranges from 0 to 12, with higher scores indicating that these laws are better designed to expand access to credit.	World Bank, Doing Buisness Project
	iscapscoravg	**Overall level of statistical capacity (scale 0 - 100).** A composite score (on a scale of 0-100) which assesses the capacity of a country's statistical system in three areas (25 criteria): methodology; data sources; and periodicity and timeliness.	World Bank
	pcpiaeconmgtcl1to6	**CPIA economic management cluster average (1=low to 6=high).** The economic management cluster includes macroeconomic management, fiscal policy, & debt policy.	World Bank, CPIA Database
Capacity	**Variable code**	**Definition**	**Source**
	scpiabdhumanres1to6	**CPIA building human resources rating (1=low to 6=high).** Building human resources assesses the national policies and public and private sector service delivery that affect the access to and quality of health and education services, including prevention and treatment of HIV/AIDS, tuberculosis, and malaria.	World Bank, CPIA Database
Social Capacity	scpiaeqofpbresuse1to6	**CPIA equity of public resource use rating (1=low to 6=high).** Equity of public resource use assesses the extent to which the pattern of public expenditures and revenue collection affects the poor and is consistent with national poverty reduction priorities	World Bank, CPIA Database
	scpiasocprorat1to6	**CPIA social protection rating (1=low to 6=high).** Social protection and labor assess government policies in social protection and labor market regulations that reduce the risk of becoming poor, assist those who are poor to better manage further risks, and ensure a minimal level of welfare to all people.	World Bank, CPIA Database
	scpiapolsocinclcl1to6	**CPIA policies for social inclusion/equity cluster average (1=low to 6=high).** The policies for social inclusion and equity cluster includes gender equality, equity of public	World Bank, CPIA Database

		resource use, building human resources, social protection and labor, and policies and institutions for environmental sustainability	
	spovheadcnational	**Poverty headcount ratio at national poverty lines (% of population).** National poverty headcount ratio is the percentage of the population living below the national poverty line(s)	World Bank
	ssocialconperofrev	**Social contributions (% of revenue).** Social contributions include social security contributions by employees, employers, and self-employed individuals, and other contributions whose source cannot be determined. They also include actual or imputed contributions to social insurance schemes operated by governments	IMF, World Bank
Controls	**Variable code**	**Definition**	**Source**
	cteccopgrantbopcurr	**Technical cooperation grants (BoP, Current US $).** Technical cooperation grants are free-standing grants to finance the transfer of technical and managerial skills or of technology with the aim to build national capacity without reference to any specific investment projects; and investment-related technical cooperation grants, which are provided to strengthen the capacity to execute specific investment projects. Data are in current U.S. dollars.	World Bank, International Debt Statistics, and OECD.
	cpoptot	**Population, Total.** Total population, counting all residents regardless of legal status or citizenship.	United Nations Statistical Division.
	cgroscapformcons2010us	**Gross capital formation (% of GDP).** Gross capital formation consists of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories. Fixed assets include land improvements (fences, ditches, drains, and so on); plant, machinery, and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings. Inventories are stocks of goods held by firms to meet temporary or unexpected fluctuations in production or sales, and "work in progress." According to the 1993 SNA, net acquisitions of valuables are also considered capital formation.	World Bank national accounts data, and OECD National Accounts data files.
	cintltournoarrivals	**International tourism, number of arrivals**. International inbound tourists (overnight visitors) are the number of tourists who travel to a country other than that in which they usually reside, and outside their usual environment, for a period not exceeding 12 months and whose main purpose in visiting is other than an activity remunerated from within the country visited.	World Bank
	cmerchimpfmhighpermerchimp	**Merchandise imports from high-income economies (% of total merchandise imports).** Merchandise imports from high-income economies are the sum of merchandise imports by the reporting economy from high-income economies according to the World Bank classification of economies. Data are expressed as a percentage of total merchandise imports by the economy.	World Bank
	cnetodaandoffreceivcon2018	**Net official development assistance and official aid received (constant 2018 US$).** Net official development assistance (ODA) consists of disbursements of loans made on	OECD, World Bank

		concessional terms (net of repayments of principal) and grants by official agencies of the members of the Development Assistance Committee (DAC), by multilateral institutions, and by non-DAC countries to promote economic development and welfare in countries and territories in the DAC list of ODA recipients. It includes loans with a grant element of at least 25 percent (calculated at a rate of discount of 10 percent). Net official aid refers to aid flows (net of repayments) from official donors to countries and territories in part II of the DAC list of recipients: more advanced countries of Central and Eastern Europe, the countries of the former Soviet Union, and certain advanced developing countries and territories. Official aid is provided under terms and conditions similar to those for ODA. Part II of the DAC List was abolished in 2005. The collection of data on official aid and other resource flows to Part II countries ended with 2004 data. Data are in constant 2018 U.S. dollars.	
	hcurhealthexppergdp	**Current health expenditure (% of GDP).** Level of current health expenditure expressed as a percentage of GDP. Estimates of current health expenditures include healthcare goods and services consumed during each year. Does not include capital health expenditures such as buildings, machinery, IT and stocks of vaccines for emergency or outbreaks.	WHO, World Bank
	hemplyrpertotemp	**Employers, total (% of total employment).** Employers are those workers who, working on their own account or with one or a few partners. Self-employment included.	ILO, World Bank
	timecode	**Time Frame.** from 2005 to 2019	
	countrycode	**Countrycodes** as used by the World Banks	
Outcome	**Variable code**	**Definition**	**Source**
	ogdppercapconst2010us	**GDP per capita (constant 2010 US$).** GDP per capita is gross domestic product divided by midyear population. Data are in constant 2010 U.S. dollars.	World Bank

Appendix A

Table 3.5. Descriptive Statistics of All Variables in NACS

Variable	Obs.	Mean	Std. Dev.	Min	Max
Sci & tech. articles	1230	1270.77	9395.79	0	135787.8
Intellectual payments (mil)	1230	65.35	492.20	-13.92	7906
Voc. & tech. students (mil)	1230	111698.6	253483.79	0	2300769
R&D expend. % of GDP	1230	.21	.16	.01	.86
R&D researchers (per mil)	1230	162.65	225.9	5.94	1463.77
R&D technicians (per mil)	1230	57.02	63.01	.13	627.73
High-tech exports (mil)	1230	6.23	9.29	0	68.14
ECI (econ. complexity)	1230	-.72	.63	-3.04	.82
Tax revenue (% of GDP)	1230	16.22	11.71	0	149.28
Business startup cost	1230	85.38	137.76	0	1314.6
Domestic credit by banks	1230	25.07	20.37	.5	137.91
Days to start business	1230	35.34	37.71	1	260.5
Days enforcing contract	1230	666.61	329.52	225	1800
Days to register property	1230	87.33	97.58	1	690
Openness measure	1230	.11	.08	.01	.44
Days to electric meter	1230	37.24	33.64	2.5	194.3
Business density	1230	1.06	1.47	.01	12.31
Financial accountholders	1230	30.94	22.53	1.52	92.97
Commercial banks	1230	10.49	11.99	.27	71.23
Primary enrollment (gross)	1230	103.36	18.18	23.36	149.96
Sec. enrollment (gross)	1230	57.49	25.99	5.93	123.03
Primary pupil-teacher ratio	1230	34.43	14.36	8.68	100.24
Primary completion rate	1230	79.41	20.89	26.1	134.54

Variable	Obs.	Mean	Std. Dev.	Min	Max
Govt. expend. on educ.	1230	4.36	2.22	.69	12.9
Human Capital Index 0-1	1230	.42	.09	.29	.69
Advanced educ. labor	1230	75.5	10.55	39.97	96.36
Compulsory educ. (years)	1230	8.45	2.16	4	15
Industry employment	1230	14.52	7	.64	32.59
Service employment	1230	39.43	15.05	7.16	75.34
Mobile subscriptions	1230	59.12	38.15	.26	181.33
Access to electricity	1230	57.02	31.3	1.24	100
Broadband subscriptions	1230	1.97	4.12	0	25.41
Telephone subscriptions	1230	5.31	7.39	0	32.85
Energy use (per capita)	1230	560.21	392.9	9.55	2246.92
Logistic perf. Index 1-5	1230	2.18	.33	1.1	3.34
Internet users	1230	16	16.3	.03	89.44
CPIA econ. mgmt.	1230	3.39	.69	1	5.5
Public sect. mgmt. & instit	1230	3.06	.5	1.4	4.2
Sructural policies	1230	3.3	.54	1.17	5
Statistical capacity 0-100	1230	59.82	14.89	20	96.67
Legal Rights Index 0-12	1230	4.83	3.1	0	11
Human resources rating	1230	3.52	.63	1	4.5
Equity of public resc use	1230	3.38	.64	1	4.5
Social protection rating	1230	3.03	.59	1	4.5
Social inclusion o..	1230	3.28	.51	1.5	4.3
National headcount poverty	1230	38.52	15.13	4.1	82.3
Social contributions	1230	3.23	7.53	0	39.74
GDP per capita 2010	1230	1969.31	1812.13	208.07	9350.75
Log GDP per capita2010	1230	7.24	.82	5.34	9.14
Tech. coop. grants (mil)	1230	92.57	108.20	0.51	1062
Total population (mil)	1230	34.61	141	0.01	1366
Gross capital (mil)	1230	15690	79490	0.00	991400

Variable	Obs.	Mean	Std. Dev.	Min	Max
Incoming tourists' no. (mil)	1230	0.96	1.80	0.00	18.01
Merch. imports frm HICs	1230	49.31	20.07	2.5	99.56
Net ODA/aid received (mil)	1230	820.70	1058	-247.40	11880
Health expenditure	1230	6.09	3.13	1.03	21.46
No. of employers	1230	2.24	2.31	0	13.76

Appendix B

Tables 3.6.1-3.6.6. Factor Loadings Tables from Six Confirmatory Analyses.

The following six tables show factor loadings obtained after six confirmatory factor analyses (CFAs) that I conduct for six capacities. Loadings indicate correlations among one of the latent factors in the first row and the variables in the column in each table. Bold values indicate that these variables load highly on a particular factor in the first row of the table.

Table 3.6.1. Technology Capacity Factor Loadings

Variable	**base sci & tech**	**medium sci & tech**	**high sci & tech**
Sci & tech. articles	**0.9503**	0.0479	0.0704
Intellectual payments (mil)	**0.933**	0.0362	0.051
Voc. & tech. students (mil)	**0.7254**	0.0288	-0.0843
R&D expend. % of GDP	0.4214	0.0703	**0.5683**
R&D researchers (per mil)	-0.0316	**0.8274**	-0.0003
R&D technicians (per mil)	0.1027	0.2936	**0.5956**
High-tech exports (mil)	-0.0749	-0.0485	**0.7651**

ECI (econ. complexity)	0.1288	**0.8233**	0.0789

Table 3.6.2. Human Capital Capacity Factor Loadings

Variable	**Specialized skills**	**Generalized skills**
Primary enrollment (gross)	0.2055	**0.8694**
Sec. enrollment (gross)	**0.9331**	0.0169
Primary pupil-teacher ratio	-0.815	**0.1271**
Primary completion rate	**0.8724**	0.2845
Govt. expend. on educ.	**0.417**	0.07
Human Capital Index 0-1	**0.8332**	0.0821
Advanced educ. labor	-0.1977	**0.1646**
Compulsory educ. (years)	**0.3599**	-0.6409
Industry employment	**0.7147**	-0.2713
Service employment	**0.7156**	-0.3428

Table 3.6.3. Public Policy Capacity Factor Loadings

Variable	**Public policy (inc. fiscal, monetary, structural policies…)**
Statistical capacity 0-100	**0.7359**
CPIA econ. mgmt.	**0.8166**
Public sect. mgmt.& instit.	**0.8591**
Structural policies	**0.8923**
Legal Rights Index 0-12	**0.4181**

Table 3.6.4. Social Policy Capacity Factor Loadings

Variable	**Social capacity (inc. equity, inclusion…)**
Human resources rating	**0.8751**
Equity of public resc. use	**0.8328**
Social protection rating	**0.8605**
Social inclusion (inc. gender equity and others)	**0.9724**
National headcount poverty	**-0.48**
Social contributions	**0.3669**

Table 3.6.5. Infrastructural Capacity Factor Loadings

Variable	**Infrastructure (ICT & energy)**	**Logistic Perf. Index (trade & transport infras.)**
Mobile subscriptions	**0.5603**	0.5062
Access to electricity	**0.7411**	0.3341
Broadband subscriptions	**0.8804**	0.024
Telephone subscriptions	**0.8376**	-0.0125
Energy use (per capita)	**0.8229**	0.0057
Logistic perf. Index 1-5	0.009	**0.9091**
Internet users	**0.8129**	0.3437

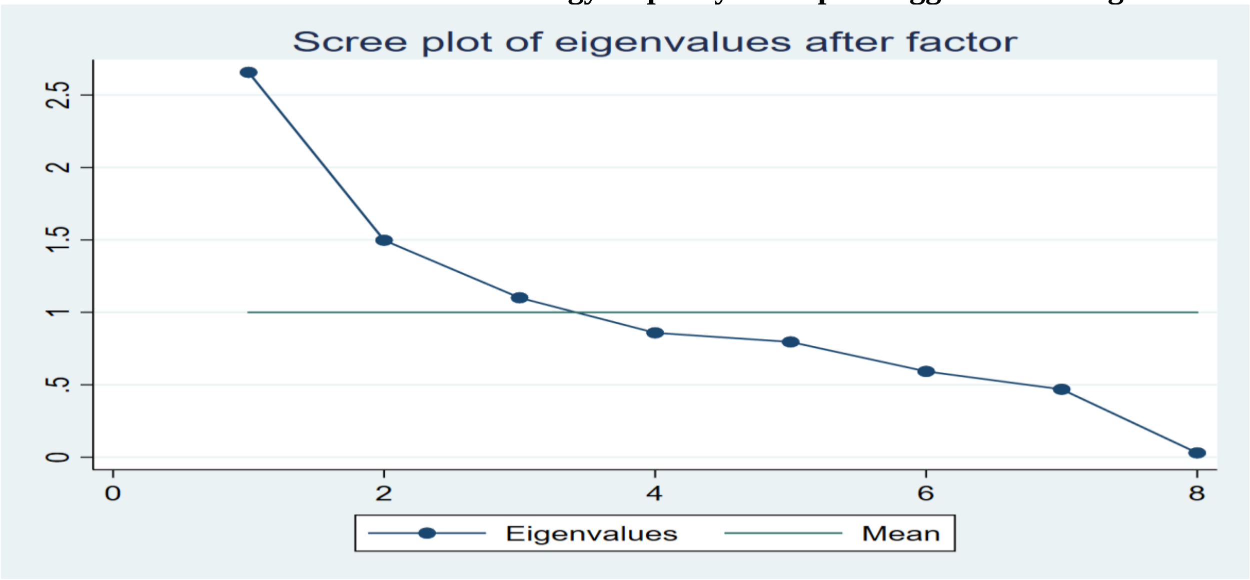
Tabel 3.6.6. Financial Capacity Factor Loadings

Variable	Financial infrastructure	Financial environment	Strength of financial regulation	Financial enabling environment
Tax revenue (% of GDP)	0.3541	0.2798	**0.5426**	-0.4327
Business startup cost	-0.4405	**0.5017**	0.0394	-0.0492
Domestic credit by banks	**0.7692**	0.1594	-0.1514	0.1406
Days to start business	-0.1497	**0.8564**	0.2287	-0.1117
Days enforcing contract	-0.095	-0.0815	**0.8511**	0.1189
Days to register property	-0.2421	0.3618	**0.3821**	0.3226
Openness measure	0.3364	**0.7956**	-0.3945	-0.0183
Days to electric meter	0.1188	-0.0908	0.0847	**0.8499**
Business density	**0.6787**	-0.0578	0.0196	-0.224
Financial accountholders	**0.765**	-0.0357	0.1769	0.0729
Commercial banks	**0.7567**	-0.034	-0.2106	0.0268

Appendix C

Figures 3.3.1-3.3.6. Scree Plots of Factors.[35]

Figure 3.3.1. Scree Plot Obtained via CFA for Technology Capacity- This plot suggests retaining three factors.



[35] Scree Plot is a powerful visual tool for determining the number of factors to be retained. It is basically a plot of the eigenvalues shown in decreasing order. The eigenvalue is calculated by summing the squared factor loadings for that factor. Factor loadings, on the other hand, are basically correlations among the variables and their latent constructed factors. Factors having eigenvalues greater than 1 are retained.

Figure 3.3.2. Scree Plot Obtained via CFA for Human Capital Capacity- This plot suggests retaining two factors.

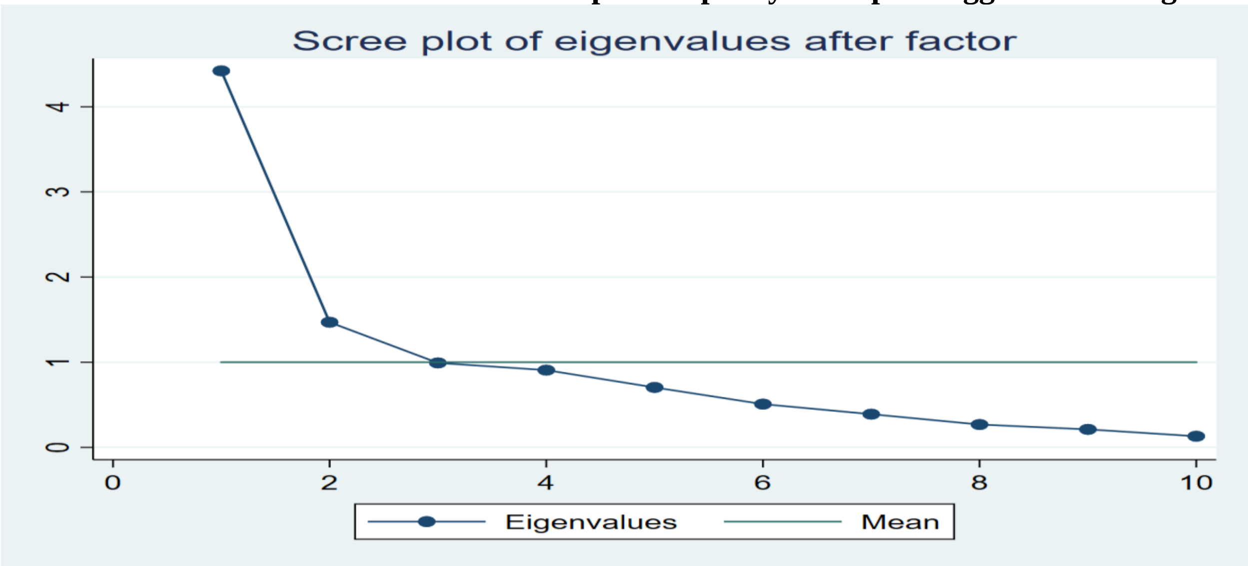


Figure 3.3.3. Scree Plot Obtained via CFA for Infrastructural Capacity- This plot suggests retaining two factors

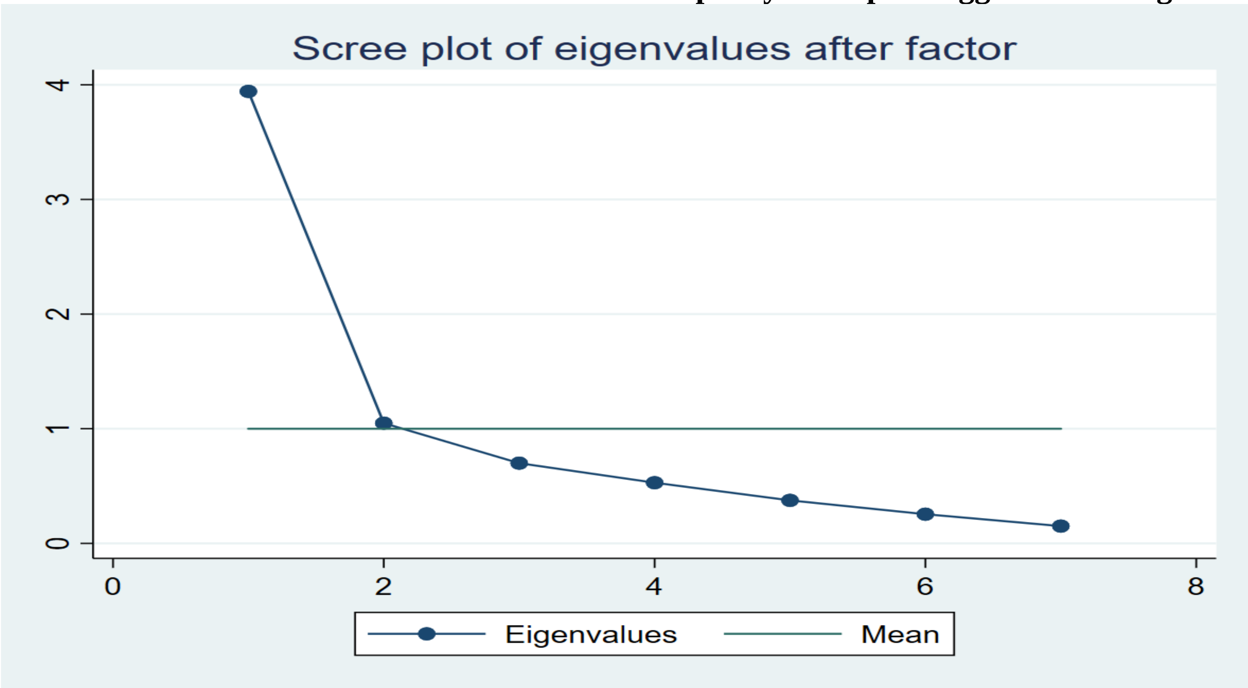


Figure 3.3.4. Scree Plot Obtained via CFA for Financial Capacity-This plot suggests retaining four factors

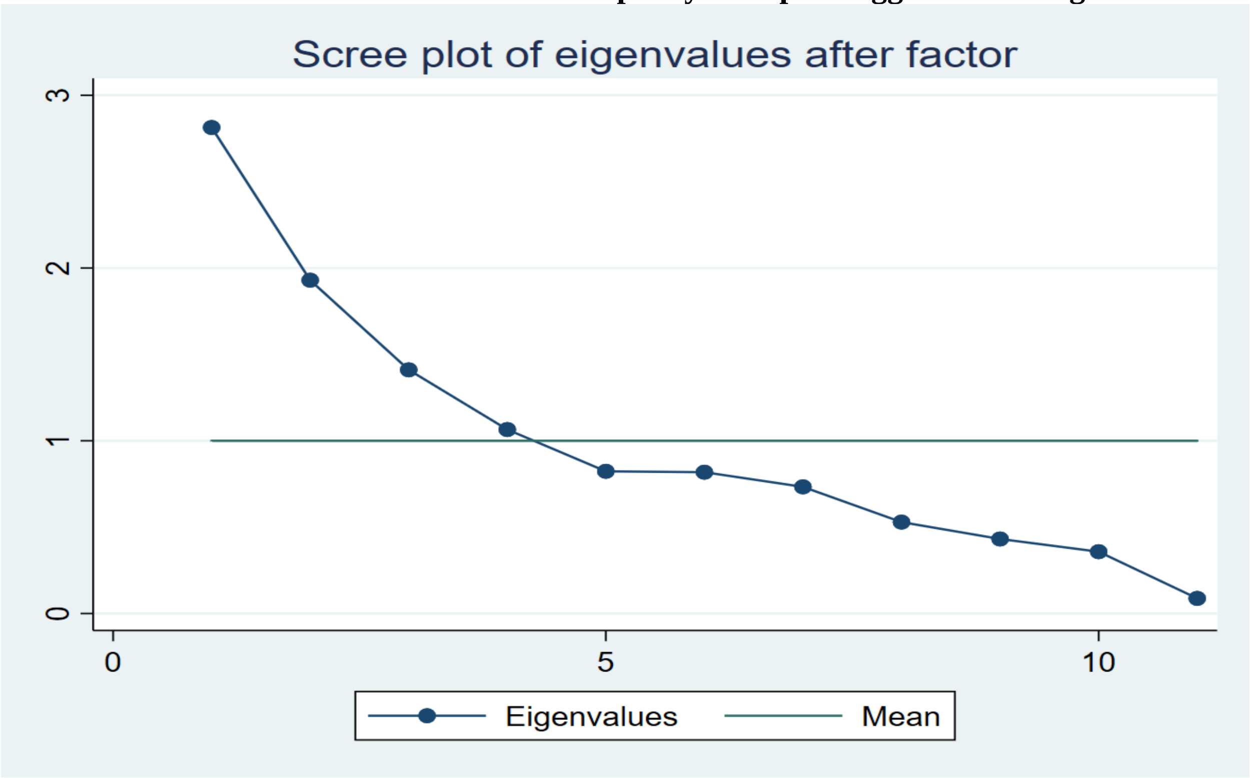


Figure 3.3.5. Scree Plot Obtained via CFA for Public Policy Capacity- this plot suggests retaining one factor

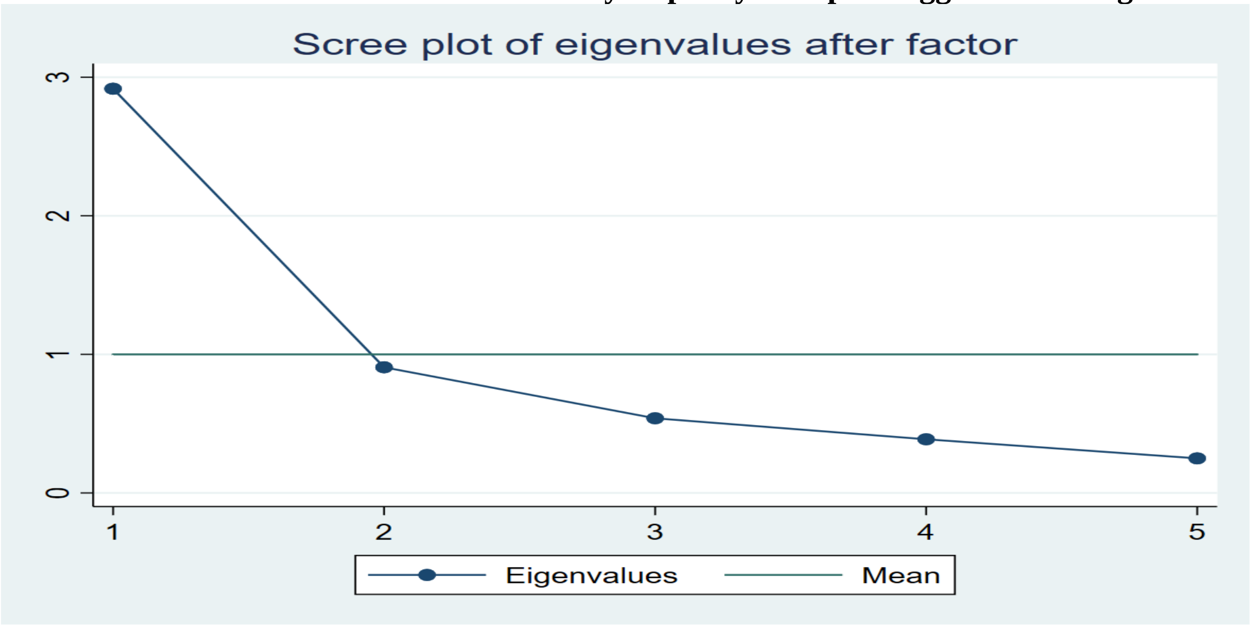
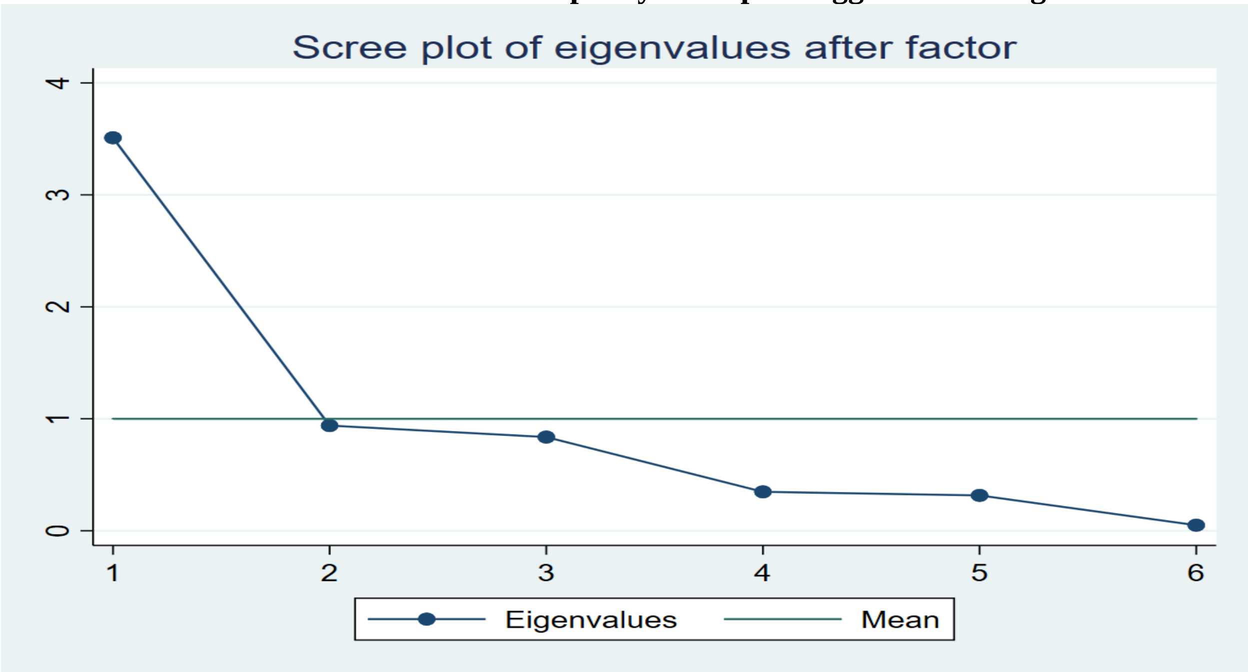


Figure 3.3.6. Scree Plot Obtained via CFA for Social Capacity- This plot suggests retaining one factor



Appendix D

Table 3.7. Main Results: Full-scale Table. Dependent Variable, Log of GDP Per Capita.

VARIABLES	Pooled OLS	Random Effects	Fixed Effects
Public policy (inc. fiscal, monetary, structural, etc.)	0.098***	0.077***	0.087***
	(0.022)	(0.025)	(0.027)
Infrastructure (ICT & energy)	0.371***	0.134***	0.095***
	(0.026)	(0.024)	(0.028)
Logistic Per. Index (trade & transp. infras.)	0.100***	0.037***	0.029***
	(0.016)	(0.009)	(0.009)
Specialized skills	0.240***	0.111***	0.061***
	(0.024)	(0.018)	(0.018)
Generalized skills	-0.081***	-0.030**	-0.018
	(0.012)	(0.015)	(0.014)
Financial infrastructure	0.109***	0.037***	0.025**
	(0.017)	(0.013)	(0.012)
Financial environment	0.047***	0.023**	0.025**
	(0.015)	(0.010)	(0.010)
Strength of financial regulations	-0.045***	0.010	0.010
	(0.014)	(0.018)	(0.018)
Enabling financial environment	0.036***	0.003	0.002
	(0.011)	(0.005)	(0.005)
Base sci & tech	-0.179***	-0.023	-0.028
	(0.034)	(0.023)	(0.025)
Medium sci & tech	-0.127***	-0.001	0.002
	(0.017)	(0.013)	(0.013)
High sci & tech	-0.061***	-0.002	0.001

VARIABLES	Pooled OLS	Random Effects	Fixed Effects
	(0.014)	(0.006)	(0.006)
Social capacity (incl. equity, inclusion, etc.)	-0.128***	0.004	-0.001
	(0.023)	(0.019)	(0.018)
Tech. coop. grants (st)	0.006	-0.024	-0.017
	(0.021)	(0.017)	(0.018)
Total population (st)	-0.373***	-0.143***	0.388
	(0.058)	(0.046)	(0.345)
Gross capital (st)	0.569***	0.155***	0.035
	(0.064)	(0.054)	(0.063)
Incoming tourists' no. (st)	-0.049***	0.005	0.021
	(0.018)	(0.012)	(0.013)
Merch. imports frm HICs (st)	0.170***	0.078***	0.058***
	(0.014)	(0.021)	(0.022)
Net ODA/aid received (st)	-0.028	-0.005	-0.001
	(0.030)	(0.017)	(0.019)
Health expenditure (st)	-0.086***	-0.054***	-0.050***
	(0.012)	(0.015)	(0.016)
No. of employers (st)	0.027**	0.037***	0.029***
	(0.012)	(0.010)	(0.010)
YR2006	-0.020	0.005	0.011
	(0.065)	(0.014)	(0.014)
YR2007	-0.037	0.015	0.033*
	(0.065)	(0.017)	(0.017)
YR2008	-0.043	0.033**	0.053***
	(0.064)	(0.017)	(0.017)
YR2009	-0.070	0.020	0.040*
	(0.064)	(0.021)	(0.022)
YR2010	-0.052	0.046*	0.071***
	(0.065)	(0.024)	(0.023)

VARIABLES	Pooled OLS	Random Effects	Fixed Effects
YR2011	-0.104	0.047*	0.080***
	(0.063)	(0.025)	(0.026)
YR2012	-0.109*	0.064**	0.100***
	(0.063)	(0.031)	(0.034)
YR2013	-0.077	0.094**	0.132***
	(0.066)	(0.039)	(0.041)
YR2014	-0.103	0.092**	0.134***
	(0.066)	(0.040)	(0.042)
YR2015	-0.129*	0.082*	0.128**
	(0.068)	(0.045)	(0.050)
YR2016	-0.120*	0.090**	0.135**
	(0.067)	(0.045)	(0.052)
YR2017	-0.167**	0.102**	0.155***
	(0.069)	(0.050)	(0.056)
YR2018	-0.171**	0.093*	0.147**
	(0.071)	(0.050)	(0.057)
YR2019	-0.115	0.115**	0.166**
	(0.072)	(0.058)	(0.065)
Constant	7.329***	7.181***	7.149***
	(0.051)	(0.068)	(0.032)
Observations	1,230	1,230	1,230
R-squared	0.799	0.727	0.468
Controls	YES	YES	YES
Year Effects	YES	YES	YES
Country Fixed Effects	NO	NO	YES
Number of countries	82	82	82

Robust errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix E

Table 3.8. Sensitivity Analysis, Only Fixed Effects Regressions—With/Without Time Effects, With/Without Controls, Robust/Standard Errors. Dependent Variable, Log of GDP Per Capita.

VARIABLES	Model 1	Model 2	Model 3	Model 4
Public policy (inc. fiscal, monetary, structural…)	0.067***	0.070***	0.087***	0.087***
	(0.012)	(0.013)	(0.013)	(0.027)
Infrastructure (ICT & energy)	0.161***	0.164***	0.095***	0.095***
	(0.012)	(0.013)	(0.017)	(0.028)
Logistic Per. Index (trade & transp. infras.)	0.054***	0.053***	0.029***	0.029***
	(0.006)	(0.006)	(0.007)	(0.009)
Specialized skills	0.089***	0.092***	0.061***	0.061***
	(0.016)	(0.015)	(0.016)	(0.018)
Generalized skills	-0.027***	-0.027***	-0.018**	-0.018
	(0.009)	(0.009)	(0.009)	(0.014)
Financial infrastructure	0.030***	0.028**	0.025**	0.025**
	(0.011)	(0.011)	(0.011)	(0.012)
Financial environment	0.004	0.009	0.025***	0.025**
	(0.007)	(0.007)	(0.007)	(0.010)
Strength of financial regulations	0.032***	0.019*	0.010	0.010
	(0.011)	(0.011)	(0.011)	(0.018)
Enabling financial environment	0.001	0.001	0.002	0.002
	(0.005)	(0.005)	(0.005)	(0.005)
Base sci & tech	0.037***	-0.029	-0.028	-0.028
	(0.009)	(0.018)	(0.018)	(0.025)
Medium sci & tech	-0.009	-0.007	0.002	0.002
	(0.008)	(0.008)	(0.008)	(0.013)

VARIABLES	**Model 1**	**Model 2**	**Model 3**	**Model 4**
High sci & tech	-0.003	-0.002	0.001	0.001
	(0.006)	(0.006)	(0.006)	(0.006)
Social capacity (incl. equity, inclusion, etc.)	0.019	0.007	-0.001	-0.001
	(0.012)	(0.012)	(0.012)	(0.018)
Tech. coop. grants (st)		-0.022**	-0.017	-0.017
		(0.011)	(0.011)	(0.018)
Total population (st)		0.646***	0.388**	0.388
		(0.176)	(0.180)	(0.345)
Gross capital (st)		-0.014	0.035	0.035
		(0.044)	(0.045)	(0.063)
Incoming tourists' no. (st)		0.017*	0.021**	0.021
		(0.010)	(0.010)	(0.013)
Merch. imports frm HICs (st)		0.046***	0.058***	0.058***
		(0.012)	(0.012)	(0.022)
Net ODA/aid received (st)		0.004	-0.001	-0.001
		(0.009)	(0.009)	(0.019)
Health expenditure (st)		-0.052***	- 0.050***	-0.050***
		(0.009)	(0.009)	(0.016)
No. of employers (st)		0.023**	0.029***	0.029***
		(0.009)	(0.009)	(0.010)
YR2006			0.011	0.011
			(0.021)	(0.014)
YR2007			0.033	0.033*
			(0.021)	(0.017)
YR2008			0.053**	0.053***
			(0.022)	(0.017)
YR2009			0.040*	0.040*
			(0.022)	(0.022)

VARIABLES	**Model 1**	**Model 2**	**Model 3**	**Model 4**
YR2010			0.071***	0.071***
			(0.023)	(0.023)
YR2011			0.080***	0.080***
			(0.024)	(0.026)
YR2012			0.100***	0.100***
			(0.025)	(0.034)
YR2013			0.132***	0.132***
			(0.026)	(0.041)
YR2014			0.134***	0.134***
			(0.027)	(0.042)
YR2015			0.128***	0.128**
			(0.028)	(0.050)
YR2016			0.135***	0.135**
			(0.029)	(0.052)
YR2017			0.155***	0.155***
			(0.031)	(0.056)
YR2018			0.147***	0.147**
			(0.032)	(0.057)
YR2019			0.166***	0.166**
			(0.032)	(0.065)
Constant	7.241***	7.241***	7.149***	7.149***
	(0.004)	(0.004)	(0.020)	(0.032)
Observations	1,230	1,230	1,230	1,230
R-squared	0.407	0.448	0.468	0.468
Number of countryname1	82	82	82	82
Controls	NO	YES	YES	YES
Country Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	NO	NO	YES	YES
Errors	SE	SE	SE	Robust

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix F

Table 3.9. Regressions with Interactions. DV, Log of GDP Per Capita.

VARIABLES	Multiple Interaction	Single Interaction 1	Single Interaction 2	Single Interaction 3	Single Interaction 4
Public policy (inc. fiscal, monetary, struct., etc.)	0.082***	0.087***	0.085***	0.086***	0.082***
	(0.026)	(0.027)	(0.028)	(0.027)	(0.026)
Infrastructure (ICT & energy)	0.098***	0.096***	0.102***	0.094***	0.087***
	(0.025)	(0.028)	(0.026)	(0.028)	(0.027)
Logistic Per. Index (trade & transp. infras.)	0.028***	0.029***	0.030***	0.029***	0.025***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Specialized skills	0.053***	0.060***	0.056***	0.057***	0.065***
	(0.019)	(0.018)	(0.018)	(0.019)	(0.019)
Generalized skills	-0.015	-0.019	-0.016	-0.017	-0.018
	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Financial infrastructure	0.021*	0.026**	0.025**	0.026**	0.027**
	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)
Financial environment	0.026**	0.026**	0.025**	0.026**	0.025**
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
Strength of financial	0.011	0.011	0.011	0.010	0.007

VARIABLES	**Multiple Interaction**	**Single Interaction 1**	**Single Interaction 2**	**Single Interaction 3**	**Single Interaction 4**
regulations					
	(0.018)	(0.018)	(0.018)	(0.018)	(0.017)
Enabling financial environment	-0.001	0.001	0.001	0.002	0.001
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Base sci & tech	-0.007	-0.030	-0.023	-0.029	-0.030
	(0.028)	(0.026)	(0.025)	(0.025)	(0.024)
Medium sci & tech	0.000	0.003	0.004	0.003	0.001
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
High sci & tech	0.000	0.000	0.001	0.001	0.001
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Social capacity (incl. equity, inclusion, etc.)	0.005	0.001	-0.002	-0.002	-0.002
	(0.016)	(0.018)	(0.018)	(0.018)	(0.017)
Tech. coop. grants (st)	-0.014	-0.010	-0.010	-0.010	-0.019
	(0.024)	(0.016)	(0.020)	(0.018)	(0.018)
Total population (st)	0.217	0.382	0.335	0.306	0.181
	(0.371)	(0.344)	(0.350)	(0.361)	(0.338)
Gross capital (st)	0.086	0.039	0.029	0.045	0.065
	(0.074)	(0.064)	(0.064)	(0.066)	(0.063)
Incoming tourists' no. (st)	0.020	0.020	0.019	0.020	0.020*
	(0.015)	(0.013)	(0.013)	(0.013)	(0.012)
Merch. imports frm HICs (st)	0.063***	0.059***	0.059***	0.059***	0.060***
	(0.023)	(0.022)	(0.022)	(0.022)	(0.021)
Net ODA/aid received (st)	-0.009	0.001	-0.001	-0.004	0.011
	(0.021)	(0.020)	(0.019)	(0.019)	(0.022)
Health expenditure (st)	-0.048***	-0.049***	-0.049***	-0.048***	-0.050***

VARIABLES	**Multiple Interaction**	**Single Interaction 1**	**Single Interaction 2**	**Single Interaction 3**	**Single Interaction 4**
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
No. of employers (st)	0.029***	0.028***	0.028***	0.030***	0.027***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Public policy X Tech. coop. grants	0.026	0.014			
	(0.018)	(0.016)			
Infrastructure X_Tech. coop. grants	0.028		0.026**		
	(0.020)		(0.012)		
Logistic Per. Index X Tech. coop. grants	0.012			0.010*	
	(0.007)			(0.005)	
Specialized skills X Tech. coop. grants	0.017				
	(0.017)				
Generalized skills X Tech. coop. grants	0.026**				
	(0.011)				
Financial infrastructure X Tech. coop. grants	-0.023**				
	(0.011)				
Financial environment X Tech. coop. grants	-0.016*				
	(0.008)				
Strength of financial regu. X Tech. coop. grants	0.022*				
	(0.011)				

VARIABLES	**Multiple Interaction**	**Single Interaction 1**	**Single Interaction 2**	**Single Interaction 3**	**Single Interaction 4**
Financial enabling envir. X Tech. coop. grants	0.001				
	(0.005)				
Base sci & tech X Tech. coop. grants	-0.014*				
	(0.008)				
Medium sci & tech X Tech. coop. grants	-0.005				
	(0.006)				
High sci & tech X Tech. coop. grants	0.003				
	(0.006)				
Specialized skills X Net ODA/aid received					0.059***
					(0.021)
Constant	7.143***	7.147***	7.151***	7.145***	7.151***
	(0.033)	(0.032)	(0.032)	(0.032)	(0.032)
Observations	1,230	1,230	1,230	1,230	1,230
R-squared	0.489	0.469	0.470	0.470	0.482
Number of countries	82	82	82	82	82
Controls	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Errors	ROBUST	ROBUST	ROBUST	ROBUST	ROBUST

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix G

Table 3.10. Instrumental Variable Regressions. Dependent Variable, Log of GDP Per Capita.

VARIABLES	**Pooled OLS IV Regression**	**Fixed Effects L1 IV Regression**	**Fixed Effects L5 IV Regression**
Public policy (inc. fiscal, monetary, structural, etc.)	0.088***	0.075***	0.070*
	(0.030)	(0.027)	(0.041)
Infrastructure (ICT & energy)	0.390***	0.164***	0.173***
	(0.027)	(0.014)	(0.020)
Logistic Per. Index (trade & transp. infras.)	0.101***	0.050***	0.050***
	(0.018)	(0.006)	(0.009)
Specialized skills	0.205***	0.090***	0.067***
	(0.028)	(0.019)	(0.023)
Generalized skills	-0.089***	-0.030***	-0.019
	(0.014)	(0.011)	(0.014)
Financial infrastructure	0.085***	0.025*	0.017
	(0.019)	(0.013)	(0.017)
Financial environment	0.087***	0.011	0.018
	(0.020)	(0.010)	(0.013)
Strength of financial regulations	-0.047***	0.014	0.007
	(0.017)	(0.014)	(0.020)
Enabling financial environment	0.031***	0.003	-0.003
	(0.012)	(0.004)	(0.005)

VARIABLES	**Pooled OLS IV Regression**	**Fixed Effects L1 IV Regression**	**Fixed Effects L5 IV Regression**
Base sci & tech	-0.149***	-0.034	-0.022
	(0.037)	(0.024)	(0.024)
Medium sci & tech	-0.118***	-0.008	-0.003
	(0.021)	(0.010)	(0.013)
High sci & tech	-0.061***	0.000	0.003
	(0.016)	(0.006)	(0.008)
Social capacity (incl. equity, inclusion, etc.)	-0.115***	0.004	0.003
	(0.029)	(0.019)	(0.020)
Tech. coop. grants (st)	0.056***	-0.014	-0.021
	(0.020)	(0.015)	(0.023)
Total population (st)	-0.375***	0.667***	0.469**
	(0.069)	(0.173)	(0.199)
Gross capital (st)	0.538***	-0.002	0.067
	(0.068)	(0.040)	(0.052)
Incoming tourists' no. (st)	-0.063***	0.018**	0.002
	(0.019)	(0.009)	(0.011)
Merch. imports frm HICs (st)	0.157***	0.049***	0.040**
	(0.017)	(0.016)	(0.020)
Net ODA/aid received (st)	-0.084***	0.000	-0.027**
	(0.020)	(0.011)	(0.012)
Health expenditure (st)	-0.092***	-0.054***	-0.057***
	(0.014)	(0.016)	(0.018)
No. of employers (st)	0.029**	0.022**	0.015
	(0.014)	(0.009)	(0.011)
Constant	7.228***		
	(0.014)		

VARIABLES	**Pooled OLS IV Regression**	**Fixed Effects L1 IV Regression**	**Fixed Effects L5 IV Regression**
Observations	820	1,148	820
R-squared	0.813	0.416	0.290
Controls	YES	YES	YES
FE	YES	YES	YES
Errors	ROBUST	ROBUST	ROBUST
Number of countryname1	82	82	82

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix H

Table 3.11. Exploratory Factor Analysis Returned 12 Factors.[36] Factor Analysis Returned Factor Analysis Returned Factor Anal

Variable	**Specialized skills plus financial infras.**	**Public policy and social capacities**	**Overall infrastructure(1)**	**Base science & tech**	**Factor5**	**Factor6**	**Overall infrastruct-ure(2)**	**Legal rights strength**	**High sci & tech and infras.**	**Factor 10**	**Factor 11**	**Factor 12**
Sci & tech. articles	0.0207	0.0764	0.0517	**0.9397**	0.02	-0.0459	0.004	0.039	0.0585	0.033	0.0335	-0.0467
Intellectual payments (mil)	0.0329	0.0566	0.0536	**0.9234**	0.0514	-0.0352	0.0245	0.0537	0.03	0.0387	-0.0158	-0.0459
Voc. & tech. students (mil)	0.005	0.0832	0.2903	**0.6875**	0.1596	0.0503	-0.0821	-0.1692	-0.1118	-0.139	0.1024	-0.0174
R&D expend. % GDP	0.2173	0.1685	0.1221	0.3663	0.2231	0.0504	0.0388	0.068	0.1569	-0.1429	**0.4843**	-0.3093
R&D researchers (per mil)	0.328	0.0992	**0.5451**	0.0015	0.1015	0.1249	0.0934	0.3916	0.1507	-0.0245	-0.0859	-0.1545

[36] I do not name all the factors for space constraints. I generally name those factors which correspond to factors from confirmatory factor analyses. Factors loadings indicate correlations between latent factors in the first row and variables in the first column. The bold values indicate high values of correlation. Based on these values, the latent factor is named accordingly to represent the variables.

Variable	**Specialized skills plus financial infras.**	**Public policy and social capacities**	**Overall infrastructu-re(1)**	**Base science & tech**	**Factor5**	**Factor6**	**Overall infrastruct-ure(2)**	**Legal rights strength**	**High sci & tech and infras.**	**Factor 10**	**Factor 11**	**Factor 12**
R&D technicians (per mil)	0.0908	0.0007	0.0825	0.1298	0.1346	-0.0225	-0.0138	0.0363	**0.7312**	-0.1723	0.2262	-0.0566
High-tech exports (mil)	0.0855	0.0856	0.0007	0.0235	**0.8081**	0.1657	-0.0219	-0.0469	0.0516	-0.0493	0.0302	-0.0302
ECI (econ. complexity)	0.3267	0.2288	0.2594	0.1837	0.1177	-0.0963	-0.2111	0.385	**0.3713**	0.0908	-0.1736	0.2039
Tax revenue (% of GDP)	0.1016	0.0307	0.0013	0.0021	**0.8555**	0.0499	-0.0437	0.0359	0.0643	0.0905	-0.1068	0.0597
Business startup cost	0.3716	0.2756	0.0372	0.1592	0.1096	0.2865	-0.1796	-0.3803	0.3488	-0.0859	-0.124	0.0816
Domestic credit by banks	**0.5465**	0.326	0.0658	0.1413	0.101	0.3119	0.1963	0.2433	0.1902	0.0579	0.0298	0.0447
Days to start business	0.1513	0.2932	0.0005	0.0772	0.3535	**0.6143**	-0.1808	-0.3413	0.0105	0.0705	0.057	0.1574
Days enforcing contract	0.0294	0.2718	0.1481	0.3224	0.3195	**-0.4383**	-0.0012	-0.1728	0.0914	0.1731	0.1768	0.2891

Variable	**Specialized skills plus financial infras.**	**Public policy and social capacities**	**Overall infrastructu-re(1)**	**Base science & tech**	**Factor5**	**Factor6**	**Overall infrastruct-ure(2)**	**Legal rights strength**	**High sci & tech and infras.**	**Factor 10**	**Factor 11**	**Factor 12**
Days to register property	0.0391	0.2637	0.1273	0.0187	0.048	0.0284	-0.7394	-0.0157	0.0061	0.1617	0.1503	0.0742
Openness measure	0.1957	0.0423	0.0647	0.0714	0.087	**0.9246**	0.0289	0.0279	-0.0014	0.0635	-0.0348	0.0541
Days to electric meter	0.0215	0.1558	0.0188	0.0356	0.1806	-0.0752	-0.0645	0.0733	0.1203	0.1072	**0.7506**	0.0985
Business density	0.3393	0.0729	0.2593	0.1768	0.2736	0.0021	0.3118	0.0602	0.422	0.114	0.0838	-0.318
Financial accountholders	**0.5086**	0.0983	0.257	0.1135	0.2207	-0.0332	0.2937	-0.0833	-0.0063	0.0674	0.2658	0.1544
Commercial banks	**0.5589**	0.1767	0.657	0.0005	0.0077	0.0632	0.0569	0.0426	-0.0158	-0.0476	-0.0121	-0.0874
Primary enrollment (gross)	0.0508	0.1639	0.0299	0.0242	0.0639	0.0674	-0.0985	0.0561	-0.0499	**0.8715**	0.0324	0.0169
Sec. enrollment (gross)	**0.8638**	0.1875	0.27	0.0234	0.0282	0.0014	-0.0406	0.0044	0.023	0.1212	-0.0491	-0.024
Primary pupil-teacher ratio	**0.8053**	0.1067	0.0438	0.0308	0.109	-0.0176	0.0864	0.0597	-0.0444	0.0586	0.0797	0.1484

Variable	**Specialized skills plus financial infras.**	**Public policy and social capacities**	**Overall infrastructu-re(1)**	**Base science & tech**	**Factor5**	**Factor6**	**Overall infrastruct-ure(2)**	**Legal rights strength**	**High sci & tech and infras.**	**Factor 10**	**Factor 11**	**Factor 12**
Primary completion rate	**0.7638**	0.1652	0.1194	0.0598	0.0067	0.1846	-0.1491	0.1555	-0.0848	0.3245	0.0115	-0.0832
Govt. expend. on educ.	0.28	0.0695	0.2493	0.0028	0.3787	-0.0429	**-0.5468**	0.1275	-0.1532	0.0295	-0.1306	-0.1087
Human Capital Index 0-1	**0.7566**	0.2144	0.2217	0.0518	0.0144	0.2599	0.121	0.1856	0.0118	0.1465	-0.0874	0.0446
Advanced educ. labor	0.1669	0.1144	0.0384	0.1449	0.0477	0.1157	-0.0041	0.0347	-0.018	-0.0041	0.036	**0.8409**
Compulsory educ. (years)	0.296	0.1469	0.307	0.0351	0.0189	-0.0217	-0.0197	0.3526	0.0905	-0.5659	-0.0281	0.0414
Industry employment	**0.7342**	0.1636	0.0579	0.1594	0.076	-0.0566	0.0121	-0.1152	-0.0131	-0.1765	0.089	-0.0011
Service employment	**0.7784**	0.0005	0.0051	0.1305	0.0378	-0.1441	-0.1718	-0.1265	0.1481	-0.2116	0.1429	-0.0938
Mobile subscriptions	**0.5763**	0.2221	0.0222	0.0247	0.0267	-0.0502	0.4972	0.1907	-0.0375	-0.0176	0.0887	0.0305
Statistical	0.0353	**0.6782**	0.1537	0.1135	0.0117	-0.0401	0.3585	0.0849	-0.1397	0.0044	0.0338	-0.0091

Variable	**Specialized skills plus financial infras.**	**Public policy and social capacities**	**Overall infrastructu-re(1)**	**Base science & tech**	**Factor5**	**Factor6**	**Overall infrastruct-ure(2)**	**Legal rights strength**	**High sci & tech and infras.**	**Factor 10**	**Factor 11**	**Factor 12**
capacity 0-100												
Access to electricity	**0.8654**	0.2106	0.1639	0.0788	0.0229	0.0366	-0.008	0.088	-0.046	-0.0924	-0.014	-0.0517
Broadbamd subscriptions	**0.5305**	0.1346	0.3801	0.0513	0.0107	0.0425	0.1857	0.1755	0.4828	0.0226	-0.0711	0.0774
Telephone subscriptions	**0.6531**	0.2577	0.3271	0.0964	0.0411	0.0434	0.012	0.0131	0.3314	-0.0094	-0.1537	0.0028
Energy use	0.4826	0.0926	**0.6948**	0.0226	0.0753	0.056	0.0694	0.159	0.2115	0.0617	0.1077	-0.0202
Logistic perf. Index 1-5	0.1844	0.2732	0.0443	0.2637	0.0407	-0.0387	-0.0249	0.3029	-0.179	-0.1601	0.3084	0.0029
Internet users	**0.6748**	0.1579	0.2608	0.0186	0.0676	-0.0349	0.2516	0.1875	0.1365	-0.0852	0.022	0.0083
CPIA econ. mgmt.	0.0378	**0.8201**	0.0014	0.0857	0.0099	0.0206	-0.0848	0.0246	-0.0413	-0.0401	-0.0413	-0.0255
Public sect.	0.3208	**0.8169**	0.0329	0.0108	0.0365	-0.0148	-0.028	0.1423	0.136	0.0115	0.0328	0.0339

Variable	**Specialized skills plus financial infras.**	**Public policy and social capacities**	**Overall infrastructu-re(1)**	**Base science & tech**	**Factor5**	**Factor6**	**Overall infrastruct-ure(2)**	**Legal rights strength**	**High sci & tech and infras.**	**Factor 10**	**Factor 11**	**Factor 12**
mgmt. & instit												
Structural policies	0.2167	**0.7876**	0.0149	0.143	0.0023	-0.0597	0.0427	0.0767	0.2125	-0.0359	0.1076	-0.0057
Legal Rights Index 0-12	0.0344	**0.1705**	0.0886	0.0418	0.0543	-0.019	0.0045	0.7368	0.0773	-0.0011	0.125	0.0483
Human resources rating	0.3217	**0.7402**	0.0807	0.0924	0.0582	-0.0466	0.2279	0.0154	0.0583	0.1122	-0.0252	0.0445
Equity of public resc use	0.0769	**0.8575**	0.0149	0.1193	0.0254	0.0661	0.0035	0.0786	-0.1037	0.0571	0.0064	0.0451
Social protection rating	0.1675	**0.8214**	0.1794	0.0012	0.0914	-0.0318	-0.0101	-0.0613	0.007	-0.0348	0.1504	-0.017
Social inclusion	0.2522	**0.9065**	0.1324	0.0621	0.0204	0.0495	0.0975	0.0526	-0.0139	0.0981	0.0036	0.0399
National headcount poverty	**0.541**	0.2239	0.0882	0.0619	0.0164	-0.1677	-0.1796	-0.0981	0.0002	0.082	-0.1755	-0.1342
Social contributions	0.3156	0.1568	0.7707	0.0253	0.0372	0.0386	-0.0585	-0.0897	-0.1406	-0.0584	0.0198	0.0164

Appendix I

Table 3.12. Sensitivity Analysis Regressions with Robust Errors Including Factors from Exploratory Factor Analysis. Dependent Variable, Log of GDP Per Capita.[37]

VARIABLES	**Pooled OLS**	**Random Effects**	**Random Effects**
specialized skills plus financial infras.	0.523***	0.236***	0.149***
	(0.015)	(0.027)	(0.032)
Public policy and social capacities	0.076***	0.115***	0.098***
	(0.012)	(0.025)	(0.031)
Overall infrastructure	0.154***	0.078***	0.050***
	(0.010)	(0.014)	(0.014)
Base science & tech	-0.290***	0.014	0.025
	(0.034)	(0.022)	(0.026)
Scores for factor 5	-0.037***	0.017	0.017
	(0.009)	(0.010)	(0.010)
Scores for factor 6	0.088***	0.022	0.020
	(0.014)	(0.014)	(0.015)
Overall infrastructure	0.024*	0.020*	0.021*
	(0.015)	(0.012)	(0.012)
Legal rights strength	0.051***	0.042***	0.036***
	(0.014)	(0.009)	(0.010)
High science & tech and infras.	0.057***	0.044***	0.033***
	(0.011)	(0.009)	(0.012)
Scores for factor 10	-0.059***	-0.008	-0.000
	(0.011)	(0.015)	(0.015)
Scores for factor 11	0.030**	0.008	0.008
	(0.012)	(0.007)	(0.007)
Scores for factor 12	-0.053***	0.000	0.005
	(0.011)	(0.008)	(0.008)
	(0.012)	(0.010)	(0.010)
Constant	7.266***	7.169***	7.140***
	(0.050)	(0.067)	(0.027)

[37] I do not name all the factors. I generally name those factors which are significant and correspond to factors from confirmatory factor analyses.

VARIABLES	**Pooled OLS**	**Random Effects**	**Random Effects**
Observations	1,230	1,230	1,230
R-squared	0.793	0.706	0.448
Controls	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Country Fixed Effects	NO	NO	YES
Errors	Robust	Robust	Robust
Number of countries	82	82	82

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix J

Table 3.13. Sensitivity Analysis: Regressions with SEs. DV, Log of GDP Per Capita.

VARIABLES	Pooled OLS	Random Effects	Fixed Effects
Public policy (inc. fiscal, monetary, structural…)	0.098***	0.077***	0.087***
	(0.021)	(0.013)	(0.013)
Infrastructure (ICT & energy)	0.371***	0.134***	0.095***
	(0.026)	(0.017)	(0.017)
Logistic Per. Index (trade & transp. infras.)	0.100***	0.037***	0.029***
	(0.016)	(0.007)	(0.007)
Specialized skills	0.240***	0.111***	0.061***
	(0.022)	(0.016)	(0.016)
Generalized skills	-0.081***	-0.030***	-0.018**
	(0.013)	(0.009)	(0.009)
Financial infrastructure	0.109***	0.037***	0.025**
	(0.019)	(0.011)	(0.011)
Financial environment	0.047***	0.023***	0.025***
	(0.013)	(0.007)	(0.007)
Strength of financial regulations	-0.045***	0.010	0.010
	(0.014)	(0.011)	(0.011)
Enabling financial environment	0.036***	0.003	0.002
	(0.012)	(0.005)	(0.005)
Base sci & tech	-0.179***	-0.023	-0.028
	(0.034)	(0.019)	(0.018)
Medium sci & tech	-0.127***	-0.001	0.002
	(0.017)	(0.009)	(0.008)
High sci & tech	-0.061***	-0.002	0.001

VARIABLES	Pooled OLS	Random Effects	Fixed Effects
	(0.014)	(0.006)	(0.006)
Social capacity (incl. equity, inclusion, etc.)	-0.128***	0.004	-0.001
	(0.022)	(0.013)	(0.012)
Constant	7.329***	7.181***	7.149***
	(0.045)	(0.045)	(0.020)
Observations	1,230	1,230	1,230
R-squared	0.799	0.727	0.468
Controls	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Country Fixed Effects	NO	NO	YES
Number of countries	82	82	82

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix K

Table 3.14. Sensitivity Analysis: Data Averaged over 5 Years Period. Dependent Variable, Log of GDP Per Capita.

VARIABLES	**Pooled OLS**	**Random Effects**	**Fixed Effects**
Public policy (inc. fiscal, monetary, structural…)	0.100***	0.071***	0.080***
	(0.022)	(0.024)	(0.026)
Infrastructure (ICT & energy)	0.363***	0.150***	0.122***
	(0.025)	(0.019)	(0.021)
Logistic Per. Index (trade & transp. infras.)	0.095***	0.043***	0.038***
	(0.016)	(0.007)	(0.007)
Specialized skills	0.242***	0.120***	0.076***
	(0.024)	(0.018)	(0.018)
Generalized skills	-0.083***	-0.032**	-0.022
	(0.012)	(0.015)	(0.014)
Financial infrastructure	0.109***	0.038***	0.027**
	(0.017)	(0.013)	(0.012)
Financial environment	0.050***	0.018*	0.018*
	(0.015)	(0.010)	(0.010)
Strength of financial regulations	-0.045***	0.014	0.016
	(0.014)	(0.018)	(0.018)
Enabling financial environment	0.035***	0.003	0.001
	(0.011)	(0.005)	(0.005)
Base sci & tech	-0.179***	-0.020	-0.028
	(0.034)	(0.024)	(0.026)
Medium sci & tech	-0.124***	-0.003	-0.001
	(0.017)	(0.012)	(0.012)
High sci & tech	-0.061***	-0.004	-0.001

VARIABLES	Pooled OLS	Random Effects	Fixed Effects
	(0.014)	(0.006)	(0.005)
Social capacity (incl. equity, inclusion, etc.)	-0.127***	0.006	0.002
	(0.023)	(0.019)	(0.018)
period = 2010-15	-0.049	0.040**	0.054***
	(0.030)	(0.019)	(0.018)
period = 2015-19	-0.096***	0.056*	0.077**
	(0.036)	(0.031)	(0.033)
Constant	7.289***	7.209***	7.198***
	(0.024)	(0.061)	(0.016)
Observations	1,230	1,230	1,230
R-squared	0.799	0.729	0.458
Controls	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Country Fixed Effects	NO	NO	YES
Robust Standard Errors	YES	YES	YES
Number of countries	82	82	82

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

CHAPTER FOUR: ABSORPTIVE CAPACITIES AND K-MEAN CLUSTER ANALYSIS OF LOW- AND MIDDLE-INCOME ECONOMIES

Abstract: Chapter 3 analyzed the relationship between the estimated capacity factors and economic growth while controlling for potential confounders. Results highlighted the criticality of infrastructure, public policy, finance, and specialized human capital. This chapter conducts K-means cluster analysis and then analyzes the results alongside regression estimates to glean patterns and classifications within the LMICs. The analysis classifies LMICs into five categories: leading, walking, creeping, crawling, and sleeping economies. I find that capacities and economic growth are higher in leading economies, followed by creeping, crawling, and sleeping economies. The analysis suggests that while LMICs may look similar from the outside, each LMIC has unique characteristics. The analysis also confirms that LMICs follow different development paths - some may build infrastructure capacity first, whereas others may strengthen their technological capacities.

1. Introduction

Chapter 3 found pooled coefficient estimates for 82 LMICs. One outcome of the chapter is a set of significant capacities that matter more in LMICs. Now to what extent these capacities vary within LMICs is unknown. This observation makes a researcher ask important questions. For instance, what is the development pattern within LMICs? Is there any variation within LMICs, or are they a homogenous set of countries? Are they following similar paths of development? Does a one-size-fits-all approach apply to LMICs? Finally, what should be the course of strategic policy choices for LMICs? To answer these questions, I conduct cluster analysis using the *Kmeans* algorithm. In particular, cluster analysis in this chapter helps probe the estimates from Fixed Effects models (as found in Chapter 3, also published in Khan 2022) in a disaggregated fashion and glean patterns out of data for policy implications.

2. K-Means Cluster Analysis

Kmeans algorithm, an unsupervised machine learning tool and analysis approach (Ni et al. 2021). As an iterative algorithm, the *Kmeans* algorithm divides a dataset based on cluster variables into *k* clusters by minimizing intra-cluster variation while keeping the clusters as far as possible. Whereas a researcher chooses cluster variables based on pre-defined criteria for classification, to arrive at an optimal *k-number* (number of clusters) for analysis, one may follow a well-established *Elbow's approach*, explained in Makles (Makles 2012). According to this approach, when k-numbers are unknown, a researcher repeatedly clusters data using a pre-defined number of clusters (Ks). Every time clustering is repeated, intra-cluster variation (i.e., within cluster sum of square or WSS) is recorded. Then the cluster solutions (Ks) are plotted against WSS. From this set of solutions, a researcher chooses the one (optimal k*-cluster solution) that leads to the maximum reduction in WSS. At k*, usually, the plot shows a kink or elbow. Sometimes, the elbow is not apparent, in which case a researcher keeps on clustering by changing initial conditions (random number). The kink, alongside other statistics, eventually helps decide in choosing the k* solution.

2.1 Dataset: For this chapter, I use a subset of the dataset from Chapter 2 composed of the latest 5-year averages (between 2015 and 2019) because it allows for a study of challenges and policy considerations currently faced by LMICs.

2.2 Cluster variables: To investigate how far countries differ and if they can be clustered to allow us to see a larger picture of the capacity trends in a comparative manner among LMICs, I choose four significant capacity factors (one per each significant capacity) extracted in Chapter 3. These four capacity factors, termed cluster variables for the k-means analysis, include the public policy factor, infrastructure capacity factor showing general infrastructure in ICT and energy, a human capacity factor of specialized skills, and financial capacity infrastructure factor.

***2.3 Number of clusters**:* Using the Elbow approach (Makles 2012), explained earlier, I find evidence for 5 clusters (I have included Scree plots, Appendix Figures 4.7 and 4.8, and other diagnostic statistics, Appendix Tables 4.3 and 4.4, for two repeated clusterings).[38]

3. Results

For the 5-cluster solution obtained above, I plot a scatterplot matrix (Figure 4.1 below) of the four standardized factors.

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[38] I perform repeated clustering by changing initial condition. In most cases, at k=5, the WSS, log(WSS), and PRE show a kink (plots and statistics in Appendix F, Figures 4.7-4.8 and Table 4.3-4.4). While the kink in the WSS is less obvious, it is more visible in the log(WSS) and PRE. This naked eye test has to be viewed in conjunction with other statistics. For instance, η2 shows a reduction of the WSS by 75% and PRE5 to a reduction of about 88%, which is considerably higher reduction when compared with the k = 4 or k = 3 solution. However, the reduction in WSS is very small for k > 5. Where η2 for a k measures the proportional reduction of the WSS for each cluster solution k compared with the total sum of squares (TSS), PREk illustrates the proportional reduction of the WSS for cluster solution k compared with the previous solution with k − 1 clusters (Makles, 2012)

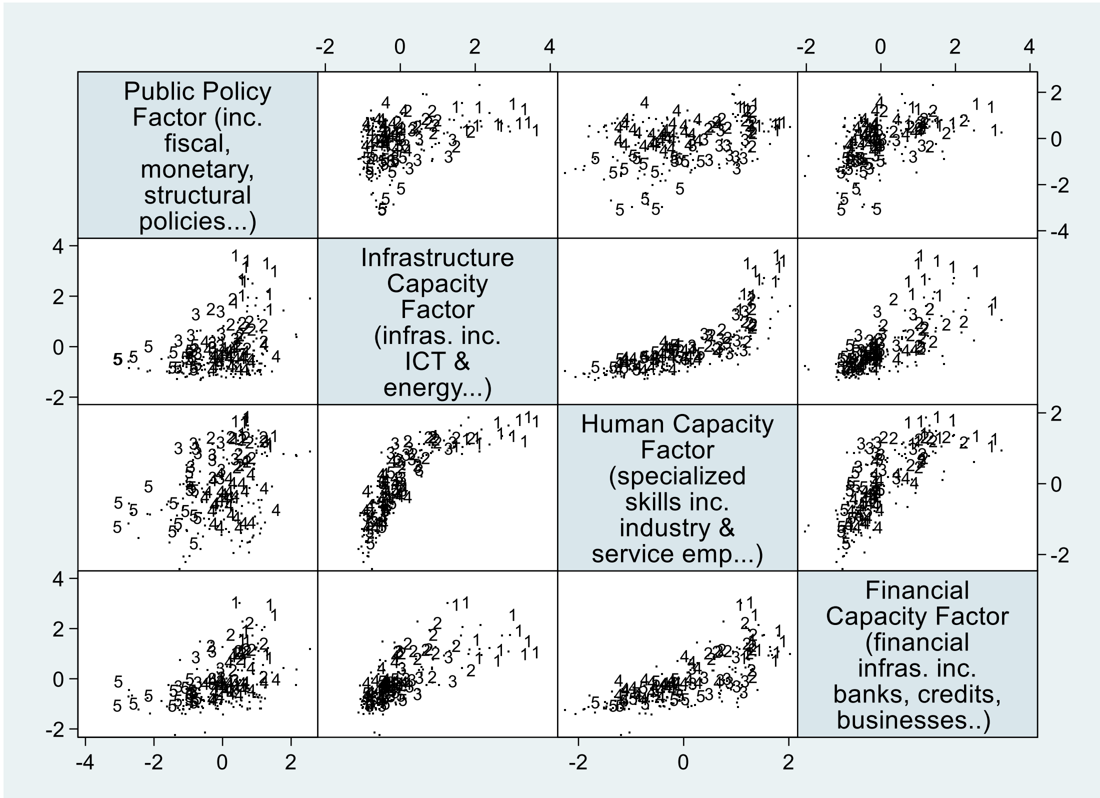

Figure 4.1: Scatterplot matrix of four capacity factors for the five-cluster solution. 1s are leaders, 2s are walkers, 3s are creepers, 4s are crawlers, and 5s are sleepers.

The scatterplot shows five groups of LMICs. Some countries or groups of countries (aka clusters) are doing better than others on the four capacity factors. While naming these clusters, I borrowed some vocabulary from the neurodevelopmental phases of human life. After all, just like humans and their bodies' neurodevelopment and thought progression, these countries are also undergoing development phases in their lifetime as part of the global world. Hence, the names of the clusters are *leading, walking, creeping, crawling,* and *sleeping*.[39] High-developed LMICs are in the leading and walking clusters, whereas lower developed LMICs are in the sleeping and crawling groups. Creeping economies are the limping middle-category countries trying to catch up with the walking and leading economies. These clusters and their respective countries are shown below in Table 4.1 below.

Table 4.1: LMICs Divided into 4 Clusters Following a *Cluster Analysis* (*K-means*)

Clusters	No. of countries	Countries (2015-2019)
1. Leading	11	Mongolia Kosovo Moldova St. Vincent and the Grenadines Grenada Bosnia and Herzegovina Georgia St. Lucia Dominica Vietnam Armenia
2. Walking	13	Tonga Sri Lanka Uzbekistan Bhutan Nepal Samoa Cabo Verde Bolivia

[39] The naming order shows a progression such that **leading>walking>creeping>crawling>sleeping**. All categories are intuitive. However, readers may rightly be confused about creeping and crawling as they are used interchangeably in everyday life. However, they are distinct neurodevelopmental stages. Creeping is level 3 in mobility after crawling, which is level 2 (please see this link: https://www.domaninternational.org/blog/creeping-a-vital-developmental-stage). In other words, creeping is higher than crawling. In crawling, the body is in contact with the surface and in creeping it is raised above the floor (McGraw 1941).

Clusters	No. of countries	Countries (2015-2019)
		Cambodia Kyrgyz Republic India Maldives Honduras
3. Creeping	12	Timor-Leste Myanmar Marshall Islands Micronesia, Fed. Sts. Tuvalu Tajikistan Guyana Sao Tome and Principe Bangladesh Nicaragua Kiribati Lao PDR
4. Crawling	30	Togo Sierra Leone Solomon Islands Djibouti Nigeria Senegal Zambia Kenya Malawi Lesotho Tanzania Mali Gambia, The Mozambique Papua New Guinea Liberia Madagascar Mauritania Burkina Faso Vanuatu Ghana Guinea Cote d'Ivoire Pakistan Uganda

Clusters	No. of countries	Countries (2015-2019)
		Benin Ethiopia Cameroon Rwanda Niger
5. Sleeping	16	Congo, Dem. Rep. Chad Angola Zimbabwe Haiti Burundi Congo, Rep. Yemen, Rep. Afghanistan South Sudan Guinea-Bissau Eritrea Comoros Somalia Central African Republic Sudan

The table shows that many countries (30) are in the crawling cluster while the least number of countries (11) is in the leading cluster. In the next step, I calculate the mean scores of the select four factors for all the clusters listed in Table 1. Results of Cluster K-means by clusters are shown below in Table 4.2 (detailed descriptive statistics for each cluster are in Appendix B).

Table 4.2: Mean Scores of Select Four Factors and Economic Growth in Five Clusters.

Clusters	Public Policy Factor (inc. fiscal, monetary, structural policies...)	Infrastructure Capacity Factor (infras. inc. ICT & energy)	Human Capacity Factor (specialized skills inc. industry & service employment)	Financial Capacity Factor (financial infras. inc. banks, credits, business...)	Total Score by each cluster	Log of GDP Per Capita	Log of GDP Per Capita Growth
Leading (11)	0.855	2.6503	1.451	1.667	6.624	8.5	3.16
Walking (13)	0.590	0.731	1.030	1.118	3.469	7.81	3.13
Creeping (12)	-0.431	0.334	0.719	0.047	0.670	7.51	1.01
Crawling (30)	0.248	-0.397	-0.418	-0.220	-0.786	6.94	0.844
Sleeping (16)	-1.444	-0.447	-0.619	-0.660	-3.170	6.8	-1.29
Total (82)	-0.045	0.288	0.189	0.198	1.361	7.24	2.13

4. Discussion

The first cluster comprises 16 *sleeping* economies from East Africa, North and Central Africa, and other regions. These economies primarily suffer from severe internal conflicts and disasters, and they exhibit poorly developed public policy capacity, general infrastructure, financial apparatus, as well as human capital, and social capacities. The second cluster, consisting of 30 countries from Africa and a South Asian country (Pakistan), distinguishes itself from the sleeping cluster by having relatively better public policy capacity, some specialized skills, and financial apparatus. While their public policy capacity is better than that of sleeping economies, their general infrastructure (energy and ICT infrastructure) is roughly the same. Since they have somewhat better capacities than sleeping economies (score of -0.786>score of -3.270), they are "awake" and in a developmental phase.

The "*creeping*" cluster consists of 12 economies, including South American (Guyana), Central American (Nicaragua), former Soviet republics (Tajikistan), South Asian (Bangladesh), Southeast Asian (Lao PDR, Myanmar, Timor-Leste), and small oceanic countries (the Marshall Islands and Tuvalu, among others). Their ICT and energy infrastructure, human capacity factor, and finance infrastructure are higher than that of the crawling and sleeping economies. However, their public policy factor is not fully developed, being higher than that of the sleeping countries but lower than that of the crawling countries. This result is a little surprising. Despite the fact that their public policy score is overall low (and lower than crawlers), creepers are still in a higher developmental stage (above the crawlers), as evidenced in their higher economic growth. I explain this partly by advancements in other capacities: because the creepers have higher finance, infrastructure, and human capacities than the crawlers, their overall development and economic growth are higher than the crawlers. To further understand this somewhat surprising result, it helps to draw an analogy from neurodevelopment. Just like the deliberate progressive movement of the older baby whose overall neural organization is of higher order is distinct from the newborn infants' crawling movements, creeping economies with an average higher capacities score are "developing" distinctly than the crawling economies. This result also demonstrates the fact that countries do not develop linearly. Some countries have better infrastructure and finance; others have strong public policy and human capacity factors. While capacities impact economic growth and their average effect varies in different countries, overall, a country is developing more if it enhances all or most of its capacities.

Then there is a group of 12 economies, which includes former Soviet Republics, South American countries, and South Asian countries, including India and Sri Lanka. They are better than all the above cases. They have reasonably good public policy, finance, infrastructure, and specialized skills. Since they are certainly in better shape than creeping and crawling, I call them "walking" economies for the sake of this analysis.

Lastly, there is a "*leading*" cluster of 11 economies from East Europe, East Asia, and the Caribbean. These economies are the best of the lot, with much more advanced capacities than elsewhere.

I have calculated the mean of the log of GDP per capita (and its growth) for each group (last two columns of Table 5). The data show leading economies have the highest economic growth, followed by walking, and then creeping, crawling, and lastly, sleeping economies.

This simple analysis bears evidence that countries with higher capacities have higher economic growths. I further demonstrate this in the following scatterplots of significant capacity factors plotted against the log of per capita GDP. The scatterplots include linear fit lines and shaded grey areas to indicate 95% CI. Figure 4.2 - Figure 4.5 plots individual factors against the economic growth, whereas Figure 4.6 plots a capacity factor index against GDP per capita. Again, I constitute the index by simply taking the average of the four significant factors.

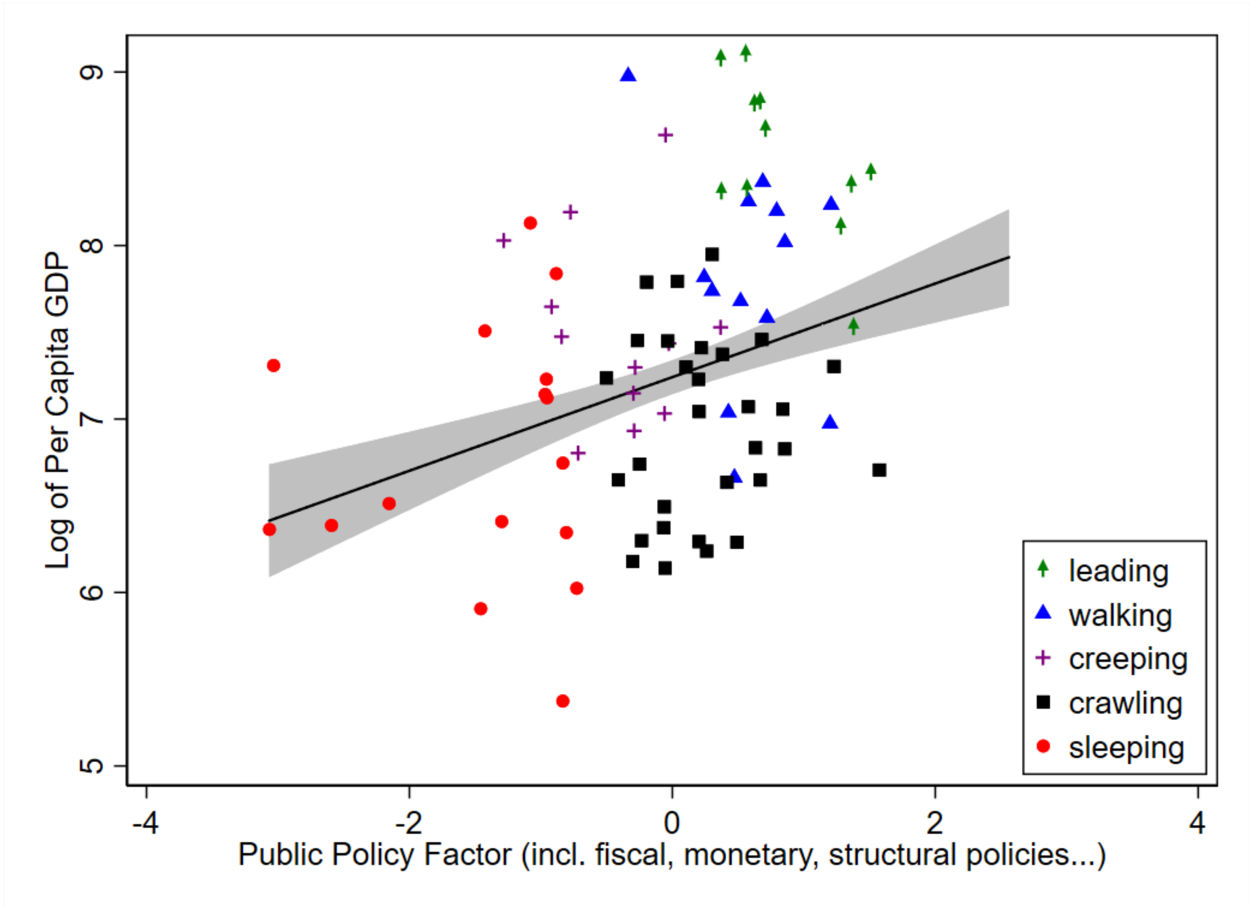

Figure 4.2: Public Policy Capacity and Economic Growth in LMICs

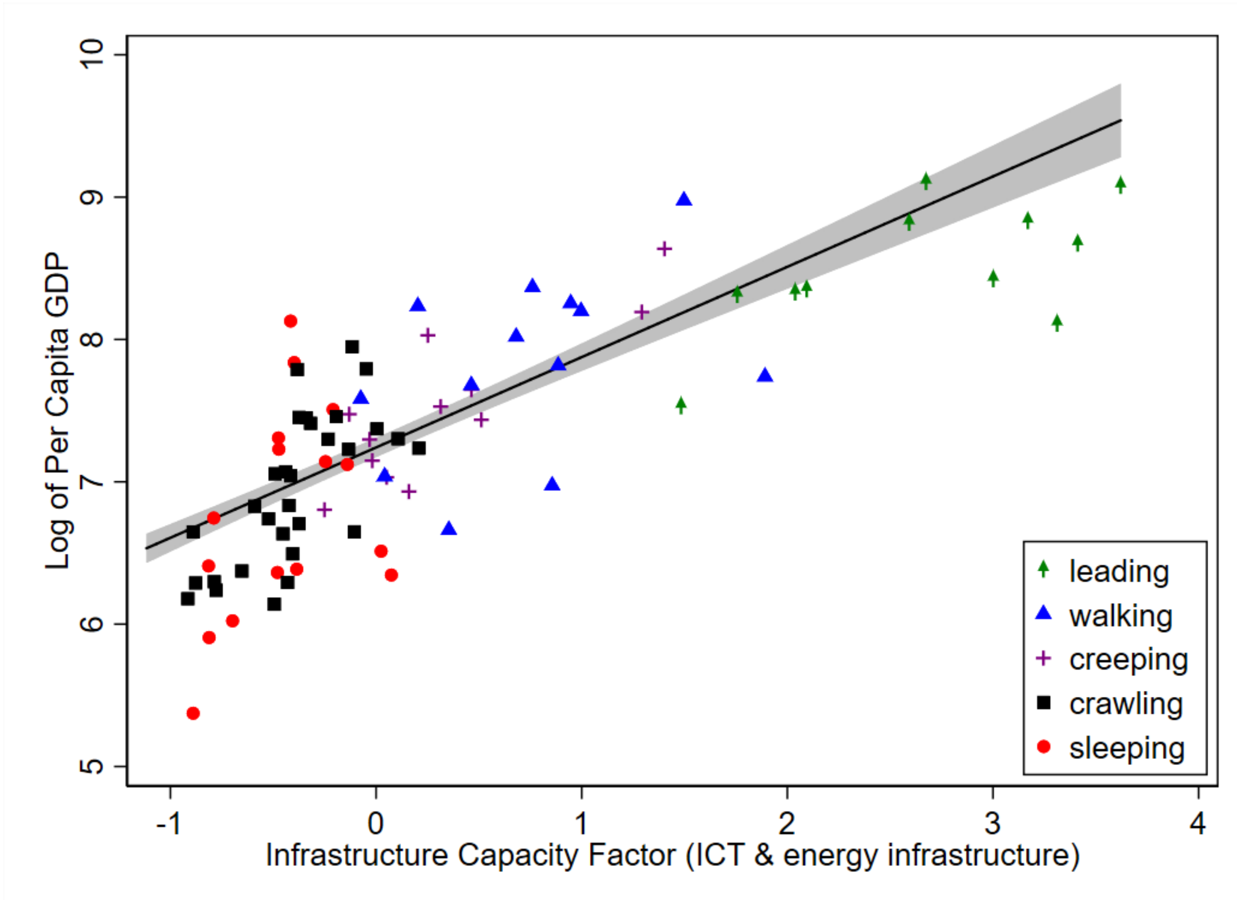

Figure 4.3: Infrastructure Capacity and Economic Growth in LMICs

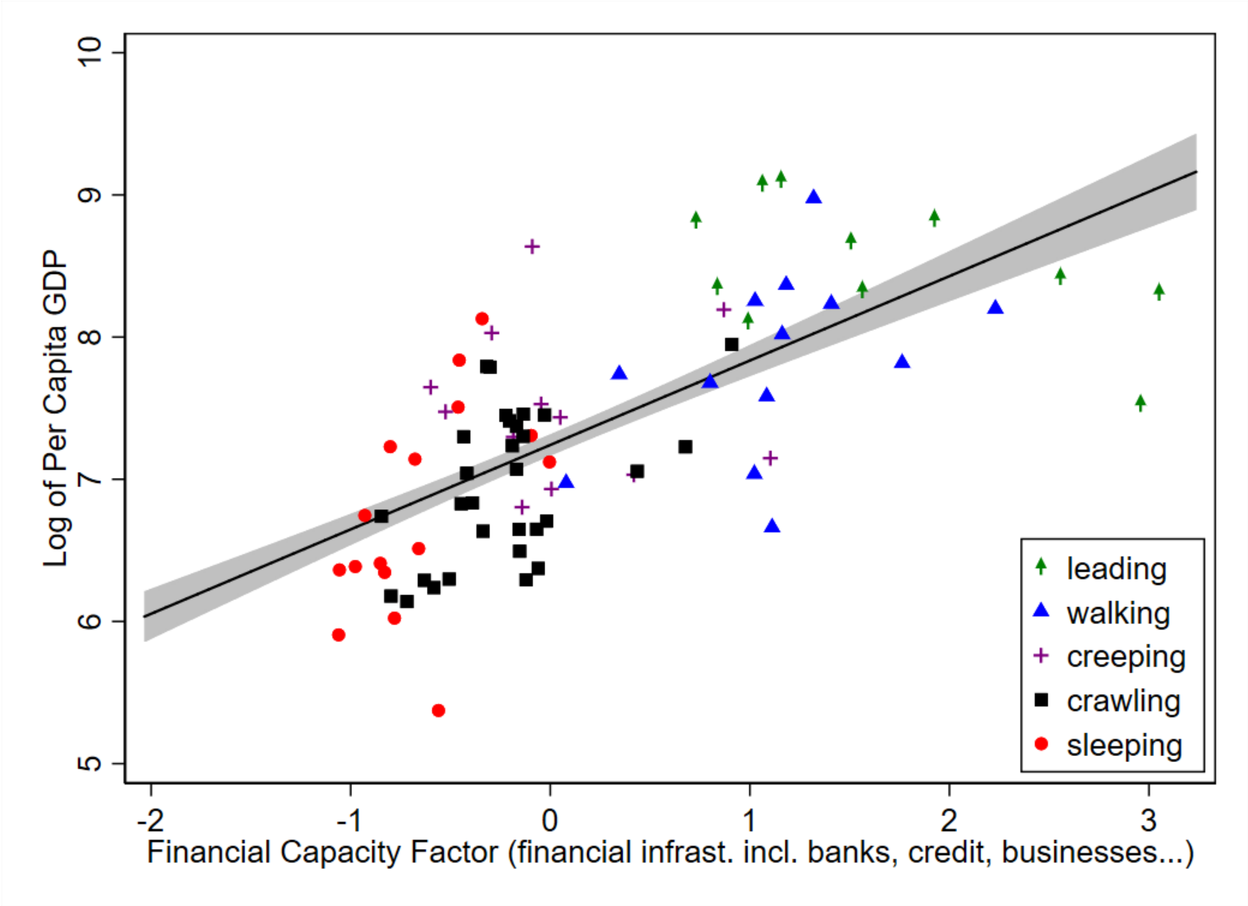

Figure 4.4: Financial Capacity and Economic Growth in LMICs

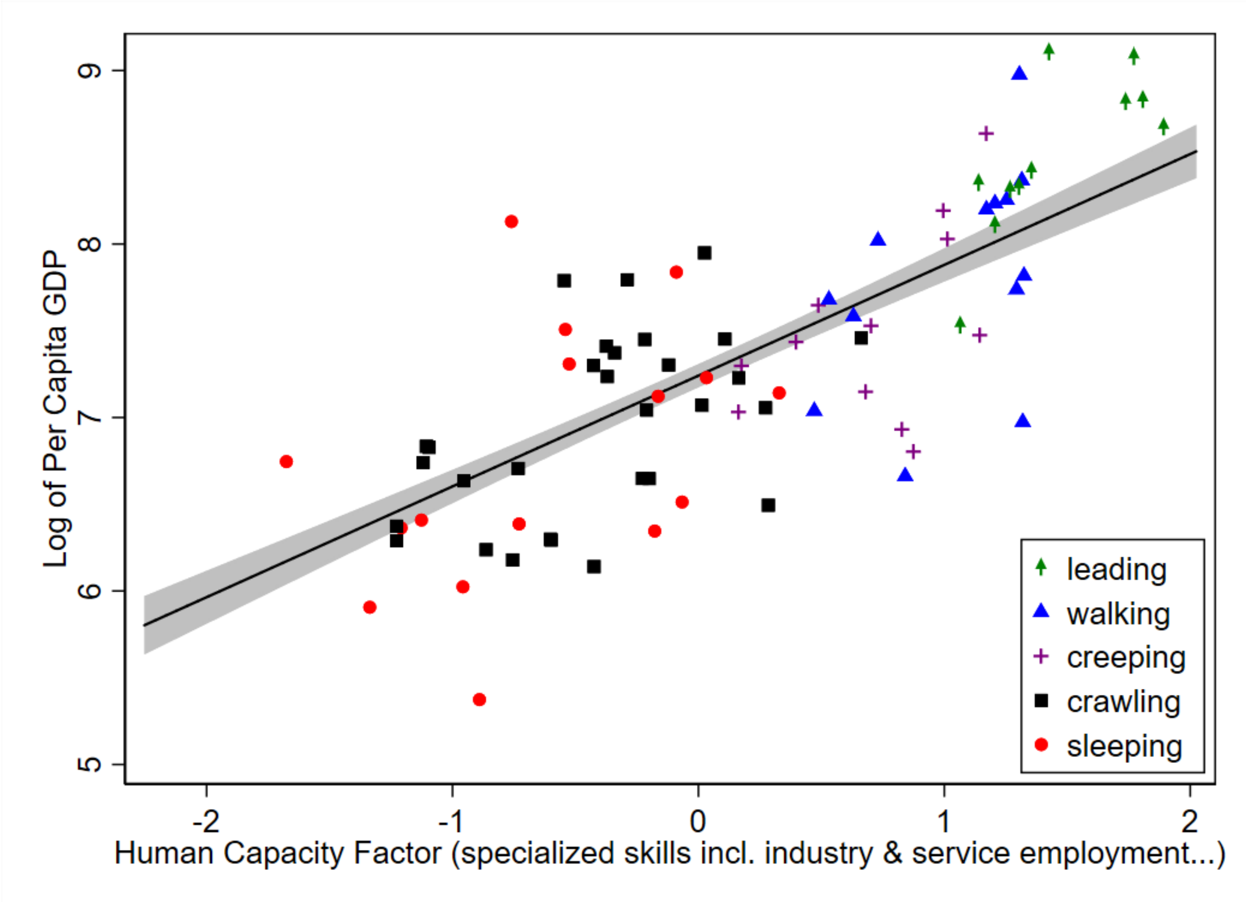

Figure 4.5: Human Capital Capacity and Economic Growth in LMICs

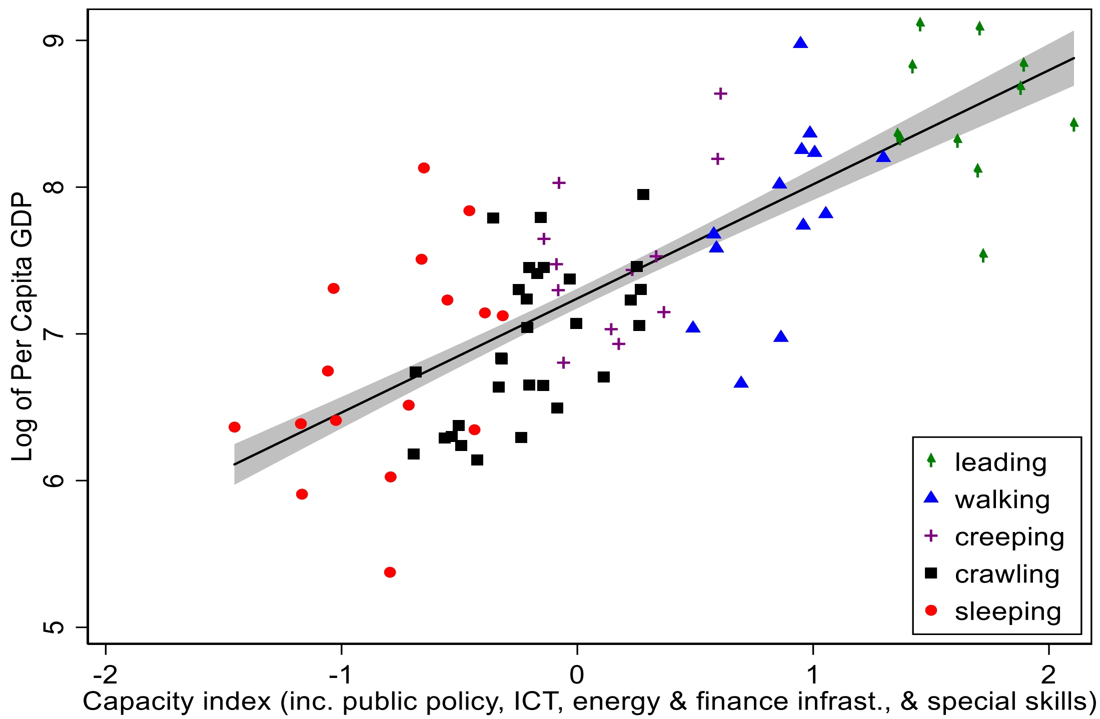

Figure 4.6: Capacity factors Index and Economic Growth in LMICs

The above scatter plots further visually demonstrate the effects of positive and significant capacities on economic growth in LMICs. On one end, there are leading and walking economies. Leading economies are developing their capacities. Walking economies are following the lead of leading economies. On the other end, there are sleeping and crawling economies. While crawling economies are showing some signs of development, sleeping economies are not yet able to overcome the many hurdles and challenges they face. Finally, right in between these two ends are creeping economies. Creeping economies are higher in the hierarchy than crawling. It seems like they are on track to achieve better capacities; however, they still need to put in an extensive effort to catch up with walking economies.

Putting data from plots here and Fixed Effects results in Chapter 3 side-by-side, it is evident that on a granular level, some capacities matter more for economic growth in LMICs. Generally speaking, countries with higher capacity scores indeed show higher economic growth. With higher capacity and economic growth, leading countries provide examples for the other economies on how they advanced on the development ladder.

A striking observation from my analysis is that countries follow different development patterns even if they are at the same level of development. While, on average, the data and figures point to a gradient in terms of economic growth and significant capacity factors, some countries are walking but still at par with leading countries at least for some capacity factors (see diffused markers or alternating markers on the scatter plots, Figure 4.2-Figure 4.6). Similarly, some crawling countries are at par with creeping economies, and likewise, creeping economies are at par with walking economies (again, notice diffused markers on the scatter plots, Figure 4.2-Figure 4.6). This is not to say that there are not five distinct groups. Instead, some groups are pooled together for some capacity factors, while overall, they differ in some other capacity factors, thus leading to five separate and distinct groups.

Nonetheless, the diffused markers may demonstrate two things: firstly, many countries, like babies in the development phase, crawl first and then creep; however, a few countries creep first and then crawl later, and some creep and crawl together. In other words, creeping and crawling, which manifests itself in economic growth, is impacted by various capacities in distinct ways. This may also mean that some countries have relatively advanced infrastructure than public policy and vice versa. Others have more advanced finance infrastructure than specialized skills and vice versa. Because of this relative strength of various capacity factors, diffusion in groups is observed. This observation, in turn, calls for heterogeneity in policy when dealing with or building the capacities of LMICs.

Since the average economic growth differences between the clusters (particularly those nearer to each other) are not large, the second observation, which is more of a hypothesis, is that some economies may have been transitioning from one group to another. A cross-country movement (transition analysis) from one group to another over time that incorporates the capacities as I have demonstrated here certainly makes a case for an interesting study. Such a study will reveal whether capacities help countries transition (or graduate) from one development stage to another. This analysis will also indicate whether or not countries are getting better in terms of developing these capacities.

5. Conclusions

The analysis shows that despite multiple similarities among LMICs, they are not a homogenous group of countries. Therefore, international policymakers should build targeted and heterogenous policy choices related to funding the programs, operations, and projects in LMICs. Similarly, the analysis indicates that development is not a linear process: like the neurodevelopment processes, an LMIC may either crawl or creep first. A country's development movement is contingent upon multiple factors, including its entrepreneurial spirit, cultural preferences, learning profile, and location within this highly globalized world. This observation does not underestimate the fact that the key ingredients to development lie in advancing capacities, although LMICs may prefer to prioritize one capacity over another, subject to their socioeconomic circumstances, political preferences, and the current development level in each capacity.

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Appendix A: Figure 4.7. and Table 4.3.

The Elbow Rule suggests that 5 clusters solution is an optimal solution. Figure 4.7. is produced at seed 1011. This figure shows at k=5, a large drop occurs in the Within Sum of Square (Intra Cluster Variation)

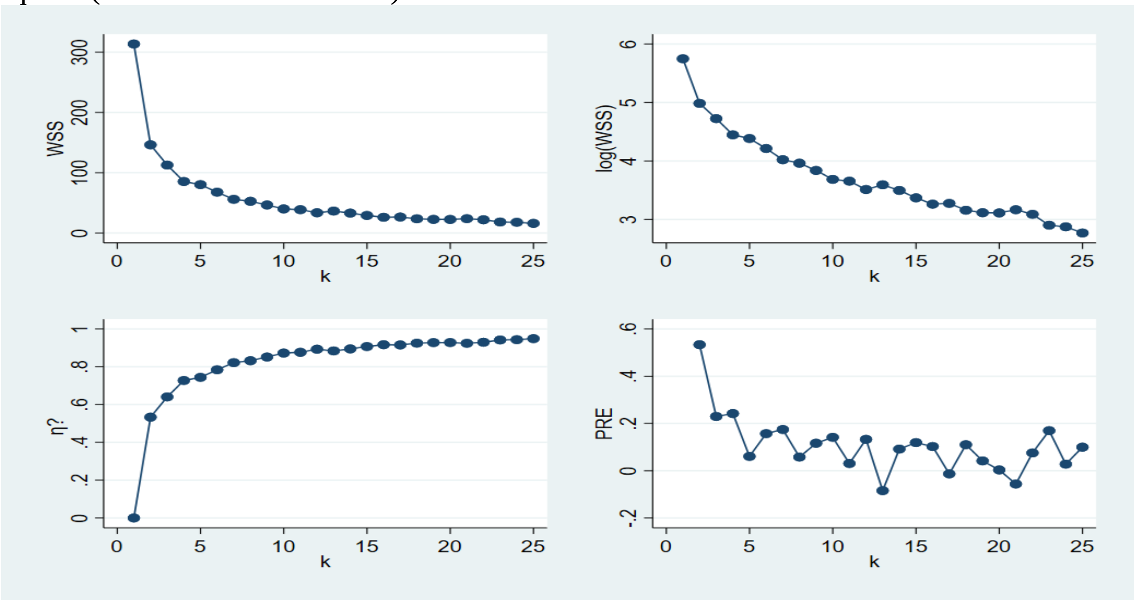


Figure 4.7. WSS, log(WSS), η2, and PRE for all K cluster solutions (seed 1011)

Table 4.3. Corresponding matrix list with Seed 1011.
The table shows the highest drop in WSS at k=5. To learn more about all the diagnostics in the table, refer to (Makles 2012).

WSS[25,5]					
	k	WSS	log(WSS)	eta-squared	PRE
r1	1	313.51995	5.747863	0	.
r2	2	146.26096	4.9853924	.53348756	.53348756
r3	3	112.68659	4.7246104	.64057602	.22955114
r4	4	85.396229	4.4473019	.72762107	.24217929
r5	5	80.222239	4.3848008	.74412397	.06058804
r6	6	67.619651	4.2138986	.78432106	.15709594
r7	7	55.816877	4.0220763	.82196706	.17454651
r8	8	52.592082	3.9625656	.83225284	.05777455

Output terminated

Appendix A: Figure 4.8. and Table 4.4

The Elbow Rule suggests that 5 clusters solution is an optimal solution. Figure 4.8. is produced at seed 789. This figure shows at k=5, a large drop occurs in the Within Sum of Square (Intra Cluster Variation)

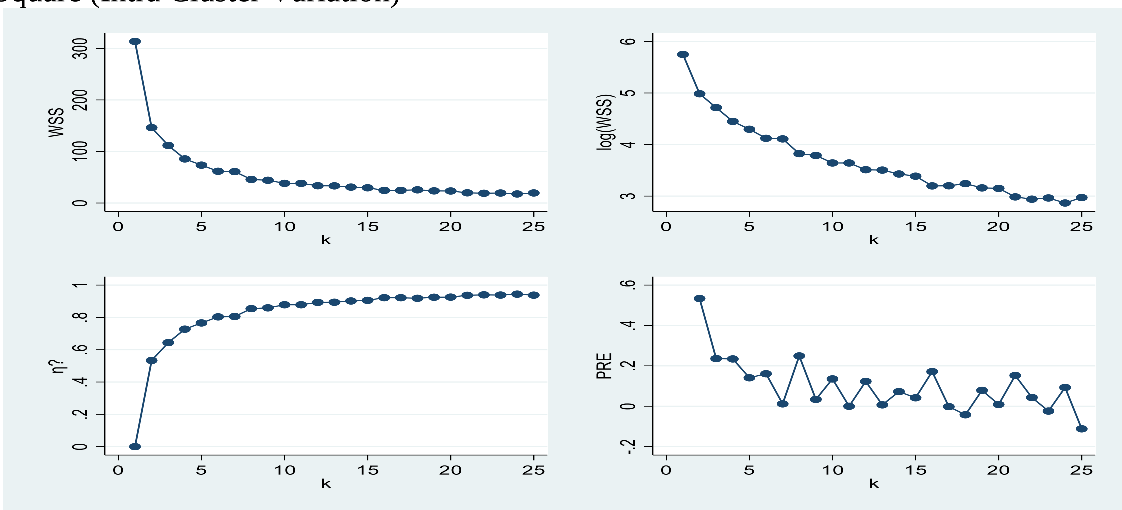


Figure 4.8. WSS, log(WSS), η2, and PRE for all K cluster solutions (generated with random number 789)

Table 4.4. Corresponding matrix list with Seed 789.
The table shows the highest drop in WSS at k=5. To learn more about all the diagnostics in the table, refer to (Makles 2012).

WSS[25,5]					
	k	WSS	log(WSS)	eta-squared	PRE
r1	1	313.52	5.747863	0	.
r2	2	146.261	4.985392	0.533488	0.533488
r3	3	111.7259	4.716048	0.64364	0.23612
r4	4	85.541	4.448996	0.727159	0.234367
r5	5	73.47712	4.296974	0.765638	0.14103
r6	6	61.65221	4.121509	0.803355	0.160933
r7	7	60.91858	4.109538	0.805695	0.011899
r8	8	45.7367	3.822901	0.854119	0.249216
r9	9	44.18006	3.788274	0.859084	0.034035

Output terminated

Appendix B

Table 4.5. Detailed Descriptive Statistics of Five Clusters Within LMICs.

CAPACITY FACTORS AND LMICs CLUSTERS	N	Mean	SD	Min	Max
1. LEADING ECONOMIES					
Public Policy Factor (incl. fiscal, monetary, structural policies…)	11	.85	.43	.37	1.51
Infrastructure Capacity Factor (infras. inc. ICT & energy…)	11	2.65	.72	1.48	3.62
Human Capacity Factor (specialized skills inc. industry, service employment…)	11	1.45	.3	1.06	1.89
Financial Capacity Factor (financial infras. inc. banks, credit, businesses…)	11	1.67	.84	.73	3.05
2. WALKING ECONOMIES					
Public Policy Factor (incl. fiscal, monetary, structural policies…)	13	.59	.41	-.34	1.21
Infrastructure Capacity Factor (infras. inc. ICT & energy…)	13	.73	.56	-.07	1.89
Human Capacity Factor (specialized skills inc. industry, service employment…)	13	1.03	.33	.47	1.32
Financial Capacity Factor (financial infras. inc. banks, credit, businesses…)	13	1.12	.55	.08	2.23
3. CREEPING ECONOMIES					
Public Policy Factor (incl. fiscal, monetary, structural policies…)	12	-.43	.47	-1.28	.37
Infrastructure Capacity Factor (infras. inc. ICT & energy…)	12	.33	.53	-.25	1.4
Human Capacity Factor (specialized skills inc. industry, service employment…)	12	.72	.35	.16	1.17
Financial Capacity Factor (financial infras. inc. banks, credit, businesses…)	12	.05	.51	-.6	1.1
4. CRAWLING ECONOMIES					
Public Policy Factor (incl. fiscal, monetary, structural policies…)	30	.25	.49	-.5	1.57
Infrastructure Capacity Factor (infras. inc. ICT & energy…)	30	-.4	.29	-.92	.21
Human Capacity Factor (specialized skills inc. industry, service	30	-.42	.49	-1.23	.66

CAPACITY FACTORS AND LMICs CLUSTERS	N	Mean	SD	Min	Max
employment…)					
Financial Capacity Factor (financial infras. inc. banks, credit, businesses…)	30	-.22	.38	-.85	.91
5 SLEEPING ECONOMIES					
Public Policy Factor (incl. fiscal, monetary, structural policies…)	16	-1.44	.81	-3.07	-.73
Infrastructure Capacity Factor (infras. inc. ICT & energy…)	16	-.45	.3	-.89	.07
Human Capacity Factor (specialized skills inc. industry, service employment…)	16	-.62	.56	-1.68	.33
Financial Capacity Factor (financial infras. inc. banks, credit, businesses…)	16	-.66	.32	-1.06	-.01

CHAPTER FIVE- ABSORPTIVE CAPACITY AND ECONOMIC DEVELOPMENT: COMPARING PAKISTAN WITH BANGLADESH

Abstract: This chapter conducts qualitative case study research through interviews and content analyses to ascertain the impact of absorptive capacity on economic growth in Pakistan and Bangladesh. A shared origin and colonial history provide a basis for their simultaneous analysis. Despite a similar origin, Bangladesh surpasses Pakistan in various economic parameters. Here I argue that Bangladesh developed a learning mindset and opened its doors to the world. Alongside strengthening its local capacities in education, information and communications technology (ICT) infrastructure, public policy, and social capacity, the country developed its brand and marketed itself as a favorable investment destination. As a result, its textile-based industry progressed, bringing significant foreign reserves to the country. All these provide valuable lessons to Pakistan, whose economic conditions are precarious.

1. What is absorptive capacity?

While I explained the concept of absorptive capacity in previous chapters, it bears repeating that absorptive capacity refers to the ability of a firm to recognize the value of new and external information, then assimilate this information, and finally apply it to commercial ends (Cohen and Levinthal 1990; Zahra and George 2002; Apriliyanti and Alon 2017). In this dissertation, I extend the concept to the national level in a low- and middle-income country (LMIC). On a national LMIC level, the adjective 'absorptive' implies that an LMIC absorbs 'knowledge from abroad.' It then utilizes the knowledge to create (economic) value subject to the strength of its local conditions (capacities). Thus, absorptive capacity includes both incoming flows (knowledge and technology, for example) and existing on-the-ground conditions (capacities). In case an LMICs' capacities are strong enough, it will absorb (or improvise on) the incoming knowledge and technology and hence convert the learning gained into economic value. In short, the absorptive capacity concept considers a nation a learning entity and emphasizes the processes of diffusion, imitation, and active knowledge consolidation and management. I use this conception of absorptive capacity in this chapter.

2. Situating this chapter in the dissertation scheme

In earlier chapters, I discuss the need for more holistic absorptive capacity approaches to analyze innovation and development processes in LMICs. I also build a framework of absorptive capacity applicable to the unique circumstances of LMICs and test the framework with secondary (quantitative) data collected and formulated using cutting-edge statistical multiple imputation techniques. Finally, I classify LMICs into five clusters to examine trends for policy implications: leading, walking, limping, crawling, and sleeping economies. I observe that economic growth and capacities are higher in leading economies, followed by walking, limping, crawling, and sleeping economies, respectively. Overall, the findings highlight the criticality of infrastructure, finance, skilled human capital, and public policy capacities to enhance economic growth. Incoming flows and skills are also found to be relevant for economic growth in LMICs. In contrast to the existing research for developed countries where technological and social capacities impact growth, I examine that such capacities do not impact growth in poor countries.

In this chapter, I switch from the focus on quantitative analyses and conduct qualitative case study research through interviews and content analyses in Pakistan and Bangladesh to add nuance to quantitative findings. The case study design, employed in many disciplines (Crowe et al. 2011), allows for in-depth study of complex issues in real-life settings (Yin 2009). By capturing information on more explanatory 'how', 'what' and ‘why’ questions, this chapter’s case studies further probe and add context to the quantitative analyses conducted in earlier chapters.

3. Methods of analysis - interpretivist approach

This case study design mainly employs interpretivist approach for analysis, which involves a researcher interpreting elements of the study (Ryan 2018; Leitch, Hill, and Harrison 2010). According to this approach, reality can be accessed through social constructions such as language, shared meanings, and instruments (Myers 2008). In such an approach, a researcher serves as a social actor appreciating differences between people (Saunders, Lewis, and Thornhill 2007). This approach aims to understand the events of interest and generate meanings from them, which are time and context-dependent. The researcher seeks information on what specific actors do, their constraints, and how they deal with issues. As opposed to quantitative (often ‘positivist’) analysis, the interpretivist approach may lead to multiple realities and meanings.

The interpretivist approach has both pros and cons. It generally leads to data that may have a high level of validity because data in such studies is more trustworthy (Rahman 2016). However, the drawback of the interpretivist approach is its subjective nature. The primary data generated in this context may not be generalized since it could be highly influenced by personal viewpoint (Rahman 2016). Thus, reliability and representativeness can be compromised to some extent.

4. Case selection for this study

For case selection, I use *collective* case study strategy in this chapter. The strategy entails examining multiple cases concurrently or successively to generate broader appreciation of a particular issue (Stake 1995). A collective case strategy permits comparisons or replication across several cases. According to Yin (2009), selecting a "standard" case may allow the findings to be generalized to theory or to test the theory by replicating the findings in a second or a third case. One may choose two or three cases (that may predict similar results) provided the theory is straightforward and five or more if the theory is nuanced, Yin (2009) suggests. Here I choose two cases for pragmatic and policy considerations that may validate the *average* or *aggregate* findings from quantitative chapters (priors).[40]

The population for the case selection includes 82 low- and middle-income countries (LMICs), eligible for the World Bank's International Development Association (IDA) support between 2005 and 2019. In Chapter 4, I perform cluster K-means analysis (based on statistically significant variables from chapter 3), which classifies LMICs into five categories mentioned earlier. The framework in this dissertation is not as straightforward. There exists variation among LMICs, as established in Chapter 4. Therefore, a more comprehensive design would pick five countries, one from each category in the classification. However, for pragmatic concerns and other Covid-19 restrictions that prevent travel, this chapter focuses on two countries, one from *creeping* (Bangladesh) and

[40] I plan to include three more cases in the future study.

the other from *crawling* economies (Pakistan). A number of *empirical* (Chowdhury, Khan, and Chen 1976; Naeem and Welford 2009; Ahmad, Khan, and Tariq 2012; Hazir et al. 2013; Asadullah 2009) and *theoretical* studies (Fazal 1999; Armstrong and Barton 1999; Zafarullah and Akhter 2001; Miller 1984) in various fields have examined the two countries together. For instance, one study measures the extent to which corporate social responsibility (CSR) contributes to sustainable development in Bangladesh and Pakistan (Naeem and Welford 2009). The study finds that companies in both countries fail to engage with many aspects of CSR, including deficiencies related to child labor, community giving and the formal representation of workers. These studies serve as a precedent for my study.

Figure 5.1: Countries in South Asia. Source: World Bank

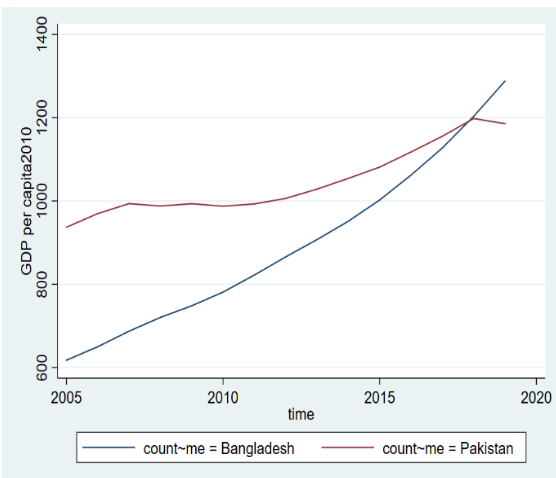
Besides guidance from the k-means analysis, I choose Pakistan and Bangladesh for many reasons. First, Pakistan (then West Pakistan) and Bangladesh (then East Pakistan) used to be one country, which split into two in the early 1970s. Because of their common origin and shared colonial history, Bangladesh and Pakistan have similar initial administrative, executive, and bureaucratic setups. It will be interesting to examine where the two countries stand with respect to their absorptive capacities after about 50 years of separation.

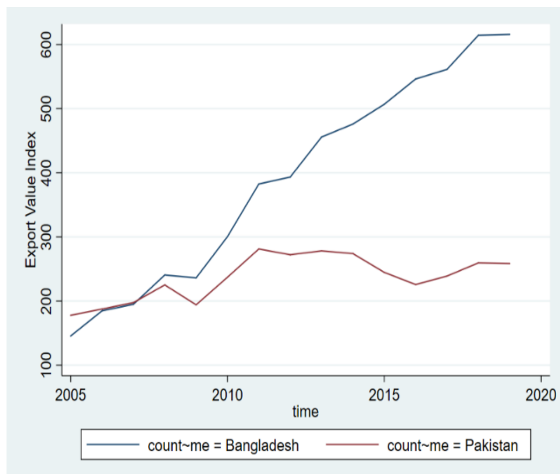
Secondly, Pakistan and Bangladesh are similar in multiple aspects. Both countries have majority Muslim populations. Religion influences culture in these countries in numerous ways. Most of their festivals fall on the same days. People in both countries have the same zeal for sports (cricket is a popular sport). The countries are geographically located in South Asia (Figure 5.1) and have comparable demographics (high population density and more young people). Table 5.1 lists details about the two countries' attributes.

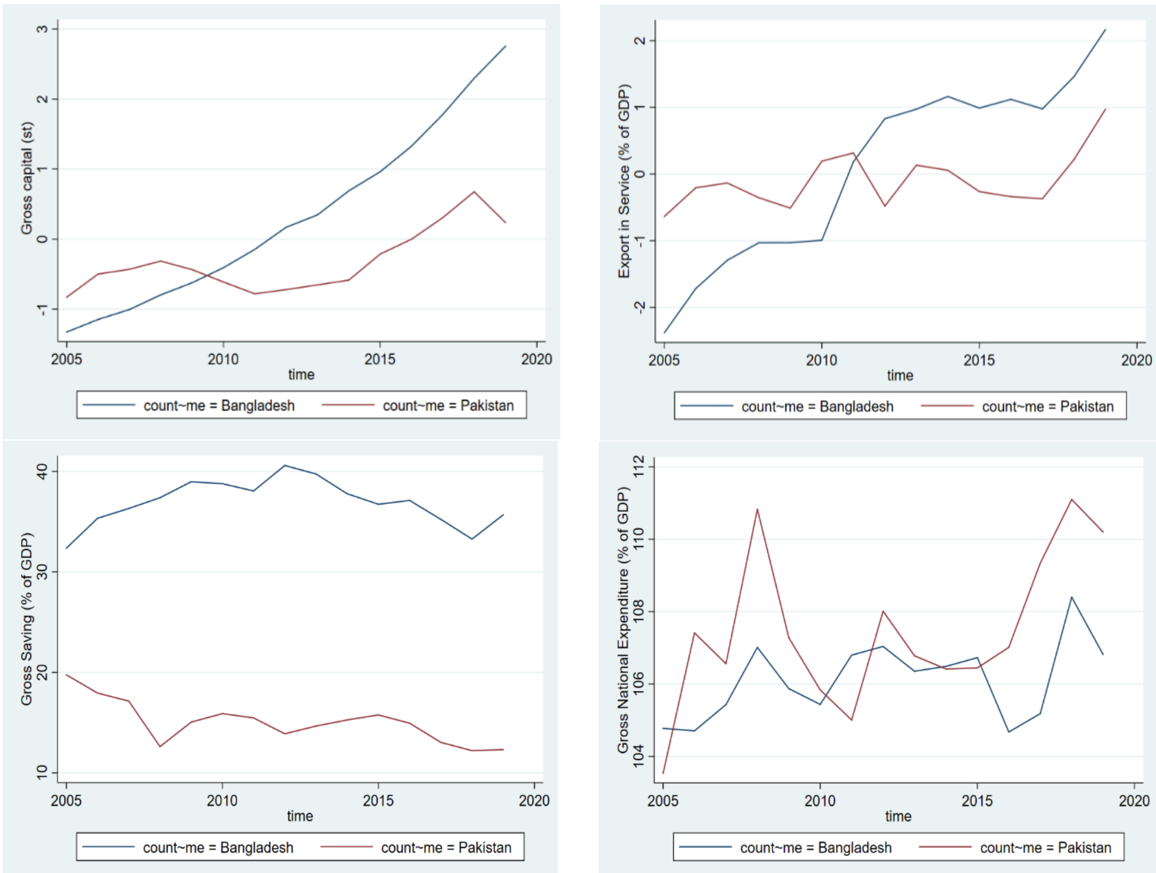
Table 5.1: Details about Pakistan and Bangladesh

Attribute	**Pakistan**	**Bangladesh**
Religion	Islam (over 95% Muslims)	Islam (over 89% Muslims)
Culture	Islamic	Islamic
Location/Geography	South Asia	South Asia
Population	220.9 million (2020)	164.7 million (2020)
Population density	742 per mile-sq (2022) High population density	3,277 per mile-sq (2022) High population density
Median age	22.8 years (2022)	27.6 years (2022)
GDP	263.7 billion dollar (2020) World Bank	324.2 billion dollar (2020) World Bank
GDP per capita (current US $)	1,188.86 USD (2020) World Bank	1,961.61 USD (2020) World Bank
GDP per capita (constant 2015 US $)	1,446.81 USD (2020) World Bank	1,643.67 USD (2020) World Bank

Third, the two countries make an excellent case choice because, despite similarities and shared origin, the two countries have considerable differences in economic parameters. In fact, Bangladesh outperforms Pakistan across all typical economic parameters. For example, a GDP of $324 billion, compared to Pakistan's GDP of $263.7 billion, makes Bangladesh one of the largest LMICs. Similarly, Bangladesh ($1,961.6) has higher GDP per capita than Pakistan ($1,188.8) in 2020. Figures (5.2-5.7) below show some economic indicators in which Bangladesh is doing better than Pakistan.







Figures 5.2-5.7: Economic Indicators of Bangladesh vs. Pakistan

The last reason the two countries make a good choice for the study is convenience in access to subjects in both countries. The investigator hails from Pakistan and has connections with Bangladesh experts, making investigating the two countries easier.

5. Descriptive observations from prior data

As I noted in earlier chapters, the national absorptive capacity framework entails a number of dimensions, including six capacities alongside incoming factors from abroad. These dimensions, in turn, are composed of several variables (a summary of descriptive stats is shown in Appendix Table in Chapter 3). Here I construct six composite indices of capacities, *incoming factors index,* and an *aggregate absorptive capacity index* from standardized data (instead of factors derived from principal component analysis) to get an overview of dimensions in Bangladesh and Pakistan. Figures (5.8-5.15) show these dimensions plotted side-by-side for both countries.

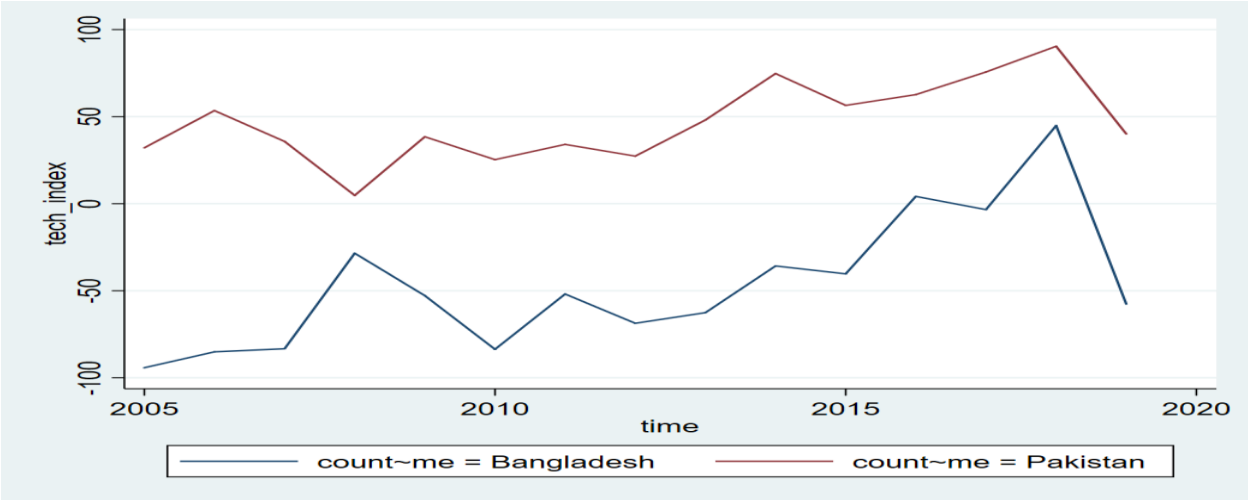


Figure 5.8: Technological capacity index for Bangladesh and Pakistan (2015-2019)

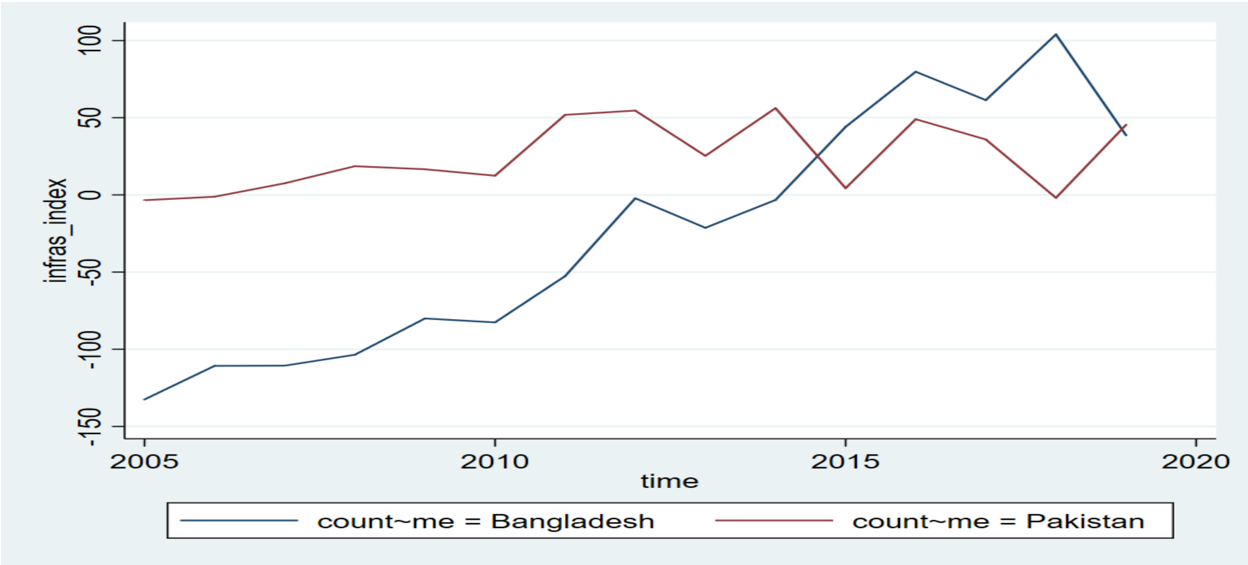


Figure 5.9: Infrastructure capacity index for Bangladesh and Pakistan (2015-2019)

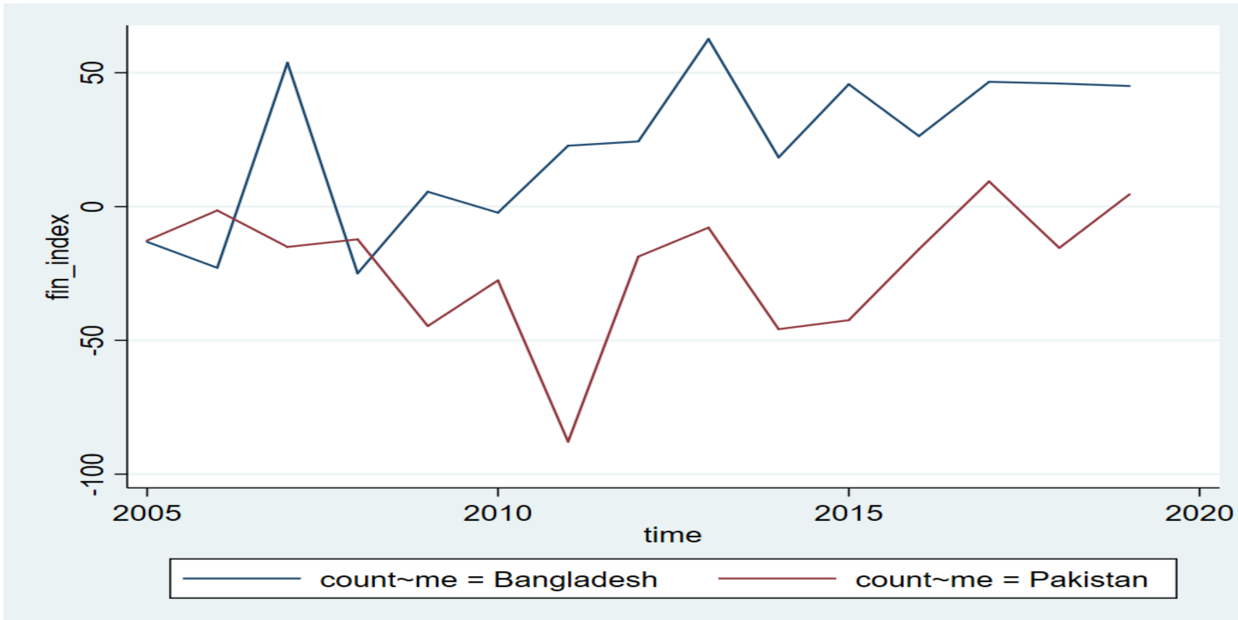


Figure 5.10: Financial capacity index for Bangladesh and Pakistan (2015-2019)

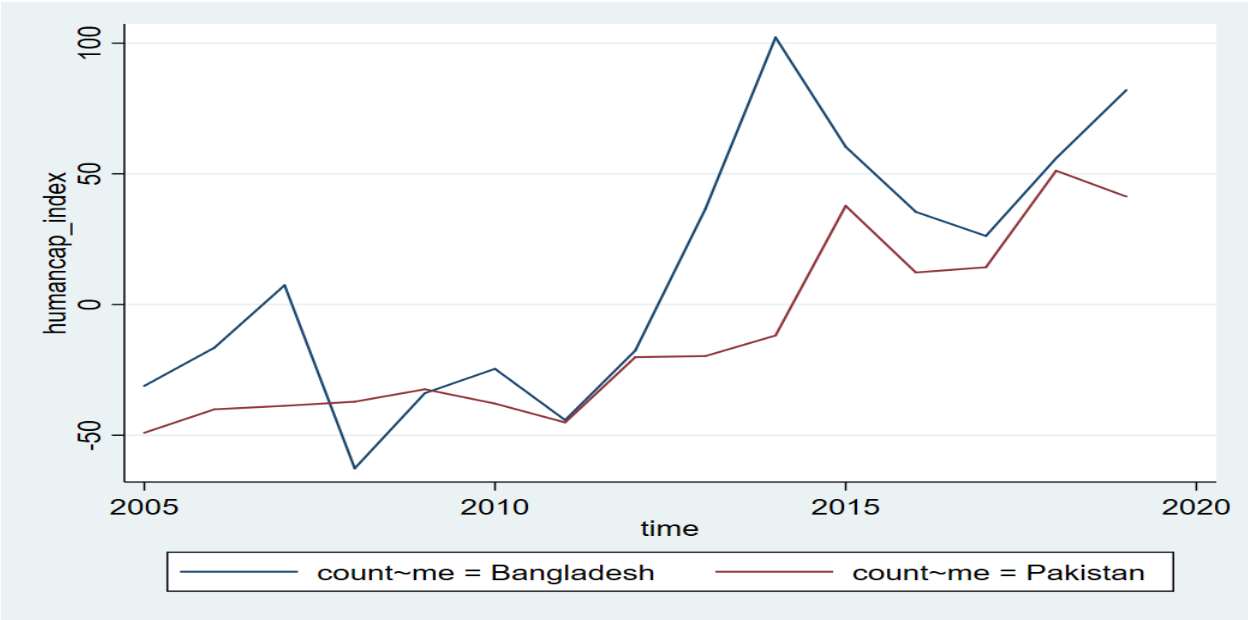


Figure 5.11: Human capacity index for Bangladesh and Pakistan (2015-2019)

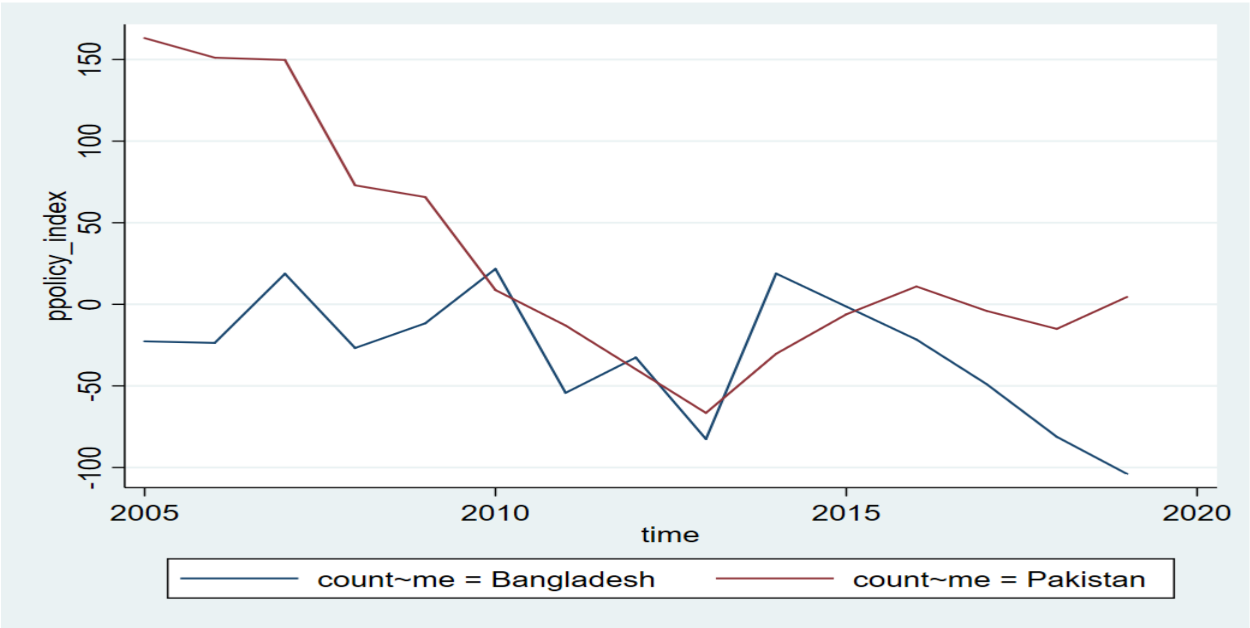


Figure 5.12: Public policy capacity index for Bangladesh and Pakistan (2015-2019)

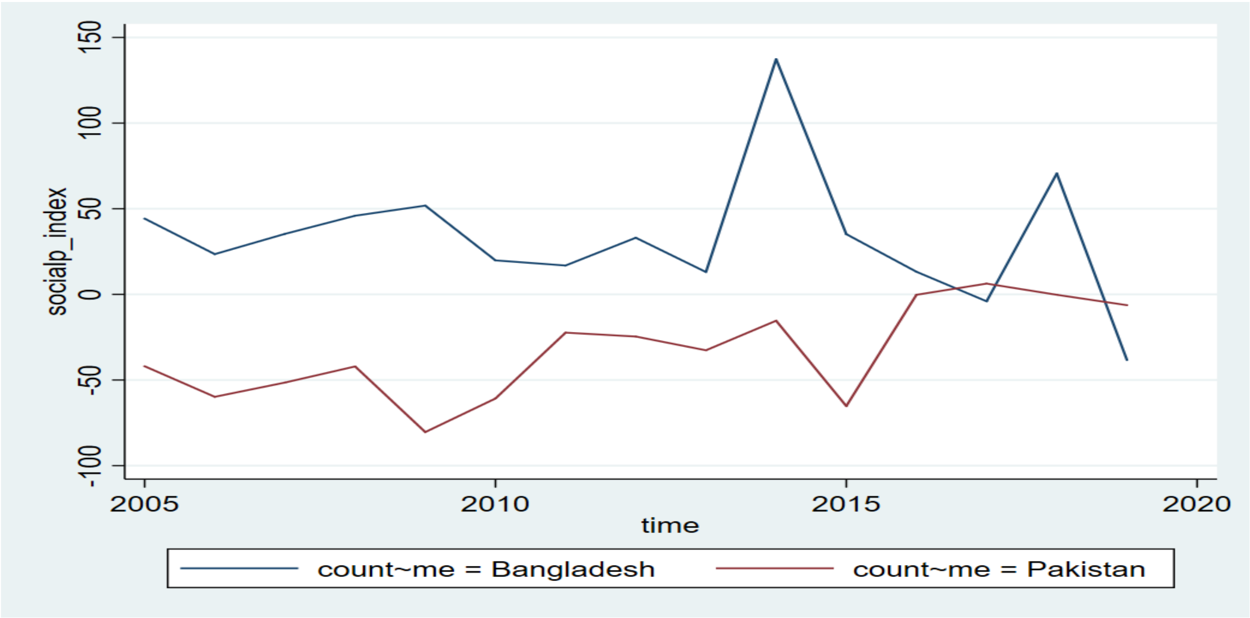


Figure 5.13: Social capacity index for Bangladesh and Pakistan (2015-2019)

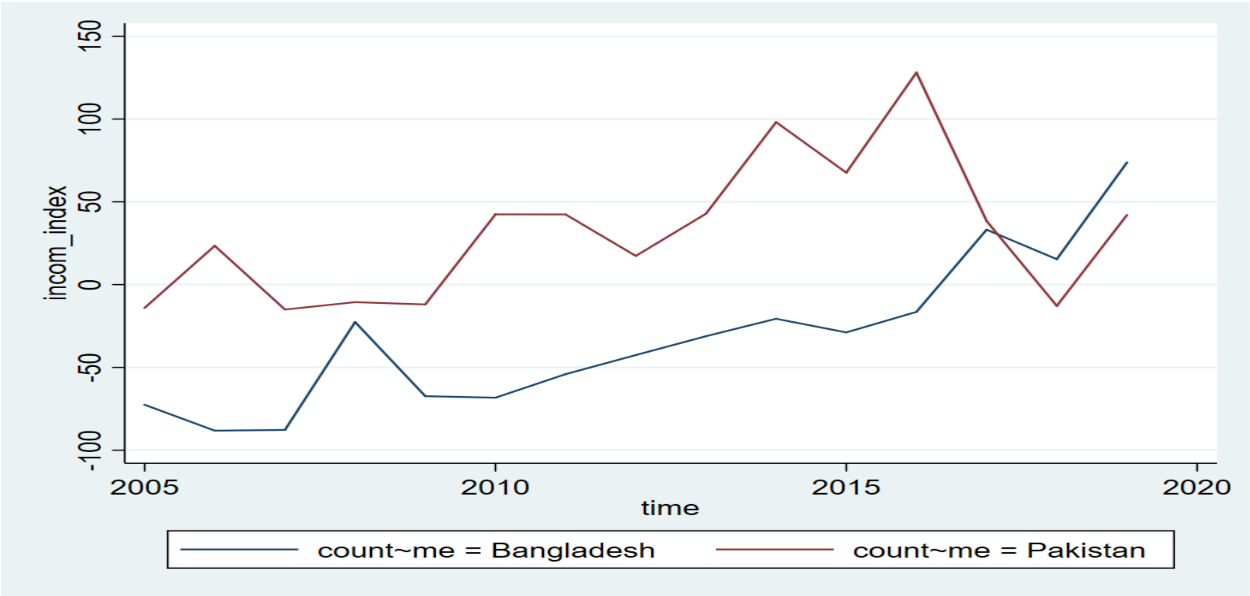


Figure 5.14: Incoming factors capacity index for Bangladesh and Pakistan (2015-2019)

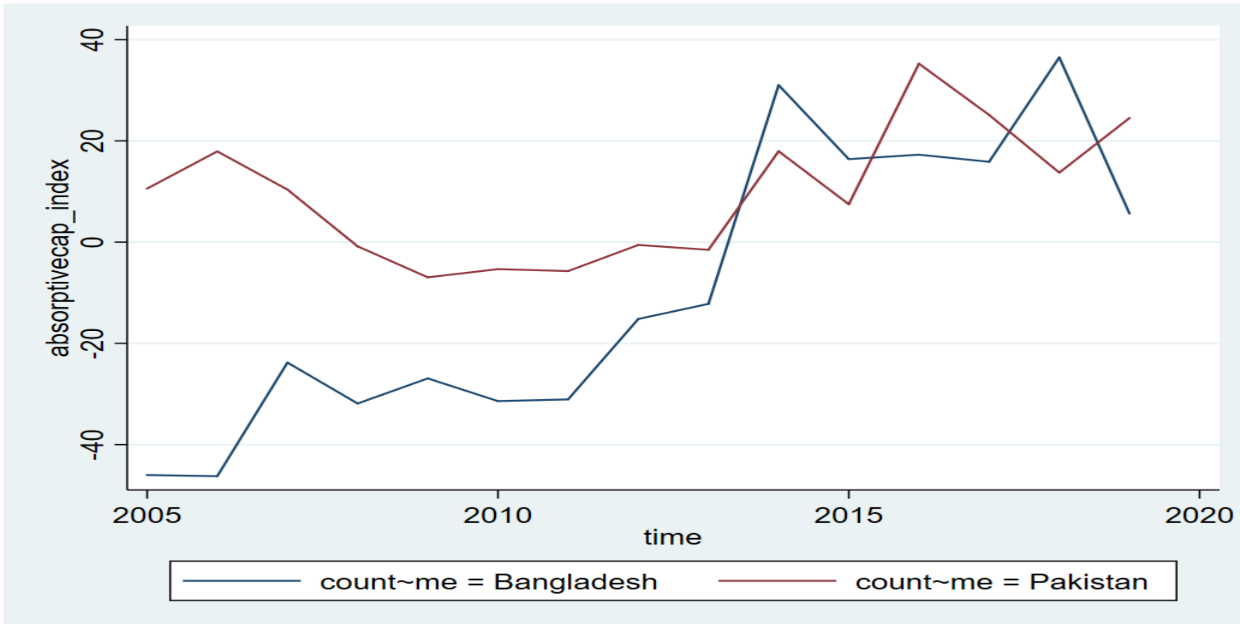


Figure 5.15: Absorptive capacity index for Bangladesh and Pakistan (2015-2019)

The figures above show that Pakistan fares better in terms of technological capacity index, whereas Bangladesh leads in terms of financial and human capital capacities indices. For other indices, the findings are mixed, with Bangladesh currently dominating in infrastructure capacity and incoming factor indices and Pakistan leading in public policy and social capacity indices. For the overall absorptive capacity index, the trend is oscillating; I notice a constant sharp rise in Bangladesh whereas a fairly downward trend for Pakistan from 2005-2010 and then a constant trend from 2010-2013 and then an oscillating trend onwards until 2019. One may say the overall trend is rising in Bangladesh, but the ebbs and flows flatten the trend in Pakistan.

From the average coefficient results in Chapter 3, I notice that infrastructure followed by public policy and then human capital and finance offer the largest bang for the buck when it comes to economic growth. I also notice that technological and social capacities do not affect economic growth in LMICs. Therefore, the fact that Bangladesh surpasses Pakistan in the capacities offering high gains in growth and Pakistan leading in insignificant capacities might partly explain the economic growth differential between these two countries.

6. Data Collection in Pakistan and Bangladesh

I collect data by conducting fieldwork and secondary document analyses in case countries. The fieldwork is specifically conducted in Pakistan.[41] Secondary-level analyses in Pakistan and Bangladesh complement the fieldwork.

The fieldwork aims to provide more nuance to the analytical framework for the impact of absorptive capacity on the country's economic and innovation growth. The fieldwork consists of semi-structured and unstructured interviews. The semi-structured interviews are driven by interviewees' responses, although I have a blueprint of the questionnaire (see Appendix A). Interviews are conducted in person, or online

[41] Logistical concerns (visa delay and Covid restrictions) do not allow the researcher to visit and conduct fieldwork in Bangladesh.

The fieldwork in Pakistan (IRBNet number: 1722945-1) was approved by the Office of Research Integrity and Assurance (ORIA) at George Mason University.

communication (Zoom), on a one-on-one basis. The choice of interview format is subject to time, travel, and the interviewee's preference. In most cases, in person interview is conducted. Verbal consent is sought in person, which is customary in such research in order to facilitate a smooth interview. Each interview takes about 45 minutes, mostly during work hours. The interviews, one-off (not to be repeated), are conducted in English or/and Urdu. Since interviewees are mostly highly educated people working in areas of science and technology, finance, commerce, and economic development, English is usually their working language.

The interviewees are experts on economic development and related policy topics. They include academics, experts, government officials, company representatives (private), and members of civil society. The interviewers are recruited through two routes. First, as I seek to interview employees of relevant government agencies, research institutions, or universities, I identify a list of participants based on publications by these entities. I then send emails to potential interviewees introducing myself, providing a brief introduction about the research, and requesting their participation. Second, snowball technique/sampling is employed to recruit more interviewees identified by interviewees and contacts. I request the current interviewees and contacts to make introductions to potential interviewees.

I interview people with professional knowledge or personal experience about science and tech policy/innovation policy and how it contributes to the economic outcomes. The interview questions lead to factual answers concerning the general practice of the case country's science and tech/innovation and economic policy. Since I am not collecting any sensitive information, I conduct the interviews at the interviewee's office and, in some cases, in public areas such as coffee shops and restaurants. In addition, most interviewees are high officials in various ministries in sensitive positions; therefore, I take notes instead of recording the interviews to solicit the most unbiased responses.

Table 5.2: Fieldwork details in Pakistan

Attribute	**Details**
Total Interviews	35
Respondent Types	• Government officials (Ministry of Finance, Ministry of Planning, Ministry of Science and Technology, Ministry of Commerce, Ministry of Industries and Production) • Universities' Professors (LUMS, NUST, IBA, Islamic International University Islamabad) • Businessmen • Civilians/NGOs
Interview Mode	• In person • Zoom
Interview Location	• Islamabad • Peshawar • Lahore • Karachi
Interview Correspondence	• Direct email • Introduction by an interviewee with other potential interviewees through email and phone (snowball sampling)

Table 5.2 shows details of fieldwork (35 interviews in four major cities of Pakistan). Alongside the fieldwork in Pakistan, secondary-level analyses in Bangladesh and Pakistan are also conducted. More than a dozen documents, research papers, newspapers, and

reports from the World Bank, World Economic Forum, Asian Development Bank, and McKinsey, among other organizations, are reviewed to inform the analysis.

7. Case Setting

Here I briefly summarize both countries as it relates to the economy, science and tech, and absorptive capacities.

7.1 Pakistan

Pakistan is situated in South Asia, adjoining the Arabian Sea. India is located in its East, Iran, Afghanistan in the West, and China in the North. With a GDP of 278,222 (current US$ Millions), the Trade Balance of Pakistan is -28,379 (current US$ Millions) in 2019 (World Development Indicators 2019). Pakistan maintains a trade deficit due to high imports of energy products, machinery equipment, and chemicals.

According to the World Integrated Trade Solution, abbreviated as WITS (World Bank),[42] Pakistan exported goods and services worth 23,749 US$ Millions, and it imported goods and services worth 50,063 US$ Millions in 2019. It exported 2,824 products to 194 partners, whereas it imported 4,039 products from 208 partners. Pakistan largely imported from China, United Arab Emirates, the United States, Saudi Arabia, and Indonesia. It mostly exported to the United States, China, United Kingdom, Germany, and Afghanistan. Textiles accounted for most of Pakistan's export earnings. Top exports included semi-milled or wholly milled rice, uncombed single cotton yarn, bed cotton linen, toilet linen,

[42] https://wits.worldbank.org/countrysnapshot/en/PAK

and kitchen linen. Top imports included petroleum oils, palm oil, liquified natural gas, and machinery. Table 5.3 shows a mix of export and import categories.

Table 5.3: Export and Import categories of Pakistan in 2019 (Data Source: WITS World Bank)[43]

Product categories	Exports Exports US$ M	 Product share (%)	Imports Imports US$ M	 Product share (%)
Raw materials	2,599	10.94	9,822	19.62
Intermediate goods	5,700	24.00	13,753	27.47
Consumer goods	14,503	61.07	15,942	31.84
Capital goods	944	3.98	13581	20.77

Pakistan's export performance has remained poor over the past two decades. According to the World Bank, Pakistan's exports as % of GDP declined from 14.31% to 8.97% from 2005 to 2018.[44] The State Bank of Pakistan (SBP) has detailed in its annual report for FY2020-21 that Pakistan's exports comprised resource-based items such as cotton, rice, and hides and skins over the past decades. Since the products lack value addition, the only gains in export receipts occur due to favorable international prices or raised surplus in domestic production. During my study period (2005-2019), Pakistan's last recorded significant surge in export growth in FY2010-11 was because of the high international price of cotton. However, as the price stabilized the following year, exports' growth turned negative.

[43] https://wits.worldbank.org/CountryProfile/en/Country/PAK/Year/2019/Summary
[44] https://data.worldbank.org/indicator/NE.EXP.GNFS.ZS?end=2018&locations=PK&start=2000

Similarly, other indicators also show negative trends. The GDP growth rate has declined from 6.519% (2005) to 1.145% (2019).[45] Likewise, total reserves as % of total external debt declined from 32.44% (2005) to 15.37% (2019).[46] Foreign direct investment (net inflows) also is mostly observing a declining trend from 1.8% (2005) to 0.80% (2019) of GDP.[47] It only sees an upward trend during the military regime (2005-2007) when foreign investment pours, mostly linked with the geopolitical situation in neighboring Afghanistan. Lastly, Pakistan's labor productivity (output per person) is not up to the mark. As per the International Labor Organization (ILO) statistics, China's productivity increased by 388%, India's by 177%, Bangladesh's by 109%, whereas Pakistan's productivity increased only by 32% during the 2000-2019 period.[48]

Why is it the case that Pakistan's economic position is precarious? It may have to do with the country's innovation and absorptive capacities. While the country definitely has a moderate level of capacities (such as R&D infrastructure, ICT infrastructure, business finance, and institutions, among others), it has yet to witness the desired change in technological sophistication. There is infrastructure (roads, Internet, electricity), but the quality and maintenance of infrastructure are dismal. For instance, the country's electric power transmission and distribution losses, while witnessing a declining trend from 24% of output in 2005, still amounts to 17.13% of the output in 2014 (Bangladesh, Vietnam,

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45 https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?end=2020&locations=PK&start=2004&view=chart

46 https://data.worldbank.org/indicator/FI.RES.TOTL.DT.ZS?end=2019&locations=PK&start=2004

47 https://data.worldbank.org/indicator/BX.KLT.DINV.WD.GD.ZS?end=2020&locations=PK&start=2005

48 https://tribune.com.pk/story/2258770/pakistans-low-productivity-and-the-way-out

and United States losses are 11%, 9% and 6% of the output in 2014, respectively).[49] Similarly, there is an R&D infrastructure. However, it is insufficient and only concentrated in the public sector. In addition, one hardly sees any research produced by academia or the public sector that is consumed by industry. On a national level, even the public sector and policymakers lack analytical insights to devise and implement sound policies.

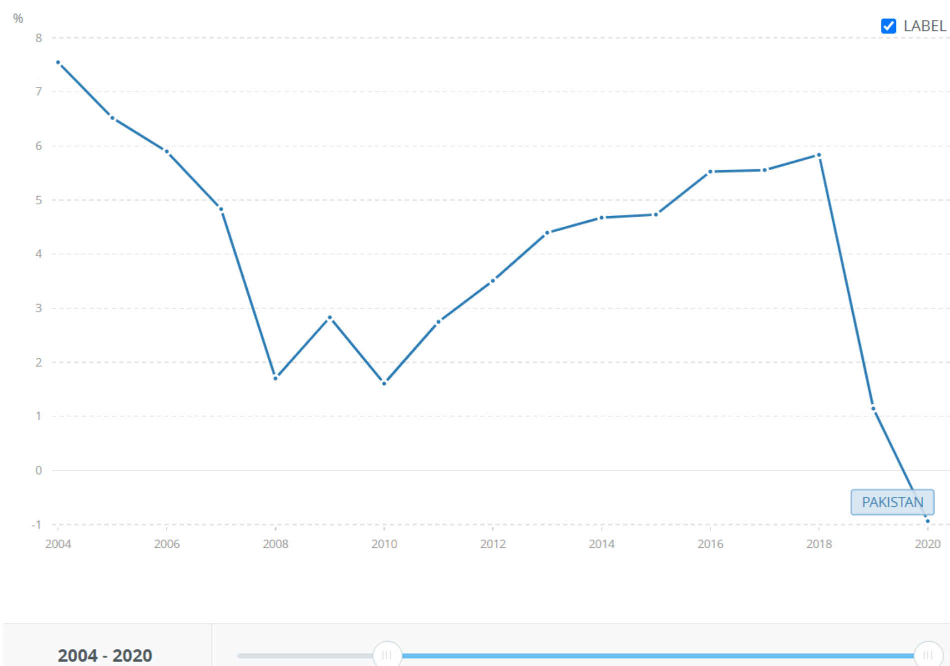

Figure 5.16: GDP growth (annual %) – Pakistan. Source: World Bank

[49] https://data.worldbank.org/indicator/EG.ELC.LOSS.ZS?locations=PK

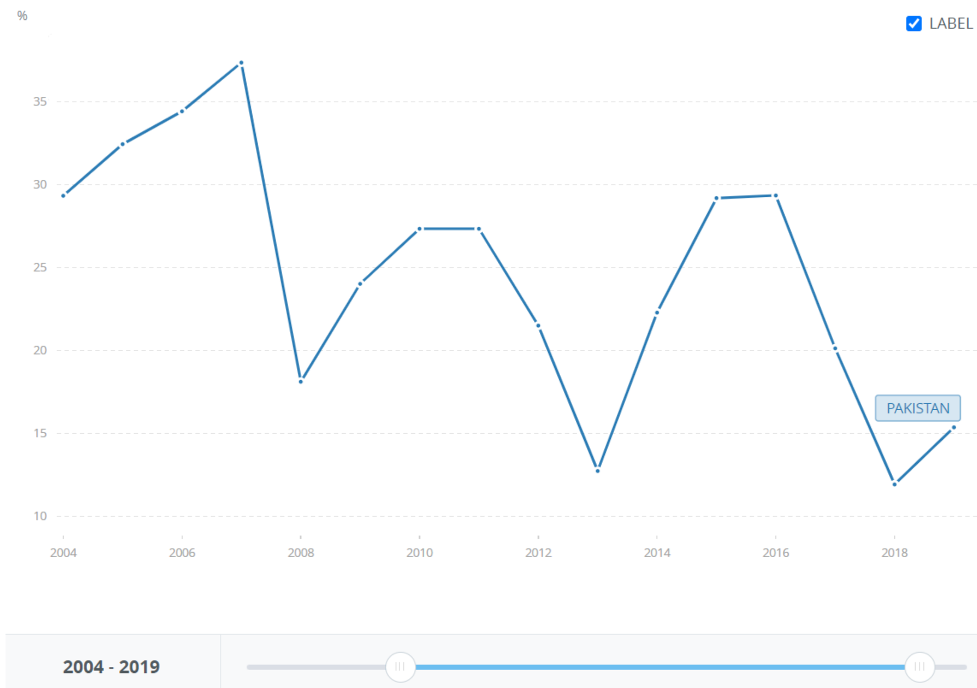

Figure 5.17: Total reserves (% of total external debt) Pakistan. Source: World Bank

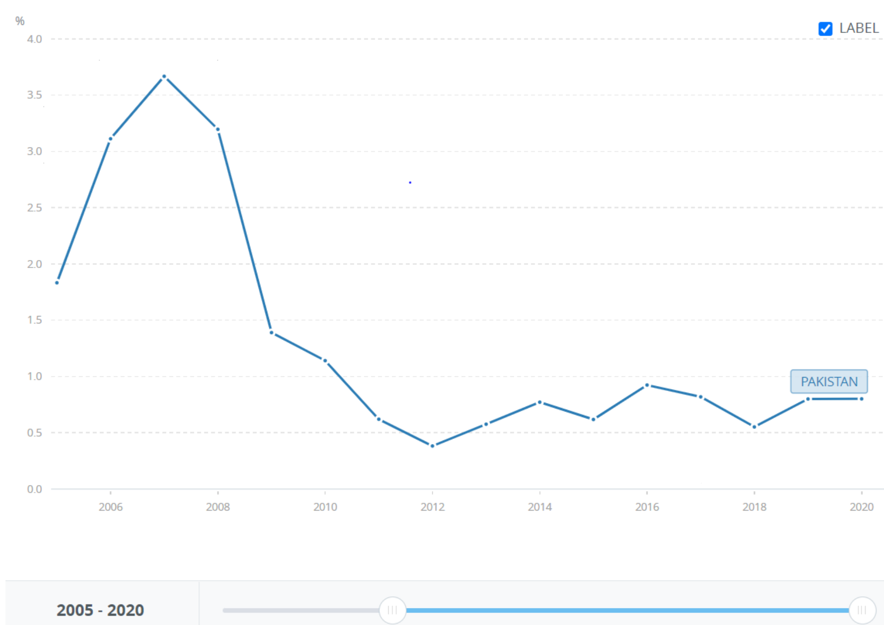

Figure 5.18: Foreign Direct Investment, net inflows (% of GDP) Pakistan. Source: World Bank

Figure 5.19: Electric power transmission and distribution losses (% of output)- Pakistan. Source: World Bank.

7.2 Bangladesh

Bangladesh (former East Pakistan) came into existence 24 years after Pakistan's foundation in 1947. Situated in South Asia, its neighboring countries are India, Nepal, and Bhutan. According to the World Development Indicators, Bangladesh has a GDP of 302,563 (current US$ million) and a trade balance of -18,495 (current US$ million) or about 6.1% of GDP. The trade deficit is due to the high import volume of energy products, including petroleum, cotton, palm oil, and soyabean oil.

According to the WITS (World Bank),[50] Bangladesh exported goods and services worth 31,734 US$ Millions, and it imported goods and services amounting to 48,059 US$

[50] https://wits.worldbank.org/countrysnapshot/en/BGD

Millions in 2015. The country exported 1,728 products to 188 countries, while it imported 4,208 products from 202 partner countries. Bangladesh largely imported from China, India, Singapore, Hong Kong, and Indonesia, whereas it mostly exported to the United States, Germany, United Kingdom, Spain, and France. Like Pakistan, textile accounts for most of the export earnings in Bangladesh. Top exports include t-shirts, singlets, shirts, trousers, jerseys, and pullovers. Top imports include petroleum, raw cotton, palm oil, durum wheat, and crude soyabean oil. Table 5.4 below shows a mix of export and import categories.

Table 5.4: Export and Import categories of Bangladesh in 2015 (Data Source: WITS World Bank)[51]

Product categories	Exports		Imports	
	Exports US$ M	Product share(%)	Imports US$ M	Product share(%)
Raw materials	824	2.60	6,089	12.67
Intermediate goods	973	3.07	22,542	46.91
Consumer goods	29,644	93.41	11,132	23.16
Capital goods	293	0.92	8,295	17.26

Bangladesh's export performance has been oscillating overall, experiencing growth in the past two decades. According to the World Bank, Bangladesh's exports as % of GDP have risen from 14.39% to 15.32% during 2015-2019.[52] Like Pakistan, Bangladesh also records a significant rise in export growth in FY 2010-11 because of the high international

[51] https://wits.worldbank.org/countrysnapshot/en/BGD
[52] https://data.worldbank.org/indicator/NE.EXP.GNFS.ZS?end=2019&locations=BD&start=2005

price of cotton. However, after the prices stabilized in subsequent years, exports' growth turned negative.

Similarly, other indicators show an overall rising trend. Overall, Bangladesh recorded an impressive GDP growth rate, increasing from 6.53% (2005) to 8.15% (2019).[53] Likewise, total reserves as % of total external debt have risen from 15.26% (2005) to 57.26% (2019).[54] Foreign direct investment (net inflows), on the other hand, experienced an oscillating trend from 1.17% (2005) to 0.63% (2019) of GDP.[55] As for labor productivity (GDP per person employed), Bangladesh witnessed 5.3% growth during the 2015-2020 period, whereas Pakistan experienced 2.2% during the same period.[56]

While Bangladesh's position is certainly not very strong but still is better than Pakistan's, particularly in those capacities that are significant for growth. What explains the differences in economic parameters between the two countries? There could be many explanations ranging from the geopolitical situation and political economy to market reforms explanations. Here I investigate if it has anything to do with Bangladesh's innovation and absorptive capacities. What is it doing so differently than Pakistan? The country is an importer of raw cotton and converts it into several value-added export commodities. It has become one of the top global clothing exporters. Does it have anything to do with Bangladesh's appetite for active learning and value addition? Such an appetite even requires strong national institutions and the right policy incentives. In subsequent

[53] https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?end=2019&locations=BD&start=2005
[54] https://data.worldbank.org/indicator/FI.RES.TOTL.DT.ZS?end=2019&locations=BD&start=2005
[55] https://data.worldbank.org/indicator/BX.KLT.DINV.WD.GD.ZS?end=2019&locations=BD&start=2005
[56] http://wdi.worldbank.org/table/2.4

paragraphs, I will explore these and other related themes while unraveling the six capacities and other themes emerging from fieldwork.

Figure 5.20: GDP Growth (annual %) – Bangladesh. Source: World Bank

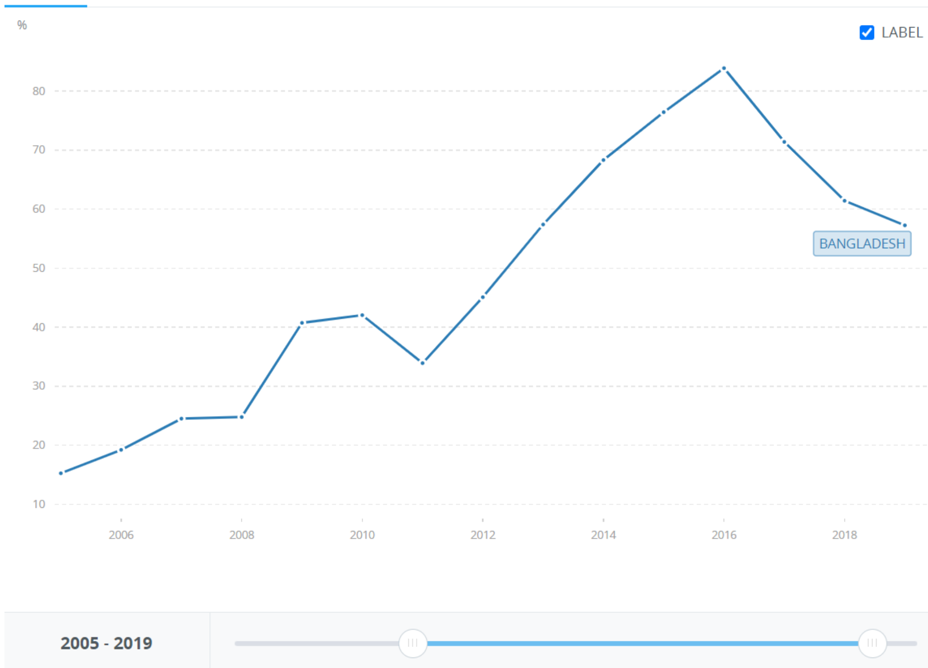

Figure 5.21: Total reserves (% of total external debt) Bangladesh. Source. World Bank

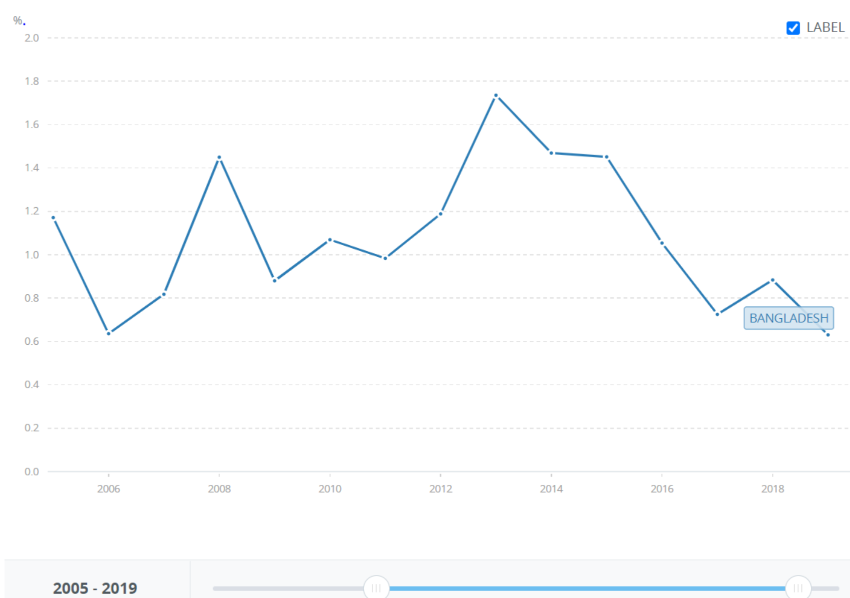

Figure 5.22: Foreign Direct Investment, net inflows (% of GDP) Bangladesh. Source: World Bank

8. Analysis:

Here I compare and analyze Pakistan and Bangladesh based on the capacities and other themes emerging from the fieldwork.

8.1 Infrastructure Capacity:

Well-maintained infrastructure is vital for economic integration and competitiveness domestically and internationally (Khan 2022; Carlsson, Otto, and Hall 2013). Infrastructure refers to transport, utility, and ICT infrastructure and adoption, as explained in Chapter 3. According to the Global Competitiveness Report (WEF, 2019), Pakistan scores 40.4/100 in the composite infrastructure, whereas Bangladesh scores 45.1/100.[57] Pakistan fares better in transport and utility infrastructure; however, substantial losses in ICT adoption trump transport and utility infrastructure gains. Bangladesh (score 39.1) is certainly better than Pakistan (25.2) in ICT adoption, which is perhaps key to a strong services sector. Pakistan's weak physical infrastructure (particularly energy infrastructure) has been a significant factor in deterring the performance of trade-related activities (Khan 2018).

Respondents in Pakistan express mixed views about infrastructure capacity. Some mention that Pakistan has just the right amount of infrastructure. Praising the excellent pace and quantity of transport infrastructure developed during the Pakistan Muslim League (Nawaz) era (2013-2018), Dr. Haroon (Deputy Chief, Macroeconomic Section, Ministry of Finance) mentions that Pakistan lacks the capacity to repair and maintain its physical

[57] We calculate the composite score by aggregating transport, utility, and ICT adoption scores.

infrastructure. According to Dr. Haroon, the lack of repair and maintenance has caused severe depreciation of physical infrastructure. On the other hand, several civil servants at the Ministry of Commerce, including Additional Secretary Dr. Syed Hamid Ateeq and Research Officer/Economist Humera, mention transmission and distribution losses leading to high debts (that Pakistan needs to pay the Independent Power Plants) and high commodity prices in the export market, which ultimately result in losing economic share in the world market. Dr. Ateeq also mentions the importance of digital infrastructures, such as online payment systems (PayPal, for instance), as prime for economic integration. He further states that the Government is working to bring PayPal to Pakistan, which could spur online commerce activities if materialized. Some respondents, such as Dr. Nadia Farooq at the Asian Development Bank, mention infrastructure projects under the China Pakistan Economic Corridor (CPEC), saying that CPEC can tackle critical infrastructural requirements of the country provided the Government handles the project with proper preparation and it asks for better terms. They mention how CPEC would cater to energy sector development and cause more connectivity through road development.

Bangladesh, like Pakistan, also inherited underdeveloped and unevenly distributed infrastructure. However, according to reports, it has addressed the problem systematically and channeled investments toward roads, highways, and airports ("Bangladesh's Remarkable Development Journey: Government Had an Important Role Too," Brookings Institute 2021). One spectacular infrastructure project is the construction of the US$1 billion Jamuna Multipurpose Bridge (the 12th-longest bridge in the world) that connects eastern and western Bangladesh for the first time ("Bangladesh's Bangabhandu Jamuna

Multipurpose Bridge," World Bank). According to Dr. Ateeq (Ministry of Commerce, Pakistan), Bangladesh is dealing with the infrastructure problem reasonably well because they were able to attract more international assistance, unlike Pakistan. However, reports quote the successful story of how the Bangladesh government's intentional investment in rural road construction led to robust connectivity ("Bangladesh's Remarkable Development Journey: Government Had an Important Role Too," Brookings Institute 2021). In about a decade, the country expanded from 3,000 km of feeder roads in 1988 to 15,500 km in 1997, hence connecting the villages of Bangladesh to the rest of the country. That said, multiple reports talk about the infrastructure bottlenecks that the country face (Business Report 2017, WEF 2019,). The reports underscore that Bangladesh needs to invest more in infrastructure to attract more FDI and remain competitive.

Overall, while both Bangladesh and Pakistan have a below-standard infrastructure compared to other economies like Vietnam or Georgia, Bangladesh still performs better in terms of the overall rate in the infrastructure development despite initial gap in the infrastructure between the two countries. The sub-standard infrastructure prevents Pakistan from reaching its full potential. Infrastructure investment is even more critical as the country further experiences growth in the years to come. It is hard to realize economic growth without strong energy, transportation, as well as urban and digital development and connectivity. Pakistan can learn from Bangladesh how it invested in rural road construction, causing robust connectivity. Parts of Pakistan—intra- and interprovincial—lack the connectivity for strong market activity. Secondly, following Bangladesh's footsteps, Pakistan can enhance its ICT and digital infrastructure to realize significant returns in growth.

8.2 Financial Capacity

Here I will discuss the cost of doing business, business environment (regulations), credit availability, and the geopolitical situation. While Pakistan is doing better in some financial indicators, overall, Bangladesh performs better than Pakistan regarding financial infrastructure.

8.2.1 Cost of Doing business

As the cost of business increases, a country's domestic manufacturers' competitiveness declines. In Pakistan, local manufacturers are not likely competitive enough because of the high cost of doing business. Costs include energy costs, labor wages, interest rates, fixed starting costs, cost of getting permits, electricity, and registration costs, among other things. Most of these costs are due to severe inefficiencies in the public sector institutions (Kessides 2013; Ijefms and Arif 2019). While the energy situation is getting better, still the challenge is real.[58] Likewise, fuel costs burden firms by negatively impacting their competitiveness (Kessides 2013). It is hard to innovate and switch overnight to alternative energy systems. Also, not all firms have the resources to do so. Hence, smaller firms are either closing or shrinking their businesses. A World Bank survey found that most respondents identified power supply as a major hurdle to business growth.[59] Similar themes appear in the field interviews. Mian Misbah-ur-Rehman, the

[58] https://thediplomat.com/2018/11/powering-the-powerless-in-pakistan/

[59] A typical business in Pakistan on average losses 5.6 percent of annual output due to power outages relative to the less than 2 percent for the average plant in China.

President of the Lahore Chamber of Commerce and Industry (LCCI) and a member of the Federation of Pakistan Chambers of Commerce and Industry (FPCCI), mentions that because of high input costs (such as energy costs), textile products from Pakistan are not as competitive as Bangladesh textile products. He further says that as Bangladesh offers cheaper products, they have a larger share of the world market.

Like Pakistan, Bangladesh is also not performing at par when it comes to the cost of doing business. The President of the Federation of Bangladesh Chamber of Commerce and Industries (FBCCI) is reported to mention that the cost of doing business is excessively high in Bangladesh (Rahman 2018). Because of the high cost of business, pharmaceutical companies like Glaxo SmithKline Beecham (GSK) and Pfizer pulled out of Bangladesh, Rahman (2018) asserts.

8.2.2. Business Environment

A friendly business environment is crucial for export-oriented enterprises (Rialp-Criado and Komochkova 2017). Such an environment would allow a free flow of information and enough provision of amenities. Though Pakistan is improving its overall business climate,[60] flaws remain in the regulatory and legal framework.[61] Entrepreneurs are expected to conform to numerous regulations regarding the work environment, including health and sanitation, product standards, and taxation. Granting a lot of power to the enforcement agencies results in harassment of enterprises and corruption, causing loss of business confidence.

[60] In 2019, Pakistan is among top ten economies with bigger improvements in business regulations.
[61] In Ease of Doing Business ranking 2019, Pakistan with score of 55.31 is at no. 136 out of 190 counties. It improved the score by 2.53 points from last year

Most interviewees, including Dr. Nadeem ul Haque and Professor Idrees Zaidi at the Pakistan Institute of Development Economics (PIDE), claim that businesses face many regulations and "sludges," which hinder their growth. The famous Pakistani banker and economist Ishrat Hussain, Advisor for Institutional Reforms and Austerity of Pakistan, mentions that Pakistan lacks high entry/exit of firms and contract enforcement, which efficient markets require. Umer Gilani, a constitutional attorney, notes that commercial contract enforcement is weak because the judicial arm has little understanding of economics and is historically geared to solve land disputes.[62] Professor Turab Hussain, affiliated with the Lahore University of Management Sciences (LUMS), while citing the State Bank of Pakistan figures, mentions that 98% of firms in Pakistan, small-medium enterprises, face redundant regulations.[63] He further says that small firms cannot handle these excessive regulations, and thus the regulations need to be abolished.

BOX 1: EASE OF DOING BUSINESS—NOT IDEAL BUT IMPROVING

While there are multiple issues with the business climate in Pakistan, one interviewee (Hamed Yaqoob Sheikh, Secretary Planning & Development Ministry) mentions that Pakistan has progressed in the Ease of Doing Business. He quotes the examples of ease in getting a driving license, a National Identity Card (NIC), and applying for Passport. He further mentions that now an ordinary Pakistani can pay utility bills online. While things are not ideal, they are certainly improving, asserts Mr. Sheikh.

[62] He made those remarks in the panel talk during the conference Opportunities to Excel, arranged by PIDE at IMSciences Peshawar in November 2021.
[63] He made those remarks in the panel talk during the conference Opportunities to Excel, arranged by PIDE at IMSciences Peshawar in November 2021.

The situation is no better in Bangladesh. A closer look at the World Bank's latest Doing Business ("Bangladesh: Improving Productivity and Technology Adoption Key to a Globally Competitive Manufacturing Sector," 2020) and World Economic Forum The Global Competitiveness Report (WEF, 2020) suggests that Bangladesh scores lower than Pakistan in enforcing contracts and efficiency of the legal framework in challenging regulations and settling disputes.

Pakistan is taking steps towards facilitating its citizens and bettering the business environment, as mentioned in Box 1. However, it needs more serious reforms as it continues to grow further. In this regard, it should enforce property rights and contracts cost-effectively and introduce reforms in the procedures to issue NOCs, permits, and licenses (in other words, minimize restrictions). Similarly, government agencies should conduct inspections smoothly. All these obligatory steps will cause improvement in the business climate in Pakistan (Husain 2017).

8.2.3. Geopolitical situation

The geopolitical situation is very crucial for attracting FDI and the overall business environment. Participants in the field interview, including Hamid Ateeq (Additional Secretary, Ministry of Industries and Production), point out that Pakistan faces tremendous geopolitical challenges as a "frontline" country fighting against terrorism, proximity with Afghanistan, and a checkered relationship with neighboring India. The country has been in the news since the early 2000s because of extremist elements and the menace of suicide attacks. On the other hand, while harboring some extremist elements, Bangladesh overall scores well on terrorism incidence. According to the WEF data, Pakistan scores 0 (high incidence), whereas Bangladesh scores 85.9 (low incidence) in terrorism incidence.

BOX 2: STORY OF SIALKOT CITY LYNCHING–WAVERING BUSINESS ENVIRONMENT

Sialkot is a city in Punjab Province, located in Pakistan's most industrialized region. Along with other cities of Gujranwala and Gujrat, it is part of the "Golden Triangle" with an export-oriented outlook. The city obtains foreign exchange over $2.5 billion annually through its sports exports. *The Economist* noted the city for its entrepreneurial spirit and productive business environment, terming it a "world-class manufacturing hub."

The researcher, during the interview, while asking respondents what made Sialkot an excellent hub, unfortunately also witnessed the day when Sialkot experienced severe mob lynching. Workers of private factories brutally lynched a Sri Lankan national, who was the operational manager at the factory. The factory workers accused him of tearing down sacred words— salutations on the Prophet of Islam (*Durood Sharif*).

Stories such as these sharply decline the business profile of the country. While the country is already witnessing a declining FDI, such incidents worsen the situation, echoed several respondents, including Mr. Hamid Ateeq, Additional Secretary Ministry of Industries and Production. For businesses and tourists to arrive in the country, the country needs to provide them with a favorable environment, including cultural amenities, expressed Mr. Ateeq. People go to Istanbul because "there they can have Ham and Drinks," which is not the case in Pakistan. He further asserts the country needs a dire brand and reputation management to stimulate its economic outlook.

8.2.4 Financial Market Development

Countries with strong financial markets perform well in international trade. However, in Pakistan, access to finance is a significant issue that requires thorough consideration. According to the Global Competitiveness Report (WEF, 2019), Pakistan ranks a dismal 99th/141 and 96th/141 in the financial system and financial depth, respectively. Particularly, small and medium enterprises (SMEs) face financial challenges; SMEs' financing scored 3.9/7. Likewise, venture capital is limited; venture capital availability scored 3.8/7. Domestic credit to the private sector is also low (Pakistan scored 17.2/100 and ranked 122/141). Participants in the field interviews agreed with SMEs' access to credit issues. Most firms in Pakistan are small firms, and they hardly exhibit any dynamism, asserted Dr. Hussain during his panel talk arranged by PIDE at IMSciences Peshawar. The low dynamism is most likely because of the meager resources and insufficient access to credit that the firms need to expand and graduate from small size to medium size.

While Bangladesh is almost similar to Pakistan in financing SMEs, it is undoubtedly better than Pakistan in providing domestic credit to its private sector (scores 48.2/100 and ranks 78/141). Perhaps because of this availability of financial resources to the private sector, one sees a thriving private sector in Bangladesh. However, since Bangladesh scores almost similar to Pakistan in terms of the financial system and depth, both countries need to strengthen their financial capacities.

The easy availability of long-term credit to finance SMEs' operational and working capital needs could reduce the firms' transaction costs, thus increasing their competitiveness in both countries. In addition, laws, including collateral and bankruptcy laws, need to be reconstituted to facilitate access to credit. Similarly, institutional support for the provision of institutional credit, boosting technical and management skills, fiscal concessions, and an effective legal system for SMEs in selected sectors with growth potential are needed.

8.3. Technological Capacity:

The state of science and technology has not been satisfactory in Pakistan compared to other emerging economies such as Vietnam.[64] Most interviewees lamented the poor state of technological capacity in the country. Because of the insufficient technological capacity, the Government cannot diversify its product mix and is stuck at a low global value chain, asserts Professor Pervez Hoodbhoy, a nuclear physicist and activist. However, another interviewee, Staff Officer Madam Seher at the Ministry of Planning and Development, points out that S&T is a priority for the current Government. She further elaborated that S&T is gaining momentum quoting 8.34 billion PKR S&T allocations of 900 billion PKR Public Sector Development Program (PSDP) budget. Others, such as Dr. Musharraf Rasool Cyan, ex-CEO of Pakistan International Airlines, also express optimism while talking about the country's rising IT exports (2 Billion PKR) as a success story.

Furthermore, Dr. Akhtar Nazir (Secretary S&T) and Dr. Syed Hussain Abdi (Chairman Pakistan Council of Scientific and Industrial Research) applaud IT initiatives such as the Electoral Voting Machine (EVM), which the Government has started working on as an example of public sector innovation. Dr. Abdi also mentions several technological opportunities in food distribution, biotechnology, hemp policy (medicinal use of hemp), and digitization in ministries. Similarly, Dr. Ateeq (Additional Secretary of Commerce and

[64] In Global Competitiveness ranking of 2019, innovation capability, R&D, Skills (including staff training, vocational training, digital skills, skillset of graduates), Pakistan ranks 79/141, 68/141, 67/141, respectively

Trade Ministry) talks about how companies like Samsung and new automobile players such as MG, Kiya, and Hyundai will spur demand for these products and impact the technological landscape in Pakistan. Dr. Ateeq notes mobile phone export from Pakistan to Africa, which China is assembling, is good news for Pakistan. He also believes that technological absorption in engineering, telecommunication, and textile is fine; however, Pakistan lacks raw materials needed for heavy industries. Finally, Dr. Ateeq asserts that for successful local absorption in all these technological sectors, energy is the main issue and that its pricing should be competitive on par with other countries.

An interviewee from the Planning Commission (Zafar ul Hassan Almas, Chief Macroeconomics Section) asserts that S&T is the least focused item in PSDP. He further mentions that there are technical departments (such as Technical Education and Vocational Training Authority, known as TEVTA) that impart technical training, but that training is almost a waste because it does not have any demand. Further, he claims that there is scientific infrastructure, labs, and training institutes throughout the country ("and in Sindh and Islamabad"), but there are no "serious teachers," which is why the institutes have turned into "deserted" places. Finally, to the question about journal articles coming from Pakistan, Dr. Almas responds that research papers published in Pakistan increase because of the HEC financing, but the results do not translate into tangible outcomes.

Dr. Hoodbhoy asserts that Pakistan lacks the skilled human capital required for technological innovation. Others note low awareness of technological needs, limited capacity of the domestic industries, lag in engineering and technical education, myopic view of bureaucracy and politicians, and lack of resources for scientific research to develop new products and to improve quality or minimize production cost, as possible reasons behind the dismal technological capacity. Further, as there is no actual demand from the industry, Pakistani R&D is supply-oriented and industrial R&D is negligible. This situation contrasts with the industrialized countries, where the industrial sector contributes enormously to the overall R&D activity of the country.

As for technological capacity, Bangladesh is no different than Pakistan. In the Global Competitiveness ranking of 2019, innovation capability, R&D, and Skills (including staff training, vocational training, digital skills, and skillset of graduates), Bangladesh ranks 105/141, 82/141, 123/141, respectively. According to a World Bank report, most firms in Bangladesh use basic or near-basic technologies ("Bangladesh: Improving Productivity and Technology Adoption Key to a Globally Competitive Manufacturing Sector" World Bank). In addition, several studies discuss weak industry-academia linkages in Bangladesh as possible reasons behind low technological innovation in Bangladesh (Tahrima and Jaegal 2013).

Despite low technological capacity in terms of international indicators, Bangladesh has been able to move to more complex products and value-added services in textiles, which practically constitute over 80 percent of Bangladesh's exports. This may be because of Bangladesh's use of existing resources efficiently and learning as well as adapting itself to changing demand patterns in the global fashion industry (Berg et al. 2021). As opposed to "complacent" Pakistan's textile business owners, Bangladesh's textile owners are "active learner" constantly upgrading their products, producing garments made from synthetic fibers and manufacturing more complex products such as outerwear, tailored items, and lingerie as well as providing new washes, prints, and laser finishings. International manufacturing brands also help Bangladesh manufacture high-end apparel (New Age 2022).

8.4. Human Capital

Countries with a skilled and educated labor force perform better in the market (Khan 2022). The experience of East Asian economies is one relevant example. Alongside heavy R&D investments, high literacy rates have been crucial for their technological innovation.[65] However, Pakistan's literacy rate and R&D expenditure are considerably low compared to these countries.

Pakistan’s labor force is not adequately trained and is mainly unskilled. This is more prevalent in textiles and chemicals. Researchers argue that unskilled labor is because of inadequate institutional training and the low quality of education (Amjad et al. 2012). As a result, the productivity growth rate is not improving. For example, from 2000 to 2010, Pakistan’s productivity growth rate in the manufacturing sector was only 2.3 percent, compared to 8 percent in China and 3.4 percent in India (Husain 2017).

While one of the panelists at the PIDE conference (Yahya Akhunzada, Secretary Education, Khyber Pakhtoonkhwa Province) appears confident that they have taken steps to digitize the education landscape of the province and move towards smart education with an emphasis on coding, entrepreneurship, and introduction to startups; generally, interviewees report that the labor force is unskilled. Dr. Omer Siddique at PIDE further

[65] The median adult literacy rate in Turkey, Vietnam, and Singapore in the last 15 years is 92%, whereas in Pakistan it stood at 58%. (Source: WDI-World Bank).

reinforces this notion noting that growth in Pakistan is mainly input-driven rather than TFP-driven, as is the case in East Asian economies. According to Dr. Siddique, a country needs TFP-driven growth (fueled by knowledge and learning absorption) for sustainable development.

Other respondents, including Dr. Ashfaque Hasan Khan, the Principal, and Dean of the School of Social Sciences & Humanities at the National University of Sciences and Technology, also emphasize that a skilled labor force is needed to climb the ladder (Box 3 mentions the saga of deteriorating human capital and its correlation with bureaucracy, as illustrated by Dr. Khan). To a question about skill teaching, respondents like Dr. Abdi (Chairman PCSIR) and Dr. Imtiaz Ahmad (Economic Advisor, Finance Ministry) quote Prime Minister *Youth Hunarmand* and *KamyabJawan* Programs (for upskilling youth) and other training programs launched by National Vocational & Technical Training Commission (NAVTTC) and Technical Education & Vocational Training Authority (TEVTA) for imparting skills to youth. However, Dr. Almas (Planning Commission) is not fond of training delivered by these institutes, terming them as waste as they are not demand-driven (as mentioned earlier). Dr. Nadeem ul Haque (Vice Chancellor PIDE) also seriously laments that Pakistani youth does not have any direction “we do not discuss ideas over conferences” and that “there is no place for research in this country.”

Upon the inquiry about the quality of education, prominent academic Dr. Faisal Bari, affiliated with Lahore University of Management Sciences, laments the poor education status, saying there are only a few good schools in the country. Also, he mentions that the quality of research is terrible because the Higher Education Commission awards "numbers" rather than "quality." Because of this emphasis on metrics, more and more schools are recognized at the expense of quality. Other participants also highlight similar themes.

BOX 3: BUREAUCRACY AND EDUCATION DECAY IN PAKISTAN

Ashfaque Hassan Khan, a seasoned bureaucrat who served as the Economic Advisor at the Planning Commission and currently serves as the Principal School of Social Sciences at NUST, mentions that bureaucracy in Pakistan is not optimally functioning. The ill-functioning is linked with the dismal quality of education. He notes the saga of declining education and bureaucracy in the country. Civil servants used to be very "efficient and smart" back in the 1960s and 1970s. However, over the decades, their quality deteriorated. The quality of education partly explains this. In the early 2000s, the Higher Education Commission (HEC) of Pakistan sent hundreds of Pakistani students to substandard institutions worldwide. When they returned, they started teaching in universities and working in different institutions. As a result, we see substandard outcomes in teaching and bureaucratic service. So, while the bureaucracy and academia flourished in numbers (from 25 institutions in 2002 to 225 institutions in 2021), their quality dropped. "One hardly sees skilled graduates," and he quoted an incidence of bureaucratic decline "think of Secretary Finance of Punjab Province asking what does BOP (i.e., Balance of Payment) mean in official negotiations (with the IMF) at Dubai. Does it mean Bank of Punjab?"

Mr. Khan asserts that there would be no value addition or market competitiveness without significant investments in human capital. Therefore, instead of increasing the number of universities and granting each university the status of awarding PhD degrees, we should strengthen the existing universities and invest in our college students, suggests Dr. Khan. Similarly, Dr. Khan advises Pakistan should build the capacity of officials in the ministries.

As for Bangladesh, it seems Bangladesh's workforce is as skilled as Pakistan's labor force. However, the difference between the two countries appears in the basic parameters: Bangladesh has a higher literacy rate than Pakistan, smaller classrooms, and higher mean years of schooling (11.2 years in Bangladesh vs. 8.5 years in Pakistan in 2018, according to ILO statistics). Moreover, Pakistan lags behind Bangladesh in girls' education (the female youth literacy rate was 94.4% in Bangladesh vs. 67.5% in Pakistan in 2017, as per the UNDP statistics). This difference in girls' education shows in disparate women's participation in the labor force. In Bangladesh, women's participation in the labor force is higher (38.6%) than in Pakistan (23.2%). While there exist quite inequities in primary education as imparted by both the Government and primary sectors in Pakistan neglecting the poor and marginalized communities, Bangladesh's informal community-based primary system targets such sections of the society.

Overall, both countries need to make a significant and consistent commitment in terms of public investment in relevant technical and general education and strengthening research and development activities. Pakistan, in particular, needs to learn from Bangladesh how it may strengthen the quality and reach of its primary education and reduce the gender gap in such education and at the workplace. Similarly, Pakistan's industry-level workforce can follow Bangladesh's approach – the Bangladeshi owners' entrepreneurial and creative mentality flows into their workers' performance. Because of entrepreneurial and open-minded industry bosses and managers, workers in Bangladesh are relatively more exposed to on-the-job training and skill up-gradation than in Pakistan, showing up in differential value addition.

8.5. Social Capacity:

Social capacity includes social inclusion, social contributions, equity of public resource use, social capital, diversity in the workforce, labor tax rate, women's employment, and labor market policies, among other things, as explained in Chapter 3. Some respondents in Pakistan seem to be aware of the importance of social capacity in economic development. For instance, Dr. Haque (PIDE) emphasizes the importance of "community development," "social capital," and "social trust" as prime for economic development in a system-view that he presents. Another respondent in Pakistan (Muhammad Ahmad, State Economist) also seems to understand the significance of social capacity by pointing out the dismal social capacity situation in the country. He mentions that Pakistan has wealth extraction but no generation, and this is because wealth generation requires cooperative behavior (trust), which is missing in Pakistan. He further asserts, "the public has a sharp, innovative sense—check out '*jugaad*' (roughly translate to frugal innovation) in our society," but claims that the "society needs proper direction and incentivization to lead to more productive activities."

Figure 5.23: An Example of Frugal Innovation—school bags hanging from the van to make more space inside the van. Source: Image captured by the author in Peshawar.

Overall, from secondary research, I see a steady trend in Pakistan's social capacity. The country, in general, is very philanthropic, and the Government also initiated programs such as *Ehsas* (and BISEP) to cover the vulnerable segments of the society. In addition, multiple nonprofit organizations are working on the ground to support vulnerable people with housing, education, and food assistance. However, the country can still be better on many vital indicators needed for inclusive development, such as female integration in the job market, female work to male ratio, diversity in the workforce, social capital, labor tax rate, and cooperation among labor and employers at workplaces.[66] Bangladesh fares better than Pakistan in those indicators, but it also needs to improve working conditions for women alongside mitigating child labor.[67]

In terms of the overall workers' safety (and, by extension, social capacity), Bangladesh provides a success story and a great example of transformation. Several workplace incidents in Bangladesh (for example, the 2012 Tazreen factory fire and the 2013 Rana Plaza factory collapse) highlight colossal problems in working conditions (Berg et al. 2021). Following these incidents, the US and other international partners withdraw from their preferential trade agreements with Bangladesh (Berg et al. 2021). However, as a great learner and resilient country, Bangladesh soon rebounded by introducing several

[66] According to WEF 2019 report, Pakistan ranks 138/141, 99/141, 97/141, 1/141, and 103/141 in female work to male ratio, diversity in workforce, social capital, labor tax rate, and cooperation among labor and employers at workplaces, respectively.

[67] According to WEF 2019 report, Bangladesh ranks 121/141, 95/141, 88/141, 64/141, and 99/141 in female work to male ratio, diversity in workforce, social capital, labor tax rate, and cooperation among labor and employers at workplaces, respectively.

initiatives for worker safety, such as the Accord on Fire and Building Safety in Bangladesh, the Alliance for Bangladesh Worker Safety, and the Ready-Made Garment Sustainability Council. While closing unsafe factories, the measures quickly restored Bangladesh's repute in the global apparel-sourcing market, leading to phenomenal growth in the last decade.

8.6. Public Policy Capacity

This capacity includes the strength of institutions, legal and regulatory structure, bureaucratic setup, as well as fiscal, monetary, and trade policies in the country (Khan 2022). Overall, public policy has been experiencing a decline in Pakistan. Participants point out the country's inconsistency and instability in policy formulation. Because of these factors, international investors find Pakistan a challenging destination, assert several interviewees (Dr. Almas and Dr. Haroon, Planning Commission; Professor Abdul Jabbar, International Islamic University Islamabad; and Zille Hasnain, Ministry of Finance). Similarly, they highlight the lack of coordination among different policies (Professor Jabbar and Umar Kamal, Ministry of Commerce). For example, trade policy lacks coordination with other related policies and is excessively influenced by external actors. They also stress how trade liberalization policies must be aligned with other macroeconomic policies, such as exchange rate liberalization, that would alleviate budgetary pressures. Others, such as Gonzalo Varela, Senior Economist World Bank Islamabad, while appreciating the country for taking steps towards opening up the economy, mention high prevailing tariff levels diminish productivity growth and impede efficient resource allocation (Pakistan ranks 138th/141 in trade openness according to

Global Competitive Index).[68] As about 20-30 percent of imported inputs are used at different stages of production in Pakistan, a tariff on imported raw materials could negatively impact the country's export performance.[69]

Similarly, most participants discuss the ill-designed incentives. For example, Dr. Asma Hyder (Professor of Economics at the Institute of Business Administration) mentions that the Government gives subsidies to mafias in the sugar and cement industries, but there are zero subsidies to entrepreneurs. Further, the Government taxes property but does not tax land holding. Other participants, such as Saad Iqbal Ahmad, an entrepreneur and businessman in the food industry in Islamabad, assert that the Government hardly provides any space for productive activities, which is why people partake their capital in real estate, the most unproductive activity for the economy. Most participants (Dr. Zaidi, Dr. Siddique, and Dr. Haque at PIDE) also point out that policymakers need to remove "frictions" and "sludges" and that they need to reform the tax system. According to them, sludges hinder investment and efficient production. Also, the Government needs to give tax credits to young entrepreneurs, as there is a youth bulge in the country, asserts Dr. Hyder.

While most participants praise how the government officials handle the Covid-19 pandemic (see Box 4 for Covid-19 strategy) within the country (Dr. Imtiaz Ahmad, Finance Ministry), respondents generally express concerns about how trade instruments are designed. For example, Mr. Umer, Mr. Ali, and Mr. Amjad (Government officials at the Ministry of Commerce) mention that Pakistan is a signatory of about 5 to 6 Free Trade

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[68] Pakistan ranks 115/141, 139/141, 49/141, 128/141 in non-tarrif barriers, tariff barriers, complexity of barriers, and border clearance efficiency, respectively

[69] For details, see Ali, A. 2014. Share of Imported Goods in Consumption of Pakistan. SBP Research Bulletin, Short notes, vol. 10(1), pp. 57-61.

Agreements (FTAs); however, these FTAs are not reciprocal. Similarly, another respondent (Dr. Ateeq, Ministry Industries and Production) asserts that the garment industry shifted from Pakistan to Bangladesh because of high energy costs, which the Government has not been able to control. Some respondents, such as Dr. Ateeq and Dr. Jabbar (IIUI), also expressed concerns about how Pakistani policymakers signed agreements with Toyota and Honda to assemble vehicles locally, and thus no value addition has been happening in the country. On the contrary, countries like Thailand chose to make parts, and now they are the Asian markets for automobile parts. As a result, even the best Pakistani engineers are only good at maintenance rather than innovation.

BOX 4: PAKISTAN’S COVID-19 STRATEGY: A SUCCESS STORY

Pakistan has been one of the countries worst affected by the Covid-19 pandemic, but its strategy of dealing with Covid-19 is a success story. The *World Health Organization* and the *Economist* all applaud the country for its successful strategy. By implementing smart lockdown, carrying out a robust communication strategy, and vaccinating millions of people quickly, the country beat the pandemic effectively. The Government also helped millions of people and businesses with cash payments and other incentives. The National COVID-19 effort in Pakistan was managed by the National Command and Operation Center (NCOC). It was assisted by the National Disaster Management Authority, Information Ministry, and Health Ministry, among other institutions. The Covid-19 strategy of Pakistan offers examples of public sector innovation and suggests that the country has the potential to design and enact successful policy interventions.

Panelists like Mr. Varela (World Bank, Islamabad) at the PIDE Conference at IMSciences Peshawar express concerns about the quality of exports and that Pakistan's product diversification lags the other regional economies and competitors. According to ITC data, Pakistan recorded a reduction of over 160 exportable products during 2011-15. However, countries such as Bangladesh and Cambodia saw an addition of over 250 and 300 exportable products in the same period, respectively. A big concern is Pakistan's reliance on resource-based exports such as cotton, rice, and hides. On the other hand, countries like Bangladesh and Cambodia compete for high-end textiles in the world market. Mr. Varela advises the Government to subsidize the industry and give incentives to the industry to produce new products. Some respondents (Dr. Abdi, Chairman PCSIR) identify several opportunities saying that China's huge market provides an opportunity for Pakistan's exports. Similarly, "halal meat," "halal economy," "dates," and "shrimp cultivation" can help the country reap significant foreign exchange reserves.

Furthermore, most respondents mention that the subsidy structure in the energy sector needs to be revamped (Dr. Ateeq, Ministry of Commerce). For example, current gas pricing is wrong, and that energy is heavily subsidized for customers, expressed Dr. Ateeq. Because of these massive subsidies, the country faces a current account deficit. Similarly, the textile sector loses internationally because of non-competitive energy pricing.

BOX 5: STATISTICAL CAPACITY NEED TO BE STRENGTHENED:

This data capturing and usage capacity is vital for overall public policy formulation. For example, a respondent from Finance Ministry (Nazia Gul, Deputy Economic Advisor, Fiscal and Monetary Section) mentions that Pakistan needs a robust statistical capacity to capture a vast informal sector and increase the tax collection capacity of the country. Similarly, Ayazzuddin, a respondent from the Pakistan Bureau of Statistics (PBS), provides valuable insights into Pakistan's statistical capacity. For instance, he mentions that the PBS reached out to 1700 IT firms in the country for the data collection on their size, number of employees, output, and profit in 2015-16, but only 300 firms completed the survey. Later, they reached the Pakistan Software Board (the regulator for IT), which provided anonymous data for the IT firms. Since then, the PBS has been extrapolating the data for subsequent years. He further notes Pakistan has been computing its GDP according to the Base Year of 2005-06 until now; however, the rebasing should be done every ten years. Finally, he mentions that the country needs to conduct a census every ten years, which is not the case in Pakistan: the 2017 Census in Pakistan marks the first census in Pakistan since 1998.

Other respondents highlight the need for strong property rights and commercial rights to make investors feel at home (Umer Kamal and Dr. Attiq, Ministry of Commerce). Similarly, most interviewees note a weak formulation of policy tools because of poor statistical capacity (see Box 5) and subsequent poor implementation of these tools. Lastly, some participants mentioned the need for skilled human capital to produce value-added goods (Dr. Hoodbhoy, Physicist, and Dr. Bari, Professor at LUMS). Dr. Ashfaq Hassan Khan (NUST) mentions how state-led nurturing of substandard human capital erodes bureaucratic quality and causes value degradation in the country. He opines that the country had smart bureaucrats in the 1960s and 1970s. However, in the late 1980s and early 2000, the quality of education significantly declined. According to him, the HEC sent students to substandard institutions across the world and in China, who, upon their return, could not deliver. As a result, bureaucratic quality declines, and this lack of skilled capital also is evident in the substandard production patterns. While the number of universities increased from 25 in 2002 to 225 universities, economic production and bureaucratic service eroded.

Bangladesh is not a different story regarding public policy, but there are some reforms that the Government has taken. For one, the country really focuses on producing quality textile products, and the Government provides support and incentives to the producers to enhance production. Similarly, as compared to Pakistan, Bangladesh's import tariffs are low, which is why it imports most of the raw cotton. Despite being an importer, Bangladesh is one of the largest cotton exporters. Also, Bangladesh has been able to market itself as a favorable destination for investment. As a result, it attracts billion dollars in investment from foreigners and grants ease of money transfer to expat Bangladeshis, increasing remittances in the country.

BOX 6: TEXTILE SECTOR – PAKISTAN VS BANGLADESH:

Pakistan is one of the largest producers of cotton. Despite being the leading manufacturing activity with an extensive production chain and natural potential for value addition at all processing stages, the textile sector in Pakistan concentrates on low-end products with limited value addition (like grey cloth and yarn). While textile owners lament the lack of a conducive environment hindering production and exports, they enjoy multiple subsidies: Duty and Tax Remission for Exports (DTRE), Drawback on Local Taxes and Levies (DLTL), Temporary Ecomoic Refinance Facility (TERF) scheme by the State Bank of Pakistan, and subsidized power and gas as well as tax exemptions (Rana 2021). With so many blanket subsidies, the sector is still not moving beyond yarn and fabric.

On the other hand, Bangladesh imports raw cotton and produces high-end products, including ready-made garments for men and women. They do so because of their ambitious plan to capture market share, learn market trends, link themselves to international markets, and provide a conducive business environment. They also have included more women in their labor force who perhaps have a strong insight into market needs.

If Pakistan wants to move towards value addition, it will have to support innovation and increase investment in new technology. The country would need to rework/shift its support structure by supporting high-value-added industries rather than low-value-added industries such as spinning. Also, the industry would have to rehaul its workforce, providing them more rights and including women in the labor force, and allocating R&D to produce sophisticated products. Finally, the industry would have to learn about the increasingly changing fashion and design trends in markets and countries.

8.7. Linkages

Within an innovation system, linkages among sectors are vital as they lead to efficient interaction and valuable learning across the system producing economic value. Dr. Nadeem ul Haque (PIDE) beautifully puts it this way:

> "..stop thinking about sectors (and intersectoral linkages), introduce system thinking..development is an emergent phenomenon and should be tackled via a system or complexity view.."

Unfortunately, the system view does not dominate Pakistan's development sphere. This is evident in weak linkages, as asserted by interviewees (such as Hamed Yaqoob Sheikh, Secretary Planning & Development Ministry). The private and public sectors are the least connected on a macro level. There is immense skepticism in the private sector about the role of the public sector, asserts Dr. Hussain (LUMS Econ Prof). Similarly, there is no learning or healthy competition between the two. Government players in the market are "handicapped," and they cannot compete with private players; for example, look at the loss-making PIA vs. the other profit-making private airlines, expresses Dr. Ishrat Hussain (Senior Economist). Dr. Hussain further states that the formal sector is detached from the informal sector, and the Government's foresight about formalization (formalizing the informal) is short-sighted. According to him, the state is focused more on tax collection instead of providing incentives to facilitate the firms to comply with various (environmental) standards.

Similarly, interviewees report linkages between industry and academia are almost non-existent (Dr. Farooq, ADB). For example, the British Government helped establish the Institutes of Technology in India (IIT) and Lahore (MacLagan Engineering College now University of Engineering Technology, known as UET). According to the interviewees (Dr. Almas, Planning Commission and Shehbaz Rana, Author at *The Express Tribune*), IIT flourished because of solid linkages, whereas UET lacks dynamism owing to its weak linkages. In addition, the Government offices seldom seek advice from think tanks and academia. While speaking with Dr. Haque, the Vice Chancellor of the PIDE—a think tank tasked to provide economic, policy, and academic research to the Planning Commission and other Ministries—I learned that the Government's ministries and Planning Commission are the least interested in research inputs from the institute. Dr. Almas from the Planning Commission asserts that PIDE conducts policy research for ministries on demand; however, the Ministries mostly ignore that feedback. Another participant from the Planning Commission mentions that PIDE is conceived on the pattern of the Korean Development Institute (KDI), but it does not provide any feedback to the Planning Commission.

Some interviewees discussed the idea of collaboration with and learning from the military. For instance, Dr. Almas points out that the Planning Commission may learn from the Special Policy Division (SPD)—the thinking Division for defense production—which has successfully collaborated with academia. Similarly, he states at present, there is no interaction between the Planning Commission and SPD, which, if it had been existing, would have led to spillover products. Dr. Muhammad Ahmad Zubair (Chief Economist at Planning Commission) also notes that the country needs to learn from the military to tackle economic problems. For example, after being mission-oriented and setting a credible threat perception, the military was able to produce aircraft, missiles, and atomic bombs, asserts Dr. Zubair.

Another interviewee, Dr. Haroon from Planning Commission, further suggests that the military-civil marriage will be a successful transformation strategy. He mentions that the military has several advantages in terms of the regulatory framework and public procurement rules. The civilian Government is inefficient as they would have three bids for purchasing a simple commodity such as a pen. In contrast, the military can buy the same item from a single vendor. The private firms that produce for the military are state-of-the-art, asserts Dr. Haroon. Such firms can be asked to produce dual-purpose technologies and products for military and civilian use. Dr. Haroon seemed to view that the military would welcome such a possibility as their fiscal space is being squeezed, whereas the military desires to be self-sufficient. Such a military-civil marriage would allow civilian firms to use military infrastructure and space and compensate the military with money.[70]

Linkages in Bangladesh appear to be stronger than in Pakistan. To a question about public sector linkages, one respondent in Pakistan quotes the example of Hassina Wajid, the Prime Minister of Bangladesh, who attends the Planning Commission meeting regularly, unlike the Pakistani Prime Minister. Similarly, another respondent mentions that in a four-hour meeting of Economic Advisory Council convened by the Prime Minister, the advisors seldom are offered an opportunity to share. Pakistan may learn from Bangladesh in this regard.

Further studies show that the status of linkages (backward linkages, for instance) in the textile sector within Bangladesh is exemplary (Hasan and Haque, 2020), and perhaps it is one of the reasons why Bangladesh delivers to the customer base in the international

[70] The idea of civil-military production may also be pursued in Bangladesh as their military holds a strong force (though weaker than the one in Pakistan) in the country's politics (Ganguly, 2020, p.).

market quickly. Similarly, a McKinsey report talks about the status of international linkages between Bangladeshi suppliers and leading global apparel brands and retailers (Berg et al. 2021). The report claims that healthy international linkages help improve efficiency and sustainability in Bangladesh's industry.

8.8. Incoming Factors: (learning from abroad)

One of the critical features of the absorptive capacity framework is how a country captures learning from abroad. The interviewees in Pakistan agreed that learning mechanisms and "diffusion pathways" in the country are extremely poor. Dr. Arshad (Vice Chancellor LUMS) remarked in a panel discussion at PIDE Conference held at IMSciences Peshawar that talent acquisition needs an environment the country lacks. Dr. Hussain (LUMS Econ Professor) contrasted the sports industry in Sialkot City with the fans (light electronics) industry in Gujranwala City, saying that the former is very forward-looking, focuses on the international market, has learning and training mechanisms, hires talented employees, and incentivizes employees to innovate. In contrast, the latter lacks standardization, uses cheap imports, and has no learning mechanism equipping employees to produce for an international market. Consequently, the sports industry serves the global market, whereas the fans industry is hardly known to anyone globally.

FDI, as an incoming flow, is essential for economic development. Participants point out that Pakistan is losing out on FDI because of policy inconsistency (Zehra, Economist World Bank Islamabad), political instability, and security situation (Dr. Ateeq, Ministry of Commerce; Zille Hasnain and Umer Farooq, Ministry of Finance). Hamed Yaqoob Sheikh (Secretary Planning & Development) expresses dissatisfaction that Pakistan has been unable to absorb returning talent from abroad. Dr. Ateeq mentions that "it is just hard to implement learning from abroad" because the "system is corrupt." Pakistanis are learning "sports and fashion" and "consumption patterns" from abroad rather than governance, economic management, sustainability, and climate change, comments Dr. Ateeq and Dr. Hoodbhoy. There is no systematic way Government learns, whereas India has proper learning mechanisms in place in each Ministry, asserts Dr. Bari (LUMS Education Professor).

After the partition, Bangladesh attracted significant foreign investment, boosting its economy. Contrary to this, Pakistan could not market or brand itself as an international destination, which is why it is losing out on foreign investment, responds one interviewee. Bangladesh also appears to have a sharp sense of commercial learning, catering mainly to the world market in textile. Compared to Pakistan, which is not innovating in textile, Bangladesh, with its international outlook, produces several value-added textile products keeping in mind its disparate customer base. Moreover, Bangladesh is learning from the world's experience by imparting skills to women and integrating them into its workforce. Bangladesh's entrepreneurs are also well aware of the changing fashion trends in European and American markets, and they are flexible enough to adapt international best practices. Finally, the Bangladeshi entrepreneurs offer a rich ground to globally known apparel brands and are willing to cooperate and negotiate, rendering their local businesses efficiency and sustainability. All these offer useful lessons to industry and entrepreneurs in Pakistan.

9. Concluding Remarks and Opportunities

This chapter aimed to provide nuance to the theoretical framework offered in this dissertation. Sections 4 and 7 of this chapter illustrate how Bangladesh performs better than Pakistan in most economic indicators. However, Section 5 notes that Bangladesh leads in some capacities, whereas Pakistan is ahead in other capacities. Section 8 partly validates these results and adds that Bangladesh has a strong "system" view of the economy owing to solid internal and external interactions. Therefore, despite the suboptimal status of some of its capacities, Bangladesh's learning spirit and international alignment improve its economic conditions. In other words, capacities interact more potently within the country and with the rest of the world in Bangladesh. On the other hand, in Pakistan, the learning spirit is dampened, and international alignment is diminished. As a result, while Pakistan may have some relatively stronger capacities, it lags Bangladesh in economic parameters. Furthermore, as per the framework in this dissertation, since capacities interact with incoming flows from the rest of the world, an economy is strengthened by active interactions with the rest of the world. Qualitative findings here suggest that Pakistan lacks such interactions. In contrast, Bangladesh actively fosters these interactions while also nurturing some of its capacities.

In terms of the total absorptive capacity index, Bangladesh has made tremendous progress. Compared to an overall stagnant rate in Pakistan's index, we see that the increasing trend in the index is faster in Bangladesh. What makes Bangladesh distinct from Pakistan is its ambition and aspiration to not only link itself with international markets (international linkage) by knowing its customers (learning) but also provide a favorite destination for foreign investors (business climate). Moreover, Bangladesh has spurred value addition in the textile industry (see Box 6) by offering incentives to its high-value-added textile industry (garments) and minimizing tariffs and trade restrictions (public policy). Bangladesh also enjoys a relatively more skilled (human capital) and diverse workforce (social capacity), integrating more females and youth in the labor force, who likely understand the changing trends in design and fashion.

Overall, the chapter identifies several ingredients of success in Bangladesh: a healthy degree of entrepreneurship, investment in productivity improvement, relative strength in linkages, robust learning and flexibility, and a diverse, hardworking workforce, among others. On the other hand, Pakistan is lagging in these essential capacities.

While comparing secondary data, one of the reasons why we do not observe striking differences between Pakistan and Bangladesh in terms of their capacities is that the capacities are likely interlinked, and maybe the effects of some capacities mix up. For instance, ICT infrastructure (Infrastructure Capacity) could correlate with technological capacity; similarly, finance capacity could correlate with infrastructure capacity.

The qualitative analysis here helps us identify various lessons Pakistan can learn from Bangladesh. The first crucial lesson that Bangladesh offers to Pakistan is strengthening its capacities. Bangladesh intentionally built its human capital capacity, made its primary education more inclusive, and recruited a diverse and skilled workforce in the industry. Similarly, Bangladesh's textile sector owners developed an entrepreneurial mindset that flowed into the entire industry, leading to high-value addition. Moreover, Bangladesh invested in ICT adoption, boosting its service sector, including IT exports.

Likewise, it invested in road connectivity and manufacturing capability, leading to strong vertical integration in the textile industry. In terms of public policy, the Bangladesh government offered the right incentives to textile owners, supporting ready-made garments production. Similarly, the Government complied with international best practices and safety standards by introducing several measures and initiatives, thus attracting clients worldwide. All these offer lessons to the Pakistani economy on how they may revive their textile industry, which has been stagnant.

Another helpful lesson that Bangladesh provides is the learning spirit that the country possesses. The country learns from abroad and from its experiential learning. There is collaboration, and the Government is keen on hearing from stakeholders. It is a resilient country—after several tragedies in Bangladesh's textile industry, the industry was able to rebound. First, it introduced measures to signal the clients that it is compatible with their preferences, and second, it learned customer mindset. Thus, by keeping up with the changing patterns in consumer demand and the fashion industry, the textile industry captured a huge market share. Because the industry does not shy away from learning, this mindset helps produce garments well received in international markets.

Moreover, Bangladesh offers an example of establishing solid linkages with the world. Again, let's consider an example of the textile industry in Bangladesh, which generates around $5bn in products annually and employs three million workers (Mace 2021). The textile industry leaders are active; they actively seek collaboration with international brands urging them to build their capacities in manufacturing high-end apparel. In addition, they participate in events such as the ones hosted by American Apparel

& Footwear Association to showcase their success stories and potential among brands and buyers (NewAge 2022). Similarly, Bangladesh welcomed over thirty global brands and manufacturers to recycle textile waste in Bangladesh, signaling its sustainability efforts (Sustainability Brands 2021). Overall, these efforts and initiatives signal how ambitious Bangladesh's industry is in attracting international investors and thus building its brand image. Pakistan's industry should follow a similar suit. The country's embassies and consulates should help identify those opportunities in foreign countries, and the Government should facilitate industry associations to promote its brand. By attracting brand manufacturers, the country may attract manufacturing technology to build high-end apparel, and it can urge the brands to increase their sourcing from Pakistan.

Lastly, Bangladesh offers an example of how it actively attracted world investment. The Government signed trade agreements and pacts with companies and richer countries alongside reducing barriers to investment, liberalizing the economy, and improving the security situation. It also effectively involved its foreign diaspora in developing the brand Bangladesh. By serving the expat market, Bangladesh makes millions of foreign reserves. Pakistan can also engage in such efforts. First, it may reduce trade barriers. Second, it should work on reputation management internally through offering and developing tourist opportunities and externally via its foreign diaspora. By serving expat Pakistanis and involving them in policymaking efforts as well as promoting tourism opportunities in the country, Pakistan can build its reputation in foreign markets. All this will lead to more inflows of skills, technologies, and investment in the country, leading to economic development.

10. Suggestions for Further Research

The tale of the two countries provides a fertile ground for applying the framework developed in this dissertation. Future studies may apply the framework to at least five case countries to fully validate the quantitative findings. Classification from cluster analysis may provide an initial basis for selecting case countries.

While from the outside, one might see many similarities across LMICs as a whole, however, each LMIC has unique characteristics. Capacities within LMICs evolve with varying degrees, as also seen in the case of Bangladesh and Pakistan. In addition, countries might have different priorities for capacities. For example, some LMICs, such as Pakistan and Myanmar, may focus on infrastructure capacities, whereas others, such as Vietnam, may build their innovation and technology capacities. Future research may explore these trends and inform how capacities evolve and whether there are any catching up, converging, diverging, or club converging phenomena within LMICs. While such phenomena are well-established for world economies (Cartone, Postiglione, and Hewings 2021; King and Ramlogan-Dobson 2016; Park, Choi, and Hong 2015), it will be interesting how they play out for LMICs exclusively.

Similarly, researchers may apply the framework this dissertation developed for LMICs in High-Income Countries to assess and confirm its general relevance. As I noted that scientific, technological, and social capacities do not majorly affect economic growth in LMICs, it would be interesting to evaluate the role of these capacities using this framework in High-Income Countries. This would also initiate a discussion within the scientific community regarding what can be done practically to increase the strength of

LMICs' economic indicators. Further, since LMICs lack data on many parameters of innovation and development, researchers, and organizations such as the World Bank, UNESCO, and Globelics may conduct innovation and absorptive capacity surveys in LMICs to collect additional relevant data in light of the framework this dissertation offers. Such data collection responsibilities can also be undertaken by institutions such as the *Center for International Development* at Harvard University, the *Center for Science, Technology, and Innovation Policy* at George Mason University, the *Center for Innovation and Development in Society* at Arizona State University, and think tanks such as the *Center for Global Development*, the *Atlantic Council*, the *INSEAD Emerging Markets Institute* and the *Information Technology and Innovation Foundation*. The collected data will apprise us of the recent and accurate trends in capacities and innovation processes in LMICs.

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Appendix A: Sample Interview Questions

Sample interview questions are provided below:

1- What factors/conditions required would help Pakistan/Bangladesh/Vietnam move up the innovation ladder? What are the conditions that would make the country capture a fair share of the world market? How can the country move from low-tech and medium-tech to high-tech products in the value chain?

2- How does the country rank in terms of performance in those conditions? What are the reasons for a dismal or unsatisfactory performance?

3- Why has STI not been a priority for policymakers?

4- Is your country learning from the experiences of the outside world? If so, how? If not, why?

5- How can we impart skills and build competence in our institutes and industry?

6- Do you think your country has formal institutions and policies to learn from other countries' experiences and technologies?

7- How do you describe the linkages between industry, academia, and the Government?

8- How do you describe the role of the Organization the interviewee is affiliated with in innovating the economy?

9- When we talk about STI policymaking in your country, what would work in your country's context?

10- Please comment on the role of human capability in driving economic growth.

11- Please comment on the role of infrastructural capability in driving economic growth.

Appendix B: Bangladesh vs. Pakistan Other Select Indicators

The following images show how Pakistan and Bangladesh compare on select economic and other indicators. The images are taken from The Business Standard.

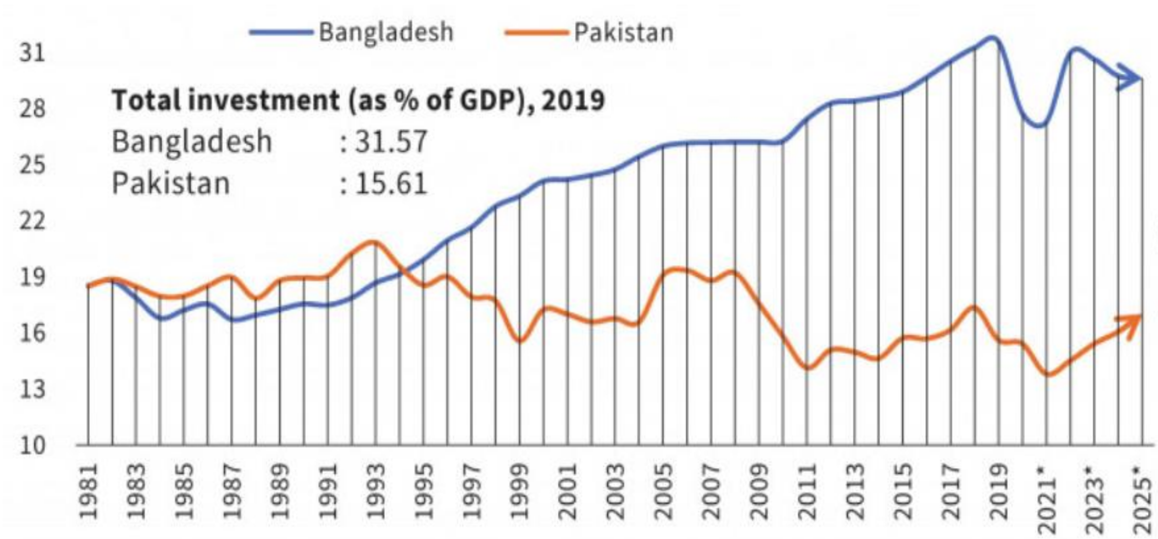

Figure 5.24: Investment Trend. Source: The Business Standard (Data from IMF)

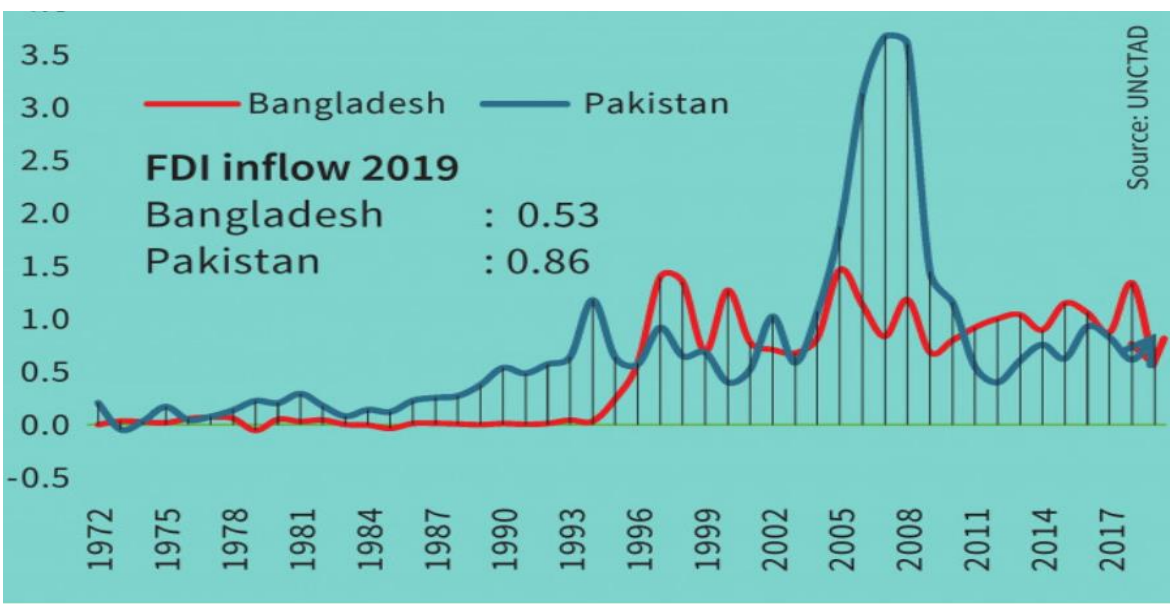

Figure 5.25: FDI Inflow (% of GDP). Picture taken from: The Business Standard

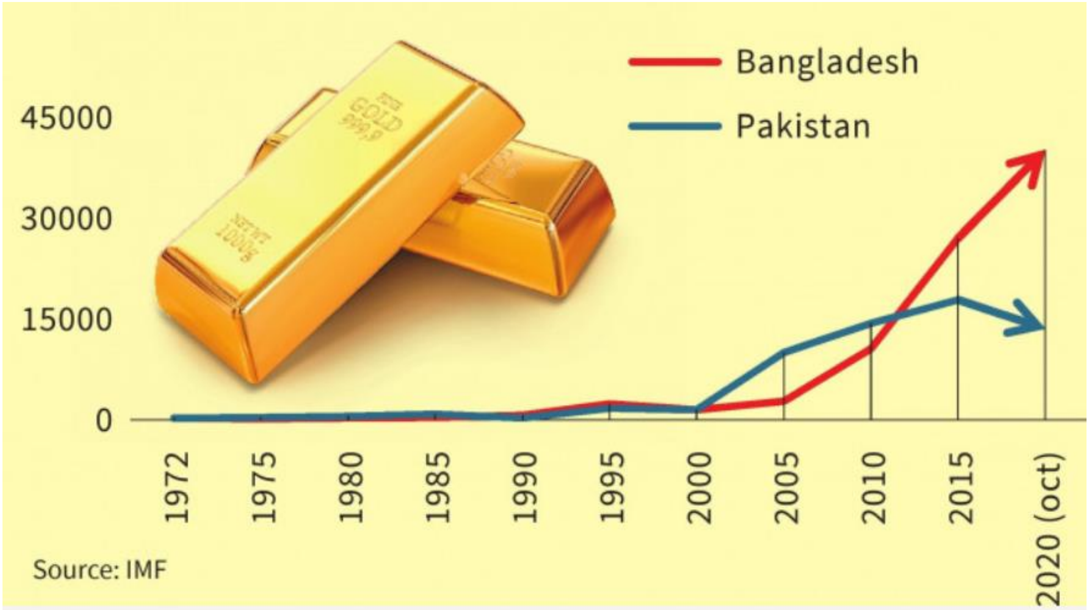

Figure 5.26: International Liquidity (Total Reserves Excluding Gold, USD). Picture taken from: The Business Standard

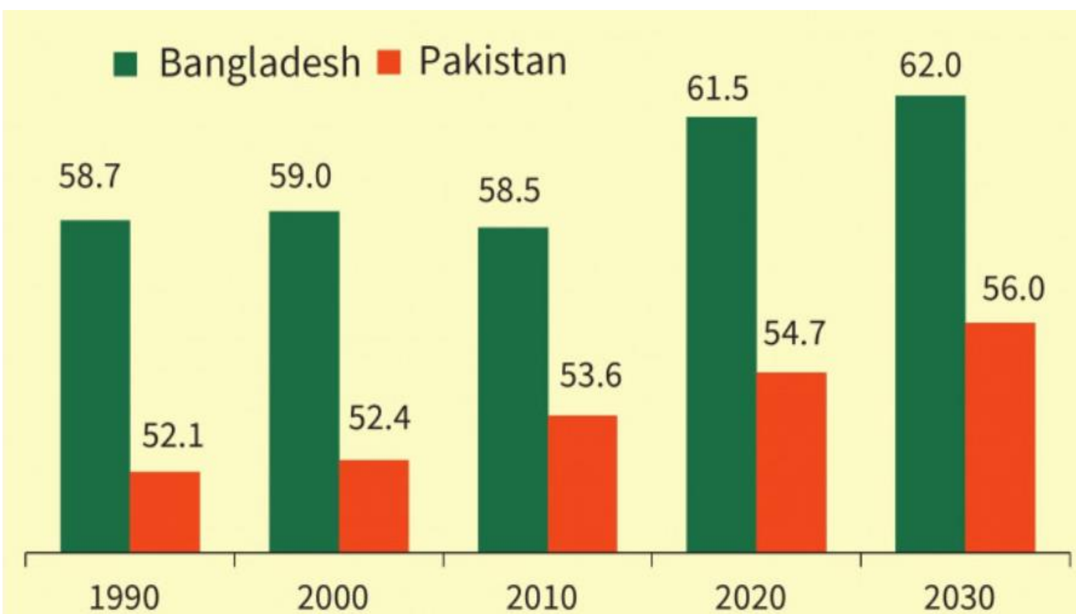

Figure 5.27: Labor Force (Aged 15-64) Participitation Rate (in %). Picture taken from: The Business Standard (Data from ILO)

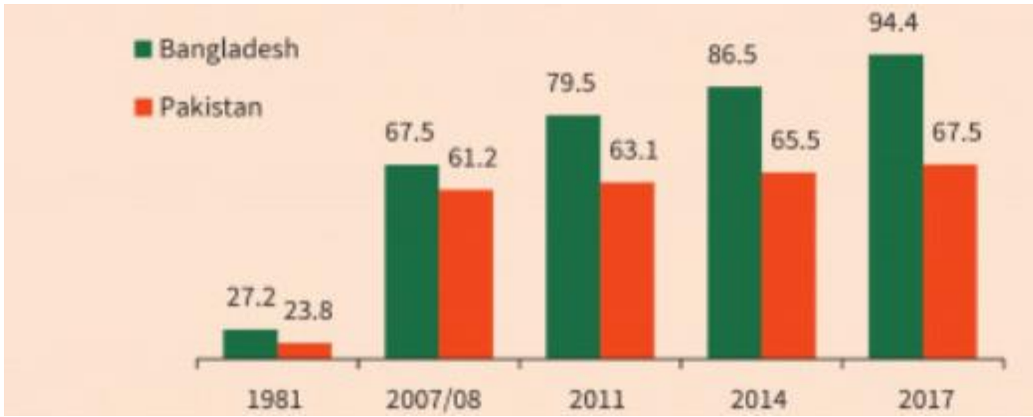

Figure 5.28: Female youth (15-24 years) literacy rate (in %). Picture taken from: The Business Standard (Data from UNDP)

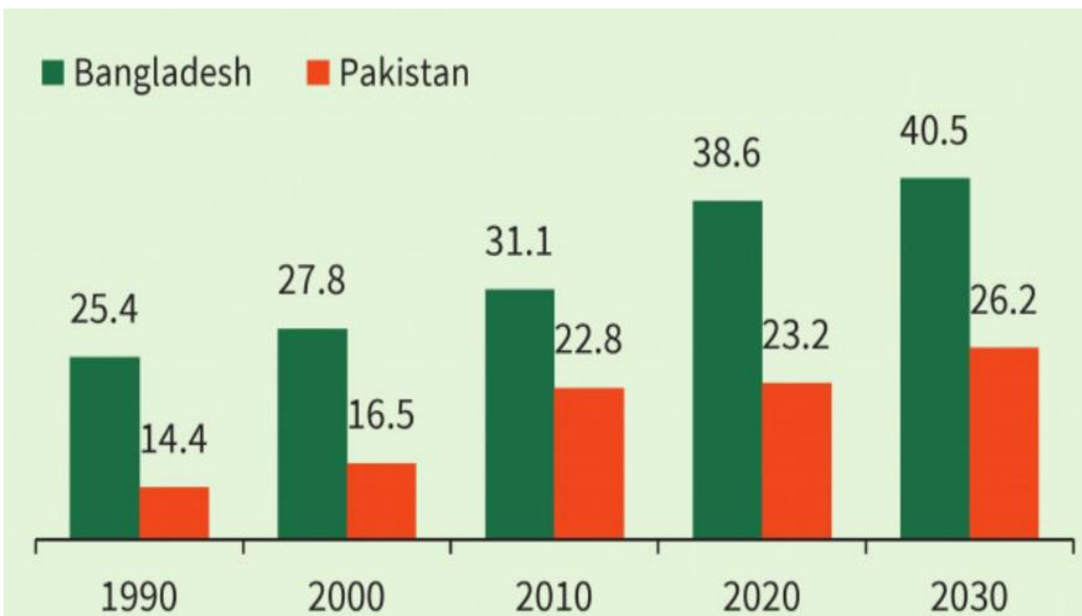

Figure 5.29: Female (Aged 15-64) Labor Force Participation Rate (in %). Picture taken from: The Business Standard (Data from ILO)

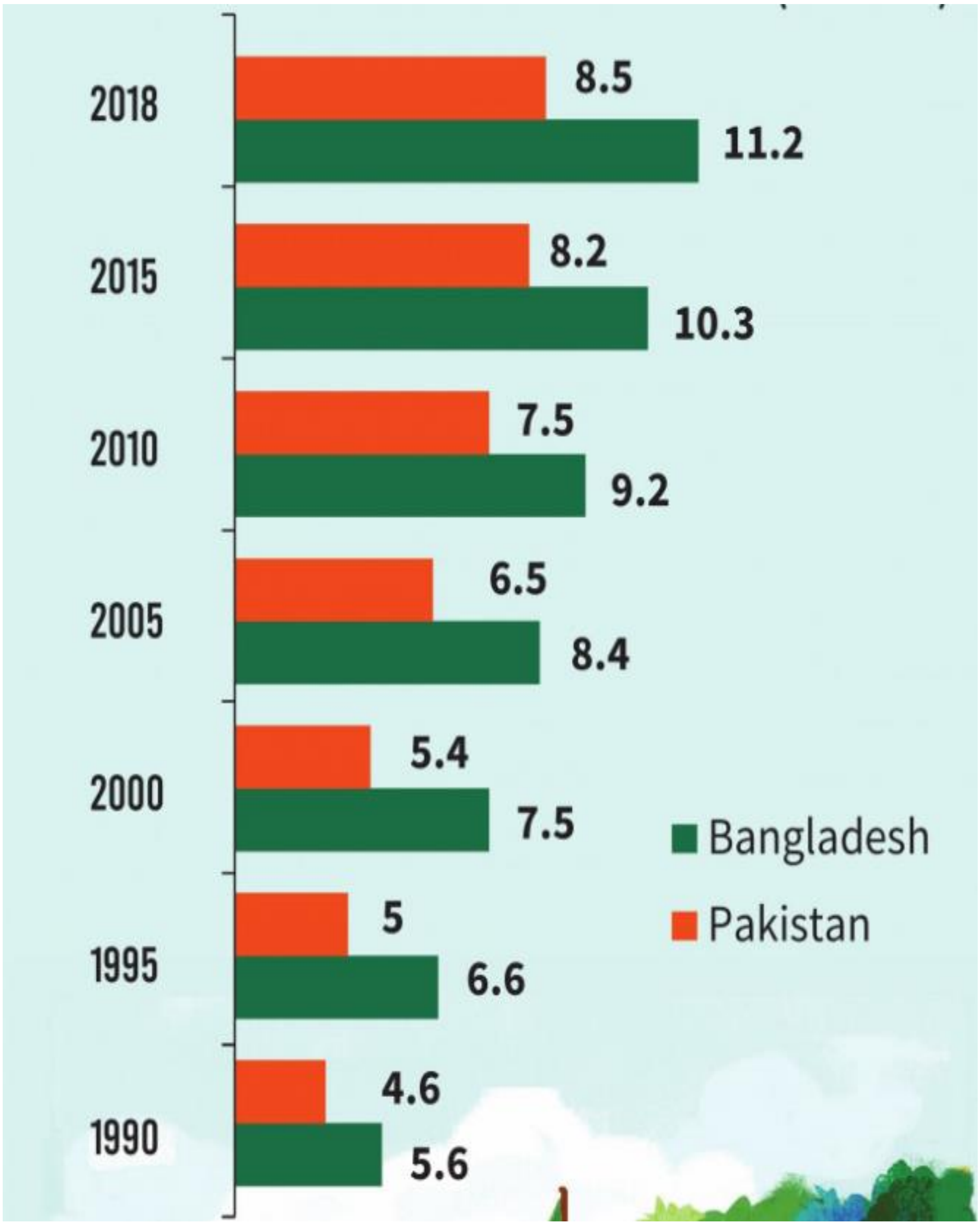

Figure 5.30: Expected years of schooling. Source: The Business Standard

BIOGRAPHY

Muhammad Salar Khan graduated with a Science major from Islamia College University, Peshawar, Pakistan, in 2009. He received his Bachelor of Science (Hons) in Economics and Politics from Lahore University of Management Sciences, Pakistan, in 2013. Before completing his Master of Public Policy (focus on Economic and Energy Policy) at Oregon State University in 2017, he worked with the British Council and European Union at the Parliament of Pakistan as well as the World Bank in Washington, DC.