INTENSITY OF RESEARCH AND DEVELOPMENT EXPENDITURE, IMPACT OF FIRM-LEVEL INNOVATION, AND PRODUCTIVITY GROWTH OF THE KENYA NATIONAL INNOVATION SYSTEM

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DECLARATION

This thesis is my original work and has not been presented for a degree in any other University or any other award.

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In loving memory of my dad

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ABBREVIATIONS AND ACRONYMS

ASTII	African Science, Technology and Innovation Indicators
CIS	Community Innovation Surveys
DEA	Data Envelopment Analysis
DID	Difference in Differences
DMUs	Decision Making Units
DSGE	Dynamic Stochastic General Equilibrium
ESR	Endogenous Switching Regression
GII	Global Innovation Index
IPR	Intellectual Property Rights
ISIC	International Standard Industrial Classification
KNIS	Kenya National Innovation System
NIS	National Innovation System
MTP	Medium Term Plan
OECD	Organization for Economic Co-operation and Development
PSM	Propensity Score Matching
R&D	Research and Development
RIS	Regional Innovation System
SFA	Stochastic Frontier Analysis
ST&I	Science, Technology and Innovation
STISA	Science, Technology and Innovation Strategy for Africa
TFP	Total Factor Productivity
WBES	World Bank Enterprise Survey
WIPO	World Intellectual Property Organization

OPERATIONAL DEFINITION OF TERMS

Science, Technology & Innovation (ST&I)	Is the generation, flow, and utilization of technical and scientific knowledge.
Research and Development (R&D)	Involves the development, dissemination, transfer, and utilization of ST&I in all national development sectors. Research is indeed part of the knowledge, technology, and innovation generation.
Firm	It's an establishment that converts inputs into outputs. The outputs could be goods or services; the inputs include labour, capital, raw materials, and sometimes knowledge from R&D. The outputs are then sold in competitive markets for a profit motive. Firms with 5-19, 20-99, and above 100 employees were considered small, medium, and large, respectively.
R&D Propensity	Is the likelihood of a firm engaging in R&D spending activities.
Firm-level R&D Spending Activities	Are usually indicated by the amount of money spent on: intramural and subcontracted R&D activities, adoption of foreign knowledge, and procurement of R&D-intensive capital. Additionally, firm-level R&D efforts can be

	indicated by the capacity of R&D personnel and the amount spent on training them (OECD/Eurostat, 2019).
R&D Expenditure Intensity	Is the total amount of money a firm spends on R&D activities.
Knowledge Management	Entails activities related to any institution's utilization, enhancement, and diffusion of knowledge.
Innovation	Refers to the operationalization of a novel or significantly enhanced product (service/good), a new marketing method or process, or a new organizational strategy in business practices, organization, workplace, or external relations.
Innovation Activities	Are all organizational, scientific, financial, and technological initiatives to implement innovation activities.
Firm-level Innovation	In this study, firm-level innovation was indicated by firm-level participation in R&D activities, the introduction of new products/services into the market, new processes, and the ownership of intellectual properties.

Successful Innovation	Refers to an activity that leads to implementing an innovation even though the realized innovation was not commercialized.
Intellectual Properties	Are the creations of human brainpower, including inventions and innovations. Government authorities issue exclusive ownership rights of inventions and innovations, which include: patents, trademarks, industrial designs, copyrights, and licenses.
National Innovation System (NIS)	Refers to interconnected economic agents within a country that collaborates in generating, utilizing, and disseminating knowledge and innovations.
Kenya National Innovation System (KNIS)	Refers to the linkages and collaborative efforts among economic agents in Kenya to generate and use new knowledge/technology and the culture/environment of Kenya's innovation. In this definition, all firms operating within Kenya's borders are considered to be in the KNIS, where social, political, and economic factors external to a firm are assumed to influence the firm's innovativeness.

Regional Innovation System (RIS)	When several NIS from the same geographical region are analyzed simultaneously, they make up a Regional Innovation System (RIS).
Efficiency	When all inputs in an economy are allocated to their most valuable uses and waste is eliminated or minimized during the production of goods and services.
Technical Efficiency	Is the effectiveness of producing a given output from a given amount of inputs. The maximum output is realized from the minimum inputs, such as technology, labour, and capital.
Productivity	Is a measure of economic performance that compares the proportion of output produced by a firm from a given amount of inputs.
Productivity Growth	Refers to an increase in the value of outputs realized from a particular amount of inputs over a specific period. A firm's value-added per worker measures a firm's productivity. The productivity of the KNIS was measured by a composite/aggregated innovation index measuring the innovativeness of all economic agents.

ABSTRACT

Since the 2010s, Kenya has embraced and invested in Science, Technology, and Innovation as the key driver of economic development and firm productivity. The strategies include establishing a National Innovation System in 2013, education reforms, and incorporating Science, Technology, and Innovation in policy goals like the Kenya vision 2030. Subsequently, efforts by Kenya to invest in Science, Technology, and Innovation have led to its categorization among the leading innovation hub in Sub-Saharan Africa. Even with these innovation efforts and achievements, Gross Domestic Product growth and the performance of manufacturing and services remained below the 2022 target. This-notwithstanding, manufacturing and services firms' Research and Development spending and innovation remained low during the 2015-2017 study period. In the context of this inconsistency, this study investigated the drivers of a firm's Research and Development expenditure intensity, the impact of firm-level innovation on firms' productivity, and productivity growth of the Kenya National Innovation System (2010-2018). The study utilized secondary cross-sectional data from the 2018 World Bank Kenya Enterprise Surveys and balanced panel data (2010-2018) from the World Development Indicators Data. Sample selection model, treatment effects models, and Data Envelopment Analysis were used as estimation methodologies. The results revealed that usage of innovation labs/hubs would increase propensity by 27.7% and reduce intensity by KES 27. Employee training on the innovation process increased propensity by 52% and reduced intensity by KES 29. Innovation partnership increased propensity by 45% and reduced intensity by KES 36. Further results indicated that only product/service innovation significantly impacted the firms' productivity out of the four measures of firm-level innovation considered. Process innovation, Research and Development propensity, and Intellectual Property Rights ownership did not matter significantly to a firm's productivity. Lastly, the results indicated that Kenya's National Innovation System was among Africa's most productive and efficient National Innovation Systems. However, it lagged in terms of technical progress. These results indicate that, at the firm level, the total gain from innovation was not realized, and at the national level, innovation was more profound. These results imply that the institutions in charge of Kenya National Innovation System, i.e., KENIA, NRF, and NACOSTI, need to re-evaluate firm-level innovation strategies to ensure maximum innovation gains are realized. Second, monitor and evaluate knowledge flow and sharing among the government industry and academia. Lastly, encourage innovation partnerships, training of employees on the innovation process, and champion for the establishment of innovation hubs to enhance firm-level research and development expenditure and innovation.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Global markets operate in an unstable environment marked by increased globalization, fierce competition, and accelerating demand change. Because of this, businesses and countries around the world are investing significantly in Research and Development (R&D), Science, Technology, and Innovation (ST&I) to maintain their competitiveness (Sukumar et al., 2020).

Innovation is defined as introducing novel ideas and methods to the firm, country, or workplace and includes imitations (Griffith et al., 2006; Hall et al., 2014). For successful innovation, especially in developing countries, the National Innovation System (NIS) is an essential concept in the innovation process (Nelson, 2013). An innovation system refers to interconnected economic agents collaborating in generating, utilizing, and diffusing knowledge and innovations. NIS shows how smooth interconnections and regular interactions of all national innovation actors can enhance firms' and countries' innovation and productivity (Lundvall, 2016; Watkins et al., 2015).

The national innovation actors include society, academia, government, and industry. Meuer et al. (2015) generally categorize the NIS actors into two broad categories: institutions and organizations. Organizations encompass research institutes, Universities, government policy organs, and private firms (Yuzhuo Cai & Liu, 2015; Fagerberg, 2018). On the other hand, institutions are rules and laws that encourage fair play in innovation, for example, patent laws. Institutions also include social norms that shape industry and academia's linkages (Yuzhuo Cai & Liu, 2015; Li, 2015) and other national traditions and social norms (Khan & Cox, 2017). This study defined the Kenya National Innovation System (KNIS) as the linkages and collaborative efforts among institutions and organizations in Kenya to generate or use new knowledge/technology and the culture/environment of innovation in Kenya. Therefore, the KNIS is the coordination of interactions framework between the research and education sub-system, intermediate institutions, the business sub-system, and the Science, Technology, and Innovation (ST&I) infrastructure in Kenya, as shown in Appendix A (Ayisi et al., 2019; the Republic of Kenya, 2015).

Successful innovation refers to an activity that leads to implementing an innovation even though the realized innovation may not have been commercialized. In this study, successful innovation among the manufacturing, retail, and other services firms in Kenya was indicated by; Research and Development (R&D) spending, the introduction of new-to-the-firm products/services, new or improved processes, and ownership of Intellectual Property Rights (IPR). IPR refers to the creation of human brainpower, including inventions and innovations. Government authorities issue exclusive ownership rights of inventions and innovations, including patents, trademarks, industrial designs, copyrights, and licenses.

Efforts towards successful innovation at the national or industry level are usually depicted by countries and a firm's investment in R&D and the establishment of sound ST&I policies and frameworks (OECD & Eurostat, 2018). ST&I refers to the production, diffusion, and use of scientific and technical knowledge. On the other hand, R&D involves the development, dissemination, transfer, and utilization of ST&I in all national development sectors. Research is part of the generation of knowledge, technology, and innovation (OECD/Eurostat, 2019). In the recent growth and development literature, R&D and ST&I are cited as crucial ingredients for economic growth and firm productivity globally.

The African region's initiative to invest in ST&I was conceived in 2003 by African Union (AU) members (AU-NEPAD, 2010; NEPAD, 2014). The African Science, Technology, and Innovation Indicators (ASTII) policy was created to enhance economic development and accelerate Africa's catch-up with the global ST&I frontier. The initiative was intended to sufficiently strengthen the capacity to measure R&D and ST&I in Africa (AU-NEPAD, 2010). Initiatives to establish and reinforce the ST&I framework have been ongoing since 2007. As a result, 43 AU member countries, including Kenya, have integrated the ASTII initiative into their national R&D policies.

In 2014, the AU member countries, including Kenya, adopted the Science, Technology, and Innovation Strategy for Africa, 2014-2024 (STISA 2014-2024) as a medium-term goal for the "Africa we want 2063 agenda." It lays out prerequisites, pillars, priority areas, and investments required to meet the necessary development in ST&I as part of achieving the Sustainable Development Goals (SDGs) (African Union Commission, 2014; AUDA-NEPAD, 2019). STISA 2014-2024 is a vision and a collaborative effort delivery model of ST&I activities involving the public and private sectors and international collaborations. Another principal aim of STISA 2014-2024 is to develop Science, Technology, Engineering, and Mathematics (STEM) capacity and integrate ST&I partnerships at the national and international levels.

Within the period of implementing the ASTII initiative, different regional economic communities and countries have integrated the program into their innovation systems to varying degrees (AUDA-NEPAD, 2019). For instance, the ASTII initiative encourages African countries to spend at least one per cent of their Gross Domestic Product (GDP) on ST&I. By 2019, only 11 countries had published data on Gross Domestic Expenditure on Research and Experimental Development (GERD/GDP ratio). None of the African countries had achieved the one per cent GERD/GDP ratio target, with Kenya having the highest GERD/GDP in Africa in 2019 at 0.98%, followed by South Africa (0.82%) and Egypt (0.80%) (African Union–New Partnership for Africa's Development, 2019). According to AUDA-NEPAD (2019), only 23 African countries had conducted national R&D surveys, and only 19 countries had data on public sector R&D activities.

Compared to other Regional Innovation Systems (RIS) globally, Africa is still lagging, with many countries lacking sufficient ST&I policy frameworks and adequate ST&I data (Egbetokun et al., 2017). For instance, the OECD and EU-member countries have set a two per cent GERD/GDP ratio target where most member countries are above this target and have sound ST&I institutional infrastructure. However, Africa's public R&D spending pattern is similar to other regions and global economies. For instance, public sector R&D expenditure in OECD member states and Latin America was approximately 0.64% and 0.7% of GDP, respectively in 2019. In Africa, R&D expenditure as a percentage of GDP ranged from 0.20% to 0.78% in 2019 (African Union–New Partnership for Africa's Development, 2019; Dobrzanski, 2020; Morsy & Amira, 2020).

The interventions provided by ASTII have led to many AU member countries with ST&I statistics as a foundation for policy development. However, some member states are still strengthening their national ST&I frameworks by creating ST&I institutions, collecting data, conducting national innovation surveys, and publishing reports (AUDA-NEPAD, 2019).

1.1.1 ST&I Policy Framework and Firm-Level R&D Expenditure in Kenya

Kenya has integrated the ASTII and STISA regional innovation policy goals with national R&D policies. For instance, Kenya has immensely invested in Science, Technology, and Innovation (ST&I) since the 2010s as a medium-term strategy for economic growth (NEPAD, 2014; Republic of Kenya, 2013b, 2013a). The efforts to invest in ST&I have been made through legislation, public expenditure on ST&I, Community Innovation Surveys (CIS), and the establishment and strengthening of the KNIS institutional frameworks (Republic of Kenya, 2012).

The Kenya ST&I institutional framework integrated into the ST&I policy is documented by the ST&I Act of 2013 (Republic of Kenya, 2013a). The R&D management institutions founded by the 2013 ST&I Act are mandated to oversee the ST&I sector in Kenya. They include: First, the National Commission for Science, Technology, and Innovation (NACOSTI), whose primary role is to determine ST&I priorities and coordinate its implementation across all government arms. The Second is the Kenya National Innovation Agency (KENIA), whose responsibility is to develop and manage the KNIS. Lastly, the National Research Fund (NRF) mobilizes resources for the KNIS. However, the new ST&I institutional framework is not fully operational independently, and largely ST&I management has been under the Ministry of Education, Science and Technology (MoEST) and public research institutes (Republic of Kenya, 2013a, 2015). Appendix B shows an organogram of R&D and ST&I management in Kenya.

Kenya has also integrated ST&I into the vision 2030 development agenda. As part of the vision 2030 goals, the 2013-2017 Second Medium Term Plan (MTP II) pinpointed ST&I as one of the government's priority spending areas (Republic of Kenya, 2013b). Investment in ST&I under MTP II focused on initiating platforms and collaborative efforts by partners and stakeholders involving MoEST, the private sector, universities, research institutions, industries, government ministries, scientists, researchers, and individual ST&I experts (Republic of Kenya, 2013b).

In the 2018-2022 Third Medium Term Plan (MTP III) of the Kenya Vision 2030, Kenya aimed to raise its global innovation and competitiveness index. The plan entailed increasing national R&D projects and establishing state-of-the-art infrastructure to enhance advanced research and technology development. This infrastructure was supposed to support nano-science, biotechnology, space science, electricity generation, and fuel exploration. Additionally, Kenya sought to enhance education institutions' capacity in the third medium-term plan. Consequently, more institutional frameworks were to be formed to improve and support the Science, Technology, Engineering, and Mathematics (STEM) program (Republic of Kenya, 2018).

According to the Africa innovation outlook III 2019 report by Africa Union Development Agency and AU-NEPAD, Kenya's Gross Domestic Expenditure on Research and Experimental Development (GERD/GDP) ratio was the highest in Africa at 0.98%. South Africa (0.82%) and Egypt (0.80%) had the second and third-highest GERD/GDP ratios, respectively (African Union–New Partnership for Africa's Development, 2019). GERD/GDP gives the fraction of a country's GDP devoted to ST&I. Kenya had not yet attained the world's 2019 GERD/GDP average ratio of two per cent. However, it was ranked among countries like India, Malaysia, and China that perform better than their economic peers' investment in ST&I (Cornell University, INSEAD & World Intellectual Property Organization, 2018).

At the firm level in Kenya, efforts to invest in R&D are indicated by the amount of money spent on intramural and subcontracted R&D activities, adoption of foreign knowledge, and procurement of R&D-intensive capital. Additionally, firm-level R&D efforts are linked to the capacity of R&D personnel and the amount of money spent on training them (OECD & Eurostat, 2018). Table 1.1 shows the number of firms that did and those that did not spend on these R&D activities between 2015 and 2017. The table captures a part of the Kenya World Bank Enterprise Survey (WBES) 2018 report that sampled 1,001 firms in Kenya.

Table 1. 1: Firm-Level R&D Spending in Kenya 2015-17

Categorization	Sub-categorization	Sample size	R&D spenders	Non-R&D firms
All Firms		1,001	16%	84%
	Manufacturing	455	22%	78%
Sector	Retail	198	15%	85%
	Other services	348	15%	85%
Firm Size	Small	412	14%	86%
	Medium	381	18%	82%
	Large	208	27%	73%

Source*: Author's computations from WBES 2018*

The survey scope was 2015-2017, wherein in 2018, the survey sought a yes/no answer on whether a firm had spent on R&D and the actual average R&D spending by firms for the past three years, i.e., 2015, 2016, and 2017. Out of the 1,001 sampled firms, only 16% reported spending on R&D activities during the study period. As one of the control pieces of information, the 2018 WBES classified the 1,001 firms into three broad categories according to their sectors and sizes using the International Standard Industrial Classification (ISIC). Under sectorial classification, the establishments were categorized as either manufacturing, retail, or other services. Under the firm size classification, the firms with 5-19, 20-99, and above 100 employees were considered small, medium, and large, respectively.

Categorization of sampled firms into sectors and firm sizes revealed that more firms in the manufacturing industry and large firms had spent on R&D compared to firms in the retail and other services industry, small and medium firms, respectively. During the study period, firm-level R&D spending remained low, even though R&D spending is a crucial business survival strategy, predominantly when a firm operates in a competitive business environment (Teece et al., 1997). Consequently, this study investigated the drivers of a firm's intensity of R&D expenditure among the Kenyan manufacturing, retail, and other services firms during the 2015-2017 study period. Drivers of a firm's R&D expenditure intensity helped explain why some firms spent on R&D and others didn't.

1.1.2 Firm-Level Innovation and Productivity of Firms in Kenya

Firms face a volatile business environment characterized by rapid globalization, cutthroat competition, and demand change. In this context, firms' innovative capabilities, competitive advantage, and productivity depend not only on their R&D initiatives but also on their potential to manage their innovation process through enhanced organizational strategies and commercialization of Intellectual Properties (IP) (Mai et al., 2019).

In this study, successful firm-level innovation entailed expenditure on R&D, product/service innovation, process innovation, and Intellectual Properties Rights (IPRs) ownership. On the other hand, firms' productivity was measured using a firm's value-added per worker. Therefore, a firm's innovativeness was measured using the following four proxies. First, a firm's expenditure on R&D. Second, a firm's ability to introduce a new product/service into the markets. Third, a firm's capacity to introduce a new manufacturing or service delivery process. Lastly, ownership of formal IPRs like patents, industrial designs, copyrights, and trademarks.

Investment in R&D activities, which is the critical input in the innovation process, leads to successful firm-level innovations (Kokko et al., 2015). Globally, innovation and adoption of ST&I have become an important strategy to improve firm productivity, competitiveness, labour productivity, industry value-added, and exporting capacity (Fazlıoğlu et al., 2018; International Trade Centre, 2018; Krammer, 2017).

At the firm level, the output of investment in knowledge production and fruitful R&D spending is commonly shown by four categorical variables: product/service, organizational, marketing, and process innovations. Besides, two continuous variables measure innovation outputs: financial gains from innovations and commercialization of IPRs (OECD & Eurostat, 2018). Table

1.2 reports the firm-level product/service innovation by firms in Kenya. The table shows the firms that introduced a new-to-the-firm product/service into the market during the study period 2015-2017 and those that did not.

Table 1. 2: Firm-Level Product /Service Innovation in Kenya 2015-17

Categorization	Sub-categorization	Sample size	Innovative firms	Non-innovative
All Firms		1,001	46%	54%
Sector	Manufacturing	455	47%	53%
	Retail	198	45%	55%
	Other services	348	48%	52%
Firm Size	Small	412	44%	56%
	Medium	381	45%	55%
	Large	208	56%	44%

Source: *Author's computations from WBES 2018*

In 2018 the WBES sought to find out with a yes/no question whether firms had launched a novel service or product into the market during the past three years, i.e., 2015, 2016, and 2017. Table 1.2 reveals an almost equal overall ratio of product/service innovators to non-product/service innovators (46% to 54%). Trend analysis of innovation activities by classification of firms by their size as either large, medium, or small revealed that 56% of sampled large firms had introduced a new product or service compared to 45% and 44% of medium and small firms, respectively. Additionally, 47%, 45%, and 48% of sampled manufacturing, retail, and other services firms had introduced a new product/service in the markets.

Firm-level innovation also entailed the introduction of new or improved processes. Process innovation includes introducing new methods of manufacturing products or offering services; logistics, delivery, or distribution methods for inputs, products, or services; or supporting activities for processes. Table 1.3 shows the process innovators and non-process innovators during the 2015-17 study period.

Table 1. 3: Firm-Level Process Innovation in Kenya 2015-17

Categorization	Sub-categorization	Sample size	Process innovators	Non-Process innovators
All Firms		1,001	26%	74%
	Manufacturing	455	32%	68%
Sector	Retail	198	21%	79%
	Other services	348	21%	79%
Firm Size	Small	412	24%	76%
	Medium	381	24%	76%
	Large	208	34%	66%

Source: *Author's computations from WBES 2018*

Table 1.3 shows that only 26% of the 1,001 surveyed firms had introduced a new or improved process during the study period. Comparing the process innovation among the various sectors revealed that more process innovation activities were concentrated in the manufacturing industry. Table 1.3 also shows that among the small, medium, and large firms sub-classification, process innovation activities were mainly concentrated within the large firms.

When a firm innovates a novel product/service, a different organizational practice, a new marketing strategy, or a new production process or technique, it can claim a formal IPR, or it can choose to keep a trade secret (informal IPR) (Hall et al., 2014). To manage the innovation process, a formal IPR issued by the Kenya Industrial Properties Institute (KIPI), such as patents, industrial designs, copyrights, trademarks, and licenses, grants a firm exclusive right to benefit from its innovation fully. IPRs ownership enables a firm to manage its organizational innovation process and earn extra revenue by commercializing innovations and leasing its IPRs. Table 1.4 shows the formal IPRs ownership by firms in Kenya for the survey period 2015-2017. In the 2018 WBES, the firms were required to give feedback on whether they had claimed ownership of at least one IP for the past three years.

Table 1. 4: Firm-Level Intellectual Property Rights Ownership in Kenya 2015-17

Intellectual Property	Overall firms	Firm size			Sector		
		Small	Medium	Large	Manufacturing	Retail	Other services
Applied for a patent concerning any product or service	6%	3%	6%	14%	11%	4%	3%
Registered an industrial design	5%	3%	6%	10%	8%	5%	3%
Registered a trade mark	17%	10%	21%	26%	25%	14%	10%
Claimed a copyright	8%	4%	10%	13%	13%	6%	9%
N	1,001	412	381	208	455	198	348
Overall Own IPR	= 23%		Non IPR owner		= 77%		

Source: *Author's computations from WBES 2018*

Table 1.4 reveals that 23% of all sampled firms claimed ownership of at least one IP during the study period. Additionally, out of 1,001 firms sampled, 77% did not apply for any IPR. Comparing IPRs ownership across firms indicated that IPR ownership was concentrated among the large firms and the manufacturing sector. Notably, the most claimed IPR by Kenyan firms was the trademark. This study investigated the impact of these product/service innovations, process innovations, and IPRs ownership on the productivity of manufacturing and services firms in Kenya from 2015 to 2017.

The manufacturing sector constitutes the most significant industrial production portion and is recognized as the critical sector spurring economic growth in Kenya. There is consensus that the industry can help Kenya achieve double-digit growth by 2030 in the Kenya vision 2030, sessional paper No. 9 of 2012 on the national industrialization policy framework for Kenya 2012-2030, and the big four development agenda. The Kenya vision 2030 MTP III (2018-2022) targeted the manufacturing sector to contribute 15% to GDP by 2022. The industrialization policy framework’s vision is to see Kenya become the most industrialized country in Africa with an expanded and globally competitive manufacturing sector. The big four development agenda targeted the manufacturing sector to contribute 20% to GDP by 2022.

On the other hand, the services sector is equally crucial due to its direct contribution to GDP, exports, and employment in the Kenyan economy (Khanna et al., 2016). The 2018-2022 MTP III of the Kenya Vision 2030 targeted the services sector to grow by 7% by 2022 (Republic of Kenya, 2018).

The services sector is extensive; it comprises ICT, wholesale and retail, hotel and restaurant, service of motor vehicles, construction, transport, and other services industries.

Compared to other sectors in Kenya, the services and manufacturing sectors are the key sectors that drive the Kenyan economy. For instance, in 2015-2019, the services and manufacturing sectors were among the leading sectors contributing to GDP and wage employment. Table 1.5 indicates that the manufacturing industry had the highest percentage contribution to GDP compared to other industrial production activities like water, mining and quarrying, sewerage, waste management, and electricity supply.

Table 1. 5: Sectorial Performance of the Kenyan Economy 2015-19

Economic Performance Indicator	The sector of the Economy	2015	2016	2017	2018	2019
% Contribution to GDP	**Manufacturing**	**9.4**	**9.3**	**8.1**	**7.8**	**7.5**
	Mining and quarrying	0.9	0.8	0.7	0.8	0.7
	Electricity supply	1.4	1.9	1.7	1.7	1.7
	Water supply; sewerage and waste management	0.7	0.7	0.7	0.7	0.7
	Services	**23.4**	**23.2**	**23.0**	**23.8**	**24.2**
	Financial and insurance activities	6.7	7.1	6.8	6.3	6.0
	Real estate	7.5	7.6	7.0	7.0	6.9
	Education	4.9	4.4	4.0	4.3	4.2
	Health	1.7	1.7	1.5	1.5	1.5
% Contribution to wage employment (both in the public & private sectors)	**Manufacturing**	**13.0**	**12.7**	**12.3**	**12.1**	**12.1**
	Mining and quarrying	0.55	0.56	0.54	0.53	0.53
	Electricity supply	0.78	0.78	0.80	0.81	0.81
	Water supply; sewerage and waste management	0.43	0.47	0.50	0.52	0.53
	Services	**27.73**	**28.34**	**28.32**	**28.63**	**28.57**
	Financial and insurance activities	2.84	2.84	2.67	2.64	2.65
	Real estate	0.15	0.15	0.15	0.15	0.15
	Education	20.33	20.36	20.12	20.25	20.43
	Health	4.85	4.83	5.11	5.20	5.39

Source*: Author's compilation from the Kenya economic survey 2020*

Furthermore, the manufacturing sector had the highest percentage contribution to direct wage employment compared to other industrial activities in the private and public sectors. Table 1.5 indicates that the services sector is equally a vital driver of the Kenyan economy compared to other industries like health, education, real estate, finance, and insurance. From 2015 to 2019, the services sector had the highest percentage contribution to GDP, with an average of 24%. Financial and insurance, real estate, and education sectors had 6.7%, 7.5%, and 4.9% contributions to GDP, respectively.

Table 1.5 further shows that the services sector had the highest percentage contribution to wage employment, with an average of 28%, followed by the education sector, with an average of 20% contribution. Therefore, the manufacturing and services sectors have the tremendous potential to drive the Kenyan economy to double-digit growth envisioned by 2030 due to being the highest contributor to GDP and wage employment. However, the two sectors' actual growth rate was below the expected targets, as shown in table 1.6.

Table 1. 6: Target versus Actual Performance of Overall GDP, Manufacturing and Services Sectors 2015-2022

Performance Measure	Sector	2015		2016		2017		2018		2019		**2022**
		Tar	Act	Tar	Act	Tar	Act	Tar	Act	Tar	Act	**Target**
% Growth rate	Overall GDP (%)	8.7	5.7	9.1	6	10	4.9	5.8	6.3	6	5.4	**7**
	Manufacturing (%)	8.6	7	10	6	10	3.4	5.8	4.3	6.4	3.2	**7.9**
	Services (%)	9.4	6.4	10	7	10	6.2	6	4.1	6.4	4.9	**7**
% Contribution to GDP	Manufacturing (%)		9.4		9		8.1		7.8		7.5	**15**
	Services (%)		23		23		23		24		24	**N/A**

Note: *Tar = target growth rate, Act = Actual growth rate*

Source; *Author's compilation from Agenda IV, MTP III, and Kenya Economic Survey 2020*

Table 1.6 shows that the overall economy, the manufacturing, and the services sectors' actual percentage growth rate was below the expected targets in all periods. By 2022 the overall economy and the services sector were expected to grow by 7% and 7.9%, respectively. The 2018-2022 MTP III of the Kenya vision 2030 targeted the manufacturing sector to contribute 15% to GDP by 2022. A targeted percentage contribution to GDP by the services sector by 2022 or 2030 was not available in policy documents due to the numerous diverse industries it entails (Republic of Kenya, 2018, 2020).

As indicated by its percentage contribution to the GDP, Kenya's manufacturing sector's performance declined from 11% in 2012 to 7% in 2019. Figure 1.1 shows that the GDP growth and the construction industry's contribution to GDP had stagnated at an average of five per cent over the years. This trend was replicated in retail and other services industries where the percentage contributions to GDP of ICT, hotels and restaurants, and other services had stagnated at an average of one per cent. Figure 1.1 shows that the percentage contribution to GDP of transport, wholesale and retail industries had been constant at an average of eight per cent over the years.

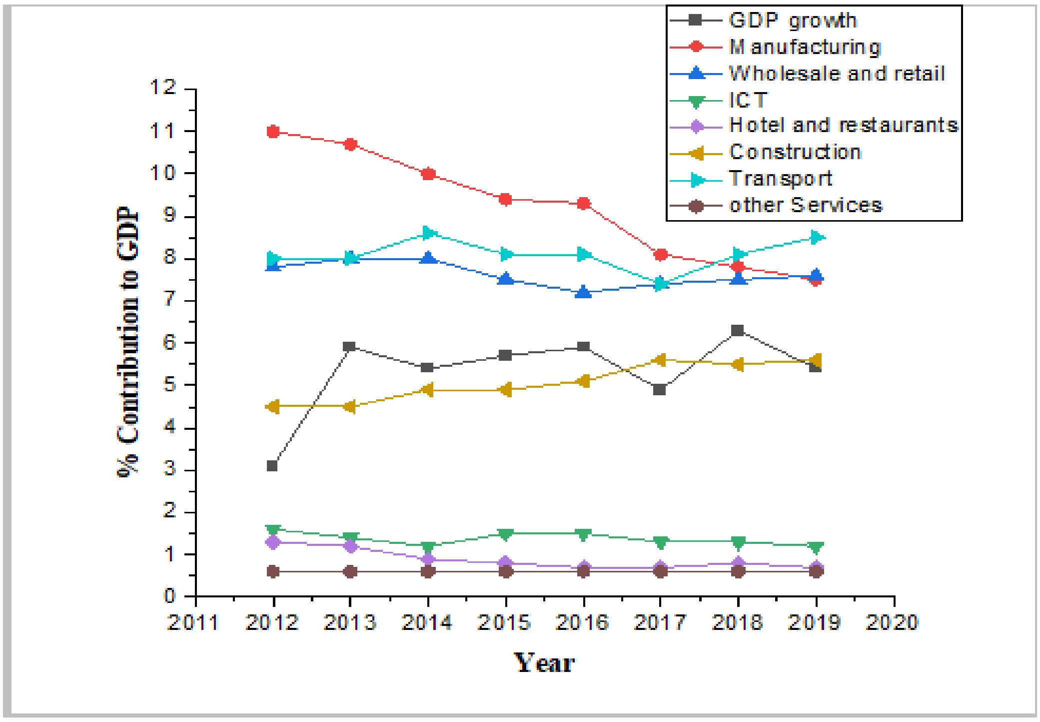

Figure 1.1: GDP Growth Rate and Contribution of Manufacturing, Retail, and Other Services Sectors to GDP 2012-2019

Source: *Author's compilation from the Kenya economic survey reports*

Despite Kenya's robust national ST&I policy intervention measures and R&D activities, the GDP percentage growth rate was still below the 7% growth target by 2022. Similarly, the performance of the manufacturing and services sectors was still below the MTP III target. On the other hand, the services sector's actual growth rate was still below the 7% growth rate expected by 2022. Additionally, the manufacturing industry's growth rate and percentage contribution to GDP were still below 7.9% and 15%, respectively, envisioned by MTP III (Republic of Kenya, 2018, 2020).

Oura et al. (2016) posit that ST&I drives economic development in developing and developed economies. Innovation enhances firms' productivity, leading to increased firm efficiency, improved products, increased demand, and reduced cost of production (Crowley & McCann, 2018; Fazlıoğlu et al., 2018). Additionally, Innovative firms are likely to experience a greater exporting capacity, more incredible funding opportunities, and increase their competitiveness, productivity, and market share (Oura et al., 2016; Santi & Santoleri, 2017; Walsh et al., 2020).

On the other hand, a firm's output or competitive advantage may stagnate or decline due to the non-adoption of R&D initiatives, poor utilization of novel ideas, and organizational failure to manage the innovation process (Papava, 2017). Moreover, a firm's output or competitive advantage may decline or stagnate due to ineffective national ST&I and IPR policies and poor commercialization of innovations and knowledge outputs (Vu & Asongu, 2020). This study evaluated the impact of R&D spending, product/service innovation, process innovation, and IPR ownership on firms' productivity. The study investigated whether innovating firms' productivity differed from non-innovating firms' productivity.

1.1.3 Productivity Growth of the Kenya National Innovation System

Successful firm-level R&D and innovation leading to enhanced firm productivity can be described as a semi-endogenous process (Comite, 2015). Therefore, a firm's stock of knowledge is assumed to be semi-endogenous. Consequently, apart from the novel expertise developed within the firm, other innovation players significantly influence a firm's R&D and innovation investment process through technical collaborations (Jun et al., 2021). Technical cooperation may be between the firm and the government, other firms, the R&D sector, society, and the rest of the world (Natera, 2015).

These innovation actors that cooperate during the innovation process, including society, academia, government, and industry, constitute a National Innovation System (NIS). Appendix A shows the structure of the Kenya National Innovation System (KNIS) and the interactions among the innovation actors in Kenya. In an efficient NIS, knowledge flows freely among the innovation actors in an interconnected manner. As a result, there are improved chances of ST&I collaboration among the innovation actors. Consequently, this leads to increased R&D expenditures and innovations by the firms within a NIS (Carayannis & Rakhmatullin, 2014).

The KNIS constitutes a few public-private partnerships between the government, industry, and academia. Nonetheless, partnerships between the government, Universities, the private sector, and public research institutes have led to the establishment of innovation hubs, technology parks, and technology incubation centres in Kenya (Ndemo & Weiss, 2017). The government has also invested heavily in providing quality primary and tertiary education and has put various measures to enhance the quality of human capital. It has done this through reforms in the education sector, updating curricula to incorporate ST&I, linking Universities with the industry, and subsidizing the cost of accessing education (Mukhwana et al., 2017; Musyimi et al., 2018).

The KNIS, however, still exposes poor linkage between the government, academia, and industry. Additionally, there is a mismatch between the industry requirements and the skills-set of graduates, and the funding of research and innovations in Kenya is still not elaborate. Further, the interaction framework has been poorly coordinated between the academia, industry, and ST&I regulatory “sub-systems” in the KNIS. The “sub-systems” entail the academia “sub-system,” which comprises the interactions of Universities, schools, TVET institutions, education networks, sector-based research centres, national research centres, and hubs. Second, the business/industry “sub-system” comprises formal and informal businesses, SMEs, and extensive multi-national companies’ interactions. Lastly, the intermediate organizations and ST&I infrastructure “sub-system” include R&D funding, IPR regime, regulatory framework, incubation centres, science and technology parks, and special economic zones. (Ayisi et al., 2019; Republic of Kenya, 2015).

The productivity growth of a NIS is measured by composite innovation indexes showing aggregated innovation activities by all innovation actors within a NIS (Lee & Lee, 2020). Various hybrid innovation indexes have been developed in the innovation literature. Indexes such as the Technology Achievement Index (TAI) and a new technology capability index were created in the classical innovation literature. Cornell University, INSEAD, and the World Intellectual Property Organization (WIPO) have recently developed the Global Innovation Index (GII) (Lee & Lee, 2020).

The annual GII ranking considers countries' NIS's average overall innovation efficiency by assessing how well a country converts innovation inputs into outputs. The innovation inputs into the NIS include the quality and quantity of human capital and research, institutions, infrastructure, business, and market sophistication. On the other hand, the innovation outputs within NIS are measured by two output measures of innovation. One of the output measures is creative outputs, for instance, new knowledge and its impact and diffusion within the NIS. The other is scientific outputs, including intangible creations such as Intellectual Property Rights (IPRs). Scientific works also entail creative goods and services such as new products or services (Cornell University INSEAD & WIPO, 2018; OECD & Eurostat, 2018). In the computation of the GII, the innovation outputs and inputs are analyzed using Data Envelopment Analysis (DEA) to establish the best performing Decision-Making Units (DMUs) and the world's efficient frontier (Cooper et al., 2007). Figure 1.2 panel A shows that Since 2011, the GII has ranked the KNIS top among the most innovative NIS in Sub-Saharan Africa after South Africa and Mauritius NIS.

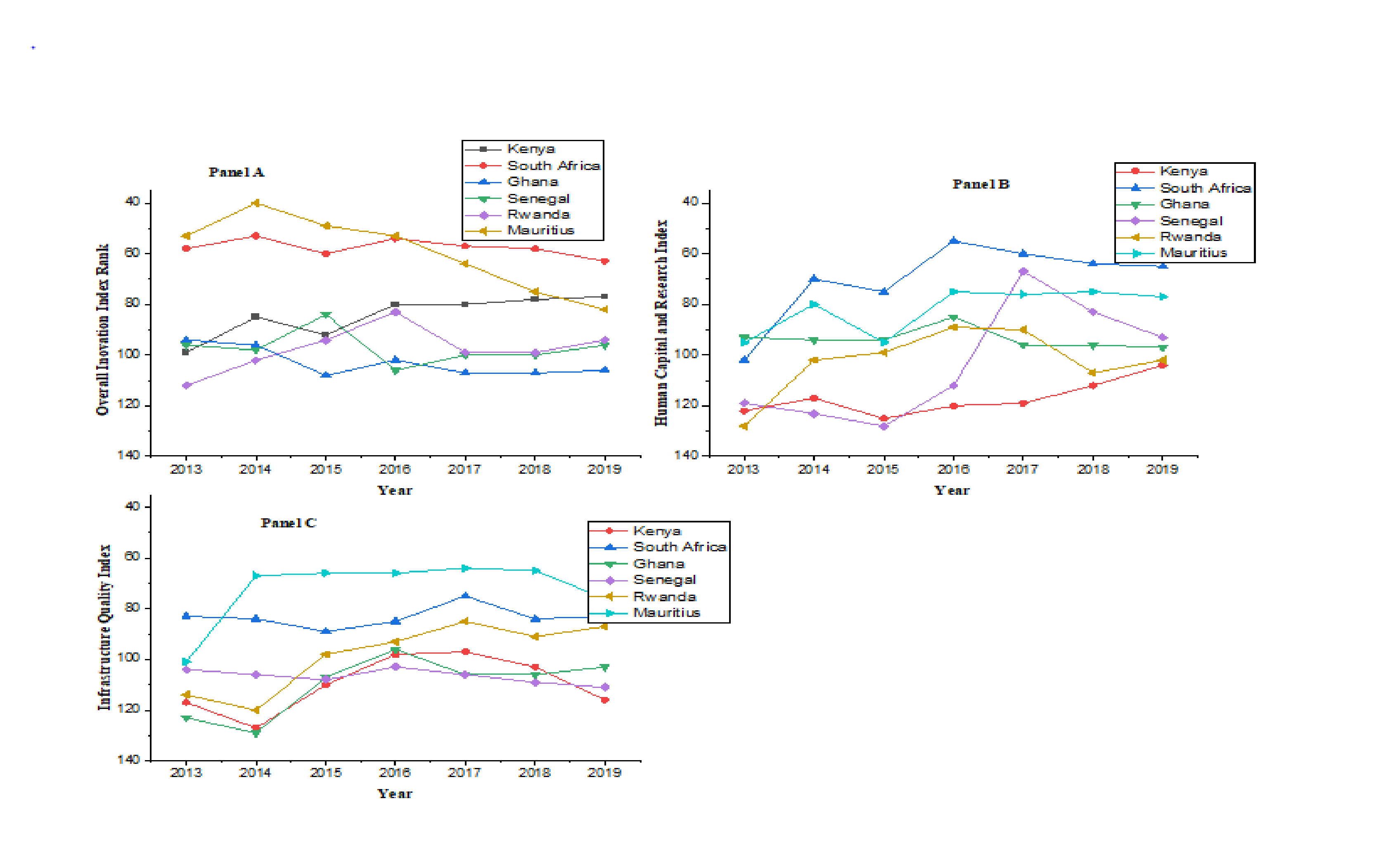

Figure 1.2: Global Innovation Index of the Kenya National Innovation System (KNIS) 2013-2019

Source: *Author's compilation from the annual GII by Cornel University, INSEAD, and WIPO*

The five innovation peers were selected based on the GII ranking of the most innovative NIS in Sub-Saharan Africa from 2010-2019. Additionally, The 2020 annual GII classified Kenya among other countries like India, Moldavia, and Viet Nam, which had consecutively set a record as innovation achievers from 2010-2019 (Cornell University, INSEAD & WIPO, 2020).

Out of the six sub-indexes considered in the computation of the overall efficiency index by the annual GII, from 2010-2019, the KNIS was ranked highly on four sub-indexes compared to its innovation peers like Mauritius, South Africa, Senegal, Rwanda, and Ghana. They include; the quality of institutions, creative outputs, scientific outputs, business, and market sophistication sub-indexes. However, the KNIS had consistently been ranked below all its innovation peers on two sub-indexes. The two sub-indexes include the infrastructure quality sub-index and human capital and research innovation input sub-indexes, as shown by panels B and C, respectively, in figure 1.2.

In an efficient, highly ranked NIS like that of Kenya, it is expected that knowledge flows freely among the innovation actors (government, industry, academia, and society) in an interrelated manner. Consequently, there should be improved chances of ST&I collaborations_among the innovation actors. As a result, the firms within the KNIS are expected to have increased R&D expenditures and innovations, leading to enhanced firm productivity and increased national output (Carayannis & Rakhmatullin, 2014). The national high production can be seen through increased high-technology exports, patent applications, scientific and technical journals, and gains from intellectual property leasing. The empirical literature has confirmed the importance of NIS and the composite innovation index on economic growth (Lee & Lee, 2020).

This study investigated the productivity growth of KNIS from 2010 to 2018 compared to its innovative peers in Africa. Instead of the GII, which compares countries' innovation performance based on the best-performing DMUs globally using over 130 countries, this study constructed an African region innovation index using 28 African countries, including Kenya. The African region innovation index benchmarked African countries' innovation efficiency based on the best-performing DMUs in Africa. Further, the index enabled the evaluation of the productivity growth and technical progress of the KNIS compared to other NIS in Africa for the past decade.

Benchmarking the KNIS with other NIS in Africa was informed by common regional innovation policy goals Kenya is also implementing. Additionally, determining whether there has been productivity progress or regress was a good indication of the innovation efficiency stance of NIS in Africa and a good indicator of the effectiveness of the current regional and national innovation policies and strategies. Moreover, it made it possible to know the best-performing NIS in Africa that other NIS can use as a benchmark to enhance regional growth.

1.2 Statement of the Problem

In a bid to catch up with the regional ST&I frontier and as part of the Kenya vision 2030 development agenda, Kenya has embraced ST&I as the critical driver of economic development. The country's efforts to invest in ST&I have been made by establishing and strengthening the KNIS and its institutional framework under the 2013 ST&I Act and regional innovation policies. Additionally, Kenya has pinpointed the ST&I sector as a critical investment sector. For instance, in 2019, Kenya led Africa in spending on research and experimental development with at least one per cent of its GDP, followed by South Africa and Egypt (African Union–New Partnership for Africa's Development, 2019). Subsequently, Kenya was described as an innovation achiever from 2010-2019. It was ranked among the most innovative countries in Sub-Saharan Africa after South Africa and Mauritius (Cornell University INSEAD & WIPO, 2020).

Even with Kenya's robust national ST&I policy intervention measures and R&D activities, the percentage growth rate of overall GDP, services, and manufacturing sectors was still below the 7%, 7.9%, and 7% 2022 growth target, respectively, as envisioned by Kenya vision 2030 MTP III (Republic of Kenya, 2018). Similarly, the percentage contribution to GDP by the manufacturing sector was still below the 15% expected by 2022 by MTP III (Khanna et al., 2016; Republic of Kenya, 2018). This-notwithstanding, manufacturing and services firms' R&D spending and innovation at the firm level had notably remained low during the study period. There had been low R&D investment and innovation even though ST&I is crucial for enhancing firm productivity and economic growth. In the context of this paradox, this study investigated the drivers of a firm's intensity of R&D expenditures, the impact of firm-level innovation on firms' productivity and analyzed the productivity growth of the KNIS over time compared to other NIS in Africa.

Few studies have focused on firm-level innovation, IPRs, and firms' productivity in Kenya. For instance, Cirera (2015), Barasa et al. (2017), and Njiraini et al. (2018) have attempted to explain the drivers of research and innovative behaviour of Kenyan firms. However, from these past studies, only Cirera (2015) and Ndicu & Wacuka (2017) attempted to empirically investigate the drivers of firms' intensity of R&D expenditure. Further, none of the prior studies has evaluated the impact of internal firm-level innovation programs on Kenyan firms' productivity using treatment effects methods. Additionally, earlier studies, for instance, Ayisi et al. (2019) and (African Higher Education Leadership in Advancing Inclusive Innovation for Development, 2018), have attempted to explain the composition and history of the KNIS. None of the past studies had analyzed the productivity growth of the KNIS or the African Regional Innovation System (RIS). This study bridged the existing gap in the literature and informed policy on firm-level innovation and productivity growth of the KNIS.

1.3 Research Questions

i) What are the drivers of firms' intensity of R&D expenditure in Kenya?

ii) What is the impact of firm-level innovation on Kenyan firms' productivity?

iii) What has been the productivity growth of the KNIS over time compared to other NIS in Africa?

1.4 Objectives of the Study

The study's general objective was to investigate the impact of firm-level innovation on the productivity of manufacturing and services firms in Kenya and assess the productivity growth of the KNIS over time compared to other NIS in Africa. The specific objectives were to:

i) Investigate the drivers of firms' intensity of R&D expenditure in Kenya.
ii) Determine the impact of firm-level innovation on Kenyan firms' productivity.
iii) Determine the productivity growth over time of the KNIS compared to other NIS in Africa.

1.5 Significance of the Study

The findings of the study's three objectives are essential to the institutions managing ST&I in Kenya and Africa, like NACOSTI, KENIA, NRF, MoEST, and AUDA-NEPAD. The study's findings presented an up-to-date impact evaluation of firm-level innovation on firms' productivity. The study evaluated the technical progress of the KNIS since its inception. This study's findings and policy implications are critical in determining how Kenya has caught up with the African ST&I frontier. Further, by evaluating the productivity growth of KNIS and assessing the innovation climate in developing countries and the economic impact of ST&I on a firm's productivity, this study bridged the gap in the literature.

1.6 Scope of the Study

This study limited itself to product/service and process innovations in the manufacturing, retail, and other services sectors and their impact on firms' productivity. Firm-level R&D expenditure and IPR ownership were also considered as measures of firm-level innovation. Other innovation proxies, such as organizational and marketing innovations, were not considered. The reason for not considering organizational and marketing innovations is that data on these kinds of firm-level innovations in developing countries like Kenya was incomplete. Kenya was still conducting its Community Innovation Surveys (CIS) and publishing its reports.

The study scope was also limited to Kenya's case as a developing nation and compared its ST&I performance with other African countries. The study period was 2010-2018 for objective three, productivity growth analysis of the KNIS. This period was appropriate since it's the period the KNIS had existed since its inception in 2013. The study period for objectives one and two, the drivers of R&D expenditure intensity, and the impact of innovation on a firm's productivity was 2015-2017. The period 2015-17 was the scope of the recent WBES 2018, which covered the most extensive number of firms than the previous surveys.

1.7 Organization of the Thesis

Each research objective is answered in its chapter as a distinct essay. However, each chapter's conclusions are linked to derive the implications of the study findings. Chapter one presents the overarching research problem’s background, the research problem’s statement, the study objectives, scope, and significance.

The remainder of the thesis is ordered as follows; chapter two presents the literature, methodology, empirical findings, and policy implication of the first essay, “drivers of the firm-level intensity of research and development expenditure in Kenya.” Chapter three evaluated the impact of firm-level innovation on firms’ productivity in Kenya. Chapter four investigated the regional catch-up and productivity analysis of the KNIS. The third and fourth chapter follows a similar structure to chapter two. Lastly, chapter five presents an overarching conclusion and research implications.

CHAPTER TWO

DRIVERS OF FIRM-LEVEL INTENSITY OF R&D EXPENDITURE IN KENYA

2.1 Introduction

Since the 2010s, Kenya has embraced Science, Technology, and Innovation (ST&I) as the key driver of economic development and firm productivity. Consequently, to catch up with the regional ST&I frontier, Kenya has integrated investment in R&D in the medium-term and long-term policy goals like industrialization policies and the Kenya vision 2030. Kenya's efforts to invest in R&D and ST&I include legislation, for instance, the ST&I Act of 2013, which established the KNIS and institutions in charge of ST&I in Kenya. Secondly, investment in R&D and ST&I has been incorporated into the Kenya Vision 2030 goals medium-term plans. Third, education reforms have been undertaken to incorporate ST&I, enhance STEM education and training, and link industry to academia. Lastly, Kenya had the highest Gross Domestic Expenditure on Research and Experimental Development (GERD/GDP) ratio in Africa during the study period. These efforts to invest in ST&I have consecutively made Kenya an innovation achiever from 2010-2019 (Cornell University, INSEAD & WIPO, 2020).

On the other hand, at the firm level in Kenya, during the study period (2015-17), firm-level R&D investment and innovation remained conspicuously low, as shown in table 1.1. Moreover, despite the heavy investment in ST&I at the national level, innovation, and R&D activities among the manufacturing and services firms were below average during the study period, as shown in tables 1.1, 1.2, 1.3, and 1.4. Consequently, this chapter investigated the drivers of a firm's intensity of R&D expenditure among the Kenyan manufacturing, retail, and other services firms during the 2015-2017 study period. The drivers of a firm's R&D expenditure intensity helped explain why some firms invested in R&D and others didn't. Successful engagement in R&D enables a firm to be more innovative and productive (Bottazzi & Peri, 2007; Crepon et al., 1998). The remainder of the chapter is ordered as follows; Section 2.2 presents a literature review; Section 2.3 presents methodology and data; Section 2.4 presents empirical results; discussion and policy implications are presented in section 2.5.

2.2 Literature Review

This section presents theoretical and empirical literature on the drivers of the firm-level intensity of R&D spending. There is diverse R&D investment literature, but in this study, firm-level R&D is discussed within the framework of NIS. Therefore the literature discusses the influence of other innovation players on firm-level R&D investment.

2.2.1 Theoretical Literature

The QUEST micro-founded macro model for R&D and innovation policies provided a theoretical anchor for analyzing firm-level R&D intensity drivers within the KNIS framework. The model was developed by Roeger et al. (2009) to model R&D investment at the national and sector level initially among the European Union member countries. It is a semi-endogenous, Dynamic

Stochastic General Equilibrium (DSGE) model. Further, it consists of four innovation actors: households, firms, government, and the research industry. The innovation actors make intertemporal forward-looking optimization decisions subject to institutional constraints, financial and technological constraints. The rest of the world enters the model through knowledge spillovers, international trade, and financial flow (Comite, 2015).

R&D involves the development, dissemination, transfer, and utilization of ST&I in all national development sectors. Research is part of the generation of knowledge, technology, and innovation (Taherdoost, 2018). Firm-level R&D entails a wide range of activities. Firm-level R&D activities are usually indicated by the amount spent on: intramural and subcontracted R&D activities, adoption of foreign knowledge, and procurement of R&D-intensive capital. R&D also involves spending on launching innovations to the market and licensing IPRs. Firm-level R&D efforts can also be indicated by the capacity of R&D personnel and the amount spent on training them (OECD/Eurostat, 2019). R&D expenditure per worker measures firm-level R&D expenditure intensity (OECD/Eurostat, 2019). Corporate R&D investment leads to innovations that enhance a firm's productivity (Martínez-Sánchez et al., 2020). The realized innovations could be a new product/service, process, marketing, and organizational strategies (Zhang & Islam, 2020). Innovating firms then own IPRs to commercialize their innovations (Hall & Sena, 2017).

In the QUEST R&D and innovation model, the stock of knowledge is assumed to be semi-endogenous, which means that apart from the novel expertise developed within the firm, other innovation players significantly influence a firm's R&D investment process through technical collaborations (Jun et al., 2021). The households, for instance, buy stocks of firms operating in the intermediate sector, enabling these firms to produce innovations. In addition, households make many intertemporal optimization decisions. For instance, households may purchase novel knowledge outputs (patents) from the R&D sector to maximize intertemporal utility. The households are assumed to have access to financial markets and face no liquidity constraints (Comite & Kancs, 2015).

On the other hand, the government influences a firm's R&D investment through subsidies and taxes (Teng et al., 2020). The subsidies can be a tax credit to the households on their receipts from knowledge outputs. Tax credits on knowledge output (patents) may encourage highly skilled workers to participate in R&D (Xu et al., 2021). The government can also encourage investment in R&D by reducing the tax levied on knowledge outputs such as patents, or it can pay a wage incentive to R&D highly-skilled workers. The government can boost firm-level investment in R&D and innovation by reducing fixed costs faced by the firms, such as energy and bandwidth costs (Comite & Kancs, 2015; Teng et al., 2020; Xu et al., 2021). The government plays a crucial role in stimulating innovations in a country, mainly in developing countries. It can directly influence R&D investment in given sectors of the economy through taxes, subsidies, and other relevant R&D policies (Crespi et al., 2020).

Comite & Kancs (2015) posits that the R&D sector is comprised of a research institute (national private, or public), institutions (academia), or a research department within a firm. The R&D sector hires highly skilled workers and utilizes R&D-intensive capital to produce novel ideas. In creating novel ideas, the R&D segment uses the prevailing domestic and foreign stock of knowledge (Yu et al., 2021). A country's R&D capacity is determined by the supply of highly skilled workers and the quality of the labour force (Ren & Song, 2021). Highly skilled workers comprise mainly the technical workers and graduates of tertiary institutions. The public expenditure on higher education and education policies influences the quality of countries' human capital (Portuguez Castro et al., 2019; Ren & Song, 2021).

The firms within the NIS framework are assumed to be operating in a monopolistic competitive industry by the QUEST R&D and innovation model. This assumption implies that there are many firms engaged in various economic activities. The firms produce innovative goods/services using tangible inputs such as capital and labour rented from the households. In creating goods/services, the firms also use the intangible knowledge inputs produced by the R&D sector (Demmou et al., 2019). When producing innovative products/services, the firms are constrained by institutional, technological, and resource-based factors (Adomako et al., 2021). These constraints affect the intensity of firm-level R&D investment and, by extension, firm-level innovation (Barasa et al., 2017; Comite & Kancs, 2015; Divisekera & Nguyen, 2018).

In the QUEST R&D model, a firm's interaction with the rest of the world through knowledge spillovers and international trade also influences its R&D investment (Comite & Kancs, 2015). Domestic or foreign Knowledge spillover from one firm, local or global, to another may be experienced through domestic or international trade with other trading partners (Gkypali et al., 2018). The ability of a firm to adopt foreign technology is also critical in its R&D investment (Fatima, 2017). Furthermore, innovation partnerships among firms for joint product/service innovation and joint use of R&D infrastructure may influence firm-level R&D intensity (Albors-Garrigos et al., 2018).

One of the strengths of the QUEST model of R&D and innovation model is being a DSGE, micro-founded macro model. Given some constraints, each economic agent in the innovation system faces an optimization objective. Another strength is the forward-looking intertemporal optimization, diverse transmission channels, and parameters to analyze (Comite, 2015). The limitations of the model, on the other hand, are the inability to analyze technology diffusion directly and differentiate between public and private R&D. The other limitation is that only one type of innovation or R&D can be analyzed at one time. Lastly, DSGE modelling of R&D is still evolving, especially in developing regions, and behavioural equations of innovation players are still being developed. These limitations and data shortages make it impossible to analyze the full general equilibrium model in developing countries like Kenya. As a result, as indicated by empirical literature, most technical studies examine the firms, partial equilibrium models.

2.2.2 Empirical Literature

Cirera (2015) investigated the factors that determined the possibility of a firm investing in R&D and the determinants of R&D expenditure intensity in Kenya as one objective of the study. The author used R&D expenditure per worker as the dependent variable to measure the firm-level intensity of R&D expenditure. The study utilized 549 firms surveyed in the WBES of 2013, covering 2010-2012. The determinants of investing in R&D were investigated using a Poisson estimator. The Poisson regression was selected to deal with the high proportion of firms with zero expenditure on R&D. The results indicated that a firm's R&D intensity increased with openness, diversification, and access to finance. Further, firm size did not matter, and foreign-owned firms invested less in R&D.

This study followed Cirera's (2015) definition and measurement of variables. In addition, the present study incorporated more factors, such as infrastructure quality indicators and human capital and research indicators, in the analysis of R&D intensity. Cirera (2015) did not distinguish between a firm making zero expenditures and firms not participating in R&D. As a result, Cirera (2015) could have justified his choice of Poisson regression instead of a sample selection model. The current study considered a sample selection model to pick R&D spending firms from many non-R&D spending firms. Cirera (2015) was the first study to analyze the determinants of R&D intensity among Kenyan firms empirically. Therefore it formed a sound basis for result comparison with the current research.

Ndicu & Wacuka (2017) examined the determinants of the firm-level extent of knowledge investment. The study utilized the first wave (2008-2011) and second wave (2012-2014) MoEST data covering 534 firms. The authors used the Crépon, Duguet, and Mairessec (CDM) (1998) model and a Tobit regression. The results suggested that R&D intensity increased with improved financial turnover and foreign ownership. The MoEST data used by the authors was not detailed and contained fewer firm-level indicators than WBES data, limiting the variables extracted for scientific analyses. The current study followed the estimation methodologies by Ndicu & Wacuka (2017), which also formed a reasonable basis for result comparison with the present study.

Tyagi et al. (2018) examined the factors influencing firm-level R&D intensity in India's drugs and pharmaceutical industry. The study used panel data from 2000 to 2013 for 91 pharmaceutical firms in India. Panel data models along with a Tobit regression were used as estimation methodologies. The findings suggested that firm size, sales, foreign ownership, globalization, and creative output influenced R&D intensity. The paper conducted a robust analysis using the random effects panel Tobit model. Due to a lack of panel data for Kenya, this study could not utilize panel data models. Instead, the study used a sample selection model to control selection bias. The current study followed Tyagi et al. (2018) in selecting, defining, and measuring variables to include in the analysis of the drivers of R&D intensity in Kenya.

Alam et al. (2019) explored institutional factors influencing R&D investment in 20 emerging economies like Brazil, Egypt, Chile, and India. The paper utilized the Generalized Method of Moments (GMM) as the estimation methodology. The authors used panel data from 2006 to 2013 with 664 firms. The findings revealed that institutional quality significantly impacted R&D investment. The results indicated that regularity quality, government effectiveness, and the rule of law positively impacted R&D investment. However, political instabilities and corruption negatively impacted R&D investment. One of the paper's strengths is GMM estimation, which can account for firm-specific factors. However, applying this kind of estimation approach in this study was impossible due to data limitations, such as data incompleteness and a panel with a small sample size.

Morsy & Amira (2020) investigated firm-level R&D intensity drivers of 52 developing and emerging countries. Of the 52 countries considered, 15 were African, including Kenya. Morsy & Amira (2020) used 81,119 firms gathered by WBES between 2006 and 2019. The authors estimated the CDM Generalized Structural Equation Model (GESM). The research equation of the CDM model was estimated using the Full-information Maximum Likelihood (FIML) method and Limited Information Maximum Likelihood (LIML). The results suggested that exporting capacity, access to foreign technology, and finance were the most significant determinants of R&D intensity. The authors included many R&D and innovation indicators from an extensive sample from diverse global regions. The current study borrowed the authors' definition and measurement of variables and the CDM-GESM framework.

2.2.3 Overview of Literature

There are various approaches to analyzing firm-level R&D choice and investment. For instance, firm-level R&D can be viewed as being endogenous or semi-endogenous. It can also be analyzed from the point of partial or general equilibrium. This study took the semi-endogenous approach of analyzing firm-level R&D investment from the macro-level or a general equilibrium approach. These are the recent approaches in the study of R&D and innovations. As a result, the QUEST micro-founded macro model for R&D and innovation provided a theoretical anchor for investigating the drivers of firm-level R&D investment. However, the QUEST model has a few limitations, the major one being that the model is still evolving. Therefore, using the Bayesian approaches to estimate the full DSGE model becomes impossible. One of the significant strengths of the QUEST model is micro-foundations and the consideration of technical collaborations among the innovation players. Consequently, the firm-level knowledge production function provided a theoretical framework for analyzing the drivers of firms' R&D intensity.

The empirical literature revealed that R&D expenditure or investment involves many activities meant to enhance a firm's innovative capacity and productivity. The literature also revealed that expenditure per employee on R&D is the primary measure of R&D expenditure intensity. Additionally, empirical literature revealed that a host of factors might influence a firm's intensity of R&D expenditure. They include 1) firm characteristics such as firm size and age, 2) institutional environment factors such as the rule of law and corruption, 3) budgetary factors or resource-based factors such as access to finance and sales volume, 4) technical factors such as access to foreign technology, R&D personnel, and capacity. However, these factors' influence on R&D may vary from country to country setting.

According to the literature review, the evaluation of the factors driving firm-level R&D investment was the subject of very little research. Therefore, no other study had tried to look into the drivers that influenced R&D spending across the study period using the WBES 2018 data. This study filled a research gap by analyzing drivers that influenced R&D spending across the study period.

2.3 Methodology and Data

This section presents the econometric models, empirical framework, and research design. This section also explains the definition and measurement of variables, description of the data, and sample.

2.3.1 Research Design

The non-experimental research design was employed to investigate the drivers of firm-level R&D intensity in Kenya. The non-experimental design can be classified as pure descriptive design, correlational descriptive design, case studies, and surveys. Moreover, the descriptive design is used to study the development or changes in the behaviour of individuals and firms. On the other hand, the correlational descriptive design describes the relationship between variables. There are three main types of correlational descriptive design: cross-sectional, longitudinal, and cohort-sequential. This chapter adopted a cross-sectional design and further used a quantitative approach.

2.3.2 Theoretical Framework

To evaluate the drivers of a firm's intensity of R&D expenditure, a knowledge production function theory at the firm level provided a theoretical framework. The study presumed two production sections/activities within a firm. A goods-producing/services provision section where output is produced and an R&D section where additions to the stock of knowledge are made (Ramani et al., 2008). R&D involves the development, dissemination, transfer, and utilization of ST&I. Research is part of knowledge, technology, and innovation generation. A firm chooses whether to invest in the goods production/services provision section or R&D section, or both. If a firm decides to invest in R&D, it participates in an internal R&D program/activity. The new ideas produced in the R&D section enhance the efficiency of the goods production/services provision section (Comite & Kancs, 2015).

The R&D section employs highly skilled labour ($L_{rd,t}$), R&D embedded capital stock ($K_{rd,t}$), and uses the existing stock of knowledge (both domestic, A_t and foreign A_t^*) to produce new designs/ideas/knowledge according to the knowledge production function (2.1) (Charlot et al., 2015).

$$\Delta A_t = v A_{t-1}^{*\sigma} A_{t-1}^{\pi} L_{rd,t}^{\beta} K_{rd,t}^{\theta} \quad \text{--} \quad (2.1)$$

Where, ΔA_t is the new knowledge (innovation such as patents) produced at a particular point in time. ΔA_t can be a latent variable, or it can be observed depending on the measure of the new knowledge. v, measures the total factor efficiency of R&D production. σ, π, β, and θ are the elasticity of R&D

production with respect to existing foreign technology, existing domestic technology, the number of researchers, and R&D embedded capital stock, respectively.

2.3.3 The Empirical Model and Estimation Strategy

The realized new knowledge (ΔA_t) in equation (2.1) depends on a firm's choice of whether or not to participate in an internal R&D program. The unobserved endogenous firm's decision to participate in an internal R&D program can be associated with the drivers of R&D expenditure intensity. To empirically investigate the drivers of a firm's R&D expenditure intensity, the endogenous firm's decision to participate or not participate in an internal R&D program was treated like a latent variable depicted by equations (2.2) and (2.3), which is a Tobit II model (Fu et al., 2018; Hall et al., 2014).

Participation equation: $P = \begin{cases} 1 \; if \; P^* > 0 \\ 0 \; if \; P^* \leq 0 \end{cases}$

Where P^* is a latent variable. Therefore, expenditures on R&D are;

Outcome equation: $y = \begin{cases} y^* \; if \quad P^* > 0 \\ unobserved \; if \; otherwise \end{cases}$

When $P^* > 0$, firm engaged in R&D activities and their expendiures y^* were observed. Assuming a linear model for latent variables,

$P^* = x_{1i}^{'}\beta_1 + \varepsilon_{1i}$ -- (2.2)

$y^* = x_{2i}^{'}\beta_2 + \varepsilon_{2i}$ -- (2.3)

Where,

$$\varepsilon_{1i} \sim N(0, \delta)$$
$$\varepsilon_{2i} \sim N(0,1)$$
$$\text{Corr}\,(\varepsilon_{1i}, \varepsilon_{2i}) = \rho$$

Equation (2.2) is the participation equation. The firm's participation in R&D activities was the observed R&D expenditure/activities. Therefore, P^*, equation (2.2) is a latent variable where the R&D spending is a binary variable, zero for the firms that did not participate in R&D activities, and one for firms involved in R&D. Equation (2.3) is the outcome equation and y^* is the observed R&D expenditure for the participating firms (Cameron & Trivedi, 2005; Fu et al., 2018).

ε_{1i} and ε_{2i}, are correlated random error terms that are independent of explanatory variables. Additionally, ε_{1i} and ε_{2i}, are distributed as bivariate normal with zero mean and one standard deviation. β_1 and β_2 are a vector of coefficients to be evaluated, X_{2i} and X_{1i} are vectors of R&D drivers influencing R&D choice (participation) and R&D intensity (outcome equation), respectively. The vectors include control variables, such as firm age, firm size, and industry dummy. The vectors also include indicator variables of infrastructure quality, human capital, research capacity, business, and market sophistication indicators, as shown in Table 2.1.

The target sample was those firms engaged in R&D; however, not all firms in the 2018 WBES survey were involved in R&D activities for some valid reasons. In the 2018 WBES survey, firms were asked to provide a yes or no answer if, in the past three years (2015, 2016, and 2017), they spent on R&D activities and the average expenditure on R&D for those past three years. We can only observe R&D expenditure for the participating firms from the resulting cross-sectional data. However, considering only those engaged in R&D during the survey period would give biased estimates of the estimated parameters of interest. Therefore to deal with this sample selection bias, equations (2.2) and (2.3) were estimated using a Full Information Maximum Likelihood (FIML) Heckman procedure which estimated equation (2.4);

$y_i = x_{2i}^{'}\beta_2 + \sigma_{12}\lambda_l + \eta_i$ -- (2.4)

Where, $\lambda_l = \frac{\phi(x_{1i}^{'}\beta_1)}{\Phi(x_{1i}^{'}\beta_1)}$, is the inverse Mills ratio of R&D spending firms to non-R&D spending firms and η_i is an error term. The sample-selection bias can be considered an omitted variable bias where the omitted variable is the inverse Mills ratio (Hill et al., 2018). When σ_{12} the coefficient of the inverse Mills ration is not significant, then sample selection bias does not affect the estimated parameters of interest. FIML estimation criteria requires exclusion of at least one variable of the selection equation from the outcome equation (exclusion criteria). Wooldridge, (2015) argues that the exclusion restriction is essential in avoiding collinearity between the Mill's ratio and other regressors in the outcome equation.

FIML is generally preferred to the Limited Information Maximum (LIML) selection model because; FIML has high predictive power and is more robust. FIML dominates the LIML, especially for the cases of high correlation between the covariates of the outcome equation X_{2i} and the covariates of the participation equation X_{1i}. Moreover, LIML is less preferred because it is sensitive to distributional assumptions of the error term (Cameron & Trivedi, 2005; Puhani, 2000). Nonetheless, the LIML, a two-step method of Heckman, also gives reliable results. This study also estimates the two-step Heckman and compares the results with the study's primary model, the FIML. The equation (2.4) results' answered the study's first objective. The outcome equation results helped establish the drivers of a firm's intensity of R&D expenditure.

2.3.4 Data Source and Type

To investigate the drivers of the firm-level intensity of R&D expenditure in Kenya, the DMUs were the manufacturing and services firms in Kenya. The secondary cross-sectional data was obtained from the 2018 WBES containing 1,001 firms in Kenya's manufacturing, retail, and other services sectors, covering 2015-2017. The 2015-2017 survey data is cross-sectional in the sense that in 2018 the WBES sought to find out whether, in the past three years (2015, 2016, and 2017), a particular establishment had introduced a new product/service, spent on R&D, etc. The 2018 WBES dataset was preferred because it was recent, had covered many establishments compared to the previous surveys, and contained numerous firm-level variables.

2.3.5 Data Challenges, Cleaning, and Analysis

The first step in data cleaning was to extract the relevant variables following innovation economics theory and empirical literature and drop the rest. Additionally, all variables with a high degree of missing information were dropped from the final data set. The major challenge with the 2018 WBES is that critical innovation variables had missing observations.

When investigating the intensity of R&D expenditure per worker (the dependent variable), only 16% of the surveyed firms participated in R&D expenditure. Any attempt to fill in 84% of unreported information would have entirely changed the study's dependent variables' structure and distribution. Therefore, this study analyzed the available data for the dependent variable (R&D intensity) and relied on the FIML to pick the few participating firms from the pool of many non-participating firms. A sample selection model helps pick a few participating individuals/firms from a large sample with non-participating firms/individuals (Cameron & Trivedi, 2005). However, explanatory variables with a small percentage of missing observation (less than 10%) were filled using their respective firm size category and industry averages. These variables include; firm age, years of management experience, and labour expenses.

Box/percentile plots were also used to identify extreme outliers among the continuous variables. The few extreme outliers present were replaced with the respective firm sector and size average. Only 16% of all firms participated in R&D activities. Due to the reduced number of firms participating in R&D spending, conducting a FIML regression as per the various firm size or industry categories was impossible. Consequently, dummy variables for firm size and industry were introduced for control purposes. The definition and measurement of these variables, among others, are discussed in detail in section 2.3.6.

2.3.6 Definition and Measurement of Variables

Table 2.1 shows the variables used in the determination of R&D intensity drivers. All monetary units were in Kenya shillings (KES). The variables represent innovation activities for the three years (2016, 2017, and 2018) scope of the 2018 WBES.

Table 2. 1: Definition and Measurement of Variables

Variables	Definition and Measurement
Control Variables	
Industry dummy	1 if a firm's main activity is manufacturing, 0 if retail or other services
Firm size dummy	1 if a large firm (100 or more employees), 0 if a medium-sized firm (20-99 employees), or a small firm (5-19 employees)
Firm age	The number of years since the firm was established until the year 2018
Manager experience	The number of years of experience of the top manager
Dependent Variable-Innovation Output	
R&D expenditure intensity	The amount of money spent on R&D activities, either in-house or contracted with other companies, excluding market research surveys, divided by the number of workers.
R&D propensity	1 if a firm spent on R&D, 0 if otherwise.
Independent Variables- Innovation Inputs	
Internet access	1 if an establishment has an official operational website, 0 if otherwise.
Incubation labs access	1 if a firm used incubation labs set by the government, Universities, or private sector, 0 if otherwise.
International certification	1 if a firm is licensed by international standards like ISO: 9001, 0 if otherwise.
Foreign technology adoption	1 if the firm uses technology licensed from foreign-owned companies, 0 if otherwise.
Physical capital spending	1 if a firm spent on acquiring new capital like machinery, vehicles, equipment, and structures, e.t.c, 0 if otherwise.
Exporting capacity	1 if a firm engaged in direct and indirect exports, 0 if national sales only.
Credit access	1 if a firm borrowed money from financial intuitions, 0 if otherwise.
Business-government relations	1 if a firm secured a government contract at the county or national government level, 0 if otherwise.
Employee training	1 if a firm conducted formal training to employees specifically on developing or introducing new products/services, 0 if otherwise.
Innovation partnerships	1 if a firm introduced a new product/service in collaboration with other companies or organizations, 0 if otherwise.
Cost of labour	The total cost of labour, including wages, salaries, bonuses, and social security.

Source: WBES 2018

2.4 Empirical Results

The empirical results are reported by the descriptive statistics results, diagnostic testing results, and regression results.

2.4.1 Descriptive Statistics Results

The descriptive statistics are presented in Tables 2.2 and 2.3; Table 2.2 represents the percentage shares under the various sizes and industries classification of the firms.

Table 2. 2: Descriptive Statistics (Percentage Shares of Categorical Variables)

Variable	Firm size				Sector			
	All firms	Small	Medium	Large	Manuf'	Retail	Other serv'	N
R&D propensity	**16%**	31%	40%	29%	56%	13%	31%	1,001
Internet access	**51%**	26%	43%	31%	50%	15%	35%	1,001
Incubation labs access	**13%**	26%	35%	39%	65%	15%	20%	1,001
International certification	**20%**	21%	39%	40%	65%	12%	23%	1,001
Foreign technology adoption	**8%**	20%	30%	50%	100%	0%	0%	1,001
Physical capital spending	**37%**	35%	40%	25%	50%	15%	35%	1,001
Exporting capacity	**30%**	24%	40%	36%	70%	10%	20%	1,001
Credit access	**60%**	37%	40%	23%	46%	20%	34%	1,001
Business-government relations	**16%**	28%	45%	27%	39%	16%	45%	1,001
Employee training	**47%**	33%	42%	25%	49%	17%	34%	1,001
Innovation partnerships	**18%**	38%	33%	29%	44%	18%	38%	1,001
N	1,001	412	381	208	455	198	348	

Source*: authors' computation from WBES 2018*

The descriptive statistics results show that out of the 1,001 sampled firms, 16% of them had spent on R&D activities. Most R&D spending firms were the medium firms and firms in the manufacturing industry. Half of the sampled firms had internet access and had trained their employees. The highest portion of firms that trained their employees and had access to the internet was concentrated among the firms in the manufacturing industry and medium firms. 60% of sampled firms, mainly small and medium, had access to credit through financial institutions. Further descriptive statistics indicated that out of the 1,001 firms sampled, eight per cent that had adopted the foreign technology were all from the manufacturing sector, with the majority being large firms.

Less than a quarter of the sampled firms had received international certification, accessed incubation labs, did business with the government, and partnered with other firms for joint innovations. Lastly, 30% and 37% of sampled firms exported their goods /services and spent on physical capital. Generally, the descriptive statistics indicated that most innovation activities were concentrated among firms' large and manufacturing categories. Table 2.3 shows the range, the mean, and the standard deviation of the continuous variables, including firm R&D expenditures per worker and labour expenses.

Table 2. 3: Descriptive Statistics (Summary Statistics of Continuous Variables)

Variable	Firm category	Obs.	Mean	Std. Dev.	Min	Max(‘000)
R&D expenditure per worker(intensity)	All firms	163	49,987	11,292	250	1,250
	Small	51	75,337	27,465	928	1,250
	Medium	64	40,330	16,309	250	1,000
	Large	48	37,499	13,443	300	476.19
	Manufacturing	91	61,442	18,769	500	1,250
	Retail	22	59,777	24,975	428	400
	Other services	50	26,281	9,173	300	333.33
Cost of labour	All firms	1,001	56,202,494	8,188,897	45,000	500,000

Source*: authors’ computation from WBES 2018*

Table 2.3 shows that the overall expenditure for all firms was approximately KES 50,000 per worker, with a standard deviation of KES 11,000. The R&D expenditure per worker ranged between KES 250 and KES 1,250,000. Comparing the R&D expenditure among the various firms and industries revealed that large firms had the least average spending at KES 37,500 per worker. The small firms had the highest expenditure per worker at KES 75,337, while medium firms spent approximately KES 40,000 per worker. The manufacturing firm had the highest average spending of KES 61,442 per worker compared to retail and other services firms, KES 59,777 and KES 26,281, respectively. On the other hand, there was an average KES 56 million expenditure on labour ranging from KES 45,000 and KES 500 million. The standard deviation was below the mean for the two variables across all categories of firms meaning that there was no high-scale heterogeneity among the firms in the respective categories.

2.4.2 Diagnostic Tests Results

The study specified linear regression models to investigate the drivers of a firm's intensity of R&D expenditures. Some diagnostic tests were conducted before obtaining regression results on drivers of a firm's intensity of R&D expenditures. The tests are essential in ascertaining whether the specified model met the regression requirements. The diagnostic tests included multicollinearity, goodness of fit, and heteroscedasticity tests. Table 2.4 summarizes the diagnostic tests and results,

Table 2. 4: Summary of Diagnostic Results Tests of the Drivers of a Firm's Intensity of R&D Expenditure Regression

Diagnostic	Test	Test Results
Multicollinearity	Variance Inflation Factor (VIF)	Mean VIF=1.17
Goodness of fit	Hosmer- Lemeshow test	Prob>chi2=0.3589
Heteroscedasticity	Breusch-Pagan test	P-value=0.615

Source*: authors' computation from WBES 2018*

A Probit model with a binary dependent variable of whether a firm spent or did not spend on R&D was estimated (Appendix C) to enable regression diagnostic testing. A variance Inflation Factor (VIF) test was conducted to check whether multicollinearity was present. The presence of multicollinearity may produce biased estimates of parameters of interest. The decision criteria of the VIF test is that any variable with a computed VIF of more than ten needs to be re-examined. The results of the VIF test are shown in Appendix D, and they indicate that multicollinearity was absent.

Hosmer- Lemeshow test was conducted to check for the goodness of fit. The H-L test tests the null hypothesis that the fit is good against an otherwise alternative. The results of the H-L test are shown in Appendix E. The null hypothesis of good fit was not rejected because the P-value was not less than 0.05. Additionally, the Prob>Chi^2 =0.00 and Pseudo R$^{2\,=}$ 0.20, as Appendix C shows, indicate a good fit. The overall significance of the model is indicated by Prob>Chi^2 =0.00 when it is less than 0.05. Pseudo R^2 =0.20 means that the full model containing the model's regressors improves the fit by 20% compared to the null model. Therefore, from the goodness of fit tests, this study concluded that the model specified to investigate the drivers of the R&D expenditure was of good fit.

The Breusch-Pagan test for Heteroscedasticity was conducted to ascertain whether the variance of the error term was constant. Heteroscedasticity is a common problem with cross-sectional data. It is possible to have a situation where large firms have significant variances compared to small firms. Therefore, it was necessary to check if Heteroscedasticity was present. The Breusch-Pagan test tests the null hypothesis that the variance of the error term is constant. The null hypothesis is rejected when the P-value is very small. Using this criterion, the results in Appendix F indicate that heteroscedasticity was not a problem in the estimation process.

The diagnostic results revealed that the data utilized and the model specified conformed to regression requirements. This notwithstanding, robust standard errors were used in the estimation process. Robust standard errors help ensure that estimated parameters are not biased by model misspecification and critical linear regression assumption violations.

2.4.3 Regression Results

Among other decisions made by firms is whether or not to invest in R&D. The firm's decision to invest or not invest in R&D is a latent variable. Those firms that choose to invest in R&D make some positive expenditure on R&D. For instance, R&D spending firms may employ high-skilled workers and purchase

R&D-intensive capital. The study investigated the drivers of a firm's R&D choice and intensity of R&D expenditure using FIML sample selection Heckman estimation.

The first step of FIML is a Probit selection with a binary dependent variable, one for the firms that spent on R&D and zero if otherwise. The second step is a truncated regression, with the dependent variable being the non-zero actual firm-level expenditure on R&D per worker in Kenya shillings (Hill et al., 2018). Apart from controlling selection bias, the FIML estimation allowed for the investigation of the drivers of a firm's likelihood to invest in R&D and the amount or the intensity of R&D expenditure per worker by R&D spending firms (Hall & Sena, 2017).

The exclusion restriction is an essential requirement of the FIML estimation. Without it, consistent estimators cannot be obtained (Cook et al., 2021). One criterion for selecting variables to exclude either in the selection or participation equation is excluding one of the highly correlated variables. The other criterion to identify the restrictions is the underlying economic theories behind the outcome and selection equations (Certo et al., 2016). The ISO certification variable is excluded from the outcome equation following these criteria. Due to reduced sample sizes, it was impossible to obtain various regressions at all the firm sizes and industries; instead, a dummy for industry and firm size was included in the regression for control purposes. Industry dummy takes a value of 1 if a firm is manufacturing and 0 if services or other services. On the other hand, the firm size dummy takes 1 for a large firm and 0 for a small or medium firm.

A sample selection model (2.4) can also be estimated using the two-step Heckman or the LIML; therefore, the LIML can be a good test for robustness in investigating drivers of R&D expenditure. The two-step Heckman estimation, or the LIML, is also estimated as the robustness test of the primary model, the FIML. The results of LIML are reported in Appendix G. Comparing the LIML and FIML reveal a fundamental difference in magnitudes of the estimated parameters of interest of the outcome equation. However, the signs of the coefficients are the same for both models. According to the empirical literature, the FIML based on MLE yields more robust results than LIML based on the Ordinary Least Square (OLS) estimation (Certo et al., 2016; Cook et al., 2021). Therefore the FIML was selected as the primary model in this study Table 2.5 shows the results of FIML estimation. R&D selection (participation equation) and R&D intensity (outcome equation) were simultaneously estimated as specified in equation (2.4).

Table 2. 5: Drivers of a Firms Intensity of R&D Expenditure FIML Regression Results

	R&D Intensity (Outcome equation)		R&D Propensity (Participation equation)	
Independent Variable	Coefficient	Robust Standard Errors	Coefficient	Robust Standard Errors
Industry	0.113	0.174	0.112	0.126
Firm size	-0.256	0.184	-0.001	0.142
Firm age	-0.004	0.004	-0.007**	0.003
Manager experience	0.010	0.008	-0.004	0.005
Internet access	0.094	0.175	0.126	0.122
Incubation labs access	-0.270*	0.142	0.277**	0.139
International certification	-	-	0.231*	0.114
Foreign technology adoption	-0.023	0.218	0.361*	0.182
Physical capital Spending	-0.461***	0.167	0.504***	0.105
Exporting capacity	-0.039	0.163	0.300***	0.128
Credit access	-0.141	0.166	0.132	0.113
Business-government relations	-0.180	0.175	0.297***	0.125
Employee training	-0.291*	0.163	0.524***	0.114
Innovation partnerships	-0. 355**	0.170	0.453***	0.121
Cost of labour	0.010	0.093	-0.008	0.077
Rho	-0.756	0.124		
Sigma	1.028	0.155		
Lambda	-0.778	0.240		

N=1,001, Wald test of independence of. Eqns. (rho=0): chi2(1) = 11..56 Prob > chi2 = 0.0007

Note: Rho=Correlation of the disturbances of the participation and outcome equations; Sigma=Adjusted standard error of the outcome equation, *, ** and *** denotes 10%, 5%, and 1% significance levels, respectively. Models 1 and 2 are simultaneously estimated using maximum likelihood on a Tobit II model (Eqn. 2.4.).

Source*: authors' computation from WBES 2018*

A negative value of rho shows that unobservable are negatively correlated. Sigma =1.028 is the adjusted standard error of the outcome equation. The value of sigma depends on the presence or absence of a statistically significant effect of selection or whether the chi-square figure for rho is statistically significant or not. The results of the Wald test, which has a chi2 distribution, Prob > chi2 =

0.0007, indicate that rho is significant. Therefore, Mill's ratio specified in equation (2.4) is significant. Consequently, those firms selected into the R&D expenditure sample have higher expenditures than firms with typical characteristics selected randomly from the population.

The participation equation is the Probit selection equation that investigates the chances that firms will participate or not participate in R&D activities. The results of the participation equation indicate that a firm’s likelihood to invest in R&D was determined by the firms’ age, usage of incubation labs, international certification, adoption of foreign technology, spending on physical capital, exporting capacity, employee training, innovation partnerships, and business-government relations.

The results indicated that a firm that had trained its employees, spent on physical capital, and had innovation partners had a 50% chance of spending on R&D. Using incubation labs, adopting foreign technology, and exporting would significantly increase the likelihood of a firm's R&D spending by 27.7%, 36%, and 30% respectively. The control information firm age, size, and industry did not matter significantly. In summary, this result suggests that more firms would participate in R&D if they had access to appropriate infrastructure, a conducive business environment, and well-trained personnel. Further results indicate that technical collaborations through partnerships, incubation lab sharing, and using foreign licensed technology will enable more firms to participate in R&D.

Considering the R&D spending firms, the outcome equation specifies a truncated regression model. The outcome and the participation equations were estimated simultaneously by MLE under the Tobit II model equation (2.4). Due to sample selection bias, the outcome equation cannot be estimated directly using OLS. The results of the outcome equation revealed the drivers of a firm's intensity of R&D expenditure. A firm's R&D expenditure intensity drivers included using incubations labs, spending on physical capital, employee training, and innovation partnerships.

The estimated parameters of the outcome equation revealed that a firm would significantly reduce its R&D expenditure if it collaborated with other innovation players. For instance, an increase in the usage of incubation labs and having an innovation partner would significantly reduce a firm's R&D expenditure per worker by KES 27 and KES 36, respectively. Increasing spending on physical capital and training employees by one shilling would significantly reduce the cost of R&D by KES 46 and KES 29, respectively.

2.5 Discussion

The results revealed that the likelihood of investing in R&D increased when firms had access to infrastructures such as incubation labs, foreign technology, and the acquisition of physical capital. Sophisticated business practices such as exporting capacity would significantly increase the chances of a firm's R&D engagement.

Finally, the probability of a firm investing in R&D would increase significantly with the quality of human capital and research, such as innovation partnerships and employee training. This result is consistent with other R&D and innovation studies. The annual GII, for instance, classifies innovation inputs into four categories. They include human capital and research quality, institutional quality, infrastructure, business, and market sophistication (Ayalew et al., 2020; Cornell University INSEAD & WIPO, 2018; Morsy & Amira, 2020).

Considering the firms that made positive expenditures on R&D, the results indicated that technical collaborations, infrastructure, and quality of human capital primarily determined the amount of spending on R&D. The results suggested that a firm's R&D intensity would be significantly reduced due to technical collaborations. These collaborations can be seen through innovation partnerships and access to public incubation labs.

The results revealed an inverse relationship between R&D expenditure and technical collaboration. This inverse relationship could be because R&D is an expensive undertaking; therefore, getting an innovation partner and access to an incubation lab would significantly subsidize a firm's expenditure on R&D. Further results indicated that the intensity of R&D decreased considerably as the firm increased its spending on physical capital. This result suggests that due to resource scarcity if a firm spent on physical capital, limited resources would be available for R&D purposes (Morsy & Amira, 2020).

These results are comparable with other studies investigating the drivers of R&D intensity from developing and developed countries. For instance, Tyagi et al. (2018) investigated the drivers of firm R&D intensity using the Indian pharmaceutical industry. They found that R&D intensity increased with increased cash flow and firm size. Elkomy et al. (2020), using Egyptian high technology firms, and Fu et al. (2018), using formal and informal firms in Ghana, found a significant effect of foreign technology adoption on R&D intensity. Morsy & Amira (2020) found that financial access was a substantial driver of R&D intensity among developing nations, including African countries. Cirera (2015) found that R&D intensity among Kenyan firms was significantly influenced by financial freedom, but financial access was an essential inhibitor of R&D intensity, and firms with foreign ownership invested less. Lastly, Ndicu & Wacuka (2017) found that R&D intensity among Kenyan firms was significantly influenced by a firm's foreign ownership and business turnover.

2.5.1 Policy Implication

This chapter analyzed the first study objective, which investigates the drivers of firm-level expenditure on R&D. The results indicated that the significant drivers of R&D expenditure could be divided into two broad categories**.** The first is resources, such as capital goods and human capital—the last is technical collaboration, such as joint innovation and usage of incubation labs.

Specifically, the result indicates that usage of incubation labs set up by the government or Universities will increase the chances of a firm participating in R&D by 27.7% and reduce a firm expenditure on R&D by KES 27. The implication to the policy of this result is that incubation labs are significant in encouraging more firms to engage in R&D and significantly reduce their expenditure on R&D. Therefore; this study argues that to encourage more firms to engage in R&D at a lower cost; the institutions in charge of managing the KNIS, i.e., KENIA, NRF AND NACOSTI need to first, establish more incubation centres in partnership with other innovation players in the country such as the academia and industry. Secondly, they should ensure that the available innovation hubs are accessible and market them to Kenyan firms. Lastly, the government needs to provide incentives such as tax reliefs to innovation players such as academia and industry whenever they intend to establish public innovation labs/hubs.

Further results indicate that acquiring R&D-intensive physical capital such as machines and equipment would significantly cut down a firm's expenditure on R&D by KES 46 and increase the firm participation rate in R&D by a 50% chance. The implication to the policy of this result is that if the fiscal authorities could subsidize the cost of R&D-intensive capital goods bought by the firms, this would enable the firms to engage in R&D at a lower cost. In Kenya, most firms import capital goods such as machines and equipment. Suppose the government could subsidize the import duty or ensure that locally available capital goods are affordable. More firms can engage in R&D activities at minimum cost.

The study findings indicated that firms that trained their employees, especially in the innovation process, and had innovation partners were likely to reduce their expenditure on R&D by, on average, KES 29. Additionally, firms that trained their employees had a 52% chance of participating in R&D activities. Consequently, the implication of this result to policy is that firms should continuously build their human capital through employee training. Secondly, more technical collaborations of firms with other innovation actors like academia, industry, ST&I institutions, and regulating bodies can help stimulate more firms to participate in R&D and significantly reduce the cost of R&D to firms and pursue their goal of profit maximization. Lastly, apart from a policy that increases the number of R&D spending firms, firms need to have a policy on firm-level training in managing R&D. Firm-level management of R&D will enhance the conversion of knowledge inputs into outputs.

CHAPTER THREE

IMPACT OF FIRM-LEVEL INNOVATION ON THE PRODUCTIVITY OF FIRMS IN KENYA

3.1 Introduction

This chapter investigated the impact of firm-level innovation on firm productivity. The study's second objective was motivated by an inconsistency where even with the robust national ST&I policies, innovation efforts, and achievements, the percentage growth rate of overall GDP, services, and manufacturing sectors was still below the 7%, 7.9%, and 7% growth target by 2022, respectively. Additionally, as indicated by their contribution to the GDP, manufacturing firms' productivity declined from 11% in 2010 to 7% in 2019. Consequently, this chapter investigated the role of innovation on firm productivity. Therefore, the chapter assessed whether innovating firms' productivity differed from non-innovating firms' productivity.

ST&I enhances firm productivity, and innovating firms are likely to perform better than non-innovating firms. For instance, innovating firms tend to improve their market share, sales, exporting capacity, and access to credit (Vendrell-Herrero et al., 2020; Woltjer et al., 2019). On the other hand, a firm's output or competitive advantage may stagnate or decline due to the non-adoption of R&D initiatives, poor utilization of novel ideas, and organizational failure to manage the innovation process (Papava, 2017). Consequently, this chapter evaluated the impact of firm-level innovation on firm productivity. Firm-level innovation was indicated by R&D spending, product/service innovation, process innovation, and IPR ownership. A firm's productivity was measured by its value-added per worker. The remainder of the chapter is ordered as follows; section 3.2 presents a literature review, methodology, and data are presented in section 3.3. Empirical findings presented in section 3.4 and section 3.5 present a discussion and policy implications.

3.2 Literature Review

Empirical and theoretical literature concerning the impact of firm-level innovation on firm productivity is presented in this section in detail.

3.2.1 Theoretical Literature

The analysis of the impact of firm-level innovation on firm productivity was anchored on the Crepon-Duguet-Mareisse (CDM) (1998) Generalized Structural Equation Model (GSEM). The theory links firm-level research activities, innovation, and firm productivity. The model summarizes the innovation process from the point when the firm decides to participate in R&D to the impact of innovations on the firm's production activities (Lööf et al., 2017). In this study, firm-level innovation entailed firm-level R&D expenditure, product/service innovations, process innovation, and IPR ownership.

Firm-level innovation effort is manifested chiefly through R&D expenditure per worker and its spending on tangible and intangible assets to produce novel or enhanced products (Baumann & Kritikos, 2016; OECD & Eurostat, 2018). R&D expenditure at the firm level includes a firm's spending on in-house R&D,

outsourced R&D, procurement of R&D-intensive equipment and hardware, procurement of software, procurement of outsourced knowledge, expenditure on training and launching of innovations to the market, and expenditure on licensing of IPRs (Korres & Drakopoulos, 2009; Potting et al., 2017).

The model utilizes a Tobit II model with two equations to explain a firm's research performance. A firm's decision to invest in R&D is assumed to be a latent variable, P^*

$$P^* = x_{1i}^{'}\beta_1 + \varepsilon_{1i} \text{ -- } (3.1)$$

$$y^* = x_{2i}^{'}\beta_2 + \varepsilon_{2i} \text{ -- } (3.2)$$

When investigating the firm's research behaviour, the first equation (3.1) is the participation equation, and it helps explain the likelihood that a particular firm will participate in R&D undertakings. The second equation is the outcome equation which describes the intensity of R&D activities. $x_{1i}^{'}$ and $x_{2i}^{'}$ are vectors of explanatory variables that explain the research participation and intensity, respectively.

Successful investments in R&D lead to the realization of innovations (Hall et al., 2016). At the firm level, innovations are measured by analyzing whether or not a firm launched a new-to-the-firm service or product, new organizational procedures, new production processes, and new marketing strategies (Baumann & Kritikos, 2016). Besides, firm-level innovation can be measured by considering the financial gains realized from commercializing innovations and licensing or ownership of IPRs (Karabulut, 2015; OECD & Eurostat, 2018). Conditional on the proxy of the innovation, the innovation equations can be expressed as;

$$INNV_i = \pi_1 y_i + \theta_1 x_i + \alpha d_s + \beta d_r + \varepsilon_i^1 \text{------------------------------------} (3.3)$$

$$IPR_i = \pi_2 INNV_i + \theta_2 z_i + \alpha d_s + \beta d_r + \varepsilon_i^2 \text{----------------------------------} (3.4)$$

Where, $INNV_i$ is innovation output in the form of new-to-the-firm products or services, new organizational procedures, new production processes, and new marketing strategies. $INNV_i$ is a function of R&D spending y_i and other explanatory variables x_i. IPR_i can be depicted by financial gains realized from the commercialization of innovations and licensing or ownership of IPRs. Therefore IPR_i is a function of $INNV_i$ plus other explanatory variables z_i. d_s and d_r is the sector and the region dummy, respectively. ε_i^2 and ε_i^1 are the disturbance terms.

Successful investment in R&D within a NIS leads to the realization of new knowledge, innovations, inventions, and IPs, leading to increased firm productivity (Delener & Schweikert, 2017). Effective IPR administration and protection set the stage for further technology diffusion by licensing IPRs to the intermediate sectors across the NIS and increasing industry output (Parker & Van-Alstyne, 2018). In the augmented CDM model, the effect of R&D, innovation, and IPR ownership is usually depicted by a Cobb-Douglas production function:

$$Q_i = A + \alpha_k k_i + \delta_1 INN_i^* + \delta_2 IP_i^* + \delta_3 INN_i^* \blacksquare IP_i^* + \alpha d_s + \beta d_r + v_i \quad (3.5)$$

Where output Q_i is a function of tangible inputs such as capital (k_i) and labour and intangible inputs such as R&D, Innovation (INN_i^*) and intellectual properties (IP_i^*). d_s and d_r are sector and region dummies, respectively. Figure 3.1 summarizes the innovation process from the firm's decision to invest in R&D to the impact of R&D and innovation outputs on firm productivity in the CDM model.

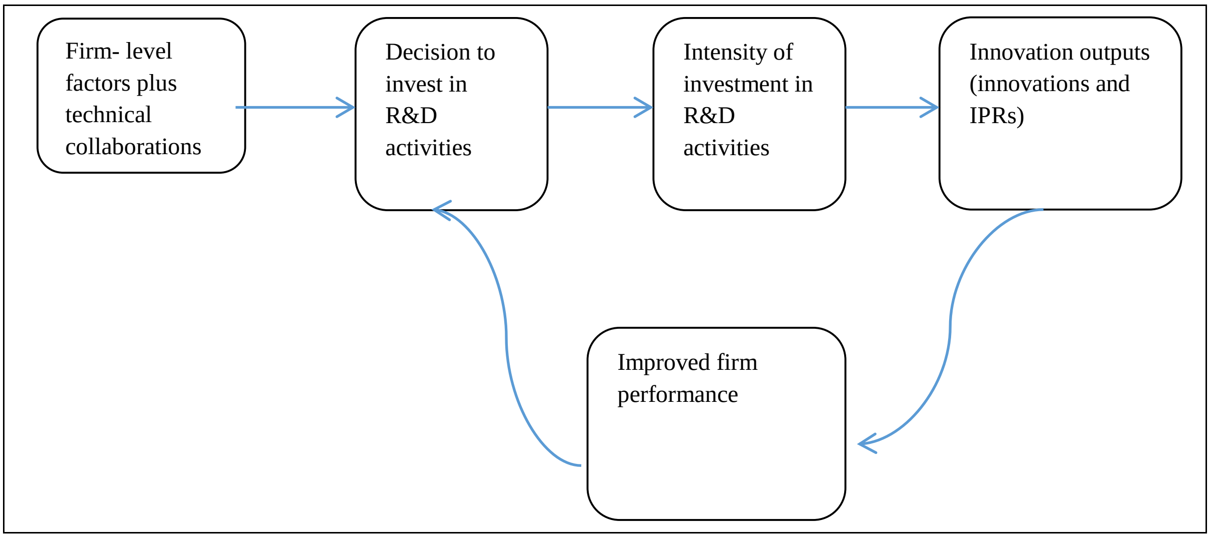

Figure 3. 1: Diagrammatic Representation of Semi-Endogenous Firm-Level Innovation Process

Source: *Author's, 2023*

In theoretical literature, productivity (labour productivity) is the conventional measure of firm performance favoured by policymakers and economists. Output per worker is the ideal measure of labour productivity. When output per worker is not available other measures such as value-added per worker, Total Factor Productivity (TFP), and sales per worker have extensively been employed in the empirical literature (Cirera, 2015; Siepel & Dejardin, 2020). Based on the available study data, firm productivity was measured using the value-added per worker in this study.

The CDM model provided a theoretical and empirical framework for analyzing the implications of research and innovation on firm productivity. The CDM-GSEM has been a crucial theoretical framework for studies investigating the impact of innovation on firm productivity for the past two decades. One of the significant strengths of the CDM theory is that it is an influential building block in the economics of innovation literature. The original version of the theory has been augmented to analyze the impact of innovation in various sectors of the economy.

According to Lööf et al. (2017), numerous authors have studied the CDM model in over 40 countries. The five equations of the mathematical form of the theory have been analyzed using different econometric methodologies. They include; Instrumental Variable (IV) estimation, Bivariate Probit, two-stage least squares, Panel data models, and treatment effect models (Lööf et al., 2017). However, despite being a powerful model, it is a partial equilibrium model. Therefore, it cannot effectively analyze innovations and technical collaborations in a DSGE approach.

3.2.2 Empirical Literature

Crepon-Duguet-Mareisse (CDM) (1998) was the first to analyze the CDM-system of equations model using French manufacturing firms. The authors used panel data (1986-1990) and a sample of 4,164 firms. The study explored the relationship between firm performance and innovation. Labour productivity, measured as the log value added per worker, was used to measure firm productivity. The results revealed that a firm's likelihood to participate in R&D increased as the firm's size became extensive. Innovation output was positively associated with R&D activities, and firm productivity was positively associated with innovation output. This study was a milestone achievement in innovation and productivity of firms' literature, and it has been the reference point two decades later. Crepon-Duguet-Mareisse (CDM) (1998) provided an excellent theoretical and empirical foundation for the current study.

Cirera (2015) explored the impact of innovation on firm productivity in Kenya. Log-valued added per employee and log sales per worker were used to measure firm productivity. The study utilized 549 firms surveyed in the WBES of 2013, covering 2010-2012. The CDM system of equations, and Tobit regression, were used as estimation techniques. The results revealed that firm-level innovation had no significant effect on firm productivity. This study adopted the author's CDM theoretical and empirical framework, the computation, measurement, and definition of variables.

Further, Cirera (2015) formed an excellent basis for results comparison with the findings of this study which used the current 2018 WBES data. Cirera (2015) provided a foundation for determining the impact of innovation on firm productivity in Kenya. However, the author did not analyze the influence of IPRs on firm productivity and the productivity growth of the KNIS. This study extended the innovation discourse in Kenya to entail IPRs, impact evaluation of ST&I on firm productivity using treatment effect models, and productivity analysis of the KNIS.

Vanino et al. (2017), using Propensity Score Matching (PSM), analyzed the effect of participation in publicly funded research on United Kingdom firms on their turnover, employment, and lab productivity. The study used data from the gateway of the research database from 2004 to 2016. The results indicated that firms participating in publicly funded research increased their employment and turnover. This study focused on applying PSM to investigate the effect of corporate participation in private R&D investments, product/service innovation, process innovation, and IPR ownership activities on firm productivity. Vanino et al. (2017) estimation methodology and conceptual framework were notably elaborate. Even though the PSM does not account for unobservable, the PSM is still reliable if panel data is unavailable and if matching and model specification is appropriately done.

Kim (2018), using Korean firms and data covering 2012-2016, examined the impact of participation in technological innovation on the employment performance of firms using PSM. The results revealed that the impact of technological innovation on employment performance varied according to the sector classification of firms. The effect of technological innovation significantly impacted non-ICT firms compared to ICT firms. Product innovation had a positive impact on the employment performance of firms, while process innovation had a negative effect. The paper utilized the recent research methodology in the empirical literature. The PSM approach has become the contemporary technique for addressing selection bias when panel data is unavailable. The current study adopted the estimation methods from Kim (2018) and investigated the effect of technological innovations, R&D investment, and IPR ownership on a firm's productivity in Kenya.

Fazlıoğlu et al. (2018) investigated the counterfactual innovation impacts on the productivity of Turkish manufacturing firms. Using data for 6,681 firms from the Turkish CIS covering 2003-12, the authors estimated an Endogenous Switching Regression (ESR) model. Firms' productivity was measured using the Total Factor Productivity (TFP) analyzed using a Cobb-Douglas production function. The main findings indicated varied firm intensities to innovate and benefit from innovations. The results also revealed that all innovation types positively influenced firms' productivity. PSM/ESR methodology was crucial in addressing endogeneity and selection bias issues when baseline data for the outcome variable is unavailable. ESR is parametric, and PSM is semi-parametric, but both are based on the same assumptions and can be used when panel data is unavailable. The current study utilized the PSM to address the two issues while estimating the innovation impacts on the productivity of Kenyan firms. Various PSM matching approaches plus ESR were used for robustness testing.

Fiorentino et al. (2020) examined the impact of innovation on startup firms in Italy. The study utilized community innovation survey data for the startup firms established in 2013 and 2014. PSM estimation methodology and nearest neighbourhood matching, radius, and kernel matching algorithms were used. The general Average Treatment Effect (ATE) results revealed that innovating startups had experienced higher growth rates than non-innovative startups. Matching results were analyzed empirically and also graphically. This study borrowed the authors' graphical and empirical matching approaches. The nearest neighbourhood matching, radius, stratified, and kernel matching algorithms were used to perform matching when estimating the impact of innovation on the productivity of Kenyan manufacturing and services firms.

3.2.3 Overview of Literature

The determination of the impact of innovation on firms' productivity was based on the GSEM-CDM model. The model provides a framework for linking firm performance to R&D and innovation. Therefore, the CDM model provided a theoretical and empirical framework for investigating the impact of innovation on a firm's performance. Empirical literature indicates that numerous authors have used different measures of firm productivity, for instance, sales per worker, total factor productivity (TFP), and value-added per worker. Based on the available study data and empirical literature, Cirera (2015), Crepon et al. (1998), and Fu et al. (2018), firm productivity was measured by the value-added per worker.

According to the CDM model, successful R&D investment leads to innovation outputs such as new products/services or processes. The innovating firms then claim IPRs on their innovation and knowledge outputs. The gains from innovations enhance a firm's productivity and profitability. A survey of empirical literature indicated that different econometric criteria had been used to analyze the link between innovation and firm productivity. The causal inference approaches, such as treatment effect approaches, have become the modern tools in innovation economics literature to explore the impact of innovation on firms' performance. However, in Kenya, no past studies have applied treatment-effect approaches to evaluate innovation's impact on firm productivity. Therefore, this study was the first to utilize the treatment effect approaches to analyze the causal inference of innovation on firm productivity.

3.3 Methodology and Data

This section presents the research design, theoretical and econometric model utilized to investigate the impact of innovation on firm productivity.

3.3.1 Research Design

The non-experimental research design was employed to analyze the impact of innovation on firm productivity. Further, a cross-sectional design and a quantitative approach were utilized.

3.3.2 Theoretical Framework

In this study, firm-level innovation entails R&D spending, product/service innovation, process innovation, and ownership of IPRs. The augmented CDM model provides a theoretical and empirical framework to evaluate firm-level innovation's impact on a firm's productivity. The CDM model provides a theoretical framework for linking firm productivity to firm-level R&D, innovation, and IPR ownership (Hall & Sena, 2017). The mathematical form of the theory provides a structural model with five equations, where each equation has different econometric estimation criteria. The structural model, as presented in detail in the theoretical literature, consists of;

$$P^* = x_{1i}^{'}\beta_1 + \varepsilon_{1i} \quad (3.1)$$

$$y^* = x_{2i}^{'}\beta_2 + \varepsilon_{2i} \quad (3.2)$$

$$INNV_i = \pi_1 y_i + \theta_1 x_i^1 + \alpha d_s + \beta d_r + \varepsilon_i^1 \quad (3.3)$$

$$IPR_i = \pi_2 INNV_i + \theta_2 x_i^2 + \alpha d_s + \beta d_r + \varepsilon_i^2 \quad (3.4)$$

$$Q_i = A + \alpha_k k_i + \delta_1 INN_i^* + \delta_2 IP_i^* + \delta_3 INN_i^* \blacksquare IP_i^* + \alpha d_s + \beta d_r + v_i \quad (3.5)$$

Equations (3.1) and (3.2) are the research equations, equations (3.3) and (3.4) are innovation equations, and equation (3.5) is the productivity equation expressed as a Cobb-Douglas production function. The productivity equation is a function of intangible (unobserved endogenous) inputs, including R&D, innovation, IPRs, and tangible inputs like labour and capital.

3.3.3 Empirical Model and Estimation Strategy

In this study, firm-level innovation entails spending on R&D, the introduction of new products/services, process innovation, and ownership of IPRs. The CDM model provided a theoretical framework to evaluate the impact of firm-level innovation on firms' productivity. To estimate the productivity equation (3.5) of the CDM model and estimate the impact of R&D spending (3.2), product/service or process innovation (3.3), and IPR ownership (3.4) on a firm's productivity, the study followed Kim (2018) and Vanino et al. (2017). It employed a random treatment assignment model, also known as the potential outcome model. A treatment assignment model such as the PSM was preferred because it accounts for selection bias and heterogeneous treatment effect bias in the estimation process.

The study hypothesized four randomized treatments for the sampled firms; Let Y= be the outcome variable Q_i in equation (3.5) measured as a firm's value-added per worker; Let the four treatments be $i = A, B, C\ and\ D$ where treatment A = firms that engaged in R&D spending and the control group be non-R&D spending firms. Treatment B = firms involved in product or service innovation and the control group as non-innovative firms; treatment C = firms that owned IPRs and the control group as non-IPRs owners. Treatment D = firms that introduced a new production process and the control group as non-process innovators.

Then the treatments participation outcome was: Y_{1A} = value-added per worker for firms that spent on R&D activities; Y_{1B} = value-added per worker for firms that introduced a new product/service. Y_{1C} = value-added per worker for firms that owned IPRs and Y_{1D} = value-added per worker for firms that introduced a new production process. The unobserved output of the same firms that participated in the treatments had they not participated in the randomized treatment was given as: Y_{0A} = non-participation value-added per worker for firms that spent on R&D; Y_{0B} = non-participation value-added per worker for products/services innovative firms. Y_{0C} = non-participation value-added per worker for firms that owned IPRs and Y_{0D} = non-participation value-added per worker for processes innovative firms. In general, for i^{th} randomized treatment $i = A, B, C\ and\ D$, Y_{1i}= treatment outcome; Y_{0i} = non- treatment outcome; Then,

$Y_{1i} = Y_{0i} + \delta_i$ or $\delta_i = Y_{1i} - Y_{0i}$-- (3.6)

Where, δ_i is the i^{th} randomized treatment effect; the objective of the randomized treatment effect models is to obtain an estimate of the value of the i^{th} randomized treatment effect δ_i. The study defined a dummy $D = 1$, if a firm had received treatment; $D = 0$, if a firm had not received treatment (Moffitt, 1991). Then, $E(Y_{1i}\ |D = 1)$, was the value-added per worker expected value of firms that had received treatment; $E(Y_{0i}\ |D = 1)$, was the value-added per worker expected value, that would have been if those who have received treatment had not gone through it. The randomized treatment effect across all firms was estimated as defined by equation (3.7).

$\hat{\delta} = E(Y_{1i}|D = 1) - E(Y_{0i}\ |D = 1)$-- (3.7)

Since $E(Y_{0i}\ |D = 1)$ is not observable for the same firm that received treatment, counterfactuals needed to be evaluated by defining two parameters. One is the Average Treatment Effect (ATE), the mean impact of treatment obtained by averaging the impact across all firms in the population, as shown by equation (3.8) (Heinrich et al., 2010).

$ATE = E(\delta) = E(Y_{1i} - Y_{0i})$--- (3.8)

The second parameter which had to be defined is the Average Treatment Effect on the Treated (ATET) equation (3.9) which is the impact of treatment on those firms that participated.

$ATET = E(Y_{1i} - Y_{0i}|\ D = 1) = E(Y_{1i}|\ D = 1) - E(Y_{0i}\ |D = 1)$--------- (3.9)

A randomized causal inference model also allows for the estimation of the Average Treatment Effect on the Untreated (ATU). The ATU is equal to the average treatment effect conditional on being untreated.

$ATEU = E(Y_{1i} - Y_{0i}|\ D = 0) = E(Y_{1i}|\ D = 0) - E(Y_{0i}\ |D = 0)$------- (3.10)

A randomized causal inference model isolates selection and heterogeneous treatment effect bias (Cunningham, 2021). Randomized causal inference is based on two crucial assumptions: the conditional independence assumption and the common support condition. The independence assumption implies that the randomized treatments had been assigned to units without regard to their potential outcomes. This ensures that the mean potential outcomes for the treatment and control groups are the same. It also ensures other variables are distributed the same for a large sample. Therefore under independence $E(Y_{0i}\ |D = 1\ ) = E(Y_{0i}\ |D = 0)$ and $E(Y_{1i}\ |D = 1) = E(Y_{1i}\ |D = 0)$. That is, average Y_{1i} and Y_{0i} is the same for the control and treatment groups (Cunningham, 2021). The common support assumption ensures that observations in the control group are comparable with those in the treatment group based on observables.

Data requirements of the potential outcome model estimation include; a large number of variables, extensive data, treatment, and control group to come from the same source, and a pool of comparison units to have sufficient observations (Hill et al., 2018). Additionally, according to Cunningham (2021), the random treatment is assumed to be a homogenous dosage when estimating a potential outcome model. Potential outcomes are invariant to who else (and how many) are treated. Further, causal inference using a potential outcome model assumes no externalities and only partial equilibrium. Homogenous dosage implies that innovation measures are uniform for all firms. No externality suggests that no other firm should benefit or lose when an individual firm participates in innovation activities.

Athey & Imbens (2017) posit that to obtain the actual estimation of the i^{th} treatment effect δ_i we assume a sharp null hypothesis (3.11).

$H_0: \delta_i = Y_{1i} - Y_{0i} = 0; \quad \forall i$ ---(3.11)

The sharp null hypothesis implies no average treatment effect (ATE=0) for all firms ($\forall i$). The hypothesis is then evaluated based on some non-parametric test statistics, not based on the distributional assumptions of the error term (Athey & Imbens, 2017). There are numerous test statistics for the sharp null in empirical literature based on D and Y. For instance, Regression Discontinuity Design (RDD), weighting and matching approaches, Instrumental Variable (IV) estimation, and Difference in Differences (DID) estimation (Cunningham, 2021).

Cross-sectional data with potentially endogenous innovation variables was used to evaluate the impact of innovation on firms' productivity. The 2018 WBES data utilized is cross-sectional; thus, the sampled firms were asked yes/no separate questions of whether they had spent on R&D in the past three years (2015, 2016, and 2017), introduced new products/services and whether they owned IPR. PSM is mainly used for cross-sectional data, allowing for causal inferences from non-experimental studies. PSM is an appropriate tool to address sample selection and endogeneity problems as long as all assumptions of the model hold.

The first step of the PSM methodology was to define selection models for each of the three treatments, estimate the propensity score $P(D=1)$ using a Probit/Logit equation (3.12) and calculate the predicted probabilities.

$$P\{y_i = 1|x_i\} = F(x_i'\beta) = \frac{\exp(x_i'\beta)}{1+exp(x_i'\beta)} \text{------------------------------- (3.12)}$$

Where x_i' is a vector of explanatory variables, including indicator variables of infrastructure quality, research capacity, business, and market sophistication indicators. The second step in PSM estimation is determining an appropriate algorithm to match the predicted probabilities. Nearest Neighborhood-Matching, Radius-Matching, Stratification-Matching, and Kernel-Based Matching algorithms were used to perform matching. The last step involved evaluating the estimates and statistical significance of the estimated algorithms (Heinrich et al., 2010; Hill et al., 2018; Moffitt, 1991).

When dealing with cross-sectional data, matching and weighting approaches such as PSM and ESR have been used in empirical literature to ensure the treatment and control groups are comparable, at least on observable characteristics (Hill et al., 2018). PSM and ESR assume that unobservable are controlled for by balancing property. The double-difference (DID) is more robust when selection is based on the unobservable and panel data (Moffitt, 1991). PSM was preferred in this study since it doesn't need a panel survey.

Further, PSM is a semi-parametric method that imposes fewer constraints on the functional form of the error term and the treatment model compared to ESR.

Additionally, PSM may compare the control and treatment groups well if selection bias from unobserved characteristics is negligible (Heinrich et al., 2010). Nonetheless, PSM and ESR have been used interchangeably; therefore, robustness was confirmed using different matching algorithms, ESR, and the Kolmogorov-Smirnov test.

3.3.4 Data Source and Type

Cross-sectional data with 1,001 firms obtained from the WBES 2018 was utilized to investigate the causal effects of innovation on firm productivity in Kenya. The same data set was used to investigate the first study objective described in chapter two, section 2.3.4.

3.3.5 Data Challenges, Cleaning, and Analysis

The 2018 WBES data used to investigate the drivers of R&D intensity in chapter two was also used to analyze the impact of innovation on firm-level productivity. Therefore, the independent variables are the same as those in chapter two. In this chapter, additional variables measuring firm-level innovation output were included. They include product innovation, process innovation, IPR ownership, and R&D propensity. Additionally, a variable indicating firm productivity is introduced; value-added per worker.

Valued added per worker was measured as the difference between a firm's total annual sales for all products and services minus the annual total cost of sales divided by the number of workers. According to the study data, the total cost of sales entailed three components: the yearly total cost of labour, including wages, salaries, bonuses, and social security payments. Second is the total cost of raw materials and intermediate goods used in production. And lastly, the total annual cost of electricity.

The total annual sales variable was 84% complete, while the total cost of sales variable had data in at least two of the three components that constitute the total cost of sales. The 16% missing data on sales per worker was filled with average sales per worker of the respective firm size in the respective industry. Afterwards, box plots and percentile plots were used to detect and deal with value-added per worker variable outliers. After data cleaning, the counterfactual innovation impacts on value-added per worker were evaluated using PSM treatment models.

3.3.6 Definition and Measurement of Variables

Table 3.1 shows the definition and measurement variables used to evaluate the impact of innovation on a firm's productivity.

Table 3. 1: Definition and Measurement of Variables

Variables	Definition and Measurement
Control Variables	
Industry	1 if a firm's main activity is manufacturing, 0 if a services firm.
Firm size	1 if a large firm (more than 100 employees) 0 if SME (less than 100 employees).
Firm age	The number of years since the firm was established until the year 2018.
Manager experience	The number of years of experience of the top manager.
Innovation Outputs	
Product/service innovation	1 if a firm launched a new product/service into the market, 0 if otherwise.
Process innovation	1 if a firm introduced a new process in the production of goods or service delivery, 0 if otherwise.
IPR ownership	1 if a firm registered a patent or an industrial design or applied for a trademark or applied for copyright, 0 if otherwise.
R&D Propensity	1 if a firm spent on R&D activities, either in-house or contracted with other companies, excluding market research surveys, 0 if otherwise.
Firm Productivity Measure	
Value-added per worker	It is measured as the difference between a firm's total annual sales for all products and services minus the annual total cost of sales divided by the number of workers.
Independent Variables- Innovation Inputs	
Internet access	1 if an establishment has an official operational website, 0 if otherwise.
Incubation labs access	1 if a firm used incubation labs set by the government, Universities, or private sector, 0 if otherwise.
International certification	1 if a firm is licensed by international standards like ISO: 9001, 0 if otherwise.
Foreign technology adoption	1 if the firm uses technology licensed from foreign-owned companies, 0 if otherwise.
Exporting capacity	1 if a firm engaged in direct and indirect exports, 0 if national sales only.
Credit access	1 if a firm borrowed money from financial intuitions, 0 if otherwise.
Business-government relations	1 if a firm secured a government contract at the county or national government level, 0 if otherwise.
Employee training	1 if a firm conducted formal training to employees specifically on developing or introducing new products/services, 0 if otherwise.
Innovation partnerships	1 if a firm introduced a new product/service in collaboration with other companies or organizations, 0 if otherwise.
Cost of labour	The total cost of labour, including wages, salaries, bonuses, and social security.

Source: *WBES 2018*

3.4 Empirical Results

The empirical results are presented using descriptive statistics, diagnostic, regression, and robustness tests.

3.4.1 Descriptive Statistics Results

Table 3.2 presents the descriptive statistics regarding share percentages of the innovation outputs. The innovation outputs include R&D propensity, product/service innovation, process innovation, and IPR ownership. The descriptive statistics of innovation inputs remain the same as in Table 2.2 in chapter two since the same dataset was used in chapter two and this chapter.

Table 3. 2: Descriptive Statistics (Share Percentage)

Variable	All firms	Firm size			Sector			N
		Small	Medium	Large	Manufacturing'	Retail	Other services	N
R&D spending	16%	31%	40%	29%	56%	13%	31%	1,001
Product/service innovation	46%	38%	25%	37%	45%	19%	36%	1,001
Process innovation	26%	38%	35%	27%	55%	16%	29%	1,001
IPR ownership	23%	27%	42%	31%	60%	16%	24%	1,001
N	1,001	412	381	208	455	198	348	

Source*: authors' computation from WBES 2018*

Table 3.2 shows that 16% of the 1,001 firms spent on R&D, where most R&D spending firms were medium and large firms. 46% of sampled firms had introduced a new product or service into the market. Small and large firms and manufacturing firms had most of the products/services innovations. Further, 26% of the firms introduced new production and service delivery methods. The majority of the process innovators were small and medium manufacturing firms. Lastly, 23% of sampled firms applied for at least one IP, with most IPR owners' being medium and manufacturing firms. Table 3.3 presents the descriptive statistics for the value-added per worker, which measures firm productivity.

Table 3. 3: Value-added per Worker Summary Statistics

Variable	Firm category	Obs.	Mean	Std. Dev.	Min	Max
Value-added per worker	All firms	1,001	6,082,977	818,160	(5,321,303)	30,293,333
	Small	412	4,034,290	736,882	(12,268,429)	23,380,000
	Medium	381	3,814,616	675,664	(9,169,444)	17,360,000
	Large	208	14,295,980	3,388,253	(8,424,444)	25,136,813
	Manufacturing	455	5,665,576	1,318,961	(8,317,850)	19,878,699
	Retail	198	7,689,074	1,658,989	(5,321,303)	15,056,213
	Other services	348	5,714,903	1,295,615	(10,100,407)	30,293,333

Source*: authors' computation from WBES 2018*

The average value-added per worker was approximately KES 6 million for all the sampled firms, with a standard deviation of KES 0.8 million. The value-added per worker ranged from KES negative KES 5 million and KES 30 million across the firms. Comparing the value-added per worker across firm sizes and industries revealed that large firms and retail industries had the highest value-added per worker during the study period, as shown in Table 3.3. Table 3.4 summarizes the treatments and the control groups and the percentage frequency of the treatment variables.

Table 3. 4: Treatment and Control Groups Percentage Frequency

Treatment Variable	Treated (N)	Control (N)	Treatment Percent Freq.
R&D propensity	163	838	16%
Product/service innovation	468	533	47%
Process innovation	262	739	26%
IPR ownership	233	768	23%

Source*: authors' computation from WBES 2018*

The treatment percentage frequencies for R&D propensity and product/service innovation were 16% and 47%, respectively. 26% of firms had participated in process innovation, while 23% of sampled firms owned IPRs during the study period. The control and the treatment groups came from the same sample and met the PSM estimation requirement, as Cunningham (2021) discussed.

3.4.2 Diagnostic Tests Results

This chapter investigates the impact of innovation on firm productivity using PSM treatment effects model matching approaches. Two critical assumptions of the PSM model need to hold for the PSM model to be successfully employed in counterfactual impact evaluation. The assumptions are validation of selection on observables and the common support requirement. The selection on observables assumption of the PSM assumes that selection is based on observed variables in the study data. It is, however, essential to note that this assumption cannot be validated empirically (Cunningham, 2021). The only alternative is to use a conceptual argument for why we think the observable characteristics sufficiently explain who received the treatment.

Consequently, it is impossible to rule out the unobservable in the treatment selection. However, the study argued the following to validate the selection based on observables. First, following the empirical literature, the study assumed that the effect of unobservables is minimal compared to observables. The study validated the selection into treatment based on observables by asking what factors affect innovation. Are they observable? and are they in the study data?

The variables influencing innovation have been categorized into four categories in the empirical literature. Therefore, the selection was primarily based on observed factors. There is no unobservable among the four innovation input categories, including control variables, infrastructure quality, human capital, and research, business, and market sophistication. Unobservable, such as managerial capability, efficiency, and talents of managers, could still be indirectly accounted for by observed factors. For instance, control variables like the number of years of experience of top managers, employee training, and innovation partnerships can come in handy as controls of the unobservable without data such as managerial capability and talents.

Common support is the second PSM assumption that needs to be satisfied. The common support assumption ensures that the control and treatment groups are comparable conditional on the observed factors. The selection of firms for each of the four treatments was specified by a probit model, as shown in Appendix H. STATA reports whether or not the specified probit model meets the balancing property. The balancing property ensures that the control and treatment groups are compared conditional on the observed factors identified in the respective selection probit model, as shown in Appendix H.

3.4.3 Regression Results

Once the balancing property was satisfied and the PSM assumptions validated, four algorithms were used to match the P-Score of the control and treatment groups. They include the Nearest Neighborhood, Radius, Stratification, and Kernel-based matching. Each treatment firm was matched to the most similar control firm using the P-Score's nearest neighbourhood matching criteria. The study matched each treatment firm to all control firms with greater weight than those with more similar P-Scores in the Kernel matching.

Stratification matching is used to balance covariates by finding strata with no difference in mean covariate values. Then those strata are used to calculate differences in means and sum over properly weighted strata (Cunningham, 2021). In radius-based matching, each P-score is matched with the control group units whose propensity scores are in a predefined neighbourhood of the propensity score of the treatment unit. Table 3.5 reports the matching results, including the Average Treatment effect on the treated (ATT), bootstrapped standard errors, and t-test of each treatment.

Table 3. 5: Propensity-Score Matching Results

Treatment	Nearest Neighborhood Matching	Radius Matching Method (0.1)	Stratification Matching	Kernel-Based Matching
A. Treatment = R&D spending				
ATT.	1,160,000	-604,000	762,000	346,000
Bootstrapped Std. Error	2,000,000	1,530,000	1,540,000	1,730,000
t-statistic	0.581	-0.395	0.495	0.200
B. Treatment = Prod/serv. innovation				
ATT.	3,760,000***	3,010,000**	3,270,000*	3,660,000**
Bootstrapped Std. Error	1,830,000	1,760,000	1,860,000	1,820,000
t-statistic	2.051	1.707	1.755	2.008
C. Treatment =IPR ownership				
ATT.	1,230,000	628,000	817,000	666,000
Bootstrapped Std. Error	3,130,000	1,680,000	2,320,000	2,190,000
t-statistic	0.393	0.374	0.353	0.304
D. Process innovation				
ATT.	-2,250,000	-2,140,000	-1,200,000	-1,120,000
Bootstrapped Std. Error	2,160,000	1,600,000	1,630,000	1,480,000
t-statistic	-1.038	-1.334	-0.741	-0.753

Note: *ATT-Average treatment effect on the treated is expected to be significant at 10% and 5% and 1% significance level when the t-test statistic is more than 1.64 and 1.96, and 2.58, respectively.*

Source*: authors' computation from WBES 2018*

The matching algorithms test the null hypothesis that no significant difference exists between the control and the treatment value-added per worker using the P-Score. For treatments A, C, and D, R&D propensity, owning IPRs, and process innovation, the t-statistic was very low. When the t-statistic is less than 1.64, 1.96, and 2.58, the null hypothesis should be rejected at 10%, 5%, and 1%

significance levels. The results implied that R&D spending had a positive ATT though not significant. Therefore, the value-added per worker for the R&D spending firms was not statistically significant from the non-R&D spending firms' value-added per worker. Similarly, the value-added per worker for IPR-owning and process innovating firms were not statistically significantly different from non-IPR holding or non-process innovating firms. IPR ownership treatment had a positive ATT, while process innovation had a negative ATT, even though not significant because the t-ratios were too low.

Results on treatment B indicated that the t-statistic was 2.051, 1.707, 1.755, and 2.008 when using nearest neighbourhood, radius, stratified, and kernel matching, respectively. Therefore, using the t-statistic results, the study rejected the null hypothesis that no statistically significant difference existed between the value-added per worker of product/service innovating firms and non-product/service-innovating firms. Therefore, ATT of approximately KES 3.5 million when using the four matching approaches was statistically significant—implying that participating in product/service innovation improved value-added per worker by about KES 3.5 million. On the other hand, R&D spending, process innovation, and IPR treatment did not significantly affect a firm's value-added per worker.

3.4.4 Robustness Tests

Even though PSM has become a vital tool for addressing selectivity and endogeneity problems recently, it has its limitations. It's primarily used for causal analysis using cross-sectional data. The limitations of the PSM include its ignorance of the unobservable. It heavily depends on the accuracy of selection into the treatment model and validating assumptions (Cunningham, 2021). Due to these limitations of the semi-parametric PSM estimation, it was prudent for this study to conduct some robustness tests when estimating the impact of innovation on firm productivity. The study used two criteria to test for robustness, the Two-Sample Kolmogorov-Smirnov (K-S) test and ESR. The K-S test tested the null hypothesis that there is equality of distribution between the value-added per worker of the treated and the control groups. Table 3.6 shows the results of the K-S test.

Table 3. 6: Results of Two Sample Kolmogorov Smirnov Test for Equality of Value-added per Worker Distribution Functions

Treatment	Smaller group	D	P-value
R&D Spending	0	0.0350	0.710
	1	-0.070	0.270
	Combined K-S	0.0693	0.529
Product/Service innovation	0	0.0598	0.168
	1	-0.0276	0.685
	Combined K-S	0.0598	0.008
IPRs Ownership	0	0.0363	0.625
	1	-0.0997	0.029
	Combined K-S	0.0997	0.057
Process Innovation	0	0.0355	0.615
	1	-0.0433	0.485
	Combined K-S	0.0433	0.862

Note*:* *1=treatment group, 0 control group; Test: ksmirnov value-added per worker, by (Treatment), exact*

Source*: authors' computation from WBES 2018*

First, for the R&D spending treatment, the first line tests the hypothesis that value-added per worker for the non-R&D spending firms (group 0) comprises lesser values than R&D spending firms (group 1). The biggest difference among the distribution functions is 0.0350. The approximate P-value for this is 0.710, which is not significant. The second line tests the hypothesis that value-added per worker for non-R&D spending firms (group 0) contains larger values than the R&D spending firms (group 1). The biggest difference amongst the distribution functions in this direction is -0.070. The estimated P-value for this small difference is 0.270, which is not significant. Finally, the approximate P-value for the combined test is 0.529. The combined K-S is also not significant. The combined K-S P-value implies that the value-added per worker for the R&D spending firms was not statistically significantly different from that of non-R&D spending firms.

Similarly, the K-S test indicated that the value-added per worker of the product/services innovating firms was statistically significantly different from those of non-product/services innovating firms. Secondly, the value-added per worker of the IPR holding firms was statistically quite different from non-IPR holding firms' value-added. Lastly, the value-added per worker of the process innovating firms was not statistically significantly different from that of the non-process innovating firms.

The second robustness test was the Endogenous Switching regression (ESR). ESR falls under the matching and weighting treatment effects models, and it has been applied in empirical literature for causal inference investigation using cross-sectional data (Crowley & McCann, 2018; Dvouletý & Blažková, 2019). In the ESR, which uses FIML estimation, the behaviour of a firm is described with two outcome equations and a selection function that defines which regime (treatment or control) the firm faces. ESR controls for selection bias and unobserved heterogeneity. Further, the ESR can be used to evaluate distinct values for ATT.

The main demerits of the ESR are difficulty in achieving convergence, primarily when there is a weak model selection. Further, the problems of weak instruments can lead to biased estimates (Fazlıoğlu et al., 2018). The study used "*movestay*" command followed by "*mspredict*" command in STATA by Lokshin & Sajaia (2004) and obtained results shown in Table 3.7. The selection results under different treatment regimes using the "*movestay*" command are reported in appendices I, J, K, and L.

Table 3. 7: Endogenous Switching Regression Results

Treatment	Participation Mean	Non-Participation Mean	Average Treatment Effect (ATT)
R&D Spending firms	5,319,119	10,700,000	(5,369,959)
Product/service innovators	15,500,000	5,724,696	9,745,867***
Process innovators	4,701,261	11,400,000	(6,682,795)
IPR Owners	6,417,716	9,460,518	(3,042,802)

Note: *ATT = the difference in participation and nonparticipation means. *** is the significance level at P<0.01 based on a simple paired t-test.*

Source*: authors' computation from WBES 2018*

Endogenous Switching Regression (ESR) results revealed the difference in firms' mean value-added per worker when they participate and when they don't participate in the four treatments. These results imply that participating in R&D spending, IPR ownership, and process innovation did not significantly affect a firm's value-added per worker. Lastly, the results revealed that participating in product/service innovation would substantially improve value-added by approximately KES 10 million per worker.

3.5 Discussion

Empirical results revealed that out of the four measures of innovation, only product/service innovation impacted firm productivity positively. On the other hand, IPR ownership, process innovation, and R&D spending did not influence a firm's productivity significantly. The impact of innovation on firm productivity was not directly comparable to other studies in Kenya and Africa because no prior studies were virtually available employing program evaluation methods. However, the results of this study were close to Cirera (2015). The author estimated the impact of Kenyan firm-level product/service innovation on firms' productivity using the 2013 WBES using Tobit regression and found no statistically significant impact of innovation on firms' productivity.

The results of this study are consistent with empirical literature from other developing and developed regions that indicate that innovation positively impacts firm productivity. For instance, Morsy & Amira (2020), using 52 countries from developing economies, among the 52, 15 are from Africa, found that innovation significantly affected productivity. Morsy & Amira (2020) relied upon FIML estimation. Using Tobit regression, Fu et al. (2018) found that innovation positively affected formal and informal firms in Ghana. Burçin et al. (2016), who used ESR, found that innovation positively affected firm productivity among Turkish firms. Fiorentino et al. (2020), who employed a PSM estimation, found out that innovation positively affected the productividity of start-up Italian firms.

3.5.1 Policy Implications

This chapter investigated the impact of firm-level innovation on their productivity. Firm-level innovation was measured using process innovation, product/service innovation, R&D spending, and IPR ownership. On the other hand, firm productivity was measured using industry value-added per worker. The results indicated that the productivity of R&D spending, process innovation, and IPR ownership was not statistically significantly different from that of non-RD spenders, non-process innovating firms, and non-IPR owners. The productivity of product/service innovators was statistically different from that of non-innovators.

The results of impact evaluation approaches indicate the effectiveness of the intervention measures of a program. Therefore the study's results also demonstrate the efficacy of firm-level innovation efforts and strategies in Kenya during the study period. The results indicate evidence of the positive and significant impact of product/service innovation measures. The results also suggest that Kenyan firms did not realize financial gains from R&D spending, process innovation, and ownership of IPRs. Therefore this result implies that it can be claimed that firm-level innovation strategies have been somehow effective even though there is potential for improvement to ensure maximum innovation gains are realized even from the process innovation, R&D spending, and ownership of IPRs.

Therefore, the results imply that Kenyan manufacturing and services firms need to re-evaluate their firm-level innovation strategies to realize maximum innovation benefits—this study advocates for a semi-endogenous firm-level innovation process embodied in the KNIS. Consequently, to realize full innovation gains, the firms should not just rely on knowledge and innovation developed within. They should also tap knowledge from other innovation players within the KNIS. For instance, joint research and innovation with academicians, innovation partnerships with other firms, and public innovation hubs could enhance the firm-level semi-endogenous process, thereby improving firms' productivity. The institutions in charge of the KNIS, such as KENIA, NACOSTI, and NRF, are responsible for monitoring and overseeing a smooth semi-endogenous innovation process within the KNIS.

Lastly, this study's findings provide evidence that it is possible to improve the productivity of firms in Kenya through innovation and thereby argue that each firm in Kenya can drive its productivity using firm-level innovation. Therefore, the ST&I regulatory institutions such as KENIA and NRF should encourage and support more firms to engage in ST&I activities, thereby increasing their productivity and consequently increasing their contribution to GDP.

CHAPTER FOUR

REGIONAL CATCH-UP AND PRODUCTIVITY GROWTH OF THE KENYA NATIONAL INNOVATION SYSTEM

4.1 Introduction

This chapter investigates the third study objective: to evaluate the productivity growth of the Kenya National Innovation System (KNIS) over time. The third objective was motivated by the inconsistency where the actual growth rate and productivity of overall GDP, services, and manufacturing sectors were still below the growth target by 2022. Moreover, their percentage contribution to GDP indicated that the manufacturing and services sectors' productivity declined from 11% in 2010 to 7% in 2019. This inconsistency occurred despite Kenya being highly ranked by the Global Innovation Index (GII) among the most innovative countries in Sub-Saharan Africa. ST&I is the critical driver of a firm’s productivity and economic growth in world economies, both in developed and developing economies (Elkomy et al., 2020; Lee & Lee, 2020; Oura et al., 2016). Therefore one would expect the high innovation achievement to be a critical driver of firms’ productivity and economic growth in Kenya.

This chapter analyzed the productivity of the KNIS 2010-2018 compared to other National Innovation Systems in Africa (NIS) in Africa. This analysis determined how Kenya has been catching up with the African ST&I frontier. In the empirical literature, the productivity of NIS has been evaluated using aggregated innovation indexes. One such index is the GII which is the recent innovation index. The GII measures the combined innovation efforts by firms, governments, households, and the society's culture in a particular country. The 2020 GII classified Kenya among other countries like India, Moldavia, and Viet Nam, which had consecutively set a record of innovation achievers from 2010-2019. The GII also consistently ranked Kenya among the most innovative countries in SSA from 2010-2019.

Instead of the GII comparing countries' innovation performance based on the best-performing NISs globally using over 130 countries, this study constructed an African region innovation index using 28 African countries, including Kenya. The African region innovation index benchmarked African countries' innovation efficiency based on the best-performing NIS in Africa. Further, the index evaluated the productivity growth and technical progress of the KNIS compared to other NIS in Africa from 2010-2018. This analysis made it possible to understand how Kenya has caught up with the African ST&I frontier. The remainder of the chapter is organized as follows; section 4.2 discusses the literature review, section 4.3 discusses data and methodology, section 4.4 presents the empirical findings, and section 4.5 presents the conclusion and implication to policy.

4.2 Literature Review

The theoretical and empirical literature on the regional ST&I frontier is discussed in detail in this segment.

4.2.1 Theoretical Literature

The efficiency analysis of KNIS and it's catching up with the regional ST&I frontier was anchored on two theories; the quintuple helix theory and the regional production frontier theory. The quintuple helix innovation theory explains the interrelated agents that constitute a NIS. The quintuple helix model consists of five helices: the education system, the political system, the economic system, the natural environment, and the media and culture-based public system (Carayannis & Campbell, 2012). The quintuple helix improves the quadruple helix, where the natural environment and society helix have been incorporated (Carayannis & Rakhmatullin, 2014). These five "sub-systems" are represented by four agents in the innovation system: the firms, the government, academia, and society (Carayannis & Campbell, 2012). Knowledge flows from one "sub-system" to another in an interconnected manner, leading to new knowledge and innovations. The fifth helix of the natural environment acts as a driver of new knowledge rather than an agent in the innovation process (Grundel & Dahlström, 2016).

Strengthening the interrelations of NIS helices and investment in ST&I by developing countries may play a crucial role in industrialization, sustainable development, and national growth (OECD, 1999). Investments and incorporation of ST&I into economic, social, and governance policies will increase developing countries' productivity, global competitiveness, and employment (Lema et al., 2018). According to the OECD (1999), intensified application of ST&I by developing nations is essential in improving living standards, enhancing financial growth, and enabling them to contribute to the world economy's growth (OECD, 1999). Successful investment in ST&I should allow developing nations to experience efficient and well-functioning NIS.

There are four types of information or knowledge diffusion among the helices experienced in any efficient NIS: 1) collaboration among enterprises, mainly multidisciplinary research and technical activities; 2) formal and informal linkages among industries, academia, and public research institute through joint research, co-publishing, and co-patenting; 3) new technology adoption by establishments leading to products and service innovation and 4) R&D workforce exchanges within the public and private sector (OECD 1999). Linking the four different information flows among the helices in a NIS to a firm performance may increase technology diffusion and technical collaboration levels. Further, exchanging R&D personnel can help a firm achieve enhanced innovative capacity (Ockwell et al., 2015). Consequently, this will improve the efficiency of NIS, thereby transforming developing countries into knowledge-based economies.

The quintuple helix theory provided a theoretical underpinning for economic agents' interactions that constitute an innovation system and how these interactions influence a firm's or country's innovativeness and productivity. One of its major strengths is being a general equilibrium model capable of analyzing the interaction of multiple innovation players leading to innovations at the national level.

The regional knowledge production frontier theory is the second theory underpinning the efficiency analysis of the KNIS and its regional catch-up. The productivity growth analysis of the regional/national innovation system hypothesizes a knowledge production function with inputs and outputs (Sagiyeva et al., 2018). A technology set, *S*, can be described as;

$S = \{(x, y): x \text{ can produce } y\}$-- (4.1)

Where, x denotes an n-dimensional vector of positive innovation inputs. y denotes an n-dimensional vector of non-negative innovation outputs. The technology set *S* contains all input-output vector (x, y) such that *x* can produce y. The production technology presented by the set *S* can be equally presented by the output set *p(x)*, which symbolizes the set of the entire output vectors *y*, which may be created from the input vector *x*, the output vector is presented as;

$p(x) = \{y: x\ can\ produce\ y\} = \{y: (x, y) \in S\}$---------------------------- (4.2)

The output set is known as production possibilities. A knowledge production function (4.3) can formalize the production technology;

$y_{it} = x'_{it}\boldsymbol{\beta} + \varepsilon_i$ --- (4.3)

Where, y_i, is a vector of innovation outputs produced by the i^{th} country at time t, x_i is a $K + 1$ vector of K innovation inputs utilized in the production process by the i^{th} country at time t. $\boldsymbol{B_i}$ is a $K + 1$ vector of coefficients to be evaluated and ε_i is the usual disturbance term. Directional distance functions such as the non-parametric Data Envelopment Analysis (DEA) are essential in describing production technology (4.3) in a manner that enables the evaluation of productivity growth of Decision-Making Units (DMUs).

Equation (4.3) can also be estimated using the Stochastic Frontier Analysis (SFA) Approaches (Kotsemir, 2013; Porcelli, 2009; Zheng, 2015). SFA is a frontier approximation method that presumes a particular functional relationship connecting the inputs to the outputs. Specifying the different underlying functional forms enables frontier estimation using econometric approaches (Aigner et al., 1977; Meeusen & van Den Broeck, 1977).

DEA is a non-parametric linear programming technique that benchmarks DMUs with the best practices of the DMUs, resulting in a convex production possibility frontier (Banker et al., 1989). The DEA technique is not based on the functional relationship between inputs and outputs. Further, it’s not based on the error term distribution, and it’s impossible to conduct inferential statistical and hypothesis tests from the evaluated efficiency scores. Additionally, the DEA approach utilizes multiple inputs and outputs to estimate best-practice frontiers (Yuezhou Cai, 2012; Dzemydaitė et al., 2016). In Empirical literature, the DEA approaches are widely preferred because they employ multiple outputs and inputs, suitable for estimating the dynamic nature of innovation. Additionally, DEA approaches help control estimation issues such as endogeneity and model misspecification (Lin et al., 2018). Therefore, using DEA for the innovation efficiency assessment of NIS in this study was rational.

This study sought to investigate the productivity of KNIS compared to other NIS in Africa over time. DEA techniques have been widely used in such time-based productivity analyses of NISs from developed and developing regions. For instance, Malmquist DEA, Window DEA, Dynamic DEA, and Dynamic Malmquist DEA have been widely used to construct productivity indices of DMUs over time using panel data (Emrouznejad & Thanassoulis, 2010; Halaskova et al., 2020; Yang et al., 2019). The window DEA and the Malmquist DEA have been used as intertemporal efficiency change measurements. However, these models fail to account for carry-over effects between consecutive periods (Tone & Tsutsui, 2010). Färe and Grosskopf, cited in Emrouznejad & Thanassoulis (2010), proposed that dynamic DEA can deal with interconnecting activities between periods.

A survey of empirical literature reveals that different DEA approach models and DEA orientations have been explored. Previous empirical studies have considered input-oriented, output-oriented, and non-oriented DEA models. Radial and non-radial approaches, Constant Returns to Scale (CRS) versus Variable Returns to Scale (VRS), have also been explored in the empirical literature from developed and developing regions.

4.2.2 Empirical Literature

Egbetokun et al. (2017) studied innovation systems research as a plan for developing countries. The authors painted a picture of innovation systems, especially in Africa. The author discussed the role of each innovation player in the innovation system. However, the authors did not attempt to conduct an empirical analysis to evaluate African innovation systems. This study extended the innovation systems discourse in Africa by identifying input and output variables in the African regional innovation system. The study then employed DEA approaches to benchmark NIS with the best-performing NIS in Africa.

Ayisi et al. (2019) presented a history of Kenya's KNIS and ST&I policy briefs. The authors explained the structure of the KNIS and its challenges. However, the authors did not conduct an empirical analysis anchored on a theoretical economic model. Further, the authors did not investigate the productivity growth of the KNIS. To evaluate the productivity growth of the KNIS, Ekinci & Karadayi (2017) and Halaskova et al. (2020) were followed to define innovation outputs and inputs and determine the cross-country efficiency of NIS using data from 28 African countries, including Kenya.

Halaskova et al. (2020) investigated the change in EU28 member countries' R&D indicators between 2010 and 2015. The output variables utilized were the number of scientific publications and the proportion of high-technology exports. Input variables used entailed R&D spending in public and private sectors as a fraction of GDP, R&D expenditure in the higher education sector, employment in the high technology sector, and the number of R&D personnel. The authors estimated a non-radial non-oriented Malmquist DEA model, showing that Italy and Germany were the most efficient countries.

Dobrzanski (2020) evaluated the efficiency of spending on R&D in the Latin American region between 2000 and 2017, using 15 countries from that region. The study utilized the annual public and private expenditure on R&D as the only input. The outputs included exports of ICT products, export of high-tech products, scientific and technical journal articles, and patent applications. The study estimated CRS and VRS input-oriented Malmquist DEA models. The results revealed that Honduras, Chile, Panama, and Guatemala were on the efficient CRS frontier. Brazil, Costa Rica, Mexico, Honduras, Chile, Panama, and Guatemala were on the efficient VRS frontier.

Klevenhusen et al. (2020) investigated innovation efficiency in OECD countries using non-parametric approaches. The four output measures employed included high-tech exports, patent applications, scientific and technical journals, and leasing of IPRs. The input measures included the number of R&D researchers, and the amount of expenditures on R&D. The radial CCR-DEA and BCC-DEA, together with Tobit regressions, were estimated. The results indicated that 11 countries were on the efficient CCR and BCC frontiers. The results also showed that gains in efficiency were correlated with being a member of the Asia-Pacific Economic Cooperation. The authors' however, did not account for the asymmetries of DMUs. In this study, a non-oriented non-radial Malmquist DEA was employed to account for asymmetries of DMUs.

Lee & Lee (2020) investigated the impact of NIS on economic growth using US patent data. The author created five NIS composite/weighted input/output variables: diversification, localization, and originality. The authors benchmarked 45 NIS from developed and upper-middle-income countries from 2011-15. DEA, Principal Component Analysis (PCA), and Benefit of the Doubt (BOD) were used as benchmarking methodologies. Their findings indicated that Japan, the US, Germany, and France were the most efficient NIS. The authors also included the NIS index as a variable in regression for GDP growth. Their results revealed that the NIS index was a significant determinant of economic growth, which supported the importance of enhancing NIS.

4.2.3 Overview of Literature

Productivity analysis of the KNIS compared to other African NIS was based on the quintuple helix innovation theory and a regional knowledge production function theory. Distance functions and the concept of Total Factor Productivity (TFP) growth based on the knowledge production function theory; provided an empirical framework for evaluating the productivity growth of the KNIS compared to other NIS in Africa. Following empirical literature, the productivity of the KNIS compared to other NIS in Africa was measured using a regional innovation index (Dobrzanski, 2020; Halaskova et al., 2020).

The literature review indicated that there are innovation inputs and outputs in the NIS. The significant inputs into the NIS include expenditures on R&D and technical knowledge. The outputs include exports of high-technology products and the publication of scientific journal papers. The regional production frontier has been widely estimated using DEA approaches. Further, prior research indicated a higher innovation index positively influences economic growth. However, a survey of empirical literature shows that the African region lags in empirical NIS research. There was no virtually available study analyzing the productivity growth, efficiency change, and technical change of NIS in Africa. Therefore, this study bridged the gap that existed in the literature.

4.3 Methodology and Data

This section presents data, research design, and methods of analyzing the regional catch-up and productivity analysis of the KNIS.

4.3.1 Research Design

The non-experimental research design was employed to evaluate the regional catch-up and productivity analysis of the KNIS. This study further adopted a longitudinal and a quantitative approach.

4.3.2 Theoretical Framework

At the macro-level, a regional knowledge production function provides a theoretical framework for determining productivity growth over time of the KNIS compared to other African NIS. Productivity growth analysis of national/regional innovation systems hypothesizes a regional knowledge production function with inputs and outputs (Sagiyeva et al., 2018). A technology set, S can be specified as;

$S = \{(x, y): x \text{ can produce } y\}$-- (4.1)

Where x denotes an n-dimensional vector of positive innovation inputs. y denotes an n-dimensional vector of positive innovation outputs. The technology set S contains all input-output vectors (x, y) such that x can produce y. The production technology specified by the set S can also be specified by the output set $p(x)$, which denotes the set of all output vectors y, that can be created using the input vector x, the output vector is denoted by;

$p(x) = \{y: x\ can\ produce\ y\} = \{y: (x, y) \in S\}$---------------------------- (4.2)

The output set is referred to as production possibilities. A regional knowledge production function (4.3) can formalize the production technology;

$y_{it} = x'_{it}\boldsymbol{\beta} + \varepsilon_i$ --- (4.3)

Where, y_i, is a vector of innovation outputs produced by the i^{th} country at time t, x_i is a $K + 1$ vector of K innovation inputs quantities utilized in the production process by the i^{th} country at time t, $\boldsymbol{B_i}$ is a $K + 1$ vector of coefficients to be evaluated and ε_i is the usual disturbance term.

4.3.3 Empirical Model

Directional distance functions such as the non-parametric DEA are essential in describing the regional knowledge production technology (4.3) to measure other things like productivity. Directional distance DEA models evaluate the efficiency over time of DMUs along the given direction. DEA models can be ordered into four categories: 1) radial, 2) non-radial and oriented, 3) non-radial and non-oriented, and 4) radial and non-radial. The Radial approach focuses on a proportionate change in input/output values, while a non-radial approach deals with slacks and does not assume a proportional change in outputs/inputs. Oriented models focus on either input reduction or output expansion, while non-oriented models simultaneously focus on input reduction and output expansion (Tone & Tsutsui, 2010).

This study investigated the productivity growth of NIS in Africa, including the KNIS, and then compared the performance of the KNIS with other NIS in Africa. This comparison enabled the evaluation of how Kenya has caught up with the African region's ST&I frontier. The productivity growth for nine years covering (2010-2018) of DMUs (28 African countries NISs including Kenya) was analyzed using a non-radial, non-oriented Malmquist Total Factor Productivity (TFP) index. A non-radial model, a Slack-Based Model (SBM), was considered to account for asymmetries of African NISs, making it possible to obtain non-uniform input/output factor efficiencies. A non-oriented model focuses on input reduction and output expansion simultaneously and helps to account for the responsiveness of innovation outputs to innovation inputs (Tone & Tsutsui, 2010). A non-radial model was preferred to a radial model because, in the latter, it's not possible to account for asymmetries of DMUs. Similarly, a non-oriented model minimizes input excesses and output shortfalls simultaneously, an approach not possible under the traditional oriented models (Tziogkidis et al., 2020).

When estimating DEA models, the returns to scale can either be Constant Returns to Scale (CRS) or Variable Returns to Scale (VRS). As opposed to the VRS, the CRS was considered where it was assumed that most DMUs were not operating at their optimal scales. Malmquist is an index signifying a certain DMU's Total Factor Productivity (TFP) by showing growth or regress in the DMU's efficiency alongside growth or regress of the frontier technology. Malmquist productivity index of a DMU is the geometric mean of the two efficiency ratios: one being the efficiency change measured by the period *t* technology and the other the efficiency change measured by the period *t+1* technology;

$$m_0\left(y_{i,t+1}, X_{i,t+1}, y_{i,t}, X_{i,t}\right) = \left[\frac{d_0^t\left(X_{i,t+1}, y_{i,t+1}\right)}{d_0^t\left(X_{i,t}, y_{i,t}\right)} \times \frac{d_0^{t+1}\left(X_{i,t+1}, y_{i,t+1}\right)}{d_0^{t+1}\left(X_{i,t}, y_{i,t}\right)}\right]^{1/2}$$

-- (4.4)

Where m_0 is the Malmquist productivity index of the i^{th} country resulting from its innovation inputs and outputs in period *t+1* $(X_{i,t+1}, y_{i,t+1})$ relative to period *t* innovation inputs and outputs $(X_{i,t}, y_{i,t})$. Using period *t* as the base, the non-radial non-oriented Malmquist index of period *t+1* can be evaluated by the slack-based linear program given as;

$$\delta^t((x_0\ ,\ y_0)^s) = \ min_{\lambda,\, s^-, s^+}\ \ \left(1 - \frac{1}{m}\sum_{i=1}^{m} {s_i^-}\Big/{x_{io}^s}\right)\Big/\left(1 + \frac{1}{q}\sum_{i=1}^{q} {s_i^+}\Big/{y_{io}^s}\right) \tag{4.5}$$

Subject to:

$$x_o^s = X^t\lambda + s^- \tag{4.6}$$

$$y_o^s = Y^t\lambda - s^+ \tag{4.7}$$

$$L \leq e\lambda \leq U \qquad (4.8)$$

$$\lambda \geq 0, \quad s^{-} \geq 0, \quad s^{+} \geq 0 \qquad (4.9)$$

The SBM non-radial non-oriented model measure of efficiency assumes that there are n DMUs with the input and output matrices $X = (x_{ij}) \in R^{m \times n}$ and $Y = (y_{ij}) \in R^{s \times n}$, respectively. $\lambda \geq 0$ is the positive intensity vector. The vectors $s^{-} \in R^{m}$ *and* $s^{+} \in R^{s}$ represent input excess and output shortfall, respectively. Further, equation (4.5) is the objective function that generates Malmquist Index and its components by simultaneously minimizing output shortfalls and input excess. Equations (4.6) and (4.7) are the optimization constraints, while equations (4.8) and (4.9) are the non-negativity constraints of the Linear Program (LP).

The functional programs can be transformed into Linear Programs (LPs). This linear programming model evaluates the non-radial non-oriented Malmquist Index and its components which entail efficiency and technical changes. The linear program enabled the evaluation of annual changes in these annual innovation indexes from one year to the next, from 2010-2018, for all the DMUs. Consequently, the results of the linear program enabled the evaluation of how Kenya was catching up with the Africa region ST&I frontier that was estimated.

4.3.4 Data Source and Type

Panel data from 2010-18 obtained from the World Development Indicators portal was utilized to evaluate the productivity growth and regional catch-up of the KNIS. DMUs used in investigating how the KNIS was catching up with African ST&I were countries in Africa. The AU and the ASTII initiative collect data on ST&I indicators from at least 20 AU member countries. However, the information is generally incomplete. Hence, this study used the World Bank's World Development Indicators.

2010-2018 was selected based on regional data availability, the ASTII initiative, and the STISA 2014-2024 vision implementation period. The ASTII initiative had been implemented for 15 years, while the STISA 2014-2024 had been in place for eight years. These two initiatives show the effort towards investment in ST&I catch-up in Africa. Therefore, the period they had existed was ample to evaluate the African NIS's productivity and technical progress.

The selection of DMUs was purely based on the availability of the regional dataset on ST&I indicators. Out of 55 African countries, 28 had extensive data, despite some gaps in some years. This study constructed a balanced panel covering nine years (i.e., 2010 to 2018). 27 African countries were dropped from the sample because of the high degree of missing information on ST&I indicators.

The final sample considered for analysis included: 4 North African countries (Morocco, Egypt, Tunisia, and Algeria), 7 South African countries (Zambia, Angola, South Africa, Botswana, Namibia, Mozambique, and Malawi), 9 Western African countries (Ghana, Cote d'Ivoire, Nigeria, Togo, Guinea, Senegal, Burkina-Faso, Niger and Gambia), 6 Eastern Africa countries (Uganda, Mauritius, Tanzania, Kenya, Rwanda, and Madagascar) and 2 Central African countries (Cameroon and Burundi). Appendix L shows a total study sample. According to the principle of DMUs and variables selection, Banker et al. (1989) provided a sample of 28 DMUs was representative and sufficient for a non-parametric DEA analysis.

4.3.5 Data Challenges, Cleaning, and Analysis

The data set used to estimate the productivity of NIS in Africa had a 5% average missing data points of the study variables missing at random, as shown in Table 4.3. The table summarizes innovation input/output variables, their units of measurement, sources, and the percentage of missing data points.

Table 4. 1: Missing Data Points of Innovation Input/output Variables of the African Regional Innovation System

	Variable	Unit of measurement	Source	% Missing data
Outputs	High technology exports	% of manufactured products	United Nations	15%
	Scientific and technological journal articles	Number of journal articles	National Science Foundation, Science and Engineering Indicators.	0%
Inputs	Fixed broadband subscriptions	Number of subscriptions	International Telecommunication Union	1%
	Imports of goods & services	% of GDP	World Bank Group	5%
	Domestic credit	% of GDP	World Bank Group	5%

Source*: authors' computation from the World Development Indicators Data 2020*

Completeness of data is required in efficiency calculations. The easiest method of dealing with missing observations is to ignore them completely. However, there are two problems associated with complete-case analysis. First, the complete-case analysis could be biased if there is a systematic difference between the units with missing values and the completely observed cases. Two, including numerous variables in a model, may not be possible since most will be discarded to ensure a complete case analysis (Atici et al., 2018). Alternatively, mean imputation may be the simplest way to handle each missing observation. Unfortunately, mean imputation can severely change the distribution of the variables, resulting in problems with summary measures. Additionally, mean imputation alters the relationships between variables (Yuan 2010).

The missing data points were assumed to be missing at random, and all the variables included in the study were continuous. In this study, multiple imputation criteria were used to fill up the missing data points, as used by Kwadwo (2018). Multivariate Normal Mode (MVN) and Multiple Imputation by Chain Equations (MICE) are the main methods of multiple imputations. MVN assumes that partially complete data under consideration has a multivariate normal distribution. MICE assumes that data points are missing at random and uses regression to estimate the missing data points (White et al., 2011). MICE has been widely applied and proven to produce better estimates of missing data than MVN (Groothuis-oudshoorn, 2011). It was therefore used to address the missing data point's problem.

4.3.6 Definitions and Measurement of Variables

The regional dataset availability, ST&I catch-up, and empirical literature were the main factors considered when choosing regional innovation input and output indicators. Since the concepts of NIS and ST&I indicators in Africa are still in their infancy compared to other regions, data on most ST&I indicators from this region is incomplete. Following empirical literature, this study settled on two innovation outputs and three innovation inputs in African NIS. The innovation inputs include domestic credit provided by the financial sector as a percentage of GDP, imports of goods and services as a percentage of GDP, and fixed broadband subscriptions. The two innovation outputs included high technology exports as a percentage of manufactured products and the number of scientific and technological journal articles.

Most African countries can be described as the least developed or developing countries, and innovation in these countries has been described as a catch-up (United Nations Conference on Trade and Development, 2021). In developed areas like the EU and the OECD, the key input in the national innovation systems analysis is R&D expenditure and R&D researchers. In contrast, Africa's innovation is predominantly a catch-up with unavailable R&D expenditure and personnel data. Consequently, the study's selection of input variables also considered variables that can enable innovation catch-up and ST&I adoption or diffusion across the African region. Therefore access to domestic credit, ICT, and importation of goods and services were among the variables of interest in this study (United Nations Conference on Trade and Development, 2021). Table 4.2 summarizes definitions and measurements of national-level innovation inputs/outputs from the African region employed.

Table 4. 2: Innovation Input and Output Variables of the African Regional Innovation System

	Variable	Definition and Unit of Measurement
Outputs	High technology exports	They are indicated by a country's percentage of annual domestically manufactured exports of products with high R&D intensity, like machinery, pharmaceuticals, and computers.
Inputs	Scientific and technological journal articles	They are indicated by a country's total number of technical and scientific journal articles published in Science, Technology, Engineering, and Mathematics (STEM) areas annually.
	Fixed broadband subscriptions	Defined as the subscriptions to high-speed access to the public internet (a TCP/IP connection) at downstream speeds equal to or greater than 256 kbit/s
	Domestic credit provided by the financial sector	Defined as the total domestic credit provided by the financial sector annually within a country in Africa expressed as a percentage of GDP.
	Imports of goods & services	It is defined as the annual total value of all goods and other market services an African country receives from the rest of the world as a percentage of GDP.

Source: *World Development Indicators Data 2020*

Each of the innovation input/output variables in the African NIS is discussed in detail;

Domestic credit

This variable is measured as the total domestic credit the financial sector provides annually within a country expressed as a GDP percentage. The financial sector, especially in developing regions, is a key player in innovation (Cornell University INSEAD & WIPO, 2020). In the empirical literature, access to credit has been associated with innovation because a cost is involved in the process of ST&I adoption (Block, 2002; Hirsch-kreinsen, 2011; Hsu, 2011).

Imports of goods and services

Importation of goods and services is measured as the annual total value of all goods and other market services a country receives from the rest of the world as a percentage of GDP. The GII uses it as an indicator of business and market sophistication innovation input sub-index. International trade and importing influence innovation, especially in developing countries that import the much-needed R&D-intensive capital goods and services (Blind & Jungmittag, 2004; Lu & Ng, 2012; Nasierowski & Arcelus, 2003; Ramírez-Alesón & Fernández-Olmos, 2019).

Fixed broadband subscriptions

This variable is measured as the subscriptions to high-speed access to the public internet (a TCP/IP connection) at downstream speeds equal to or greater than 256 kbit/s. ICT infrastructure is critical in ST&I catch-up in developing economies (United Nations Conference on Trade and Development, 2021). ICT infrastructure access and usage have been associated with innovation in the empirical literature (Kurniawati, 2020). In the empirical literature, the GII and Hollanders & Celikel-Esser (2007) have used internet access as indicated by fixed broadband subscriptions to indicate infrastructure quality innovation inputs when estimating national innovation systems' efficiency.

High technology exports

High technology exports is an innovation output indicator measured as a country's percentage of annual domestically manufactured exports of products with high R&D intensity, like machinery, pharmaceuticals, and computers (Matei & Aldea, 2012).

Scientific and technological journal articles

This variable is measured as the number of scientific and technological journal articles published annually in Science, Technology, Engineering, and Mathematics (STEM) areas (Dobrzanski, 2020). High technology exports and the number of scientific and technological journal articles have been extensively used as indicators of the innovation output of NIS (Dobrzanski, 2020; Halaskova et al., 2020; Klevenhusen et al., 2020; Matei & Aldea, 2012).

4.4 Empirical Results

The descriptive and regression/mapping results present the empirical analysis of the productivity growth of the KNIS compared to other NIS in Africa.

4.4.1 Descriptive Statistics Results

Table 4.3 shows the descriptive statistics of regional innovation input/output variables. The variables were also compared to the global average from the World Development Indicators.

Table 4. 3: Descriptive Statistics of Innovation Inputs/outputs in Africa

Variable	Obs.	Mean	Std. Dev.	Min	Max	World average(2019)
High technology exports	252	4.82	6.73	0.03	60.30	19.34
Scientific and technological journal articles	252	1,452	2,777	9.52	13,326	2,246,545
Fixed broadband subscriptions	252	339,592	832,945	350	6,579,762	782,336,176
Imports of goods & services	252	38.72	13.53	10.79	84.22	29.08
Domestic credit	252	38.00	29.19	0.10	125.673	129.33

Source*: authors' computation from the World Development Indicators Data 2020*

Table 4.3 indicates that the standard deviation exceeded the mean for fixed broadband subscription input and the two innovation output variables. When the standard deviation exceeds the mean, it implies a high spread in these three variables in the sample. The high spread revealed the asymmetries of NIS in Africa. The results indicated that, on average, high technology exports during the study period in Africa were 5% of total manufactured goods in the region, while the 2019 world average was 20%.

The mean number of scientific and technological journal articles published in the STEM area during the African region's study period was 1,452 journal articles. The African region's mean published journal articles was 0.06% of the 2019 world's scientific journal articles published in this area. The mean fixed broadband subscriptions in the region were 0.01% of the 2019 world average fixed-broadband subscriptions, which indicated low internet access during the study period. The mean imports of goods and services as a percentage of GDP during the study period was about 38% against a world average mean of 29%

in 2019. The result indicated an unbalanced balance of payments where more countries in the region were importers during the study period.

The mean domestic credit as a percentage of GDP provided by the financial sector was 38%. Africa's mean domestic credit access was considerably low compared to the 2019 world average of about 129% of GDP. This result points to limited financial access in the African region. The result also implies that the region's business and market sophistication was below the world average during the study period. In conclusion, the descriptive statistics revealed that Africa's innovation outputs and inputs were strikingly below the world average.

4.4.2 Regression Results

The estimated CRS non-radial non-oriented Malmquist Productivity Index is a Slack Based Model (SBM). The Malmquist index comprises the efficiency change (Catch Up-CU) measure and the Technological progress (Frontier Shift-FS) measure (Tone & Tsutsui, 2014).

The non-radial non-oriented model's efficiency indices differ from the usual economic interpretation. For example, an efficiency score of 1.350 does not indicate a 35% growth but is simply interpreted as progress (Halaskova et al., 2020). Values of the indices larger than one show progress, and indices' values less than one indicate a regress in productivity, efficiency change, or technical progress. However, the non-radial non-oriented model allows us to compare the degree of relative progress or regress between periods or between DMUs.

Changes in the Malmquist productivity index can be attributed to technological progress (frontier shift) and efficiency change (the catch-up index). Adopting the best practice frontier and the movement of DMUs towards the efficient frontier are shown by technological change and efficiency change, respectively.

The distribution of innovation activities within a Regional Innovation System (RIS) is not randomized but tends to be concentrated in particular regions (Coccia, 2015). Therefore, the distribution of innovation-related activities of NIS within Africa's RIS was expected to be non-random in terms of productivity growth, efficiency change, and technical progress. Consequently, the results of the SBM CRS non-radial non-oriented Malmquist Productivity Index model revealed that six NIS in Africa experienced an improvement in the average productivity growth during the study period.

As shown in Table 4.4, the Ghanaian NIS recorded the highest average productivity growth, followed by Senegal, South Africa, Morocco, Nigeria, and Namibia. Furthermore, the results revealed that NIS in Ghana, South Africa, Nigeria, Kenya, and Tanzania experienced progress in average efficiency change. Additionally, the finding of this study showed that NIS in Senegal, South Africa, Nigeria, Tunisia, and Egypt experienced average technological progress during the study period. Furthermore, South Africa's and Nigeria's NIS improved in all three average efficiency measures, as shown in Table 4.4.

Table 4. 4: Malmquist Innovation Efficiency Analysis of the African Regional Innovation System

Rank	DMUs	Efficiency change	Frontier shift	Malmquist index
1	Ghana	1.03314	0.89178	1.205730
2	Senegal	0.89191	1.00143	1.113235
3	South Africa	1.00286	1.10552	1.103949
4	Morocco	0.78053	0.83967	1.054370
5	Nigeria	1.00000	1.05123	1.051235
6	Namibia	0.71716	0.88477	1.000956
7	Mozambique	0.63650	0.74013	0.993410
8	Tunisia	0.73071	1.19225	0.992092
9	Angola	0.67771	0.96842	0.961545
10	**Kenya**	**1.05153**	**0.77012**	**0.958397**
11	Botswana	0.60940	0.85473	0.957254
12	Cameroon	0.70006	0.76807	0.945159
13	Tanzania	1.03546	0.83229	0.899501
14	Egypt	0.68213	1.22941	0.889747
15	Guinea	0.44645	0.73918	0.845573
16	Togo	0.67511	0.84935	0.815395
17	Uganda	0.88316	0.99185	0.795296
18	Cote d'Ivoire	0.91259	0.88324	0.769299
19	Zambia	0.70033	0.90826	0.740995
20	Mauritius	0.48744	0.99356	0.686782
21	Rwanda	0.52014	0.66704	0.674517
22	Algeria	0.84752	0.80209	0.671266
23	Madagascar	0.83322	0.62959	0.665720
24	Burundi	0.49810	0.80464	0.644995
25	Burkina Faso	0.69225	0.66772	0.636865
26	Niger	0.72384	0.78076	0.607837
27	Malawi	0.69600	0.84058	0.603660
28	Gambia	0.27683	0.77950	0.478527

Note: *The ranking is realized by arranging the Average Malmquist Index in descending order*

Source*: authors' computation World Development Indicators Data, 2020*

The average Malmquist index for the entire study period indicated that Kenya's NIS was among the most productive in Africa. Kenya ranked 10/28 in Africa and 7/28 in SSA's most productive NIS. The Kenya NIS also ranked as the most productive NIS in East and Central Africa on average from 2010-2018.

Efficiency analysis of a set of DMUs (i.e., firms or countries) identifies the best-performing DMUs on the efficient frontier. All other DMUs are benchmarked against the best-performing DMUs. The benchmarking findings of this study revealed that Nigeria and South Africa had the most efficient NIS in Africa since they were on the efficient frontier, as shown in Table 4.5. The study also evaluated the number of periods with efficiency progress over the past decade. Table 4.5 reports NIS's annual regional efficiency change in Africa from 2010-2018. The table also indicates the average efficiency change and the years with efficiency progress.

Table 4. 5: Regional Efficiency Change of National Innovation Systems in Africa 2010-2018

DMU	2010 - 11	2011-12	2012-13	2013-14	2014-15	2015-16	2016 - 17	2017-18	Average	progress years
Nigeria	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	8
South Africa	1.000	1.000	1.000	0.860	1.163	1.000	1.000	1.000	1.003	7
Uganda	1.824	1.090	0.064	1.369	0.475	1.050	0.194	1.000	0.883	5
Niger	0.083	0.083	1.000	1.000	1.000	0.168	1.328	1.128	0.724	5
Egypt	0.235	1.000	1.000	1.000	1.000	1.000	0.111	0.111	0.682	5
Algeria	1.000	1.000	1.000	1.000	0.017	1.877	0.455	0.431	0.848	5
Tanzania	0.244	1.297	0.555	0.678	1.118	1.980	0.972	1.439	1.035	4
Malawi	1.000	0.422	0.235	1.182	0.490	0.239	1.000	1.000	0.696	4
Kenya	**0.118**	**1.350**	**0.516**	**1.016**	**1.808**	**1.915**	**0.803**	**0.887**	**1.052**	**4**
Ghana	0.341	1.889	0.801	0.974	1.664	1.051	0.410	1.135	1.033	4
Tunisia	0.531	0.784	0.490	1.006	0.288	1.028	1.031	0.688	0.731	3
Senegal	0.415	1.042	0.626	1.393	0.488	1.648	0.815	0.709	0.892	3
Rwanda	1.000	0.066	0.374	0.176	1.000	0.272	0.272	1.000	0.520	3
Morocco	0.409	1.018	0.541	1.076	0.266	0.957	1.309	0.668	0.781	3
Cote d'Ivoire	0.831	0.608	0.649	1.020	1.472	0.908	1.164	0.650	0.913	3
Togo	0.366	0.717	0.575	1.133	0.450	0.378	0.374	1.408	0.675	2
Namibia	0.225	1.198	1.028	0.926	0.789	0.308	0.940	0.323	0.717	2
Mozambique	0.037	0.347	0.219	0.840	1.151	0.404	1.675	0.420	0.637	2
Guinea	0.402	0.069	0.060	0.060	1.000	1.000	0.348	0.633	0.446	2
Cameroon	0.300	0.860	0.379	0.403	1.565	1.153	0.293	0.648	0.700	2
Burundi	1.000	0.045	0.448	1.631	0.033	0.092	0.674	0.062	0.498	2
Burkina Faso	0.205	1.481	0.640	0.236	0.990	0.883	1.074	0.028	0.692	2
Botswana	0.728	1.173	0.281	1.052	0.158	0.535	0.293	0.655	0.609	2
Angola	0.218	0.931	0.708	1.196	0.875	0.415	1.059	0.021	0.678	2
Madagascar	0.696	0.194	0.295	1.891	1.611	0.392	0.738	0.849	0.833	2
Zambia	0.174	0.078	0.748	0.871	0.494	1.825	0.969	0.445	0.700	1
Mauritius	0.300	1.435	0.494	0.060	0.068	0.822	0.179	0.542	0.487	1
Gambia,	1.000	0.098	0.098	0.004	0.183	0.157	0.127	0.548	0.277	1

Note: *an index = 1 or index > 1 indicates years with progress in efficiency change, an index < 1 shows the years with regress in efficiency change.*

Source*: authors' computation from the World Development Indicators Data 2020*

Benchmarked with other NIS in Africa, the KNIS ranked among Africa's top 10 most efficient NIS. Table 4.5 revealed that the KNIS had recorded efficiency gain in four years and had experienced efficiency regress in four years. This result indicates that Kenya performed well in catching up with the region's ST&1 frontier. The distribution of efficiency change in East and Central Africa revealed that Rwanda and Uganda were on Africa's efficient frontier for three periods and one period, respectively, during the study period. Kenya, Uganda, and Tanzania experienced the highest number of years with progress in efficiency change.

On the other hand, technological progress is adopting the best practice frontier or the shift of the production frontier. Consequently, the technical progress with a set of DMUs is experienced when a DMU utilizes advanced production techniques. According to Table 4.6, no country recorded progress in the average technical change in East and Central Africa during the study period. Further, the results indicated that Mauritius and Tanzania had more periods of technical progress in this region. The KNIS ranked lowly compared to other African NIS in adopting new innovative techniques. Consequently, Kenya experienced technical progress only in two periods and regress in six periods, as shown in Table 4 6.

Table 4. 6: Regional Technical Progress of National Innovation Systems in Africa 2010-18

DMU	2010 - 11	2011-12	2012-13	2013-14	2014-15	2015-16	2016 - 17	2017-18	Average	Progress years
South Africa	1.008	1.059	1.006	1.465	1.182	1.113	1.023	0.989	1.106	7
Nigeria	1.256	1.070	1.025	1.139	1.000	0.762	1.029	1.128	1.051	7
Egypt	1.122	1.985	1.010	0.483	1.349	1.871	0.948	1.066	1.229	6
Namibia	0.243	1.019	1.018	1.103	0.678	0.555	1.073	1.389	0.885	5
Cote d'Ivoire	0.189	1.034	1.146	1.096	0.459	0.720	1.041	1.381	0.883	5
Tunisia	1.850	1.114	1.980	1.054	0.355	0.980	0.854	1.352	1.192	5
Mauritius	0.460	1.193	1.626	0.884	0.252	1.274	0.873	1.386	0.994	4
Tanzania	0.360	0.979	1.370	1.003	0.394	1.008	1.075	0.469	0.832	4
Morocco	0.473	1.060	0.481	1.045	0.315	1.064	0.812	1.468	0.840	4
Burundi	0.449	0.624	1.653	0.787	0.053	0.264	1.023	1.584	0.805	3
Uganda	1.834	0.957	0.329	0.877	0.424	0.880	1.016	1.618	0.992	3
Angola	0.219	0.995	1.550	0.960	0.928	0.647	1.080	1.369	0.968	3
Botswana	1.927	0.711	0.245	0.740	0.282	1.191	0.728	1.014	0.855	3
Mozambique	0.099	0.680	0.391	1.052	0.871	0.355	1.004	1.469	0.740	3
Guinea	0.431	0.119	0.147	0.292	0.243	1.742	1.243	1.697	0.739	3
Senegal	1.983	0.877	0.407	0.906	0.745	0.567	1.082	1.444	1.001	3
Togo	1.952	0.861	0.274	0.406	0.390	1.023	0.688	1.200	0.849	3
Cameroon	0.337	0.946	0.363	0.714	0.512	0.715	1.027	1.530	0.768	2
Kenya	**0.405**	**0.932**	**0.481**	**0.915**	**0.510**	**0.674**	**1.050**	**1.195**	**0.770**	**2**
Rwanda	0.397	0.865	1.996	0.305	0.183	0.308	0.252	1.029	0.667	2
Zambia	0.475	0.872	1.156	0.957	0.739	0.518	0.963	1.586	0.908	2
Malawi	0.434	0.586	1.839	0.776	0.504	1.045	0.712	0.828	0.841	2
Gambia,	0.847	0.467	0.484	0.455	0.298	1.124	0.670	1.891	0.780	2
Ghana	0.461	0.932	1.334	0.882	0.510	0.944	0.789	1.283	0.892	2
Niger	0.299	0.606	0.200	0.811	0.134	1.686	0.934	1.577	0.781	2
Algeria	0.864	0.954	0.529	0.102	0.522	1.083	0.793	1.569	0.802	2
Burkina Faso	0.209	0.866	0.252	0.587	0.290	0.830	0.910	1.398	0.668	1
Madagascar	0.231	0.728	0.323	0.766	0.355	0.825	0.836	0.972	0.630	0

Note: *an index = 1 or index > 1 indicates years with progress in technical progress, an index < 1 shows the years with regress in technical progress.*

Source*: authors' computation from the World Development Indicators Data 2020*

Total factor productivity growth of DMUs is usually indicated by technological progress and efficiency change of DMUs. This study revealed that in East and Central Africa, Kenya, Uganda, and Tanzania had the highest number of years of productivity growth. Kenya ranked among the top 10 African countries that gained tremendous productivity growth from 2018-2010, as shown in Table 4.7. KNIS experienced productivity growth in four periods and productivity regress in four periods.

Table 4. 7: Regional Productivity Growth of National Innovation Systems in Africa 2010-18

DMU	2010 -11	2011-12	2012-13	2013-14	2014-15	2015-16	2016 -17	2017-18	Average	Progress years
South Africa	1.008	1.059	1.006	1.259	1.375	1.113	1.023	0.989	1.104	7
Nigeria	1.256	1.070	1.025	1.139	1.000	0.762	1.029	1.128	1.051	7
Morocco	0.865	1.079	1.124	1.124	1.182	1.018	1.062	0.981	1.054	6
Namibia	0.927	1.221	1.046	1.021	0.535	1.800	1.009	0.448	1.001	5
Kenya	**0.291**	**1.258**	**1.073**	**0.929**	**0.921**	**1.291**	**0.843**	**1.061**	**0.958**	**4**
Angola	0.993	0.926	1.097	1.148	0.811	1.558	1.144	0.015	0.962	4
Ghana	0.739	1.760	1.069	0.859	0.848	0.991	1.923	1.456	1.206	4
Senegal	0.822	0.914	1.539	1.262	1.528	0.934	0.882	1.024	1.113	4
Egypt	0.209	1.985	1.010	0.483	1.349	1.871	0.105	0.104	0.890	4
Tanzania	0.678	1.270	0.761	0.680	0.440	1.996	1.045	0.326	0.900	3
Uganda	0.299	1.044	0.195	1.200	0.893	0.924	0.191	1.618	0.795	3
Botswana	1.402	0.834	1.150	0.779	1.789	0.637	0.403	0.664	0.957	3
Mozambique	0.367	1.959	0.558	0.883	1.003	0.878	1.682	0.617	0.993	3
Guinea	0.932	1.730	0.406	0.204	0.243	1.742	0.433	1.075	0.846	3
Tunisia	0.983	0.873	0.970	1.060	1.233	1.007	0.880	0.930	0.992	3
Cameroon	0.890	0.814	1.044	1.771	0.802	0.824	0.426	0.991	0.945	2
Burundi	0.449	0.028	0.740	1.284	1.584	0.346	0.689	0.039	0.645	2
Mauritius	0.652	1.712	0.803	0.053	0.271	1.048	0.205	0.751	0.687	2
Rwanda	0.397	0.057	0.188	1.734	0.183	0.884	0.924	1.029	0.675	2
Cote d'Ivoire	0.227	0.629	0.744	1.118	0.675	0.653	1.212	0.897	0.769	2
Gambia,	0.847	0.046	0.047	0.002	1.625	0.140	0.085	1.036	0.479	2
Niger	0.278	0.138	0.200	0.811	0.134	0.284	1.240	1.778	0.608	2
Togo	0.188	0.617	0.477	0.460	0.867	0.387	1.839	1.689	0.815	2
Madagascar	0.332	0.141	0.915	1.449	0.572	0.475	0.617	0.825	0.666	1
Zambia	0.083	0.068	0.865	0.833	1.496	0.945	0.933	0.706	0.741	1
Malawi	0.434	0.247	0.433	0.917	1.029	0.229	0.712	0.828	0.604	1
Burkina Faso	0.980	1.283	0.393	0.402	0.287	0.733	0.977	0.040	0.637	1
Algeria	0.864	0.954	0.529	0.102	0.009	0.492	1.744	0.676	0.671	1

Note: *an index = 1 or index > 1 indicates years with progress in productivity growth, an index < 1 shows the years with regress in productivity growth*

Source*: authors' computation from the World Development Indicators Data 2020*

4.5 Discussion

From the 2010s, empirical results and literature indicate that Kenya has been doing well in catching up with the regional ST&I frontier. The empirical findings of this study confirm that from 2010-2018, the KNIS ranked among the best-performing NISs in terms of productivity and efficiency gains. However, the results revealed that KNIS ranked lowly in its technical progress, as shown in Figure 4.1.

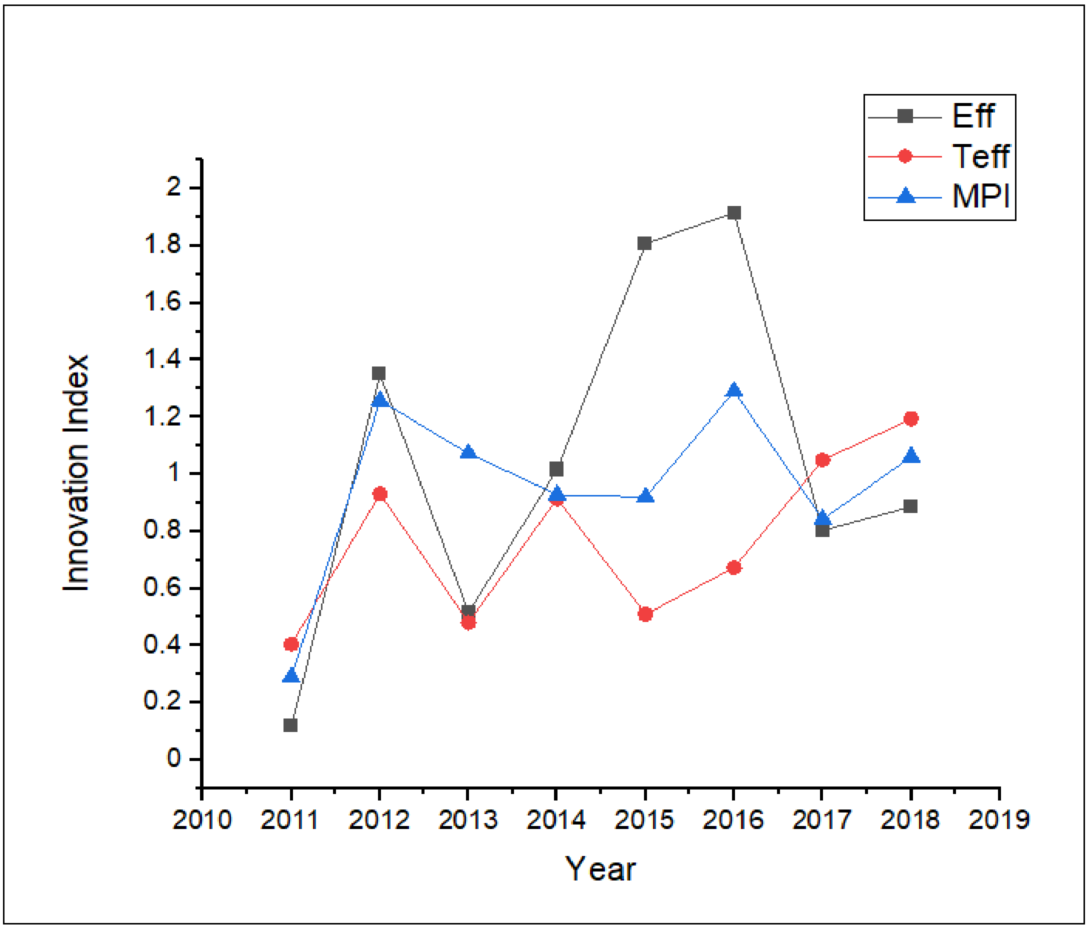

Figure 4. 1: Efficiency Change, Technical Change, and Total Factor Productivity of the KNIS, 2010-18.

Source: *authors' computation from the World Development Indicators Data 2020*

Benchmarked with other NIS in Africa, figure 4.1 indicates an upward trend in efficiency measures of the KNIS from 2010-2018. This result is comparable with other innovation rankings which entail the KNIS. For instance, Benchmarked with other NIS globally, the 2020 GII classified Kenya among countries like India, Moldavia, and Vietnam that had set a record of innovation achievers from 2010-2019 (Cornell University, INSEAD & WIPO, 2020).

The results indicate that from 2010-2018, the KNIS was successfully laying the foundation for investing in ST&I and catching up with the regional ST&I frontier at the national level. The high ranking of the KNIS can be attributed to the robust national ST&I policies, such as the ST&I Act of 2013 and the adoption of regional innovation policies. Africa's regional and national innovation policies aim to accelerate economic growth and catch up with developed regions. The critical innovation policies in Africa include the ASTII initiative and STISA 2014-2024.

According to the empirical literature, in a highly ranked productive NIS like that of Kenya, it is expected that knowledge should flow freely from one innovation actor (firms, government, academia, and society) to another. It is further expected that, due to the free flow of knowledge from one actor to another, more technical collaborations by NIS actors should lead to more R&D expenditure and innovations by firms. Additionally, it is expected that the high ranking of the KNIS should be positively correlated with firm productivity and economic growth in the country (Lee & Lee, 2020). In this study, it was impossible to explore the connection between the innovation index and productivity at the national level (GDP growth) due to data shortages. However, it's widely appreciated in the empirical literature that ST&I drives economic development (Lee & Lee, 2020).

4.5.1 Policy Implications

In this chapter, the study investigated the productivity of the KNIS compared to other NIS in Africa. The results revealed that the KNIS ranked highly as one of the most innovative NIS, even though not yet on the African region's efficient frontier. Further results indicated that the KNIS ranked low regarding technical progress during the study period.

Determining the productivity and technical progress of the KNIS was crucial to realizing the Kenyan innovation vision in two ways. First, evaluating whether there was productivity progress or regress indicates the innovation efficiency stance of the KNIS. It can also indicate the effectiveness of the current innovation policies and strategies. Secondly, it is possible to know the best-performing NIS in Africa that Kenya can use as a benchmark to enhance regional growth. Consequently, the results imply that the KNIS is among Africa's most innovative and productive NIS, even though there is room for further improvement. Consequently, to ensure that the KNIS becomes fully efficient, this study recommends benchmarking activities with NIS like Nigeria and South Africa, the NIS which the results show were on the African region efficient ST&I frontier.

The findings indicated that the KNIS was performing well in terms of efficiency and productivity change and poorly in technical progress. There is a need for the institutions in charge of the KNIS, such as the NACOSTI, NRF, and KENIA, to develop a policy to enhance the technical progress of the KNIS. The policy should focus on strengthening the coordination framework of the helices/subsystems of the KNIS. This implies that the ST&I regulating institutions need to regularly monitor and evaluate knowledge flow among the helices of the KNIS. A Well-coordinated KNIS will lead to multidisciplinary technical activities, research, and innovation in Kenya's private and public sectors. Lastly, cross-border ties with other regional innovation players such as AU-NEPAD and full integration of regional policies such as ASTII and STISA strategies with national R&D policies might further improve the technical progress of the KNIS. Consequently, innovation output, such as high technology exports, patents, and technical journal articles, would be realized, making the KNIS technically advanced.

CHAPTER FIVE

CONCLUSION

5.1 Introduction

Global economies are driving their economic growth through ST&I due to globalization and technological advances in the 21st century. Kenya has also not been left behind in adopting ST&I as the critical driver of its economy. Subsequently, the country's efforts to catch up with the regional ST&I frontier have made Kenya an innovation achiever country from 2010-2019. It was ranked among the most innovative countries in Sub-Saharan Africa. Despite being an innovation achiever and the fact that ST&I is the critical driver of economic development and firm productivity, the country's GDP growth stagnated during the study period. The productivity of the manufacturing and services sectors declined and stagnated during the study period, respectively. This notwithstanding, there were below-average innovation activities at the firm level during the study period.

The productivity analysis of the Kenya innovation system and the impact of innovation achievements by Kenya on its economic development and firm productivity has not been adequately analyzed empirically. This study, therefore, sought to bridge this gap in the literature. Consequently, this study aimed to investigate the drivers of firms' R&D expenditure intensity, determine the impact of firm-level innovation on firm productivity and evaluate the productivity growth of the Kenya national innovation system.

5.2 Summary of the Empirical Findings

Each of the study objectives was analyzed in its chapter. In chapter two, the study investigated the drivers of R&D expenditure intensity using the WBES 2018 data and the FIML model. Chapter three used the WBES 2018 data to analyze the impact of firm-level innovation on firm productivity using PSM/ESR treatment effects models. The productivity of the Kenya innovation system is analyzed in chapter four using world development indicators data and a DEA model. The summaries of the main empirical findings are presented in sections 5.2.1, 5.2.2, and 5.2.3.

5.2.1 Drivers of the Firm-level Intensity of R&D in Kenya

Investigating the drivers of a firm's R&D expenditure intensity was anchored on the QUEST micro-founded macro model for R&D and innovation. The firm-level knowledge production function, which has the firm R&D expenditure per worker as the innovation output, provided an empirical framework for analyzing the drivers of R&D expenditure intensity. A FIML Tobit II regression model was used as the estimation methodology.

The results revealed that R&D propensity and intensity increased when firms had access to infrastructures such as incubation labs, foreign technology, and the acquisition of physical capital. Additionally, sophisticated business practices such as exporting capacity and the quality of human capital and research such as innovation partnership and employee training significantly influenced a firm's R&D propensity and intensity. The results further indicated that technical collaboration would increase the probability of firms participating in R&D and minimize a firm's R&D expenditure.

5.2.2 Impact of Firm-level Innovation on the Productivity of Firms in Kenya

The impact assessment of innovation on firm productivity was anchored on the CDM model, which provided a theoretical and empirical framework. The PSM treatment effect model was analyzed to evaluate the impact of innovation on firm productivity. In this study, innovation entailed R&D spending, product/service innovation, process innovation, and ownership of IPR. Robustness tests were conducted using the ESR and K-S tests. The results indicated that R&D spending, process innovation, and IPR ownership did not significantly impact firm productivity during the study period. Firm-level product/service innovation significantly impacted firm productivity. The results revealed that participating in product/service innovation would substantially improve value-added by approximately four million. The robustness test results complemented the results of the primary model, the PSM.

5.2.3 Regional Catch-up and Productivity Analysis of the Kenya National Innovation System

The productivity growth analysis of the KNIS compared to other NIS in Africa was anchored on the quintuple helix theory. A regional knowledge production function provided an empirical framework. A non-radial, non-oriented Malmquist productivity index DEA model was estimated. This estimation approach was best suited to account for asymmetries of African NIS. The results revealed that the KNIS was among the top 10 most innovative NIS in Africa and the most innovative NIS in East and Central Africa. This study confirmed other empirical studies' findings, like the GII, that Kenya NIS is among the most innovative NIS in Africa.

5.3 Research Implications

The most significant R&D intensity drivers entail using innovation labs, having an innovation partner, Spending on R&D-intensive physical capital, and training employees on the R&D and innovation process. The study advocates for the following four policy measures to ensure that more firms engage in R&D activities at lower costs and the same be able to pursue their central goal of profit maximization. First is the public-private partnerships in establishing more innovation hubs accessible for all firms in the country. Second is fiscal authorities' subsidy and tax reliefs on R&D-intensive physical capital purchased by local firms. Thirdly, a firm-level policy on training employees on R&D management and innovation process in partnership with other innovation actors in the KNIS is necessary. Lastly, firms need to get into innovation partnerships through collaborative research and innovation.

Research findings indicated that only product/service innovation significantly impacted the firms' productivity out of the four measures of firm-level innovation considered and the data utilized. Process innovation, R&D

propensity, and IPR ownership did not matter significantly to a firm's productivity.

This result implies that firms could not convert the other innovation outputs into significant financial gains. This result has the following three implications for policy. First, product/service innovation substantially impacted firm productivity, suggesting that the firms can drive their productivity using ST&I. Secondly, other measures of firm-level innovation, such as IPR ownership, process innovation, and R&D spending, did not matter significantly to a firm's value-added. This result implies a need to re-evaluate firm-level innovation strategies to realize more innovation gains. Lastly, the study argues that firm-level innovation needs to be re-examined to strengthen the semi-endogenous innovation process embodied in the KNIS.

Benchmarked with other NIS in the region, the KNIS was among the most productive and efficient NIS in Africa. However, the KNIS lagged in terms of technical progress. This research finding implies that the institutions in charge of the KNIS, i.e., the NRF KENIA, need to develop a policy for improving the technological progress of the KNIS. Technological progress can be enhanced by benchmarking activities with NIS that have advanced technology, such as Nigeria and South Africa. Lastly, the NRF and KENIA need to continuously monitor and evaluate knowledge flow among the helices of the KNIS.

The findings suggested that Kenya is an innovation achiever at the national level. This result implies that if there were more enhanced technical collaborations at the firm and national levels, more innovation gains could be realized even at the firm level. Lastly, the government catalyses firm-level and national-level innovation in developing countries like Kenya. Consequently, governments can influence innovation and invention in any economic sector (Lundvall et al., 2011). Therefore, if the institutions in charge of KNIS, such as KENIA, NRF, and NACOSTI, are fully empowered to perform their mandate, more innovation benefits could be realized. Consequently, these innovation gains can translate to economic growth and enhance the productivity of Kenyan manufacturing and service firms.

5.4 Limitations of the Study and Areas of Further Research

Just as in much other technical research, this study faced some bottlenecks that raised further opportunities for research. Innovation is a dynamic concept that keeps on changing from time to time. However, the CISs in Kenya are not conducted regularly. MoEST has conducted two CIS in two waves in 2012 and 2015. The 2012 survey covered 158 firms covering 2008-2011. The 2015 survey, on the other hand, covered 376 firms covering 2012-2014. One of the limitations of MoEST data is the small sample size of the gathered cross-sectional data. Further, MoEST did not conduct repeated surveys making it impossible to create panel data from their CIS.

There is an existing panel of WBES data, even though it contains a small sample size of only 60 firms resulting from sampling in CISs in Kenya and the emergence of new data collection tools. As a result, the study settled on 2018 WBES cross-sectional data that covered 1,001 firms. The 2018 WBES was better because it covered a bigger sample size with many firm-level variables. One of the limitations of the WBES 2018 data is that it can only be used to conduct partial equilibrium analysis. Therefore, using Bayesian methods to analyze a full general equilibrium model was impossible.

Similarly, it was also impossible to explore panel data models. Apart from limitations emanating from data, the study estimation methodologies utilized had their limitations. For instance, the PSM model does not account for unobserved factors, the ESR is likely to be affected by weak instrument challenges, and the DEA models don't rely on the distribution of disturbance terms. Due to these limitations, future research avenues arise. First, to analyze Kenya's R&D expenditure intensity and innovation using extensive panel data and robust panel data models such as GMM, DID, fixed, and random-effects models to explore Kenya's R&D intensity and innovation. Secondly, to use a comprehensive, robust dataset to analyze R&D expenditure intensity and technical collaborations using full general equilibrium model Bayesian approaches.

The other limitation of the WBES 2018 dataset is that most innovation outputs/inputs were categorical variables. Therefore, it was impossible to use the firm-level data to analyze the efficiency of the KNIS using sectorial or county-level data. Since it was impossible to use the 2018 WBES data to analyze the efficiency of the KNIS since it contains mainly categorical innovation inputs and outputs, the study utilized national-level regional data in Africa.

The limitation of using African regional ST&I data is that the concept of NIS is still in its infancy compared to other regions of the world. Furthermore, Africa is a developing region that is still lagging in catching up with the ST&I frontier, and incomplete ST&I data and data availability are essential limitations. Data on some innovation inputs like R&D personnel, business and government expenditure on R&D, and innovation outputs like patents, among other intellectual properties, are very scanty.

Due to these limitations, future research avenues arise. First, to employ quantitative firm-level, county-level, or industry-level innovation data to analyze the productivity of the KNIS, whereby the DMUs will be industries or counties in Kenya. Further research avenues arise to include the critical regional innovation inputs (like R&D expenditure and personnel) and outputs (like patents) indicators in the efficiency analysis of Africa RIS, as is the case for studies conducted in developed regions. Further, areas of future research could be to investigate the link between the innovation indexes and economic growth of African NIS, including KNIS.

5.5 Contributions

Few studies analyzing the drivers of R&D intensity among Kenyan firms are virtually available. Consequently, the drivers of R&D choice and expenditure intensity have not been adequately analyzed scientifically. This study becomes the recent study to contribute to the R&D intensity in Kenya literature using the most recent data, the 2018 WBES. The study also presents current implications to the policy, which may be crucial in stimulating more firm-level R&D investment.

Few studies have focused on firm-level innovation, IPRs, and firms' productivity in Kenya and the larger African region. For instance, Cirera (2015), Barasa et al. (2017), and Njiraini et al. (2018) have attempted to explain the factors that drive the research and innovative behaviour of Kenyan firms. However, only Cirera (2015) attempted to empirically investigate the impact of innovation on firms' productivity from these past studies. This study used the PSM treatment effect model and introduced IPRs in the innovation discourse, an approach new to Kenya's and Africa's economics of innovation literature. This study contributes to innovation and productivity literature in the context of developing countries in a unique way. The study employed a counterfactual analysis approach in evaluating innovation impacts by employing a treatment effects model that had not been applied in the African context.

The study of the productivity of NIS in Africa and other developing regions, especially in Africa, is still in the initial stage and gaining momentum

(Egbetokun et al., 2016). Consequently, earlier studies, for instance, Ayisi et al. (2019), have attempted to explain the composition and history of the KNIS. None of the past studies had analyzed the productivity growth of the KNIS. This study empirically assessed the productivity growth of the KNIS compared to other NIS in Africa. Therefore this study bridged the gap that existed in the empirical literature.

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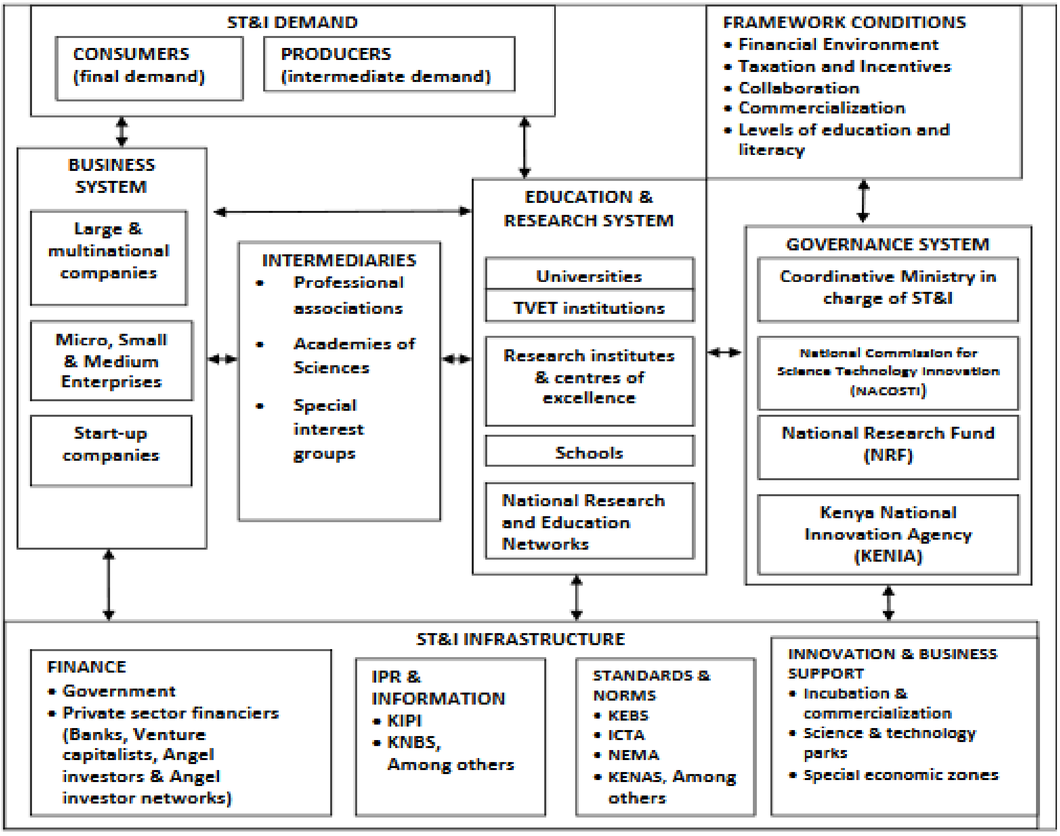
APPENDICES

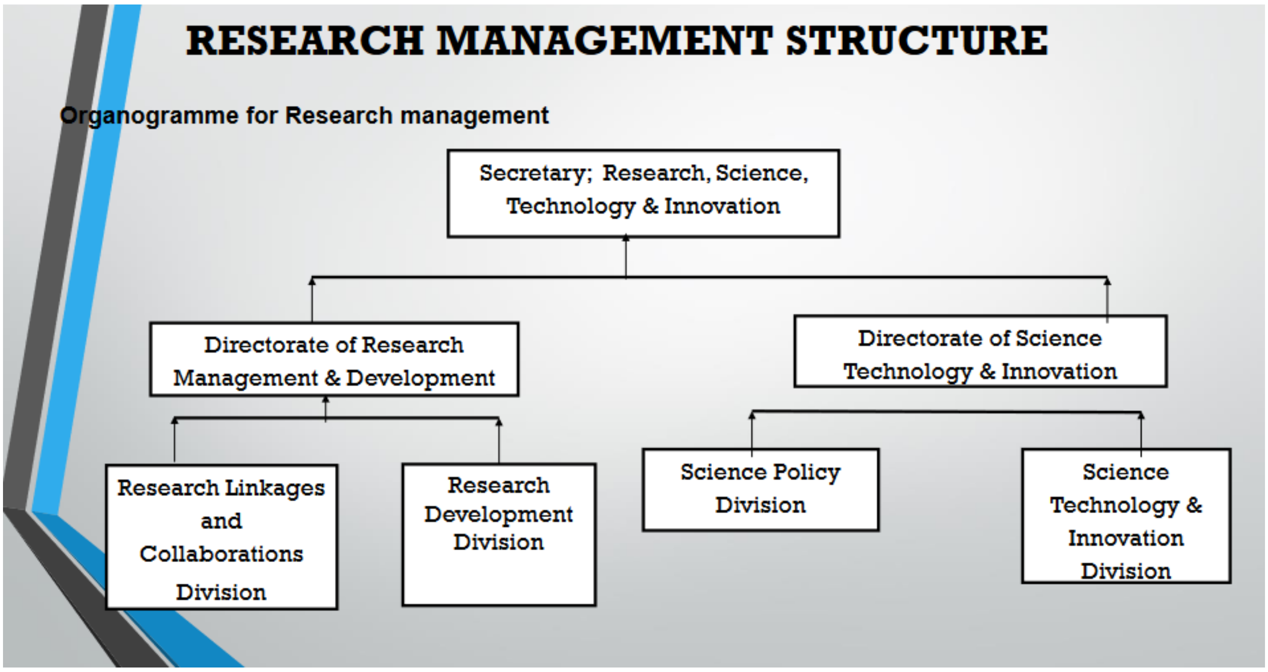
Appendix A: Structure of the Kenya National Innovation System (KNIS)



Key: STI – Science Technology and Innovation; TVET – Technical, Vocational, Education and Training; NRF – National Research Fund; NACOSTI – National Commission for Science Technology and Innovation; KENIA – Kenya National Innovation Agency, IPR – Intellectual Property Rights; KIPI – Kenya Industrial Property Rights; KNBS – Kenya National Bureau of Statistics; ICTA – Information, Communication and Technology Authority; NEMA – National Environmental Management Authority; KENAS – Kenya National Academy of Sciences.

Source: *Adapted from (Ayisi et al., 2019)*

Appendix B: Research Management Structure in Kenya



Source**:** *Adapted from (Ayisi et al., 2019)*

Appendix C: Results of Drivers of Participation in R&D Expenditure Probit Model used in Diagnostic Testing

Dependent variable = 1 if a firm spent on R&D and 0 otherwise				
Independent Variable	Coefficient	Robust Std. Error	Z-Value	P-Value
Firm age	-0.007	0.003	-2.024	0.025
Manager experience	-0.004	0.005	-0.850	0.397
Internet access	0.044	0.115	0.910	0.363
Incubation labs access	0.287	0.140	2.050	0.041
International certification	0.257	0.295	0.870	0.383
Foreign technology	0.433	0.338	-0.480	0.633
Physical capital spending	0.047	0.170	2.540	0.011
Exporting capacity	0.310	0.118	2.630	0.008
Credit access	0.147	0.112	1.320	0.187
Business-govt. relations	0.299	0.135	2.210	0.027
Employee training	0.512	0.114	4.480	0.00
Innovation partnerships	0.422	0.124	4.400	0.001
Constant	-1.831	0.146	-2.240	0.000

Note N=1,001 LR chi2 (12) =165.04 Prob>chi2=0.000 Pseudo R2=0.20

Source*: Authors' computation from WBES 2018*

Appendix D: Results of VIF Test of Multicollinearity on Drivers of Participation in R&D Expenditure

Variable	VIF	1/VIF
Internet access	1.17	0.855
Firm size	1.38	0.725
Exporting capacity	1.25	0.799
Business-govt relations	1.05	0.951
Manager experience	1.26	0.792
Physical capital spending	1.08	0.923
Foreign technology adoption	1.13	0.882
Incubation labs access	1.03	0.970
Innovation partnership	1.13	0.882
Credit access	1.04	0.964
Firm age	1.38	0.725
Employee training	1.19	0.840
International certification	1.29	0.775
Mean VIF	1.17	

Note: *a VIF> 10 indicates the presence of multicollinearity*

Source*: Authors' computation from WBES 2018*

Appendix E: Results of the Hosmer-Lemeshow Goodness of Fit Test on the Probit Model for Drivers of R&D Expenditure Intensity

Number of observations	1,001
Number of covariate patterns	960
Hosmer-Lemeshow Chi2 (947)	962.14
Prob > Chi2	0.3589

Note: *Ho= good fit, command estat gof*

Source*: Authors' computation from WBES 2018*

Appendix F: Results for Test for Heteroscedasticity using Breusch-Pagan for the Probit Model for Drivers of R&D Expenditure Intensity

Source	chi2	Df.	p
Heteroscedasticity	41	40	0.4265
Skewness	14.03	18	0.727
Kurtosis	0.21	1	0.647
Total	55.24	59	0.615

Note: *Ho=Variance of residuals is constant; test; estat imtest*

Source*: authors' computation from WBES 2018*

Appendix G: Drivers of a Firms Intensity of R&D Expenditure LIML Regression Results

	R&D Intensity (Outcome equation)		R&D Propensity (Participation equation)	
Independent Variable	Coefficient	Standard Errors	Coefficient	Standard Errors
Industry	0.033	0.312	0.094	0.123
Firm size	-0.223	0.309	-0.029	0.140
Firm age	-0.004	0.061	-0.008**	0.003
Manager experience	0.013	0.015	-0.004	0.005
Internet access	0.035	0.334	0.100	0.117
Incubation labs access	-0.523	0.570	0.271*	0.143
International certification	-0.336	0.516	0.250*	0.134
Foreign technology adoption	-0.297	0.728	0.374*	0.181
Physical capital spending	-0.933	0.963	0.497***	0.108
Exporting capacity	-0.306	0.605	0.294**	0.122
Credit access	-0.244	0.355	0.151	0.112
Business-government relations	-0.419	0.596	0.305**	0.136
Employee training	-0.076	0.103	0.521***	0.115
Innovation partnerships	-0.726	0.832	0.442***	0.127
Cost of labour	-0.001	-0.011	0.001	0.001
Mills				
Lambda	-2.0201	2.469		
Rho	-1.000			
Sigma	2.020			

Note: N=1,001 Rho=Correlation of the disturbances of the participation and outcome equations; Lambda = the inverse Mills ratio, *, ** and ***, denotes 10%, 5%, and 1% significance levels, respectively. Models 1 and 2 are simultaneously estimated using OLS on a Tobit II model (Eqn. 2.4.).

Source*: authors' computation from WBES 2018*

Appendix H: Results of Selection into the Treatment Sample Logit Models

	R&D Spending		Product/service innovation		Process Innovation		IPR Ownership	
	Coefficient	Std. Error.	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient.	Std. Error
Internet access	0.125	0.0121	0.075	0.096	-0.318	0.108	0.342***	0.098
Incubation labs	0.292**	0.139	-0.095	0.131	0.163	0.133	0.509***	0.125
International certification	0.217*	0.131	-0.347***	0.121	0.163	0.123	0.062	0.117
Foreign technology	0.409***	0.169	0.352**	0.178	0.438*	0.171	0.607***	0.161
Physical capital spending	0.478***	0.106	0.304***	0.091	0.333***	0.097	0.308***	0.096
Exporting capacity	0.252**	0.115	0.004	0.103	0.040	0.111		
Credit access	0.159	0.111	0.228*	0.089	0.022	0.097	0.041	0.094
Business govt. relations	0.296**	0.133	0.232**	0.121	0.168	0.124	0.024	0.123
Training	0.488***	0.113	0.429***	0.091	0.425***	0.101	0.104	0.099
Partnership	0.42***	0.123	0.836***	0.132	0.938***	0.115	0.126	0.121
Cost of labour	-0.492	0.067	0.161***	0.055	-0.009	0.061		
R&D spending					0.301**	0.125	0.153	0.25
N	1,001		1,001		1,001		1,001	
LR (ch2)	157.46		236.68		202.07		191	
Pro>chi2	0.000		0.000		0.000		0.000	
Pseudo R2	0.177		0.171		0.1756		16	
Balancing Property	Satisfied		Satisfied		Satisfied		Satisfied	

Note: *Balancing property must be satisfied for the p-score to be generated; *, **, and *** denote 10%, 5%, and 1% significance level, respectively.*

Source: *authors' computation from WBES 2018)*

Appendix I: Endogenous Switching Regression with R&D Spending as the Treatment

	Value-added per worker_1	Value-added per worker_0	R&D spending participation
Internet access			0.194*
			(0.114)
Incubation labs access			0.309**
			(0.138)
Foreign technology adoption			0.402***
			(0.170)
International certification			0.252**
			(0.132)
Physical capital spending	-0.659**	-0.743	0.509***
	(0.319)	(0.002)	(0.106)
Exporting capacity			0.250**
			(0.114)
Credit access			0.147
			(0.112)
Employee training			0.472***
			(0.115)
Innovation partnerships			0.436***
			(0.123)
No of workers	-0.240	-0.241	-0.001
	(0.765)	0.357	(0.000)
Likelihood test of independence of eqns. chi2(1) = 2.36 Prob. > chi2 = 0.1241			

Note: ****, ** and *, denotes 1%, 5%, and 10% significance level, respectively. LR test of Independence of Equations tests whether the selection in both regimes is potentially exogenous or not.*

Source: *authors' computation from WBES 2018*

Appendix J: Endogenous Switching Regression with Product/Service Innovation as the Treatment

	Value-added per worker_0	Value-added per worker_1	Product/service innovation participation
Internet access			0.017
			(0.048)
Incubation labs access			-0.073
			(0.066)
Foreign technology adoption			0.119
			(0.116)
International certification			-0.041
			(0.064)
Physical capital spending	0.980***	-0.269	0.237***
	(0.306)	(0.167)	(0.079)
Exporting capacity			-0.003
			(0.053)
Credit access			0.055
			(0.044)
Buss-govt relation			0.042
			(0.063)
Employee training			0.018
			(0.050)
Innovation partnerships			0.245**
			(0.223)
Cost of labor	0.854***	-0.174*	0.266***
	(0.170)	(0.924)	(0.046)
Likelihood test of independence of eqns. Chi2(1) = 260.65 Prob. > Chi2 = 0.0000			

Note: ****, ** and *, denotes 1%, 5%, and 10% significance level, respectively. LR test of Independence of Equations tests whether the selection in both regimes is potentially exogenous or not.*

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Source: *authors' computation from WBES 2018*

Appendix K: Endogenous Switching Regression with IPR Ownership as the Treatment

Variable	Value-added per worker 1	Value-added per worker_0	IPR Ownership
Physical capital spending	-0.358	-0.116	0.315***
	(0.389)	(-0.218)	(0.095)
No. of workers	-0.125	-0.273	0.092
	(-0.226)	(-0.110)	(0.057)
R&D spending			0.215*
			(0.123)
International certification			0.055
			(0.122)
Innovation partnerships			0.193
			(0.118)
Incubation labs access			0.508***
			(0.126)
Credit access			0.046
			(0.094)
Foreign technology adoption			0.649***
			(0.162)
LR test of Indep. Eqns,	Chi2(1) 0.46	Prob>chi2 = 0.4954	

Note: ****, ** and *, denotes 1%, 5%, and 10% significance level, respectively. LR test of Independence of Equations tests whether the selection in both regimes is potentially exogenous or not.*

Source: *authors' computation from WBES 2018*

Appendix L: Endogenous Switching Regression with Process Innovation as the Treatment

Variable	Value-added per worker 1	Value-added per worker_0	Process innovation participation
Physical capital spending	-0.103	-0.126	0.367***
	(0.267)	(0.245)	(0.094)
No. of workers	-0.126	-0.364	0.094
	(0.139)	(0.115)	(0.059)
International certification			0.156
			(0.118)
Innovation partnerships			0.928***
			(0.112)
Employee training			0.458***
			(0.112)
Foreign technology			0.375***
			(0.164)
LR test of Indep. Eqns,	Chi2(1) 1.44	Prob>chi2 = 0.2298	

Note: ****, ** and *, denotes 1%, 5%, and 10% significance level, respectively. LR test of Independence of Equations tests whether the selection in both regimes is potentially exogenous or not.*

Source: *authors' computation from WBES 2018*

Appendix M: A Sample of African Countries used in Efficiency Analysis of the African Region Innovation System

Ghana
Senegal
South Africa
Morocco
Nigeria
Namibia
Mozambique
Tunisia
Angola
Kenya
Botswana
Cameroon
Tanzania
Egypt
Guinea
Togo
Uganda
Cote d'Ivoire
Zambia
Mauritius
Rwanda
Algeria
Madagascar
Burundi
Burkina Faso
Niger
Malawi
Gambia

Source: *World Development Indicators Data 2020*

Appendix N: PhD Research License

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