UNIVERSITY OF PARDUBICE

FACULTY OF ECONOMICS AND ADMINISTRATION

KNOWLEDGE SPILLOVER EFFECTS AND METHODS OF THEIR MEASUREMENT

Dissertation

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2025

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Raymond Kwame Adane Darfo-Oduro by own hand

ACKNOWLEDGEMENTS

Thanks be to Lord God almighty for bringing me to a successful end of my PhD studies. It would not have been possible without the grace of God.

I acknowledge the immense contribution of my supervisor, Prof Jan Stejskal. You have been an inspiration through your guidance and mentorship throughout my study period. I sincerely appreciate your effort and guidance to ensuring the successful completion of my study.

I register my appreciation of Prof Oto Hudec whose suggestions and comments on my dissertation have helped to bring this work to a successful conclusion.

I appreciate the efforts of all teaching and non-teaching staff of the Faculty of Economics and Administration who in diverse ways helped groom me to this point. I will single out Doc. Ing. Viktor Prokop, Ph.D for the numerous academic support he offered me through this study journey.

My sincere appreciation goes to Mrs. Bartonickova Radka for her genuine kindness and support she offered me.

I recognise and appreciate the friendship and support of Dr. Solomon, Dr. Yee and course mates Mohammed Gariba and Ebo Arthur. These are true friends that made my stay in this university less stressful. Your kindness and love cannot go unnoticed.

To Stella my wife, Rayna my daughter and Reagan my son. You have endured my absence. The success is yours.

DEDICATION

This work is dedicated to my father, Mr. Kofi Darfo-Oduro. This is in recognition of the lifelong support you continue to offer me.

ANNOTATION

Knowledge spillovers as externality gain by countries from other countries' R&D investment come at no cost to the beneficiary country. This makes international knowledge spillovers a rich source of input in the knowledge production function of countries. Innovation policies of countries have been centered around knowledge spillovers, their effectiveness and exploitation. Despite the relevance of knowledge spillovers to innovation and economic policies for growth, studies on their effect and measurement remain relatively limited. This study contributes to the knowledge spillover and innovation literature by assessing the effect of knowledge spillovers and their measurements. Using data from selected countries in Europe in a panel study, various measures of knowledge spillovers were investigated for their reliability and validity. The study also assessed the complementarity and the joint effect of knowledge spillover and countries' own R&D for innovation purposes as well as the role of absorptive capacity in the complementarity between international knowledge spillovers and countries' own R&D. The study shows that knowledge spillover measures based on geographic proximity and technological proximity show some marked differences in their outcomes. The different technology proximity measures of knowledge spillovers investigated are found to be valid, but their reliability differ depending on the type of reliability estimator used. The findings of the study also reveals that the R&D intensity and relational capacity of countries are critical for the complementarity and joint use of international knowledge spillovers and countries' own R&D for innovation.

KEYWORDS

Innovation, R&D intensity, Geographic proximity, Technological Proximity, Knowledge Spillover

Efekty přelévání znalostí a metody jejich měření

ANOTACE

Přelévání znalostí jako externí zisk zemí z investic jiných zemí do výzkumu a vývoje nepřináší přijímající zemi žádné náklady. Díky tomu je mezinárodní přelévání znalostí bohatým zdrojem vstupů do funkce produkce znalostí v jednotlivých zemích. Inovační politiky zemí se zaměřují na přelévání znalostí, jeho efektivitu a využití. Navzdory významu přelévání znalostí pro inovace a hospodářské politiky pro růst zůstávají studie o jejich účincích a měření relativně omezené. Tato studie přispívá k literatuře o přelévání znalostí a inovacích tím, že hodnotí vliv přelévání znalostí a jeho měření. S využitím dat z vybraných evropských zemí v panelové studii byla zkoumána spolehlivost a validita různých měřítků přelévání znalostí. Studie rovněž hodnotila komplementaritu a společný vliv přelévání znalostí a vlastního výzkumu a vývoje jednotlivých zemí pro inovační účely, jakož i roli absorpční kapacity v komplementaritě mezi mezinárodním přeléváním znalostí a vlastním výzkumem a vývojem jednotlivých zemí. Studie ukazuje, že měřítka přelévání znalostí založená na geografické a technologické blízkosti vykazují ve svých výsledcích určité výrazné rozdíly. Různé zkoumané metody technologické blízkosti pro efekty přelévání znalostí se ukázaly jako validní, ale jejich spolehlivost se liší v závislosti na typu použitého odhadu spolehlivosti. Zjištění studie rovněž ukazují, že intenzita výzkumu a vývoje a relační kapacita zemí jsou klíčové pro komplementaritu a společné využití mezinárodních efektů přelévání znalostí a vlastního výzkumu a vývoje zemí pro inovace.

KLÍČOVÁ SLOVA

Inovace, intenzita výzkumu a vývoje, geografická blízkost, technologická blízkost, přelévání znalostí

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Introduction

Background to Study

Knowledge spillover is considered an important source of innovation performance of firms and growth of economies (Bernal, Carree, & Lokshin, 2022; Li & Bosworth, 2020). Studies in knowledge spillovers have linked knowledge spillovers to several economic outcomes such as economic growth, profitability of firms, innovation performance and other economic and financial performance variables. The effect of knowledge spillovers is influenced by several other factors that may compromise or enhance the effectiveness of knowledge spillovers on innovation and some other economic outcomes. The position of the literature on knowledge spillovers is generally in the direction that knowledge spillovers are good for innovation performance. There is a consensus among authors that the social gains of knowledge are greater than the private gains (Kaiser, 2002). There are therefore efforts by governments, policy makers and researchers to encourage knowledge spillovers for the public good. Knowledge spillover has gained attention in the innovation literature because of its role in interfirm knowledge flows and as an important driver of R&D collaboration (Li & Bosworth, 2020). As a catalyst for growth of firms and economies, knowledge spillovers have been given attention both in businesses, management of economies and in academia. In the management of economies, several policy tools such as R&D tax credit have been deployed to encourage and facilitate the creation of knowledge and knowledge spillovers (Aghion & Jaravel, 2015) and in business organisations, open innovation and partnerships have been an important learning strategies of firms in the knowledge spillover space (Perri & Peruffo, 2016). However, there is also a long-standing debate that knowledge spillover has been a disincentive to innovators if knowledge they create from their investments are involuntarily transmitted to their competitors (Arrow, 1962). Knowledge spillovers are considered as a phenomenon of a failed market. The appropriability of knowledge as a source of incentive to inventors is also championed by some other earlier researchers. Spence (1984) showed that the inability of firms to fully appropriate knowledge is a disincentive to increased R&D expenditure. However, there is a gradual shift from the position of appropriability to a position of collaboration and knowledge sharing. Current literature on innovation studies provide evidence that authors are of the view that treating knowledge as a public good rather than appropriating knowledge is the way to go as far as improving innovation for the social good is concerned (Bernal, Carree, & Lokshin, 2022). This does not mean that there are still no pockets of studies that believe that appropriation of knowledge is important for innovation performance.

Some recent studies have shown the relevance of knowledge appropriation for innovation performance (Acs & Sanders, 2012). Intellectual property rights, such as patenting are considered as limiting knowledge spillover and creating incentive mechanisms for inventors to do more to improve innovation performance (Acs & Sanders, 2012). This contrasts with the dominants position of literature that suggests that blocking access to knowledge is detrimental to innovation performance. Given the importance of knowledge spillover to the performance of firms and the economy, newer areas of knowledge spillover continue to emerge which require further investigations for their improvement and development. Specifically, the attempts to understand knowledge spillover and its contribution have opened a wave of studies in the areas of the distribution of knowledge spillover, measurement of knowledge spillover and their effects.

Knowledge spillovers have been widely and intensively investigated for the past fifty years. Apart from the focus on the factors that determine the distribution of knowledge spillover that has mainly been based on (Lucas, 1989), in more recent times what has engaged the attention of the knolwedge spillover literature is the effect and measurement of knowledge spillover (Xu, Wang, Zhou, & Zhang, 2019; Zhang, 2017). Other studies have also focused attention on why some countries and specific industries have withnessed more knowledge spillovers than others (Stephan et al.,2019)   Attempts to underastanding the distribution of knowledge spillover across regions and industrial sectors have followed the widely known polar argument of technological proximity (Jaffe, 1989) and geographic proximity (Jaffe, Trajtenberg, & Henderson, 1993; Marshall, 1980). These have been the source of controversy and improvement in the measurement of knowledge spillovers. The challenges of measuring knowledge spillover has also been a source of inacuracies in determining the effect of knowledge spillover. In this area of study, there is a recognition that eventhough knowledge externality abound in space (Simonen & McCann, 2008) the effect of such knolwedge spillovers on innovation outcome have been estimated with varied approached and the consequence has been that the outcomes of these studies have been varied.

The status of the empirical literature is convoluted with different outcomes depeding on the approaches used in measuring knowledge spillovers. The effect of knowledge spilovers, being an offshoot of knowledge spillover measurements has also been affected by the varied approaches to measuting knowledge spillovers. This thesis aims to diggest the different measures and assess the efficacy of these measures based on their validity and reliability and also analyse the effect of knowledge spillovers. Contrary to what has been done in many studies, the current study recognises that the effect of international knowledge spillover on domestic countries innovation is a complicated process and not as simple as some empirical studies have presented. The combination of international knowledge spillover and countrys' own R&D will have some adjustment cost. The relationship between knowledge spillover and innovation performance is therefore expected to be nonlinear. In this study, it is also recognised that the effect of knowledge spillover on innovation performance is also dependent on the complementarity between international R&D from knowledge spillovers and domestic countrys' R&D as well as absorptive capacity of countries. I postulate two theses: knowledge spillover from abroad complements countrys' own R&D to improve innovation and absorptive capacity of domestic economy is important for inward knowledge spillovers.

1 Literature Review

In this section of the study, there is a theoretical review to determine the relationship between existing theories on knowledge spillover, the extent to which these theories have been investigated and to provide a base upon which the current study is grounded.

1.1 Theories

In this section of the chapter, the theories which guide the study are discussed. These theories include the theory of knowledge, social exchange theory, social learning theory, knowledge spillover theory of entrepreneurship and the endogenous growth theory.

1.1.1 Theory of Knowledge

Epistemology is concerned with a variety of knowledge related questions but what the focus has been is to understand the extent of our knowledge. **Epistemology is a branch of philosophy that attempts to answer questions related to nature, origin and the boundaries of knowledge.** These are what culminate in the theory of knowledge. Philosophically, there is a plethora of views on the extent of knowledge. **From the 'common sense' tradition, the level of knowledge is lower than what we think we know (Lemos, 2007)**. The thought of knowing very little is not just akin to the commonsense tradition but some other philosophers are also skeptical about the extent of knowledge and have suggested that the extent of knowledge is scanty. The theory of knowledge therefore attempts to set the boundaries of knowledge and understand the extent of knowledge. **Epistemologically, knowledge emanates from three main sources of what is known, propositional, acquaintance and 'how to' knowledge sources (Lemos, 2007)**.

Propositional knowledge is knowledge that is justified to be true. Moser (1987) explained that propositional knowledge is the knowledge that some proposition is true. This knowledge requires justified true belief. The justification of knowledge is essential, however in the view of Shope, (1983), the justification of propositional knowledge is as important as the knowledge itself. Propositional knowledge has been described as knowledge of fact and the object of the knowledge is the true proposition (Lemos, 2007).

From the theoretical perspective, propositional knowledge contrasts with acquantance knowledge which, unlike just knowing facts and describing facts that have not been experienced suggests that a person must have experienced or acquainted with the subject (what is being discussed). Acquanitance knowledge explains knowledge that requires a person to have experienced a phenomenon or a situation than just have information about a situation (Lemos, 2020). Having proportional knowledge will therefore not necessarily mean acquaintance knowledge. Knowledge about an issue could only be informative and not acquaintance. Thus, what 'know' means could be two different things, propositional or aquaintance knowledge. When an individual state a fact about something, espistemology suggests that it is propositional knowledge when the individual is stating just the fact without actually having acquaintance with the subject but it is acquaintance knowledge where the person has a personal experience with the subject. There is a possibility of having propositional knowledge without a corresponding acquaintance knowledge. In the case of propositional knowledge a person can describe a phenomenon without actually having acquaintance (experience) with it.

There is another type of knowledge, the how to knowledge (Lemos, 2020). This ascribe ability to the knower. From the epistemology point of view, 'how to' knowledge suggests that the knower has the ability to execute a task. It is considered that the 'how to' knowledge is the tacit knowledge embodied in the knower of knowledge (Leshed, Haber, Matthews, & Lau, 2008). This contrasts with knowledge that affords the knower to describe a process but not capability to execute which could either be propositional or acquaintance knowledge. From the theory two main sets of knowledge is identified, knowledge that describes (propositional and acquaintance knowledge) and an action knowledge (how to knowledge). Having the how to knowledge could be exclusive of propositional knowledge to the extent that tacit knowledge are hard to explain even though such knowledge gives the ability to execute a task.

1.1.2 Social Exchange Theory

The social exchange theory has generally been used to understand the interaction among employees in the workplace and workplace behaviour (Cropanzano & Mitchell, 2005). Even with the emergence of other exchange theories, a dominant phenomenon that has been accepted as cardinal in all these exchange theories, highlighted very much by the social exchange theory is interaction among actors in a social system (Cropanzano & Mitchell, 2005). These interactions are what generate gains and responsibility to actors in a social system (Emerson, 1976). In the social exchange theory, interaction within the social system is what maintains the social balance in the social system (Blau, 1964). These interactions are governed by rules and are symbiotic in nature. This interaction determines the quality of the relationship. However, this is dependent on how the actors in the social system adhere to the rules. Social exchange theory has been used as the basis for explaining phenomenon across several disciplines. Its explanatory power is only rivalled by few other theories in the field of social sciences. Networks in social systems and in organisations board independence and organizational justice and leadership are the typical areas exchange theory has been useful (Cropanzano & Mitchell, 2005). **Knowledge spillover and knowledge transfer are important social system activities that are grounded in the tenets of social exchange theory**. The overlapping point between the social exchange theory and knowledge spillover and diffusion is that the social exchange theory and knowledge spillover explains individual behaviour in a resource sharing endevour (Emerson, 1976). Consistent with knowledge spillover and knowledge diffusion, knowledge as a resource is transferred or transmitted voluntarily and involuntarily among actors. The transmission of knowledge as the knowledge spillover and knowledge diffusion literature suggests, interaction, which is an important component of the social exchange theory is the main reason or mode of knowledge spillover and diffusion.

The social exchange theory advances the argument that the exchange of resources between actors is a way to maximise benefit and minimise cost (Yan, Wang, Chen, & Zhang, 2016), for which an actor's intention of transferring resources is the expected gain in return. This is an important rule of exchange espoused by the social exchange theory called reciprocity. **In the social exchange theory, reciprocity has been defined in the context of interdependent exchanges**. Exchange in the social exchange theory is considered a bidirectional where in any interaction, an actor must give up something to get something in return (Molm, 1994). This is critical in explaining the transmission of knowledge. The literature on knowledge transfer states that knowledge sharing is a form of exchange (Bock, Zmud, Kim, & Lee, 2005) and actors in a social system sharing knowledge do so in expectation of getting something in returns (Kankanhalli, Tan, & Wei, 2005). **From the social exchange theory's point of view, consistent with empirical literature, the owner of knowledge will naturally want to exchange it for some gains otherwise appropriate it.** Reciprocity as an interdependent exchange is a source of transaction in the social exchange theory (Cropanzano & Mitchell, 2005). In a social system the need for affection is considered a social capital that accrue gains to people and organisations (Laursen & Hartup, 2002). The social exchange theory, however, falls short of providing the foundation for transfers without a commensurate gain in return such as involuntary knowledge transfers or knowledge spillovers. **The social exchange theory is a reciprocity or a tit for tat type of relationship where both parties gain from each other.** For example, firms, countries and economic agents engaged in interaction provide the basis for knowledge exchange only and not knowledge spillover where one is only a 'predator' and the other is a 'prey'. This relationship is not a symbiotic one. Contrary to the social exchange theory, in knowledge spillovers there are gainers who are the predators who use their high absorptive capacity to break the filters of knowledge diffusion barriers to syphon from its prey. This mechanism is not explained through the social exchange theory. Generally, people are not willing to share knowledge unless there is motivation to do so. This is in sync with the idea espoused by authors who have argued that knowledge is regulated by the originators and owners of knowledge (Crevoisier, 2016 ; Dalrymple, 2003). **The social exchange theory assumes with interaction, knowledge is automatically diffused.** However, empirical literature has shown that there are filters that block knowledge diffusion (Padilla-Meléndez, Fuster, Lockett, & del-Aguila-Obra, 2021)

1.1.3 Social Learning Theory

The social learning theory (Bandura, 1977) is a theory of development of psychology that is focused on how people learn and imitate or observe others through modelling influences. The theory further metamorphosed into a social cognitive theory (Bandura, 1986). The basic question the cognitive theory attempts to answer is how people acquire competencies, styles and behaviour and how behaviours are motivated and regulated (Bandura, 2001). "Social cognitive theory provides an agentic conceptual framework within which to analyze the determinants and psychosocial mechanisms through which symbolic communication influences human thought, effect and action" (Bandura, 2001, p. 265). From the perspective of social learning theory, learning and the creation of knowledge happens through conversation and interaction between people (Easterby-Smith, Crossan, & Nicolini, 2000). **Such learning happens between social agents through mechanisms such as collaborations, developing relational capabilities (Pahl-Wostl, Mostert, & Tàbara, 2008)**. Other authors have shown that within a social learning system communication between agents in a social system is a main means on learning (Mezirow, 1995). Social learning is also considered instrumental, allowing learners through communication with peers gain knowledge and reinterpreted to create newer ideas using information gathered from their peers (Mezirow, 1995).

It takes a collective effort of parties in an interaction to produce and share knowledge. In the social exchange theory, knowledge is considered an intangible that cannot be transmitted like a physical object but rather it is generated and transmitted through a collaborative effort of all parties (Noorderhaven & Harzing, 2009). This position has been earlier espoused by John Dewey and quoted in a study by (Plaskoff, 2003, p. 163). Plaskoff (2003) explained that knowledge is a socially constructed asset that is created and transmitted through the collaborative effort of actors. This position seem to suggests that knowledge is created and transmitted in a single process, which gives credence to the public good nature of knowledge but only restricted to a particular group. Based on this propostion of the the social learning theory, it has been explained that “With regard to intra-MNE knowledge flows, this means that in the view of social learning theory such ‘‘flows’’ will be possible only where individuals working in different units of the MNE engage in social interaction” (Noorderhaven & Harzing, 2009, p. 723)**. It can be deduced, therefore from the social exchange theory and argument thereof made by (Noorderhaven & Harzing, 2009) that knowledge and its transmission are localized.** Actors must be close to the source of knowledge generation and transmission for knowledge transfer and or spillover to occur. The social learning theory emphasises the role of observational learning in inducing human behaviour (Chia, Hsu, Lin, & Tseng, 2021). This further confirms the importance of geography in the generation and transfer of knowledge. A large portion of the knowledge spillover literature has highlighted the importance of geographic proximity in the processes of knowledge spillover, a phenomenon that has been given credence by social learning theory. For example, in a study the argument is made that the position of an actor in a social network affects the knowledge the actor can access (Tsai, 2001). The author explained that actors who are centrally place in a social system network are better able to access knowledge than others.

1.1.4 Knowledge Spillover Theory of Entrepreneurship

From the failures of the knowledge production function which assumes that firms exogenously exist but invest in research and development as an augmentation factor for human capital (Griliches, 1979), the traditional view is that knowledge is endogenous to the firm. To deal with the challenges of the knowledge production function and the new growth theory, Audretsch (1995) introduced the knowledge spillover theory of entrepreneurship. The theory’s central theme is that low level of knowledge-based entrepreneurship emanates from the failure of private and government institutions to generate new knowledge and the failure of individuals to exploit knowledge.

The knowledge spillover theory of entrepreneurship adopts a more realistic approach by assuming that entrepreneurship opportunities exist endogenously and are more prevalent in some industries such as high technology industries than low technology industries (Acs et al., 2009). This means that some industries are more predispose to knowledge spillovers than others. This makes capacity on the part of the originator of knowledge and absorptive capacity on the part of the recipient of the knowledge an important ingredient of knowledge spillover. The knowledge spillover theory of entrepreneurship assumes that incumbent firm’s knowledge spillover to help start up firms with limited capacity to generate their own knowledge (Acs et al.,2009). At minimum, startups must have the absorptive capacity to transmit knowledge spillovers from the incumbents to the startups (Acs et al., 2009). Absorptive capacity of startups has been important in explaining the relationship between new knowledge, tacit knowledge and entrepreneurship.

Contrary to earlier literature position on knowledge spillover which suggested that knowledge spillover was automatic (Acs, Audretsch; Braunerhjelm & Carlsson, 2009), in which case entrepreneurs benefit automatically from new knowledge created. The knowledge spillover theory of entrepreneurship, however, departs from this notion. **The theory suggests that the capacity of the entrepreneur to absorb the knowledge is important for knowledge spillover.** The knowledge spillover theory of entrepreneurship takes the position that knowledge is exogenous to the firm. The proponents of the knowledge spillover theory of entrepreneurship opine that the source of knowledge is economic agents. This makes the knowledge exogenous to the firm. Start-up firms benefit from knowledge inter temporal knowledge spillover from incumbent firms (Acs et al.,2009). Failure to appropriate the gains of the knowledge, knowledge spills over to endogenously create new firms (Audretsch & Lehmann, 2005). This makes new firms or startups the channel by which knowledge spills over per the theory (Acs et al., 2009). The knowledge spillover theory of entrepreneurship generally would suggest that the most important way firms would have access to new ideas or knowledge is through exploiting knowledge overlooked by originating firms. This captures the underlying mechanism of innovation in the Schumpeterian sense. Start-up firms, through their R&D activities, generate knowledge. These firms generally are unable to use this knowledge for various reasons and therefore are unable to fully appropriate the full extent of the knowledge generated. The unused knowledge therefore becomes susceptible to spill to entrepreneurs who may commercialise this knowledge (Ghio, Guerini, Lehmann, & Rossi-Lamastra, 2015). The inability of incumbent firms to fully appropriate and commercialise knowledge creates an opportunity for startups to improve on their innovation and economic growth.

1.1.5 Endogenous Growth Theory

The internal economy is an important source of long-term economic growth. Internal forces of an economy are what determines economic growth. This is the central theme of the endogenous growth theory. This is a departure from the neoclassical view that economic growth is an exogenous activity and therefore dependent on factors outside the economic system. **The endogenous growth model assumes that technical progress is the reason why economies grow (Romer, 1990).** Technical progress in the endogenous growth model is the results of researchers' and entrepreneurs' who respond to incentives in the economy. In the production function the producer has two main types of inputs, non-knowledge production factors such as physical capital, human capital and labour and knowledge resources such intellectual capital. It has been argued that the role of technological knowledge or technical progress in economic growth stems from the fact that ideas from such technical progress, unlike other growth or production inputs are nonrivalry (Jones, 2019). In a production function with non-technological inputs Jones (2019) argues that such as production function exhibits constant returns to scale since inputs are rivalrous and scarce, thus doubling outputs require doubling inputs. The mechanism through which technical progress leads to growth is when the ideas generated from technology which is non-rivalry is combined with the non-knowledge-based inputs which generally exhibit constant returns (Jones, 2019). Combining non-knowledge-based inputs and technical progress defined by ideas, knowledge and innovation ensures that the production function exhibits increasing returns to scale because of the non-rivalry nature of knowledge. The empirical literature points out that with increasing returns to scale growth follows naturally (Jones, 2019).

Consistent with empirical study on knowledge spillover and innovation, Romer (1990) argues that in the endogenous growth theory, technical progress as a channel for economic growth is based on the level of investment that is made in innovation. From the knowledge spillover literature, investment in human capital and R&D are the source of economic growth (Audretsch, Keilbach, & Lehmann, 2006) The endogenous growth theory remains one of the best explains the mechanism through which new knowledge and technologies are transmitted to ensuring economic growth (Delmar, Wennberg, & Hellerstedt, 2011). **The theory's acknowledgement of technical progress as a source of growth falls in line with Schumpeter's (1934) study that links entrepreneurship to innovation.** It is argued that investment in innovation creates an opportunity for knowledge spillover to other actors who employ this new knowledge for the creation of new products (Acs & Audretsch, 1988). Arrow (1962) attempt to endogenise growth suggested that knowledge transfer is interpersonal, where actors must be in close contact with the source of knowledge. Arrow (1962) explained that knowledge is tranfered through learning by doing. This is in tune with the thinking that knowledge spillover is influenced by the extent to which an actor is close to the source of the knowledge. Arrow (1962) introduced the concept of disembodied knowledge and its role in the endogenous growth theory even though an important part of the neoclassical growth theory (Döring & Schnellenbach, 2006). In the viewe of the endogenous growth model, it is this part of the knowledge that is a subject of spillover. Thus, eventhough the endogenous growth theory admits that innovation is dependent on both embodied and disembodied knowledge, only the disembodied knowledge is a subject of spillover (Döring & Schnellenbach, 2006). Empirical literature position is however, at variance with the position of the theory. Empirical findings posit that rather than not being a subject of spillover, embodied knowledge (tacit knowledge) are slow in transmission and are transmitted through inter personal channels.

1.2 Conceptual Review

1.2.1 Knowledge

An important area neglected by knowledge-based view theories is failure to provide a concise and precise definition of the construct knowledge. It is obvious that these theories, just like what pertains generally in empirical literature, there is a lack of consensus on what defines knowledge. The contention stems from the different contexts of application of knowledge. For example, there is contrasting definition of knowledge offered by authors who view knowledge from the individual's perspective (Grant, 1996) as opposed to studies that view knowledge as an embodiment of the organization (Levitt & March, 1988; March & Simon, 1958). In the view of authors who view knowledge from the perspective of the organisation, the scope of knowledge is beyond that of the induvidual. They contend that through organisational learning, organisations accumulate knowledge which is beyond the scope of individual embodied knowledge. Earlier studies have made distiction between two sets of knowledge in line with the opposing ideas espoused by Grant (1996) on one hand and Levitt and March (1988) and March and Simon (1958) on the otherhand. A distiction is made between pure knowledge and pecuniary or rent knowledge (Griliches, 1992). Griliches (1992) explained that pure knowledge are disembodied ideas whereas pecuniary knowledge are embodied in output of organisations. This is corroborated in more recent studies where authors have made such distinction in knowledge. Breschi, Lissoni, and Montobbio (2005) have indicated the theoretical, analytical and policy relevance of this distiction to knowledge spillover, but admit that the empirical literature is yet to develop this distiction and fully access its effect on knowledge spillover. The authors argue that the distiction is difficult to perceive empirically, despite its potential impact on knowledge spillover. Other aspect of the literature also split knowledge into tacit and explicit. In a study by Singh (2007), it was revealed that knowledge can either exist in a explicit or tacit forms. The literature suggests that this dichotomy is based on characteristics of the knowledge that determine the ease with which knowledge is transmitted. Tacit knowledge, contrary to explicit knowledge- knowledge in blueprint which makes it easy to transmit, tacit knowledge is not in blue print making its transmission complicated and difficult.

Characteristically, explicit knowledge is considered as knowledge that is expressed and communicated (Stover, 2004). There is however a thin line between knowledge that is explicit and that which is codified. Stover (2004) expressed that when explicit knowledge is documented it become a codified knowledge. Clearly the use explicit and codified interchangeable stems from the fact that codified knowledge can exist in a documented or orally. This contrasts with tacit knowledge in various aspects. **Apart from the fact that tacit knowledge is considered an unexpressed knowledge (Stover, 2004), the literature also suggests that such knowledge are embodies in practitioners making transmissions of knowledge in this cartegory challenging (Mclnerney, 2002).** The critical difference between tacit and explicit knowledge lies with the way these two knowledge cartegories are transferred. It has been shown that the channels of knowledge transfer is dependent on the cartegory of knowledge. Whereas tacit knowledge is transmitted by the acquaintance with the object of knowledge because the knowledge is embodied, in the case of tacit knowledge, the transmission is by immitation or accessing the blueprint of the knowledge through (Martinez-Brawley & Zorita, 2007) mainly through mass media (Hicks, 1995).

The distinction between tacit and explicit knowledge has engaged the attention of the literature because of the its importance in the management of knowledge. The literature recognises that these two cartegories of knowledge have an effect on how knowledge gets transferred. The characteristics of tacit knowledge has been cited as the reason why tacit knowledge is sticky in transfer (Turner, et al., 2014). The degree to which knowledge can be transferred with ease is influenced by whethere knowledge is tacit or explicit (Nonaka & Takeuchi, 1995; Nonaka, 1994). The more tacit knowledge is, the more difficult it is to transfer the knowledge (Heng-Li & Ted, 2008). Specifically, the stickiness of tacit knowledge in transmission is attributed to the fact that it is not codified and may not be communicated in a language but exchanged through the sharing of experiences, imitation or observation (Hall & Andriani, 2002). This does not mean tacit knowledge cannot be codified to make it easily transmittable. Hall and Andriani (2002) makes the point that tacit knowledge can be codified, however, whether or not tacit knowledge will be codified is dependent on the cost benefit analysis of codifying such knowledge. From the argument made by Hall and Andriani (2002) the distiction between tacit and codified knowledge may be considered trancient. Tacit knowledge and codified knowledge are two extremes on the same spectrum of knowledge. For the purposes of transfer, from the position of Hall and Andriani (2002), it can be argued therefore that, the stickiness of tacit knowledge can be reduced but at a cost. However, this position has not sufficed good enough reason for authors of knowledge spillover studies to treat the two cartegories of knowledge as the same. This is in spite of the fact that there is literature evidence to suggests that this dichotomy is rather simplistic (Dalkir, 2011). The dominant position of the literature remains that interms of knowledge spillover, knowledge can either be tacit or implicit and cordified or explicit.

The contention among authors on distinguishing between tacit and codified knowledge has an important palce in the knowledge literature. Dalkir (2011) makes an argument that give credence to the ascertion by Hall and Andriani (2002) that tacit and codified are on the same spectrum of knowledge and not actually different knowledge cartegories. “Explicit knowledge tends to represent the final end product whereas tacit knowledge is the know-how or all of the processes that were required in order to produce that final product” (Dalkir, 2011, p. 10). This position espoused by Dalkir (2011) suggests a complementary relationship between tacit and codified or explicit knowledge in a single process. In this study, there is an admision of the contention among authors as to whether there is a distiction between tacit and explicit knowledge. However, it is also evidential that the tilt of the literature is towards a distinction between tacit and explicit knowledge. For the purposes of transmission of knowledge, such as distinction is important to set knowledge that is easily transmitted apart from knowledge that is more difficult to transmit. Eventhough there is a logical reason to the proposition of the tacit/explicit spectrum, the relevance of their dichotomy has not been eroded. In this study, tacit and explicit knowledge are considered distinct. The basis for this distinction is based on (Polanyi, 1958), the originator of the concept of tacit knowledge who distinguished between explicit and tacit knowledge. The author explained that tacit knowledge, in contrast with explicit knowledge, is embodied and transmitted through personal contact rather than mass media as in the case of explicit knowledge.

In the knowledge management literature, the central role assigned to knowledge in organisation has been knowledge as source of competitive advantage to firms especially in a rapidly changing external business environment (Alavi & Leidner, 2001).The dichotomy between tacit and codified or explicit knowledge plays an important role in how firms manage knowledge for competitiveness. Heng-Li and Ted (2008) in recognising the importance of knowledge explained that knowledge is powerful and a scarce resource for organisations. The authors futher stressed that individuals in an organisation, being rational will naturally not want to share knowledge. However, for effectiveness in the utilisation of knowledge for innovation, organisations would would want to ensure individuals unselfishly share knowledge (Heng-Li & Ted, 2008). **The importance of the split between tacit and codified or explicit knowledge come up here again. Depending on wherether knowledge is tacit or explicit, innovation activities of the organisation may be compromised.** Turner, et al. (2014) assertion that tacit knowledge is more sticky than explicit knowledge come to bear in ensuring that individuals in an organisation do not appropirate knowledge to the detriment of innovation output. In situations where knowledge is tacit, managing knowledge to improve information flow within the organisation will be a challenging task. However, the situation will be easier if the knowledge is explicit. The public good nature of knowledge as explained by Stiglitz (1995), alluded to the fact that improving innovation requires that knowledge is treated as a public good rather than a private good. This will mean that increasing access to knowledge must by critical. However, knowing that the two cartegories of knowledge, tacit and explicit could affect the transmission of knowledge differently, the need to underscore the importance of the divide between tacit and explicit knowledge should not be underestimated.1

1.2.2 Tacit and Explicit Knowledge

In this review a distinction is made between tacit knowledge and explicit knowledge. This distinction is important for two main reasons. The aim of the study is to assess the role of the two knowledge types in knowledge spillover. It therefore important to draw a line between these two knowledge cartegories to give focus to the study. Secondly, the literature on the distiction between tacit and explicit knowledge has not been well developed and authors are yet to reach a consensus on the split between these two main categories of knowledge. Before the early part of the 20th century, knowledge was considered as a composite, normally refered mainly to scientific ideas or knowledge.

Polanyi (1958) in his book ‘ Personal knowledge’ kick start the debate on what knowledge is and the constituents of knowledge. **In his book the argument he made is that to assign a complete objectivity to knowledge is untenable because knowledge is highly personal.** He further argues that “into every act of knowing there enters a passionate contribution of the person knowing what is being known and that this coefficient is no mere imperfection but a vital component of his knowledge (Grant, 2007, p. 175).” Polanyi (1958) in his book personal knowledge make an important point that makes clear the distinction between tacit and explicit knowledge. He recounts the importance of language in sharing knowledge. Language in his view and as generally accepted is the medium for sharing knowledge. Polanyi (1958) emphasised that “we can often know how to do things without either knowing or being able to articulate to others why what we do works” (Grant, 2007, p. 175). According to Grant (2007) an important example cited by Polanyi (1958) in his book ‘Personal knowledge’ that has been largely ignored by the economics literature is riding a bicycle where the rider ofsets centrifugal and gravitational forces. This part of what the cyclist does but cannot communicate to other is what Polanyi calls tacit knowledge. It is important to stress that contrary to what some authors have said attributing to Polanyi, he never said this tacit knowledge cannot be transferred. What Polanyi rather stated is that tacit knowledge has a limited capability of transfer. From the accounts of Grant (2007, p.175) Polanyi (1958) explained that “Art which cannot be specified in detail cannot be transferred by prescription, since no prescription for it exists. It can be passed on only by example from master to apprentice. This restricts the range of diffusion to that of personal contacts.” Interpersonal channels are therefore important when it comes to the transfer of tacit knowledge (Hicks, 1995) because of the characteristics of this type of knowledge. In distinguishing between tacit and codified knowledge, the review will continue to rely on Polanyi (1958) account as presented in Grant (2007). Admittedly, there is a thin line between tacit and explicit knowledge. It is therefore not surprising that some authors argue that with time tacit becomes explicit. This is an untenable position to the extent that tacit knowledge by nature is the ability or skill do to something or to resolve a problem. In the view of Polanyi (1958) tacit and explicit Knowledge are two distinct knowledge. He asserts that tacit is something personal, an ability to do something or to resolve a problem. Ascribing ability to do something to tacit knowledge is not new to literature. In a study by Döring and Schnellenbach (2006), the authors explained that the broader description knowledge splits knowledge into a cognitive part and another part that gives ability to solve problems, make decision and understand information. Polanyi (1958) further stressed that all knowledge has a tacit component and that there is always a cooperation between tacit knowledge and what he calls formal knowledge. Tacit knowledge is the result of one’s own experiences and learning and the outcome of such tacit knowledge is what is known as explicit or formal knowledge (Grant, 2007). So, in the view of Polanyi (1958), the split between tacit and explicit knowledge should not be part of the knowledge conversation, it is rather the degree of tacit or explicit in knowledge that must engage the attentions of scholars. In this study, knowledge is defined broadly to include both tacit and explicit. However, the split between tacit and explicit knowledge is recognized.

1.2.3 Economics of Knowledge

The intense application of knowledge in economic activities is considered a desireable property of economic transformation (Vertesy & Van Roy, 2013). The intensity of knowledge is the force behind successes of firms and economies (Grigorescu, Zamfir, & Mocanu, 2020). Studies on the economics of knowledge have centred on externalities and the public and private good nature of knowledge**. Knowledge has largely been considered as public good (Drahos, 2004), once created it is availabile for all (Nico, 2020). However, a lot of debate surrouds the public nature of knowledge.** In this section of the study, the focus is to navigate through the arguments and situate knowledge in its right place in the economic literature. Caracteristically a public good is formally defined by its non-rivalry in consumption and non-excludability in use (Stiglitz , 1999). It is argued that public goods are accessed and consumed costlessly. Knowledge as a public good retains these two characteristics to an extent (Rice, Heinz, & Van Zoonen, 2019).

The marginal cost of consumption is zero and therefore the extra consumption of knowledge does not diminish the quantity and quality of knowledge available to others to consume. This qualifies knowledge as being nonrivalry in consumption. Knowledge per its nature exhibits that property of non-excludability in use. The marginal cost of exclusion is greater than the marginal cost inclusion. Rationailty, would therefore require that, as a cost minimising strategy, excluding people from the consumption of knowledge is not efficient. Knowledge is seen as exhibiting the two characteristics of public good, non rivalry in consumption and non excludability in use (Frost & Morner, 2010). This has been the source of debate and controversy in the knowledge economics literature. Central to this controvesy is the polar argument positions that knowledge in most cases cannot be classified as a pure public good because characteristically knowledge does not fully exhibit the public good property of non excludability. Other authors also take the position that knowledge exhibit fully the propertites of public good, non rivalry in consumption and non excludability in use. Among authors who suggest knowledge is a pure public good (Drahos, 2004; Cornes & Sandler, 1996; Samuelson, 1954). **Stiglitz (1999) explains that knowledge is not a mere public good but a global public. It is important to stress that pure public goods are rare, however, the difference between pure public good and impure public good is just the degree of publicness (Stiglitz, 1999).** There are however, a group of authors who have also argued that knowledge show some elements of a common good in so far as access to knowledge can be regulated (Crevoisier, 2016). The author makes the argument that knowledge as a private good set the basis for trading knowledge. Knowledge generally is considered a public good, however, for profit gains knowledge appropirations has been used as an exclusive mechanism (Crevoisier, 2016). The basis for this argument is that intellectual property right have expanded the spheres of private control of knowledge at the expense of the domain of public knowledge (Dalrymple, 2003). The argument that knowledge is generally a public good is well grounded by the theory of public good. Because of the free nature of knowledge as a public good, knowledge is under produced in the private sector because motivation to produce is limited. This has been the basis of government support in the production of knowledge including technology.

Economists' attempt to explain the production of knowledge or technology in economies has been based on the knowledge production function. Generally authors acknowledge the important role of two main factors, human capital and Research and Development (R&D) capabilities of firms in the production of knowledge or technology. For example Charlot, Crescenzi and Musolesi (2015) have argued that human capital and R&D spending as well as their intensity in the innovation of firms in Europe. Likewise, other studies that have given credence to human capital and R&D as the basic input of innovation (Guo, Ning, & Chen, 2022; Gallié & Legros, 2012). The basic theoretical foundation for the knowledge production function (Griliches, 1979) shows the causal relationships among productivity, unobservable knowledge capital, and its observable input (i.e. R&D) and output (i.e. patents) after controlling for other relevant factors (Charlot, Crescenzi, & Musolesi, 2015, p. 1230)**.** This has been the basis for modelling knowledge in innovative literature. **The key role of human capital in knowledge production has been very much highlighted.** Mitra, Abubakar and Sagagi (2011) explained the knowledge is a function of the development of human capital. Human capital is an important resource in an organisation to determine the firm's absorbtive capacity (Charlot, Crescenzi, & Musolesi, 2015). Firms rely on both internal and external sources of R&D. In most cases, the ability of firms to use external sources of knowledge is explained by the capacity of the firm to be able to absorb these external sources of knowledge. This makes the human capital component an indispensable part of the firm. The human capital theory (Becker, 1964), posits that the human capital stock of a firm, in itself, a function of eduacation and experience is a source of firm productivity which is a manifestation of knowledge acquired. In a study coducted by Mehralian, Nazari, Akhavan and Rasekh (2014), it was revealed that the most important factor that influence the knowledge creation process id human capital. The authors further makes the argument that the relationship between intellectual capital and the knowledge creation process is mediated by human capital.

In the same vein, research and development has been given prominence as an important source of knowledge. There is a plethora of studies that have attributed the variation in knowledge to changes in R&D spending. There is a long-standing consensus among researchers that R&D is important for the creation of knowledge. There is a theoretical as well as empirical support for the important role R&D in knowledge creation. Theoretically, the knowledge spillover theory of entrepreneurship recognizes the role of R&D in the creation of knowledge (Acs & Sanders, Patents, knowledge spillovers, and entrepreneurship, 2012). Empirical literature is consistent with theoretical literature. In a study by Vila, Cabrer, and Pavia (2015) the authors showed that R&D spending is important in the knowledge creation process. This is not an issolated findings. The literature generally shows that there is a consensus among authors on the important role of R&D spending in the knowledge creation process.

Another aspect of the economics of knowledge that is worth discussing is the distribution of knowledge in space. Knowledge or innovation is not concentrated; it is dispersed across space. The literature account indicates that globalization has influenced the distribution of R&D across geographic areas (Lahari, 2010). R&D, being an important determining factor of knowledge has further influenced the distribution of knowledge. The position of the literature is that distribution of knowledge is not balanced geographically, some geographical areas are more endowed than others (Castellacci & Archibugi, 2008). The uneven distribution of knowledge and technology among countries has been an important reason why some countries are more competitive than others. There exists a sharp cross-country difference in the distribution of knowledge and innovation. This has been the source of the sharp differences in the distribution of wealth across the globe. Based on the long-held view of the positive relation between knowledge held by groups and group performance (Shaw, 1981), recent studies have modeled performance of firms and growth of economies as a function of the available technology (Mabula & Han, 2018; Erumban & Das, 2016; Stuart, 2000). **An important recognition by the knowledge literature is that human capital and R&D are the basis of knowledge creation.** This is anchored on both theoretical and empirical basis. Theoretically, Schumpeter's growth model has been an important basis why R&D is assumed to be the driving force behind knowledge creation and innovation. From the Schumpeter growth model, the underlying source of technological progress is the research sector and human capital (Goren, 2022). This is in line with Romer (1986) growth model. In the Romer (1986) model, knowledge is modelled as a function of human capital. In later years as we can see from current literature on innovation, knowledge has been modelled as a function of both human capital and investment in R&D.

1.2.4 Knowledge Diffusion

Knowledge originating from a source can be distributed by transfer or by a spillover. The innovation literature treats these two diffusion channels as distinct as both have different implications on the effect on both the beneficiary and originator of the knowledge. In this study, even though the focus is on knowledge spillover, the distinction is important to make clear what knowledge spillover is and what is not since the line between these two concepts is faint and the confusion must be cleared. In the innovation literature the split between the two types of knowledge diffusion is based on market mediated channels and non-market mediated channels (Mowery & Ziedonis, 2015). Non-market mediated channels of knowledge diffusion are the channels that do not reflect exchange of knowledge for compensations whilst market mediated channels are the knowledge diffusion channels that are transactional in nature and the exchange of knowledge is for full compensation (Mowery & Ziedonis, 2015). Typically, in extant literature, the two divides of knowledge diffusion define knowledge spillover which is not market oriented where the beneficiary of such knowledge does not compensate the originator. However, the case of market mediated diffusion channels is such that the beneficiary of the knowledge is in a contractual agreement with the innovator and the beneficiary of the knowledge fully compensates innovator. Knowledge spillover, contrary to knowledge transfer is an externality (Antonelli, Patrucco, & Quatraro, 2011) in that the beneficiary of such knowledge does not fully compensate the owner of the knowledge. The distinction between knowledge spillover and knowledge transfer, even though may seem blur, the channels used and the extent of compensation for the use of another firm's knowledge shows a clear distinction between the two knowledge diffusion channels. When the channels are market mediated requiring full payment for the use of the knowledge, the diffusion is a knowledge transfers, but it is knowledge spillover when it is not market mediated and does not require full payment for the use of knowledge. Here emphasis is on market mediated knowledge and not product. As will be shown later in this review, market mediated products can transmit knowledge in the form of knowledge transfer by way of pecuniary knowledge spillover.

1.2.5 Knowledge Spillover

As argued earlier in this study, the literature posits that knowledge is either embodied in the individual with the knowledge or resides in the output generated based on the available knowledge. The nature of knowledge, whether embodied or disembodied, is important in determining the extent to which knowledge generated from a focal firm can find its way to another entity that did not contribute to the creation of the knowledge. This captures the essence and meaning of knowledge spillover. Romer's model of growth as well as other models that emerged later have recognized the importance of knowledge. **Whereas Romer (1986) explained that human capital spillover drives economic growth, models that emerged later suggest that economic growth is a function of spillover from R&D investment (Henderson, 2007)** has become important for economic growth. The Romer (1986) idea as well as more recent models of growth agree to the role of knowledge spillover but diverge on the channels of knowledge spillovers. Whereas in the case of Romer (1986) mobility of labour provides the channel of knowledge spillover, the other models suggest knowledge spillover is transmitted through means other than labour mobility.

The concept of knowledge spillover is grounded in growth theories. The concept has been explained to mean an externality in the knowledge generation process. Thus, economic agents make gains from other entities' R&D activities. **From the knowledge spillover theory of entrepreneurship, it is known that knowledge spillover is a consequence of the inability of the originator of knowledge to fully appropriate knowledge (Audretsch & Lehmann, 2005)**. This is important in distinguishing knowledge spillovers from knowledge transfer. Knowledge spillovers should be viewed as a leakage rather than a mere transfer. The latter could only mean knowledge spillover when such a transfer is not a deliberate action by the originator of knowledge. This distinction is important to set knowledge spillover from other knowledge transfers that are a consequence of collaboration or a transfer as an altruistic measure. Knowledge spillover must necessarily be an externality, where an economic agent makes gains from another agent's R&D activity without commensurate payment. Such a transfer must not be altruistic in nature, but the beneficiary makes gains because the owner of the knowledge has not been able to fully block access to the knowledge. It is important to note that whereas knowledge spillover has generally been considered as a positive, such a unidirectional flow of knowledge represents a cost to the originator of knowledge. For example, the literature account suggests that Multinational entities (MNEs) see as negative such unintentional leakage of their intellectual property (Mariotti, Piscitello, & Elia, 2010).

The extent of knowledge spillovers have been observed to be determined by several factors as suggested by the prior literature. **Knowledge spillover is not confined to a specific locality of knowledge, it has been argued that knowledge can cross local boundaries (Mariotti, Piscitello, & Elia, 2010)**. The question of whether knowledge spillover is a local phenomenon or crosses local boundaries is a subject matter of this study and will be discussed in detail at a later stage. However, this is a subject matter that has engaged the attention of authors in knowledge spillover and innovation since the works of Jaffe, Trajtenberg and Henderson (1993) and Audretsch and Feldman (1996). These authors provide a contrasting view of the knowledge spillover. Whereas Jaffe and his colleagues believed that knowledge spillover is between related technologies, Audretsch and Feldman (1996) argue that knowledge spillover is within clusters, the further away one moves from the source of knowledge the less likely there will be knowledge spillover.

1.2.5.1 Types of Knowledge Spillovers

The literature on innovation distinguishes between two types of knowledge involved in knowledge spillovers. There is a pure knowledge externality and pecuniary knowledge externality. This distinction has become critical in the study of knowledge spillover. A study conducted by Scitovsky (1954) introduced the concept of pecuniary externality and set it apart from technological externality where the authors states that pecuniary externality involves are benefits accruing from activities of other through a market mediated channels whereas technological externalities are benefit from others not mediated by market mechanism. Griliches (1992) provided a more detailed explanation to the distiction between pure knowledge spillover and peuniary knowledge spillover. He explained that pure knowledge spillover occurs when technological ideas are diffused to another gaent without compensation to the originator. On the other hand pecuniary (rent) knowledge spillover occurs when new or improved inputs are sold but the producers are unable to fully appropirate the increased quality of the products. This means that whereas pure knowledge spillovers are non market pecuniary knowledge spillover are mediated by market process. A clear disticntion between the pecuniary knowledge spillover is that whereas pure knowledge spillovers can be seen as knowledge that retains all the tenets of a pubolic good, because pecuniary knowledge spillover is mediated by market mechanism, the element of publicness is eroded. Access to the knowledge in the case of pecuniary knowledge is tied to access to the product in which the knowledge is embeded. The price of the product therefore make the embeded knowledge excludable and rivalrous. In the case of pure knowledge spillover, the knowledge invoved is disembodied as they are not attached to any product or service but are rather ideas of an aggent that positively impact the activities of another (Breschi, Lissoni, & Montobbio, 2005). Even though this distiction is releveant for theoretical and policy purposes, the empirical literature has not been able to statistically make this distinction except on few occasssions. This has contributed to the errors in the measurement of knowledge spillover. Griliches (1992) expressed this when he stated that in the estimation of R&D productivity based on the knowledge production function, the pure knowledge spillover is over estimated whiltst the pecuniary knowledge spillover is underestimated. The inability of the empirical literature to make this distiction is an important source of error in the measurement of knowledge spillovers. “The Point however, is that most of the econometric tests produced so far within the knowledge production function approach are observationally equivalent with respect to the role of the two kinds of externalities, i.e. they are unable to separate their respective effects” (Breschi, Lissoni, & Montobbio, 2005, p. 2). It is however, important to note that whereas the pure knowledge spillover correspond to nonrivalry and non-excludability in the case of pecuniary knowledge spillover it is more as a result of exchange of goods and services (Griliches, 1979) that takes away the public nature of knowledge. What is critical here is that, the knowledge is still an externality in so far as the beneficiary, even though, pays for the product within which the knowledge is embedded he does not pay for the knowledge. The main distinction between the two knowledge externalities is that in the case of pecuniary knowledge externality it originates solely from economic transactions whereas pure knowledge externalities are not embodied in economic transactions (Griliches, 1979).

1.3 Channels of Knowledge Spillovers

The channels of knowledge spillover are generally the different methods of learning about a competitor’s technology (Harabi, 1997). The literature recognises that there is a plethora of means through which knowledge spillover can occur. Harabi (1997), in a study to identify the effectiveness of channels of R&D spillovers revealed that there are several channels through which knowledge spillover over occurs. The author showed that there are several of these channels with varied effectiveness. Independent R&D was identified as the most effective R&D spillover channel followed by reverse engineering for product. The authors also showed that other channels identified including publications and information from technical meetings for process innovations, conversations with employees of innovating firms and hiring of employees from innovating firms which are interpersonal in nature. From the findings of Harabi (1997), knowledge spillover channels are either interpersonal or non-interpersonal. Interpersonal knowledge spillover channels are learning methods based on interpersonal communication. R&D has been found to have two faces, apart from being a source of innovation, it is also a source learning competitor’s innovation which are usually superior knowledge in the market

(Eliasson, 1994; Cohen & Levinthal, 1989). The study at this point presents a discussion of the channels of knowledge spillover in turn.

1.3.1 R&D Channel

R&D expenditure of firms is generally considered to be geared toward conducting research to develop new goods, services and processes. **However, it is known from the findings of Cohen and Levinthal (1989) that the other important role of R&D expenditure is to allow the firm the capacity to learn competitors' innovation activities.** This means that rather than to think of R&D as a means to generate innovation internally we can perceive R&D a means by which firms are able to tap into the knowledge stock of other firms. The literature shows evidence that firms that in firms with high internal R&D, there is high absorptive capacity that allows tham to learn and pursue development in new technological field (Choi & Lee, 2021). R&D intensity of the firms gives the firms the learning capabilities to imitate what others do or the reengineer what the competitors have done. In a study by Cuervo-Cazurra, Nieto, Rodríguez (2018), the authors showed that the extent of R&D diversification to include private business R&D, **Government R&D and outsourcing R&D determines the absortive capacity and the extent to which firms are able to absorb spillover from FDI.** It is important to state that each of these sources of R&D bequeath different capabilities and at different degrees to a firms that allows that firm to absorb and access different knowledge sources at different degrees. It has been argued that when firms continue to conducts research and development activities firms accumulate technological competences that narrow the knowledge gap between receiving and trafering firm's knowledge which provides the basis for knowledge exploitation (Lin, 2014; Grifth, Redding, & van Reenen, 2003). Lin (2014) further in a complicated learning process, a strong R&D base of a firms becomes a critical remedy to navigate the learning process to ensure a firm is able to learn and imitate what other firms are able to do. Another aspect of the diversity of a firm R&D is government R&D. In the view of Foray, Mowery and Nelson (2012) government R&D is normally geared towards achieving specific technological breakthrough which serves as an avenue for government to injects resources into firms to reduce firms' R&D burden and improve their knowledge base. The signaling effect of government R&D to firms cannot be ignored. In a study by Kleer (2010), the author showed that government R&D provides a signal to foreign firms about the potential of local firms as a means to link local firms to foreign to access external knowledge. Authors such as Radas, Anić, Tafro and Wagner (2015) and Foray, Mowery and Nelson (2012) observed that government R&D for firms in a particular technology area provides information is a technology performance that could be used as a channels to attract external knowledge through FDI. The other aspect of R&D identified by the prior literature is R&D outsourcing. In a study by Guo, Ning and Chen (2022), the authors explained that R&D outsourcing is an external R&D borne out of contractually paid R&D conducted by an external entity for a firm. Apart from the fact that this type of R&D improve the absorptive capacity of the contracting firm (Denicolai, Ramirez, & Tidd, 2016; Murovec & Prodan, 2009), the network formed with the external entity becomes a channel through which knowledge can spillover to the local firm (Cuervo-Cazurra, Nieto, & Rodríguez, 2018). The R&D activity of firms therefore presents several important channels through which spill over knowledge can reach a firm.

1.3.2 Reverse Engineering

Reverse engineering as a channel of knowledge spillover can be seen in simple terms as imitating what has bee done by anather entity. In a study by Kraft and Rammer (2023), **the authors explained that reverse engeneering to mean a reconstruction of a product including process technology**. The authors futher expalined that when products are disassembled the technical properties become known and imitating the product becomes possible. In agreeing with reverse engineering as a channels for knowledge spillover, **Zhang and Zhou (2016) showed that reverse engineering has been used as a means to learn to improve existing products competitors**. Zhang and Zhou (2016) also explained that China investment in overseas technology are geared towards reverse engineering products and using the knowledge to create new and superior products. Reverse engineering will require that the process of making the product is understood. Nathan and Sarkar (2014) have shown that reverse engineering is a process innovation that use cheap R&D to achieve product innovation. Reverse engineering is a way a firm’s R&D enable learning by studying product innovqation of others. The literature has shown that reverse engineering involves adopting and adapting existing knowhow by extracting knowledge from autopsies of final product (Eun, Lee, & Wu, 2006; Samuelson & Scotchmer, 2002). This makes reverse engineering as a channel for knowledge spillover non interpersonal as it does not involve a person from the innovating firm. The two faces as explained by (Eliasson, 1994; Cohen & Levinthal, 1989) will suggests that learning from the autopsy of a product can only happen when the R&D of the learning firm improve their absorptive capacity to be able to understand a product’s knowledge.

1.3.3 Hiring away Employees from Innovation Firms

The institutional memory of firms is held by the individual employees of the firm. When a firm engages in R&D and innovation activities, the memory of such innovation activities is held by the individual employees and may this memory with them when they are hired by another organization. Hiring employees of an innovator is considered one of the important channels of knowledge spillovers (Harabi, 1997). Harabi (1997) noted that hiring employees of an innovator is an interpersonal knowledge spillover source because it involves person to person transmission of knowledge, or the spillover is through individual employees. Labour mobility across firms is acknowledged as one of the channels of knowledge spillover. In a study by Mika, Pierre and Petri (2008), the authors showed that when firms hire employees who worked in the innovator's R&D lab of the innovator is employed in a non-R&D sector of a firm, they increase productivity of firm which the authors interpreted as transmitting knowledge. However, Mika, Pierre and Petri (2008) showed that recruiting the innovator's R&D staff of the innovator to ones own R&D lab did not prove to be significant R&D spillover channel. This may suggests that recruiting R&D staff of a competitor to ones own R&D sector requires that the R&D staff adjust with time to be effective to ensure spillover. This confirms the adjustment cost of R&D (Bloom, Griffith, & Reenen, 2002) that is known to lag the effect of R&D spillover. Another interpretation that can be given to the findings of Mika, Pierre and Petri (2008) is that R&D spillover translates faster through the employee mobility channel when spillover knowledge is such that it can be applied directly than when the knowledge will have to be adapted. **It is important to note that hiring employees of the innovator or the employee mobility channels of knowledge spillover in a study by Harabi (1997) was found to be only moderately effective in Switzerland**. The author attributed this to cultural and transparency in the Swiss labour market. However, a large portion of the literature has shown that interfirm labour mobility as one of the most important channels of innovation. In a study by Kim and Marschke (2005), the authors showed that the turnarover of employees is an important source of small firm patent rate. Kim and Marschke (2005) observed that firms reduce their R&D investment because of firm's anticipation that employees mobility will diffuse knowledge and raises the propensity for firms to patent. In a related study Franco and Filson (2006) showed that start up firms rely on technological know-how of incumbent firms' through the incumbent firm's employees. Franco and Filson (2006) confirms Kim and Marschke (2005) ascertion that eventhough employee mobility is a channel for knowledge spillover, the fear that their technological know how will diffuse through their employee negatively affect the amount of resources deployed for R&D.

1.3.4 Trade as a Channel of knowledge Spillover

Closely associated with reverse engineering as a channel of knowledge spillover is the product that is being diassembled and learnt. The question that requires an answer is obviously is the process that brings the product to allow the learning to take place. **The literature on knowledge spillover acknowledge the importance of trade in the transmission knowledge** (Grossman & Helpman, 1991; Rivera-Batiz & Romer, 1991; Grossman & Helpman, 1990). In a study by Keller (2021), the authors stated that import of intermediate goods is an important source of foreign knowledge spillover for countries with capabilities to learn from such intermediate goods. It is known that embodied in goods imported are technologies that can be learnt given the R&D of the receiving firms (Rivera-Batiz & Romer, 1991; Grossman & Helpman, 1991; Grossman & Helpman, 1990). Keller(2021) argues that the source of a country's import is important for knowledge spillovers. He argued that when imports are from a relatively high R&D source the knowledge spillover is higher than when goods are imported from low R&D source. This makes economics sense in that firms and countries will learn more from countries with superior knowledge than countries or firms with inferior knowledge. Countries with higher R&D are generally in a position to innovate and produce goods and services that are new and carry new technology essential for the development of innovation in other countries and firms and therefore a candidate for knowledge spillover.

1.4 Measuring Knowledge Spillovers

Measuring knowledge spillover is considered a daunting task to undertake. The literature presents a number of ways of measuring knowledge spillover. The knowledge spillover measures have gone through evolution with the aim of improving the measurement of innovation.

1.4.1 The knowledge Production Function Approach

Griliches (1979) introduced the knowledge production function to measure the contribution of R&D and to measure knowledge spillovers and their contribution to productivity growth (Fritsch, 2002). **The basic assumption of the knowledge production function approach to measuring knowledge spillover is that innovation output is a function of R&D investment:**

$$R\&Doutput = a(R\&D\ input)^{b} \qquad (1)$$

Applying the double logarithmic to both sides of equation 1 produces the R&D output elasticity in responses to changes in R&D inputs. Griliches (1979) states that R&D input is internal R&D and external R&D coming from other firms or regions (Fritsch, 2002). In a study by Fritsch

(2002), the author showed that the logarithmic transformation of equation (1) results in equation (2):

$$ln\ R\&Doutpu = ln\ a + b\ ln\ R\&D\ input \quad (2)$$

An inclusion of regional knowledge spillover pool variable to equation 2 is a measure of knowledge spillover (Fritsch, 2002). For example, in a study by Fritsch and Franke (2004) to investigate the impact of knowledge spillovers and R&D cooperation on innovation activities in three German regions, the authors used the knowledge production function approach by extending equation 2 to include three knowledge spillover pools as in equation (3):

$$\ln\ R\&Doutput = \ln\ a + \beta_1 \ln\ R\&D\ input + \beta_2 \ln R\&Dsameind +$$
$$ln\ \beta_2 R\&Dexpbrs + ln\beta_3 ext_{funds_{PRI}} + Cont + \varepsilon \quad (3)$$

Equation 3 is the extended knowledge production function in equation to include three knowledge spillover pools, R&D expenditure in the same industry ($R\&Dsameind$); R&D expenditure in business related service ($R\&Dexpbrs$) and external funds attracted by public research institutions ($\beta_3 ext_{funds_{PRI}}$). Fritsch and Franke (2004) interpreted the associated coefficients, β_1 , β_2 and β_3 as the size of the knowledge spillover. Kaiser (2002) condensed equation 3 into the basic model in a study and explained that production function approach regresses the innovation output on spillover pool as in equation 4:

$$s_i = \sum_{j \neq i}^{N} k_j \quad (4)$$

In equation 4, Kaiser (2002) explained this model to mean that *N* is the number of firms both within and without the firm's sector, K_j is the stock of knowledge for firm j and S_i being the firm's own stock of knowledge. The firm's own stock of knowledge, S_i has been captured in the literature by several variables. This according to Kaiser (2002) is dependent on the interest of the reseacher and the available data. In the view of Kaiser (2002) other variables that can adequately proxy firm's own stock of knolwedge include the number of patent count of a firm, innovation expenditures, R&D investment, R&D capital stock which must ordinarily in their lag forms and R&D personnel. To find a proxy for *K*, Kaiser (2002) explained that the type of knowledge, whether the knowledge that is being spilled is tacit or explicit is an important consideration. Given the data used by Kaiser (2002), the author proxied *K* the number of R&D employees and innovation expenditure.

Even though the knowledge production function can be complemented for its simplicity, its simplicity makes the approach simplistic and therefore lacks the regour and robustness to make it a good measure of knowledge spillover. For example Bernstein (1988) showed in a study the major set back of the knowledge production approach to measuring knowledge spillover. The author makes reference to equation 4 which suggests that all firms or countries gain equal amount from the knowledge pool. Besides, this approach relegates the importance of the R&D of firms and distance between firms and their technologies in measuring knowledge spillover to the background. **The quest to improve this basic approach to measuring knowledge spillover to account for the role of distance between firms, countries and regions in a knowledge spillover space, has ushered into the knowledge spillover literature several approaches to measuring knowledge spillover including the Jaffe'(1988, 1986)** uncentered correlation approach, the Euclidean distance approach, the Branstetter approach and the other variants of the uncentered correlation and the euclidean distance approaches. These approaches impose weight (distance between entities in knowledge spillover space or plane). This then transform equation 4 as follows:

$$s_i = \sum_{j \neq i}^{N} \omega\text{ij}\, k_j \qquad (5)$$

In equation 5, ωij is a measure of the distance between the entities in the knowledge spillover plane or space (Kaiser, 2002; Encaoua et al. 2000; Jaffe 1988,1986). The literature on knowledge spillover define this weight as either physical distance or technological distance between entities in the knowledge spillover plane.

1.4.2 Uncentered Correlation Approach

The uncentered correlation approach to measuring knowledge spillover by Jaffe (1988, 1986) is an improvement of Griliches (1979) knowledge production fucntion approach to measuring knowledge spillover by introducing weight as a measure of technological distance. The main idea behind the uncentered correlation approach to measuring knowledge spillover is that firms related in terms of technology are more likely to experience knowledge spillover than firm that are not related.

Jaffe (1988,1986) developed this idea into measuring the technological distance between firms. **The original uncentered correlation is a measure of the extent to which the patent portfolio of two firms are similar** (Encaoua, Hall, Laisney, Mairesse, & Branstetter, 2000). Encaoua et al.(2000) explained futher that the technological distance between two firms i and j as used by

Jaffe (1986) is approximated by ω_{ij} which is the uncentered correlation of the F vectors of the two firms. The weights are estimated as follows:

$$\omega \text{ij} = \frac{f_i f_j'}{[(f_i f_i')(f_j f_j')]^{\frac{1}{2}}} \tag{6}$$

Where f_i and f_j are the researchers' technological variable of interest for i and j but patent citation in the case of Jaffe(1986, 1988). From the uncentered correlation weighting as a measure of technological distance as presented in equation 6, the focus is to estimate a similarity coefficient between the R&D of firm i and firms labeled j and constituting the spillover pool of knowledge (Encaoua et al, 2000). Equation 6 gives a figure between 0 where there is no similarity or overlap between the technologies of i and j to 1 where there is perfect overlap in their technologies. The closer two different entities are within a technological space the higher the possibility of one entity's research activities affect the others researh outcomes (Cincera, 2005). In the case of Jaffe (1986), the f vector is patent citation data that naturally comes with the problem that patent citation is not a true measure of innovation as it could underestimate knowledge spillover. Again, even though this seeks to cure the problem of the inability of the knowledge production function approach to determine the extent to which differences in firm and country characteristics can influence knowledge spillover, the use of cosine similarity in equation 6 as a measure of similarity between firms is problematic. It is important to under score the fact that technological distance is basically a measure of the difference between companies' technological knowledge bases (Gilsing et al.,2008). The uncentered correlation as a measure of similarity is actually an angular separation between a technological vector of two firms (Cincera, 2005). **The questions that remains to be answered is whether this is a true and good measure of technological similarity?** Technologies are similar when the technologies are related and in the same or similar fields, a phenomenon that is not fully determined by using cosine similarity as is done in the uncentered correlation analysis. **An important draw back of the uncentered correlation approach as highlighted by Cincera (2005) is that the uncentered correlation is symmetrical, the technological from A to B for example is the same as from B to A**. The challenge with this symmetric indexation is that ωij in equation 6 is a measure of the extent of knowledge i will draw from j in equation 5 or 4. It cannot be that both i and j are drawing the same from each other or from the same pool. The role of R&D as a measure of firm's absorptive capacity is suppressed by the uncentered correlation approach. Even though the uncentered correlation approach to measuring knowledge spillover is touted as one of the most used, there are some important challenges that limits its efficacy as a measure of knowledge spillover. Jaffe (1986) also hinted of a limitation with the uncentered correlation approach. By the nature of the approach, firms that are technologically diversified are at the center of the technological plane relatively far away from group of firms that are not diversified. However, in reality diversified firms have their patent and R&D distributed evenly across sectors are therefore able to draw from all technological classed. Even though the uncentered correlation is considered an important approach, these limitations have ushered newer versions of uncentered correlation that have attempted to improve the uncentered correlation.

1.4.3 Encaoua et al Approach

In a study conducted by Encaoua et al (2000) which replicated the idea of location in a technological space, the authors argued that the firm's R&D activities can be decribed by vector f_i where $f_i = (f_1 \dots \dots \dots f_k)$. Each of the elements f_i up to k defines the R&D resources and expertise in the k-th techological area. Consistent with Jaffe(1986), Encaoua et al (2000) determined $f_1 \dots \dots \dots f_k$ by inference from the number of patents in the different technological fields but also included technological expertise. Encaoua et al (2000) makes some changes by also including expertise of the different technical field. Jaffe(1986) model has therefore been adjusted with time to accommodate newer R&D inputs to make the model reflect changing trends in the R&D space and to reflect reality. Other studies, even though have used the Jaffe (1986, 1989) uncentered correlation, the authors have made some variations.

1.4.4 Branstetter Approach

In a study to investigate foreign direct investment as a channel of knowledge spillover using evidence of Japan and United State, **Branstetter (2006) used the aggregated patent count obtained by Japanese firms from the United States.** This is a variation from the original Jaffe (1986, 1989) approach. In this case the various cartegories of technologies are aggregated into f_i and f_j for US and Japan respectively in equatia on 6. This approach allows the Branstetter approach to treat all US firms as though the belong to one entity. Branstetter also argued that variables that enter the the weighting indexation (ωij) as in equation 5 must be consistent with the knowledge pool (k_j) in equation 5. This approach cures the arbitrariness in the choice of variables the enter the estimation as suggested by Kaiser (2002). Besides, in the view of Branstetter (2006), this consistency is important to make the weight relevant to the spillover pool.

In emprical works where the uncentered correlation and its variants as weights of technological distance have been used, s_i in equation 5 is entered into a production funtion for the i-th firm as a covariate for international spillover pool. These production function are modeled along the lines of equation as given by Antonelli, Patrucco and Quatraro (2011) where the production function recognises the three part covariates as the demand side inputs, the external R&D inputs and the internal R&D inputs where the explained variable is a knowledge output variable. For example in Encaoua et al, (2000), the authors regressed innovation on firm's own R&D representing internal innovation input, domestic spillover and international spillover pools representing external innovation inputs analysed using fixed effect model. Explicitly left out is the demand side factors explained by Antonelli, Patrucco and Quatraro (2011) is the demand side factors. However, the fixed effect model estimated by the authors, theoretically controls for unobserved variables that will include these demand side factors not explicitly specified in the model. In Jaffe's 1986 original application of the uncerntered correlation to determine knowledge spillover, the author regressed firm's innovation on four covariates, firm's own R&D, domestic spillover pool and interaction term between own R&D and external R&D to capture the effect of R&D spillover in improving the productivity of firm's own R&D. Jaffe (1986) estimated a fixed effect model and found domestic spillover to have positive effect on firm's productivity. The results of Jaffe (1986) is that own R&D is an important reason why firms will benefit from spillover from neighbouring firms in their technological space.

1.4.5 Physical Distance Approach

There is another strand of literature related to knowledge spillover measurement that suggests, just as in the case of Jaffe (1988,1986) and others who believe in the use of uncentered correlation to capture a weight of characteristics a firm must poses to be able to access the pool from related firms. **This group of authors have shown that physical distance between entities, firms or economies are important reason why knowledge spillover will occur or not occur. Keller (2000) recognised the importance relationship between firms in knowledge spillover as suggested by Jaffe(1988,1986).** However Keller (2000) departed from Jaffe's technological distance weight and rather suggested that physical distance between firms and countries. Since then several variation of distance weight have been estimated. In more recent times the role of physical distance in knowledge spillover has been modelled and one of the most appealing intutively specification is by Abramo, D'Angelo, & Di Costa, (2020) in a study to investigate the effect of geographic proximity on knowledge spillover across research fields. Abramo, D'Angelo, & Di Costa, (2020) spillover variable of interest is the number of citation to publication. The model is based on the gravity model where distance is seen as a source of friction and therefore modelled as an inverse function to spillover as follows:

$$C_{ij} = k * \frac{M_i^{\alpha} M_j^{\beta}}{d_{ij}^{\gamma}} \quad (7)$$

Abramo, D'Angelo, & Di Costa, (2020) defined C_{ij} as the number of publication citations made in articles in location i sourced to publications in location j. k is a constant term whilst M_i is the number of publication made in location i and M_j represents the number of publications made in j. The authors also defined the distance between the location of i and the capital of j by d_{ij}. The parameters estimated by the authors are γ,β and α. The authors, using log-log model found that citations decrease with increasing distances. This suggests that the further apart econmic agents are the lower the knowledge spillover. This is consistent with intuitive thinking and the technological distance approach by Jaffe (1988, 1986) with the main difference being that the variable that detrmines the association is no more technological distance as in the case of Jaffe but physical distance. Applying double log to equation 7 simplifies the model into equation 8 below:

$$lnC_{ij} = lnk + \alpha lnM_i + \beta lnM_j - \gamma lnd_{ij} + \varepsilon \quad (8)$$

The interpretation Abramo, D'Angelo, & Di Costa, (2020) put on the distance coefficient (γ) as measure of knowledge spillover is that an elasticity of one (γ=1) is that a proportionate change in distance by one per cent is associated with one per cent decrease in citation spillover.

1.4.6 Euclidean Distance Approach

Another important variant to the distant based matrix to measuring knowledge spillover is Euclidian distance appraoch by (Inkmann & Pohlmeier, 1995) who explained that technological distance between two entities must be estimated to allow two or more entities in the knowledge spillover process to be leading and lagging in a technological space. **The argument proponents of euclidean distance appraoch to measuring knowledge spillover make is that it is easy for technologically leading entities to tap into lagging entities knowledge through spillover but the lagging entities draw more on the average from the technologically leading entities (Kaiser, 2002)**. This position from these proponents is counter intutive considering the role of R&D in both innovation and ability to learn from others' technology. It is known that R&D play two main roles, innovation and learning (absorptive capacity) (Eliasson, 1994; Cohen & Levinthal, 1989). This means that the low R&D of technologically lagging which explains why firms and countries are not able to be innovative to contribute to the knowledge pool is the same reason why they cannot absorb technologies from other entities. The position by the euclidean approach proponents is however in tune with Coe and Helpman (1995) who makes the point that knowledge spills from high R&D concentrated zones to lower R&D concentration zones.

In computing the technological distance or weight ω_{ij} in the analogy of Jaffe (1986) in equation, Inkmann and Pohlmeier (1995) in the estimation of the euclidean distance weight used vector of firm characteristics such as firm size demand expectation and sectoral affiliation. Inkmann and Pohlmeier (1995) computed the technological distance based on the euclidean distance approach as follows:

$$\omega_{ij} = \sum_{p=1}^{p} \sqrt{\left(\frac{x_{ip} - x_{jp}}{SD.(x_p)}\right)^2} \quad (9)$$

In the estimation of equation 9 ω_{ij} according to Inkmann and Pohlmeier (1995) ranges from 0 where the entities involved in knowledge spillover are identical to infinity where the entities are different. In the context of euclidean distance the larger the ω_{ij}, the higer the entity draws from the pool of knowledge.

1.4.7 Social Network Analysis

At present, social network analysis remain one of the effect ways of measuring knowledge spillovers. The mobility of R&D scientists is considered a source of knowledge exchange forming a network of cross firm and cross border knowledge spillovers (Breschi & Lissoni, 2005). Social network analysis is based on the social exchange theory which states that the interaction between actors is the main reason for knowledge spillover (Cropanzano & Mitchell, 2005). Actors are connected to each other through interaction, forming a network of interdependence called a social network. Co-located actors in the same region get embedded in a thick web of social ties forming a channel for tacit knowledge spillover (Breschi & Lissoni, 2005). The social network analysis approach to measuring knowledge spillovers is based on the thinking that interaction between inventors of different entitie drive knowledge spillovers (Zacchia, 2020).

From the various approaches of measuring knowledge spillover, the variations in the measures ranging from the similarity measure, the pool of knowledge from which the different countries access knowledge brings differences in the knowledge spillover measurement outcomes depending on the measure used. It is important at this point to point out the challenges of the different measures of measuring knowledge spillovers.

1.5 Challenges of Knowledge Spillover Measures

In the Jaffe (1986) uncentered correlation approach to measuring knowledge spillover, the use of patent data presents a problem as not all inventions are patented (Kaiser, 2002). Authors such as Kaiser (2002) who has tried to deal with this problem of patent replaced patent as a measure of technological proximity by university and technical college graduates, workers with completed vocational training and unskilled labour in the total work force, expenditure for continuing education and vocational training of the employees per employess, labour cost per employee, investment. These corrective measures in themselves presents other problems as they are not wholistic and encapsulating. For example, these measure used by Kaiser (2002) focus only on pure technological knowledge and totally neglect pecuniary knowledge sources and therefore potentially underestimate knowledge spillover. The choice of variable that is used in estimating the pool of knowledege is also an important source of concern and a source of challenge. In equation 6 the pool of knowledge stock or the pool of knowledge, K_j has been proxied by various variables by different authors depending on the available data. For example in the Jaffe (1986) approach to measuring knowledge spillover K_j is proxied by patent count whilst in the case of Branstetter K_j is R&D. Some other authors have proxied K_j by measures that focus on pecuiary knowledge. These measure have introduced some incosistencies in the outcomes of the knowledge spillover measured. For example Branstetter (1998) used R&D spending as the pool of knowledge whereas Jaffe (1986, 1988) used patent citation and Adam(1990) used share of research scientists. The multiplicity of measured to represents the knowledge stock from which the individual firms or countries tap the knowledge complicates the computations of knowledge spillover and most importantly lead to incosistencies in knowledge spillover measures.

Post Scherer (1982) and the extention made to it by Jaffe (1986, 1988) there ha been a growing penchant for technology proximity in the estimation of knowledge spillover. Even though technological proximity provides the weight provides an indication of the extent to which a country or firms is able to draw from the knowledege pool otherwise the knowledge spillover assumes all firms or countries draw equal amount of knowledge from the pool (Kaiser, 2002), it presents a source of great distortion and inconsistencies among the various measures of knowledge spillovers. For example there are as many ways of computing these weights as there are different knowledgte spillover measures. Whereas the uncentered correlation approach to measuring technological distance considers the relatedness of technologies where perfect similarity takes the value of one when the technologies are not related the value is 0 (Kaiser, 2002), the euclidean distance approach measures the extent to which firm characteristics differ between firms (Inkmann & Pohlmeier, 1995). **These two approaches for measuring technological distance between firms or countries obviously lead to different outcome and hence differences in in knowledge spillovers.** Quite apart from this, in the euclidean distance approach there is no standadisation, the researcher decides which variables must be involved. This opens the flood gate for different variables to enter the weighting system depending on what the researchers wishes. The consistency of the measure is therefore compromised. Studies by Coe and Helpman (1995) have used bilateral trade between countries as weight. However, this has been criticised on the basis that such a weighting system make an assumption that trade is the main channels for the knowledge spillover (Branstetter, 1998). Even though the bilateral trade weight partly deals deals with the problem of unstandardised weight, it will only work for situations where trade is the primary channel for spillover. This is especially useful if the knowledge spillover is pecuniary in nature. However Keller (1996) after replacing the bilateral trade weights with random number and estimating Coe and Helpman (1995) analysis using same data the results of Coe and Helpman (1995) was replicated. The conclusion from Keller (1996) is that Coe and Helpman (1995) spillover estimates are doubtful. It is known from the e,prical literture that knowledge spillover weight use different bands or range making them incomparable. For example whereas the uncentered correlation weight ranges from zero to one, in the case euclidean distance the weight ranges from zero to infinity. Kaiser (2002), whilst praising the potency of the uncentered correlation approach to measuring knowledge spillover, the author derides the euclidean distance approach for being counter intuitive. (Kaiser, 2002, p. 133) has however, admitted that "Due to the non-measurability of knowledge spillovers, there is no natural way of testing which spillover pool construction is superior to the others". This is about the biggest challenge in empirical works on knowledge spillover. Authors are now left to decide which approach to use which further complicates the issue of measuring knowledge spillover as the choice of measure is gradually becoming arbitrary.

Geographic distance as an important variable in the measurement of knowledge spillover is sometime over emphasised. Different knowledge spillover types may be affected differently by geographic proximity. Lumping all knowledge spillovers together and treating them as one is erroneous. **For example, in a study by Lee (2019), the author argues that the effect of geographic proximity on knowledge spillover is only relevant when the knowledge**

involved is tacit which requires face to face interaction and not codified knowledge which can be be transmitted easily without distance friction. However, in most of the knowledge spillover measures, proximity between the knowledge source and beneficiary location is treated as a critical factor. **In the innovation literature, there is the admission that geographic proximity enhances the absorptive capacity of tacit knowledge (Breschi & Lissoni, 2001; Howells, 2002; Döring & Schnellenbach, 2006).** However, the literature stress that codified knowledge is not affected by geographic proximity. This is a confirmation that knowledge spillover measures such as Beise and Stahl (1999) which, inspite of the fact that the knowledge pool involved products integrated into the the knowledge spillover measure geographic proximity paints a wrong picture and actually underestimate knowledge spillover. Lee (2019) has been emphatic about the inappropirateness of using geographic proximity in knowledge spillover measures when the knowledge involved is not tacit such as patent disclosures, trade journals and fairs. He makes the claim that such knowledge spillovers are not sensitive to geographic distance.

Mispecification of the knowledge spillover models have been an important concern that have led to the miscalculation of the size of knowledge spillover. It is important to recognise that for lack of data on sector specific R&D expenditure, nost studies that have investigated R&D spillover between countries have reliedon agreggated data. One such culprate is Bernstein and Mohnen (1998) study, which for lack of data on R&D prices and capital goods prices that vary across sectors could not control for technological heterogeneity within the sectors. Rather the authors used used aggregated data to investigate R&D spillover between US and Japanesse R&D intensive sectors. The results of the study obviously will be biased and overstate the knowledge spillover. It is also important to state that most of the studies that have estimated knowledge spillover have been conducted in a static model. However, static models models assume that the knowledge spillover is a contemporaneous effect which to an extent defies economic logic. One would expect that knowledge spillover will have some adjustment cost and therefore a dynamic model that analyses the lag effect and as a consequence a long run effect will be important to determime the actual size of knowledge spillover over time. Empirical studies have shown that R&D is sluggish to changes in environment and requires time to have a real effect. Amendola (2023) argues that several factors are ascribed to the inertia with which R&D responds to new environment and therefore requires that such analysis be considered in the longrun rather than contemporaneously. Amendola (2023) emphasised strongly that relying on contemporaneous betas in any R&D effect analysis is highly misleading.

1.6 Regional Economics and Spatial Dynamics for Knowledge Spillovers

The knowledge spillover literature has shown that knowledge spillover does not just happen, the main precurser for knowledge spillover is proximity between the source of knowledge and benefitiary of the knowledge. Proximity can be viewed from two main perspectives, geographic or physical proximity and cognitive proximity.

1.6.1 Geographic Proximity and Knowledge Spillover

The literature on knowledge spillovers and how geography affects the extent of knowledge spillovers splits knowledge spillovers into their two main types. **The effect of geography varies depending on the type of knowledge spillovers considered.** Pure knowledge spillovers and pecuniary knowledge spillovers (rent spillovers) are distinguished in the knowledge spillover literature. The distinction between pure or technological spillovers and pecuniary or rent spillovers is widely accepted in the knowledge spillover literature (Gehringer, 2011), especially this distinction becomes an imperative when the effect of geography on knowledge spillover is being assessed. The geography of knowledge spillovers is also influenced by two main dimensions of knowledge, explicit knowledge and tacit knowledge. The general position of the extant literature is that knowledge spillover is geographically bounded (Autant-Bernard, 2001). This remains the basis for knowledge clusters (Audretsch & Feldman, 1996) which is network of interdependence among firms and countries and source of knowledge spillovers.

The location of an entity in a cluster determines how much knowledge an entity can generate from others in the cluster (Malmberg & Power, 2005). It is argued that interaction within clusters is what determines the extent of knowledge diffusion. The more an entity is centrally located in the cluster the more the interaction relative to entities in the periphery. The characteristics of location an entity is, or the geography of an entity's location determines the extent of interaction in the cluster and knowledge spillover gains the entity makes. Geography is therefore considered central to knowledge spillovers.

Based on Marshall's explanation on localized external agglomeration economics (Marshall, 1920), local information and knowledge spillovers are the main reason for the growth of entities in the clusters. **Being in an advantageous position in the cluster determines the amount of spillover gains that accrue to an entity.** The general hypothesis in empirical literature is that geographic regions with industrial clusters pose some performance advantage due to access to knowledge spillovers (Gilbert, McDougall, & Audretsch, 2008). For example, the empirical literature has shown that cluster firm's performance is usually higher than other firms because of the benefit from knowledge spillover (Bell, 2005). In a study by Gilbert, McDougall and Audretsch, (2008), the authors investigated the role of technological spillover on the performance of new ventures in cluster regions. The findings of the study showed that ventures within geographic clusters draw more knowledge spillovers than those located away from the clusters. This is a confirmation of the interaction between actors as a channel through which knowledge spillover occurs. It is also known that firms in clusters are normally very innovation as this is necessary to be able to withstand competion that exist in the cluster (Porter, 1998). Clusters are seen as important source of knowledge spillover with geographic locations close to the cluster being an incentive to knowledge spillover gains. Knowledge spillover in clusters is a function of proximity, the closer the entity is to the core of the cluster, the higher the gains of knowledge spillover. Entities in the periphery gain less from the knowledge spillover. Knowledge spillover is considered local, it takes place within the cluster and a movement away from the center of the cluster reduces the knowledge spillover effect (Huber, 2012).

The tacit knowledge or pure knowledge has generally been the basis for the argument that knowledge spillovers are geographically or spatially bounded (Breschi, Lissoni, & Montobbio, 2005). This is because when knowledge is considered tacit then the only way for a spillover to occur is through interaction with the knowledge source. The closer an entity is to the knowledge source the higher the interaction with the knowledge source and therefore the higher the knowledge spillover gains. Some of the most influential studies in the role of geography in knowledge spillovers have been Audretsch and Feldman (1996) and Feldman and Audretsch, (1999). Emprical studies by Audretsch and Feldman (1996) shows that knowledge spillovers cluster spatially. They argue that new economic knowledge, in the form of industry R&D, University R&D and skilled labour are more prevalent in co-located indutries because these industries are clustered together are learn from each other. The authors envisaged the complication of interprating knowledge among clustered industries as geographically based knowledge spillover because industries cluster also because of reasons such as production concentration. However, the authors, even after controlling for production concentration, the authors still found knowledge spillover to be geographically bounded. A related study by Feldman and Audretsch, (1999) also admits that knowledge spillover is geographically bounded, however, the authors also found that knowledge spillover withing a geographical space is also influenced by the type of economic activities the firms in the space are engaged in. The findings of Feldman and Audretsch, (1999) revealed that knowledge spillover within a geographical space is reduced when firms are specialised but there is higher knowledge spillovers where firms within the geographical space are diversed with complementary knowledge base.

The idea that knowledge spillover is geographically bounded is widespread and authors by consensus generally accept this hypothesis. This has been the bases of more modern approaches such as social network analysis in the investigation of knowledge spillovers. However, just like in the case of Feldman and Audretsch, (1999), there are some nuances such as technology base of firms, whether these technologies are complementary or not and in more recent times the role of digital tools that seem to reduce technology distances between firms. The main proponent of gergraphic proximity as the main determinant of knowledge spillover, (Jaffe, 1986), he brings the dichotomy between codified and tacit knowledge to bear. The author argues that codified knowledge such patent, academic articles and books are able to travel distances and are not geographical bouded, the issue of tacit knowledge cannot be traeted the same way. Tacit knowled in the view of Jaffe (1986) as it is bounded to the individual who owns the knowledge and therefore limited to a particular geographic space. The transmission machanism of such bounded tacit knowledge is the interaction and coversation you can have with the person in whom the knowledge is bouded. This is confirmed in a study by (Belitski & Desai, 2016) where the authors revealed that local content characteristics is what drives ICT clustering at country and city level. The authors, in agreement with allies and proponents of geogaphic proximity as the reason for knowledge spillover showed that the proximity to University explains the Clustering of ICT firms and knowledge spillovers in 227 cities across 22 European countries. However, recent studies and the development of digital means of communication teaches that geography is no filter to conversation and communication. There are therefore calls to review the position that knowledge spillover is geographically bounded in the face of digital means of communication.

Both empirical and theoretical literature emphasises the important role of spatial or geographic proximity in knowledge diffusion. Theoretically, the innovation diffusion theory places emphasis on the interaction between social actors as a prerequisite for knowledge diffusion (Lee, Hsieh, & Hsu, 2011). This is consistent with the empirical findings which have shown that geographical proximity is critical to knowledge diffusion interaction between actors and a consequential effect of knowledge spillover (Porter, 2000; Oinas, 2000). In a study by Murata, Nakajima, Okamoto and Tamura (2014), the authors showed that knowledge spillover is localised and that knowledge spillover reduces with distance away from the source of the knowledge.A growing number of studies have attributed interaction between actors in an economy to their geographic or spatial proximity. The closer an actor is to the source of knowledge the higher the likelihood of interaction with the source of knowledge. The literature recognises that interaction among actors in an economy is the source knowledge diffusion and spillover. For example it is widely known that knowledge and informantion at the local level plays an important role in interactive learning at the local level (Storper & Venables, 2004; Gertler, 2003). Geographic proximity, eventhough expected to be complemented by other forms of proximity to be effective in knowledge transfer, and spillover (Garcia, et al., 2008), there is a consensus among authors that the importance of geographic proximity in knowledge spillover cannot be over emphasised (Paci, Marrocu, & Usai, 2014). Findings of Autant-Bernard (2001) in a study to investigate the geography of knowledge spillover and technological proximity validated the assertion that knowledge spillover is induced by the extent to which actors are in close geographic proximity. This is in sync with David and Foray (2002) who states that knowledge spillover is community based and it is an outcome of intense community interaction.

The literature on knowledge spillover partly throws a lot of support to Marshall (1980) position that agglomeration of firms is explained partly by the need for firms to stay in geographic proximity for the purposes of interaction and benefit from knowledge spillovers. The literature suggests that beyond just geograhic distance, national boundaries are also important for knowledge spillover. Findings of a study by Fischer, Scherngell and Jansenberger (2009), who investigated geographic localisation of knowledge spillovers using patent citation in high technology firms in Europe revealed that geographic distance reduce knowledge spillover. However, what is more important in limiting knowledge spillovers is national borders. Fischer and his colleagues revealed that knowledge spilloiver is easy among European countries than across to countries outside Europe. There is every indication that spatial or geographic distance is important in determining knowledge spillover. However, some associated factors highlited in the literature influence the effect of geographic proximity on knowledge spillover.

1.6.1.1 Digital Tools and the Role of Geography in Knowledge Spillovers

Even though the extant literature highlights that knowledge spillover is geographically bounded (Acs, Audretsch, & Lehmann, 2013; Jaffe, 1986), there is a growing body of empirrical literature that highlights the important role of digitalisation in influemcing and diminishing the effect of geogarphic proximity in knowledge spillovers. In a study, Martínez-Climent, Mastrangelo and Ribeiro-Soriano (2021) have argued that improvement in digitalisation and communication has changed the narative for the role of geographic proximity in knowledge spillover. Given, that knowledge spillover is a function of interaction and communication between firms, countries and economic entities (Jaffe, 1986), recent studies make the argument that digitalisation have improve communication between these entities and such communication are no more restricted by disstances, for which reason the argument of geographic bound knowledge spillover no more suffices (Martínez-Climent, Mastrangelo, & Ribeiro-Soriano, 2021). Digitalisation has brought into the innovation econosystems new relational processes that have now included formerly geographically suppressed groups from knowledge spillover clusters (Autio, Nambisan, Thomas, & Wright, 2018).

One of the main arguments of the geographic proximity as a cine qua non for knowledge spillover is that the distances increases the transaction cost of receiving knowledge spillover which is 'freely available' public good (Acs, Audretsch, & Lehmann, 2013; Jaffe, 1986). The introduction of information technology has brought into the communication space the magic that heeds no respect for distances in communication. Martinez-Climent et al.(2021) states that the introduction of informations technology has led to the spread of innovation and disemination of technology from different sources reaching and broadening the reach and sphere of the innovation ecosystems.

Digitalisation has revolutionarised companies and their business models, allowing the use of internet and reaching and accessing hetherto knowledge sources that were not possible to reach. This has reduced the distance between firms and countries in terms of access to knowledge resources including knowledge externality. Access to information through the internet, for example has been argued in the prior literature as diminishing the effect of geographic distance in assess to knowledge and knowledge spillovers (Gupta & Bose, 2019). Digital entrepreneurship which defines the transfer of part business processes into digital form has been enabled by firms by the emrgence of internet (Kraus, Palmer, Kailer, Kallinger, & Spitzer, 2019). In such digital sectors the influence of geographic clusters in knowledge spillovers in reduced as the interaction and communication and market access fostered by these clusters are being taken over by information and communication technologies at a relatively cheaper cost and in some instances more effective (Evans, 2019).

The literature acknowledge the widespread use of digital tools among firms and countries in the quest to improve productivity and access to knowledge. It is for this reason that authors such as Rippa and Secundo (2019) as well as Autio et al. (2018) argued that the role played by geographic clusters in knowledge spillover have become digitally intrinsic characteristics of many sectors of national economies thereby reducing the importance of geographic clusters. Digitalisation is seen as creating a broader social network and across border unlike geographic clusters that are normally at national level without an international dimension. International knowledge spillovers are cross border, between countries and are more affected by digitalisation than geographic clusters.

Even though authors agree by consensus the important role of digitalisation in knowledge spillover, the empirical literature also acknowledge that in the process of digitalisation, natioanl institutions face tremendous challenges stemming from the radical changes institutions and society have to endure (Hinings, Gegenhuber, & Greenwood, 2018; Loebbecke & Picot, 2015). Digitalisation is considered as an avenue that is bridging the knowledge gap between firms and countries from research to market adoption (Sussan & Acs, 2017). Knowledge spillover is therefore incumbent on the ability of countries and firms to have in place these information communication infrastructure. Unfortunately countries and firms are not at par in terms of their digital infrastructure and therefore interaction and communication between firms and countries as a channels for knowledge spillover could be comprised and reduce dissemination of information. It has been argued that countries that are unable to weave into their business fabric digitalisation and absorb radical digital transformation lose out on knowledge spillover gains (Proeger & Runst, 2020). It is important to note that digitalisation is generally considered an alternative route to geographic clusters for knowledge spillovers. Hoever, the success of digitalisation and its dimishing effect on the relevance of geographic clusters is dependent on the ability of the country or firms to invest in digital infrastructure and absorb the radical changes digitalisation impose on sociaty and firms.

1.6.2 Cognitive Proximity and Knowledge Spillover

One important source of interaction between actors for knowledge exchange is cognitive proximity (Petruzzelli, Albino, & Carbonara, 2007). This has become known as the knowledge related hypothesis which suggests that when the knowledge of actors is related knowledge transfer among the actors is easy (Phene & Almeida, 2008; Cohen & Levinthal, 1990). Recent studies have shown that related technology improve the absorbtive capacity of actors and therefore a good recipy for knowledge tranfer (Fang, Wade, Delios, & Beamish, 2013). The concept of cognitive proximity as developed by (Nooteboom, 2000) is a relational attribute which has been used by authors to mean community of users of similar or related technologies absorptive. Using cognitive proximity to mean a community of practice or similarity in knowledge has come to be known as an important source of interaction between actors of this comminity and therefore regardless of the geographical distance between actors there is interaction and knowledge transfer (Nooteboom, 2000). The position of the prior literature is therefore in tune with knowledge related hypothesis-when actors’ knowledge is related knowledge transfer and spillover is enhanced. Empirical literature geared towards investigating the effect of cognitive proximity on knowledge diffusion has revealed varied outcomes. However, there is a tilt towards cognitive proximity as a source of knowledge spillover.

For example some literature sources have shown that geographic proximity effect is weak as a source of knowledge spillover for scientific publications when cognitive proximity is accounted for (Wuestman, Hoekman, & Frenken, 2019). In a study by Capello and Caragliu (2018) where the authors investigated the interrelationship between the different proximities and their effect on knowledge flow and knowledge spillover using scientific publication citation data, the authors findings showed that when geographic distance between actors is high, there should be close cognitive proximity for knowledge spillover to take place. However aspects of Capello and Caragliu (2018) findings also points to synergies between geographic proximity and cognitive proximity. Capello and Caragliu (2018) argues that when spatial proximity reduces there should be an increase cognitive proximity for collaboration to occur. Increased cognitive proximity compensates for the loss of geographic proximity to ensure that there is collaboration. This means that both geographic proximity and cognitive proximity are important in the distrbution of knowledge spillover of scientific publication across space. One area of cognitive proximity apart from technological proximity that has not been very much highlighted even though very important is organisational cognitive distance. Organisational cognitive distance measure the difference between organisational strategies of firms engaged in interaction for knowledge transfer (Wuyts, Colombo, Dutta, & Nooteboom, 2005). The literature suggests that when firms are closely related in terms of size, diversification and scope they tend to adopt similar business models and their interpretation and perception (Wuyts, Colombo, Dutta, & Nooteboom, 2005). Accordingly, such a similarity could be an important hinderance to interaction and knowledge spillover due to commonality and the absence of uniqueness. This idea is supported by (Wuyts, Colombo, Dutta, & Nooteboom, 2005) who found that organisational cognitive proximity hinders knowledge sharing but distance increase the fertility for collaboration and knowledge sharing. On the otherhand as cognitive distance increase, thus as firms become disimilar, understanding each other becomes difficult and problematic for knowledge sharing and collaboration. Wuyts and his colleagues therefore argue that the relationship between cognitive proximity and knowledge transfer is an inverted U shaped with the optimal knowledge transfer at the point of cognitive distance where knowledge sharing or collabotation is at maximum.

1.7 Effect of Knowledge Spillover

This section of the study presents a review of the role of knowledge spillover. The literature on the effect of knowledge spillover has been conducted on two streams, the effect of knowledge spillover on innovation and the effect of knowledge spillover on economic performance. Other studies have also investigated the role of knowledge spillover on collaboration (Montoro-Sánchez, Ortiz-de-Urbina-Criado, & Mora-Valentín, 2011). However, there are economically justifiable reasons to suggest that knowledge spillover can influence the behaviour of firms and countries towards their own R&D investment. The idea of localized knowledge which as expressed by authors including Anselin et al.(2000) suggests that some knowledge spillovers may not be complementary if the knowledge is not related to R&D in the destination. This section of the study presents a review that captures the effect of knowledge spillover on inniovation and economic growth as well as the complementarity of destination R&D and the spillover knowledge.

1.7.1 Knowledge Spillover and Innovation

The link between knowledge spillover and innovation cannot be over emphasised. The literture has given a good account of the effect of knowledge spillover on innovation performance. **The propensity to innovate has been considered a function of knowledge spillovers.** The empirical literature position on innovation has been that the propensity with which firms innovate is determined partly be knowledge spillover. In a study by Montoro-Sánchez, Ortiz-de-Urbina-Criado and Mora-Valentín (2011) where the authors investigated the effect of knowledge spillover on innovation. Unlike other studies that have investigated the effect of a single measure of knowledge spillover on an innovation variable Montoro-Sánchez and her colleagues investigated the analysed the effect of several measures of knowledge spillover based on the source of knowledge on innovation performance. The five knowledge spillpover sources the authors considered are competitor knowledge spillover, customer knowledge spillover, supplier knowledge spillover, public knowledge spillover and a global knowledge spillover which is an aggregation of the first four types of knowledge spillovers. Regressing four measures of innovation, product innovation, process innovation, organisational innovation and commercial innovation on the five measures of knowledge spillovers, the study found that all the measures knowledge spillover are positive and significantly related to all four measures of innovation. This findings confirms the importantce of knowledge spillover on innovation performance of firms and countries. From the findings of Montoro-Sánchez et al.(2011), there seem to be the impreswsion that the positive effect of knowledge spillover is general. However, in a study conducted by Vujanović et al. (2022) the effect of knowledge spillover on innovation differs between advanced and emerging economies. In the findings of Vujanović et al. (2022) shows that advance economies are more of knowledge generators whilst trheir emerging counterparts are knowledge users and therefore interms of the impact of knowledge spillover, it is stronger in emerging economies than in the advanced economies eventhough in both cases the impact is significant. Vujanović et al. (2022) have shown that knowledge spillover from Foreign Direct Investment is stronger in emerging economies is stronger in emerging economies than in advanced economies.

The challenge with emerging economies include lack of manageinal and organisational competencies and low absorptive capacity and low learning capabilities (Zhu, Hitt, & Tihanyl, 2007; Bahl, Lahiri, & Mukherjee, 2021) compel firms willing to improve their innovativeness to source external knowledge including relying on spillover knowledge (Eapen, Yeo, & Sasidharan, 2019). This is an indication that emerging economies even though constraints by their limited absorptive capacity are more receptive to foreign knowledge. This thinking is line with the principle that knowedge spillover is in the direction of low R&D regions knowledge (Kanea, Argote, & Levine, 2005). Firms and countries learn from superior counterparts. The irony, however, is that low R&D, being the reason for their low innovation, is the same reason why in the abundance of ‘free knowledge’ these firms are unable to absorb knowledge. Thus, even though the empirical literature generally agrees that knowledge spillover positively affects innovation outcomes it not a straightforward matter as though the impact is the same for all countries and firms. For example, the literature accounts suggest that the extent to which the firms or countries involved are related in terms of proximity of technology or physical distance becomes an influencing factor. In a study to assess knowledge spillovers in Europe for example, Maurseth and Verspagen (2002) showed that there are important barriers to knowledge spillovers in Europe. Physical distance is a friction that reduces the extent of knowledge spillover. Again the authors showed that patent citation are industry specific and that cross polination of patent citation is hindered.

Tang et al. (2022) in a study on the impact of borders and distance on knowledge spillovers, the authors used evidence from cross-regional scientific and technological collaboration and their findings showed that administrative borders are a major hindrance to the impact of knowledge spillover. This is not an isolated case of the restrictive effect of administrative borders on the effect of knowledge spillover. In similar findings, Fackler, Giesing and Laurentsyeva (2020) showed that borders limit the face-to-face interaction of talents which necessarily reduces the interpersonal relationship which remains the main channels of tacit knowledge spillover. This is further confirmed in a study by Marx, Strumsky and Fleming (2009) have shown that factors that curtail mobility have reduced knowledge spillover and its impact. It is, however, important to add that the role of mobility of employees or R&D personnel in knowledge spillover is more in relation to tacit knowledge which is embedded in organizational processes and its members. Labour mobility is considered the most important in the transmission of tacit knowledge in a productive system since such knowledge is embedded in the human capital of firms (Cartillo, Garone, Maffioli, Rojo, & Stucchi, 2020). The authors further explained that in such circumstances the only way such knowledge gets spilled to other firms and organisations is by hiring workers from the knowledge origin firm. The literature recounts a high number of studies that have attributed tacit knowledge spillover to the mobility of workers and the reason has been that tacit knowledge is embedded in the employees in the knowledge source (Almeida & Kogut, 1999; Maskell & Malmberg, 1999; Cooper, 2001; Power & Lundmark, 2004). It has therefore been suggested that econometric estimations of knowledge spillover effect that fails to account for the contribution of disembodied direct spillover effect will be biased (Lee, 2006).

Studies on the effect of knowledge spillover on innovation have generally in agrement with Breschi, Lissoni and Montobbio (2005) assumed the equivalence between pure knowledge spillover and pucuniary or rent knowledge spillover. However, going by Lee (2006) assertion such assumption of equivalence leads to bias estimates in the effect of knowledge spillovers. In the seminal work of (Griliches, 1979) who is credited with the idea of the split between pucinary and pure knowledge spillover, the author revealed that R&D is embodied in human capital, documents and in some cases oral tradition and patents. Griliches (1979) admonished against aggregation of such diverse components into one notion is errornous and may not accurately capture the exact effect.

Studies on knowledge spillover effect have taken several approaches. In a study by Vujanović et al.(2022), the authors investigated the effect of Foreign Direct Investment (FDI) on innovation activities. The study specifically investigated the effect of FDI on the different phases of innovation. The results of the study showed that in emerging economies FDI knowledge spillover does not improve novel product but rather inmmitation of existing FDI outputs. However, the study showed that firms that are users of innivation had greater FDI effect than firms that generate knowledge. The study also showed that local firms at the early stage of their innovation benefit from foreign knowledge through FDI. The findings of Vujanović et al.(2022) is an indication that the effect of knowledge spillover on innovation is broader than just the size of the innovation but there are some other dynamics such as the firm characteristics and how it influences the effect of knowledge spillovers. In a related study, knowledge spillover from FDI has beeen found to improve the R&D of domestic firms but productivity growth level have been shown to vary accros regions (Zhang, 2017).

The importance of spliting the effect of knowledge spillover on innovation and other firm performance variables has also been advocated is has been made more important in the literature by the findings of authors that suggests that knowledge spillover may not have the same effect on innovation as it doers on other firm performance variables. For example the empirical literature has shown in a study aimed to find the complementarity between R&D and knowledge spillover (Audretsch & Belitski, 2020). The findings of the study shows that R&D and knowledge spillover have different effects. Whereas R&D works to improve innovation and productivity of firms, knowleege spillover is more effective in improving productivity of firms than R&D. It is however, important to state that the findings of Audretsch and Belitski (2020), even though has caught the attention of several authors and has generated discussions in the empirical literature, the estimation of the effect of knowledge spillover need to be looked into further. Knowledge spillover is an external knowledge that comes into a new system. The receiving firm or entity requires time to adjust to make the new knowledge have its full effect. However, in the estimation of the effect of knowledge spillover on innovation performance Audretsch and Belitski (2020) did not allow for adjustement cost. Another possible explaination to the reason knowledge spillover may not have the expected effect on innovation has been explained in the empirical literature (Mowery, 2009; Balland, Boschma, & Frenken, 2015). These authors argue that knowledge spillover can only have a significant effect on innovation in the recepient firm when there is close technological and cognitive proximity. This is the idea that knowledge spillover takes place within a community of similar or shared ideas and that cross pollination with inter sectoral knowledge is not effective. This remains a contentious issues in the literature to date. The divide between the apostles of geographic and technological proximity as discussed in the ealier sections of this work comes to play.

An interesting twist to the debate on how technological and physical proximity affect knowledge spillover has been investigated in a study by Wang and Wu (2016). The authors investigated regional FDI knowledge spillover effect on product innovation of indigenous electronic firms in China. Their results showed that when the FDI investment is technologically related to indigenous Chinese firms product innovation of domestic firms is enhanced. Wang and Wu (2016) also showed that horizontal knowledge spillover are more dominant compared with veritcal spillover but cross sector knowledge spillover is more important than intra industry knowledge spillover when it come to improving indigenous innovation. It is clear from Wang and Wu (2016) that even though technological proximity is an important factor in knowledge spillover it is not always the case that technological proximity prevails. The challenge with the role of proximity, both geographic and technological is that it has an inherent assumption that the heterogenous characteristics does not play a role in knowledge spillover (Wang & Lin, 2013).

1.7.2 Knowledge Spillover and Organizational Productivity

From Audretsch and Belitski (2020) the expectation is that the effect of knowledge spillover will be more towards firm productivity than firms innovation. Unfortunately, the literature has generally failed to analyse these effect differently. This is partly because there is generally a co-movement between productivity and innovation and hence the assumption that the effect of knowledge spillover will be the same on these organisational performance variables. However, portions of the empirical literature have suggested otherwise.

A study by Ahamed, Luintel and Mallick (2023) investigated the role of knowledge spillover on firm productivity. In this study, the authors specifically were interested in assessing the effect of inter and intra industry knowledge spillover on productivity. The authors also investigated the effect of international knowledge spillovers such as import intensity and FDI productivity. The results of theie study showed that the two different international knowledge spillovers, import and FDI have different effect on productivity. Whereas the productivity of import intensive firms were low, the FDI showed improve productivity for knowledge extensive exporting firms.

1.8 Regional and Sectoral Differences in Knowledge Spillover

One of the undoubted issues with knowledge spillovers is that they are generally distance decay, thus knowledge spillovers occur in clusters and as one moves away from the source knowledge spillover reduces. For example, it has been shown that 20% of average knowledge generated is learned inside the average region and only 9% is learned outside the country of origin (Peri, 2005). Periphery regions benefit less from knowledge spillovers relative to core regions. In his study also, Peri (2005) revealed that different sectors of the economy show marked differences in knowledge spillover. His findings revealed that knowledge spillovers from computers and electronics travel faster and farther than average knowledge. In some other studies, the role of clusters in knowledge spillovers has also been confirmed, however, this is more a consequence of the similar technology used in the sector. There are therefore doubts on assumptions and thinking that when knowledge spillovers take place in clusters it is a consequence of localization effect or geographic distance effect. It could also be a consequence of similar technology or technological distance effects.

Regional and sectoral knowledge spillover is influenced by a complex set of variables which is further complicated by firms and country specific factors. For example, the decision to make and not rely on external sources of knowledge such as knowledge spillover is complexly determined by absorptive capacity. Absorptive capacity is known to play a complex role in knowledge spillover. A high absorptive capacity of neighbouring firms, regions or countries could reduce or increase knowledge spillover (Caragliu & Del Bo, 2011). The authors found that when absorptive capacity is high firms may choose to operate a closed innovation where knowledge spillover means very little. Caragliu and Del Bo (2011), however, admits that high absorptive capacity could also be a good reason why knowledge spillover can be heightened as it gives learning abilities which is a sine qua non for knowledge spillover.

The type of knowledge involved in knowledge spillover has implications on knowledge spillover between regions and sectors (Doring & Schnellenbach, 2006). Mobility of individuals and transfer of goods remain important channels of knowledge spillovers (Doring & Schnellenbach, 2006). The authors note also that pure knowledge spillovers also occur through licensing of patented technologies and shared research projects. The authors argue that channels for transferring pure knowledge such as scientific publications, licensing and shared research projects compared with those for pecuniary knowledge spillover such as transfer of goods through trade differ due to cost involved resulting in regional and sectoral differences in knowledge spillovers. Pure knowledge spillovers are less costly and travel over great distances compared to transfer of goods, individuals and physical production facilities (Doring & Schnellenbach, 2006). Some important reasons for the differences in knowledge spillover between reasons and sectors that literature highlights include source or origin of the knowledge. In a study it was revealed that when the source of the knowledge is private sector, there stickiness in the spillover channels because the private sector tries to appropriate knowledge relative to the public sector that are likely to treat knowledge as a public good (Caniëls, 2000).

This is an indication that in regions or sectors dominated by the private sector knowledge spillover will be restricted compared with regions and sectors dominated by the public sector. Regional knowledge spillover ecosystems favour intra-regional and intra sectoral knowledge spillovers rather than cross border knowledge spillovers. The empirical literature shows that knowledge spillover is distance decay both in terms of geographic distance and technological distance (Caniëls & Verspagen, 2001). The authors explained further that, like most economic activities, innovation activities and process are organized based on regional specific and sector dynamics with littles attention to cross border dynamics. Natural, the dynamics of knowledge spillover are specific to regions and sectors and therefore depending on the how these dynamics that affect knowledge spillover are organized and the capabilities within a region or sectors knowledge spillovers may be higher or lower. This feeds into the axiom that knowledge spillover is geographically bounded (Autant-Bernard, 2001), clarifying that movement away from the source of knowledge suggests reduction in knowledge spillover.

Beyond, regional and sectoral arrangement influencing regional and sectoral disparities in knowledge spillovers, capability differentials between regions and sectors remain important in explaining why some regions and sectors have higher knowledge spillover than others. It is widely known within the knowledge spillover literature that capability of the receiving region, sector or entity is critical to learn and utilize spillover knowledge (Kapoor & Klueter, 2020; Poldahl, 2012; Doring & Schnellenbach, 2006; Cohen & Levinthal, 1989). Regions and sectors with high R&D have experianced high levels of knowledge spillovers than regions woth moderate to low levels of R&D intensity or R&D learning capabilities. It is general known that high R&D intensive sectors of pahrmaceutical, biotechnology, science and medical instruments, aerospace, and chemical sectors of the economy are more fluid and suceptible to knowledge spillovers than low R&D intensive sectors (Isaksson, Simeth, & Seifert, 2016).

1.9 Geographic Distance, R&D and Knowledge Spillover Complementarity

The role of geographic distance in innovation has been highlighted in the prior literature. This is especially the case because an important input in innovation, knowledge spillover is known to be geographically bounded (Phene & Tallman, 2002; Jaffe et al.,1993). **This is premised on the empirical findings that knowledge externalities are confined to a geographic space and therefore as the distance between firms and the focal firm increases the role of knowledge spillover reduces.** There is a close relationship and linkages between firms and countries that are located in close proximity allowing for better collaboration and innovation. The extant literature contends that firms and institutions in close proximity share common practices and therefore are better able to be innovative and generate knowledge spillovers that create a pool of knowledge shared among firms within a geographic area (Phene et al., 2006; Wejnert, 2002). The effect of geographic proximity on recombination of R&D resources during R&D collaboration has been investigated. The results shows an inverted U shaped relationship (Nan, 2024) which suggests that at close proximity the recombination innovation is high, but as distance increases recombination innovation reaches a maximum and futher falls as distance between source of knowedge and the focal firm increases. This is an indication that the ability of firms to combine different internal and external R&D resources is determined by geographic distance between the focal institution and the source of external knowledge.

Collaboration between organisations for R&D resources and the use of R&D externality in recobination innovation is influenced by geographic proximity (Nan, 2024).The literature has shown that geograhic proximity among collaborators influence the recombination innovation (Nan et al., 2018; Boschma, 2005). It is worth noting that especially in the case of tacit knowledge which is normally embodied and transmitted through mobility of human capital, geographic distance cannot be ignored in recombination innovation. When entities in a knowledge spillover plane are geographically far apart the benefit of knowledge spillover is hindered (Nonnis et al., 2023). What the literature has generally glossed over is the fact that proximity, both in terms of technology and geographic may be counteractive to the benefit of knowledge spillover. When knowledge base of entities in a knowledge spillover plane are too similar, internal R&D gains very little from external R&D and the recombination effect is limited (Noseleit & de Faria, 2013). The role of geographic distance, even though increase interaction between knowledge spillover and internal R&D, has been ignored. If well explored, geographic distance could be seen as an asset for firms and organisation. This can be seen as the social capital that enhances the absorptive capacity that of firms and countries that makes it easy to explore and exploit external knowledge resources.

In the European context and especially within EU, empirical studies have proven that interregional knowledge spillover are high and influenced by both geographic and technological proximities of regions (Greunz, 2003). There is an admission that even though the related literature underscore the fact that knowledge spillover is due to geographic and technological proximity, very little has been done to examine interregional knowledge spillover in Europe (Greunz, 2003). Subsequently studies in this area have shown that in Europe, knowledge spillover is higher when the regions in a knowledge spillover plane are of different R&D levels (Di Cagno et al., 2016). European countries with high knowledge spillover are predisposed to combining knowledge spillover with internal R&D resource for innovation. However, given the importance of geographic distance in these dynamics (Greunz, 2003), the influence of these two inputs will not be fully explained if geographic distance is not integrated into the analysis.

1.10 The Role of Absorptive Capacity in Knowledge Spillovers

The role of absorptive capacity in knowledge spillover cannot be over emphasised. The extant literature has highlighted the important role played by entrepreneurial absorptive capacity in knowledge spillover. For example, in a study by (Qian & Acs, 2013), the authors state that the level of knowledge spillover, beyond the speed of knowledge creation and the size of knowledge creation also depends on the ability of the entrepreneur to be able to absorb 'the freely existing external knowledge' which is technically referred to as knowledge spillover or knowledge externality. This knowledge is unintentionally transmitted to other entities. What is critical is that knowledge is not designed per se to be used by external entities or entrepreneurs. It is therefore important on the part of the external beneficiary to have the capacity to identify such freely existing external knowledge resources, assimilate them and to put them into commercially useful purposes. This defines the absorptive capacity of an entrepreneur or the external entity that potentially benefits from knowledge spillover. Formally, absorptive capacity is defined in agreement with (Cohen & Levinthal, 1990, p. 128) as "the ability to recognise the value of new information, assimilate it, and apply to commercial ends". There are four dimensions to absorptive capacity that an entity must exhibit to have the capacity to absorb knowledge externality: acquisition, assimilation, transformation and exploitation (Zahra & George, 2002). An entity benefits from knowledge spillovers when the entity has what it takes to attract knowledge externality, this will usually require that the entity has invested enough in its human capital and other resources to learn from other entity's knowledge production function. Beyond this, the beneficiary entity must have what it takes to digest the knowledge into a form that is understandable or to contextualise the external knowledge to be meaningful as well as change the knowledge or transform the knowledge and to make it useful to the beneficiary entity.

The size of an entities R&D is a critical ingredient here for knowledge spillovers. Knowledge spillovers have two sides, all of which are influenced by the absorptive capacity of the potential beneficiary. To the extent that knowledge spillover is unintentional, it should be made known that there is an attempt on the part of the originator of the knowledge to fully appropriate the knowledge otherwise it is a transfer and not a spillover. It will therefore take an entity with a strong desire and ability to acquire the knowledge in the face of effort on the part of the originator to fully appropriate the knowledge. Zahra and George (2002) acquisition dimension of absorptive capacity has been explained to mean the ability of the entity to identify the value in the knowledge or information that is freely existing. This is dependent on the intensity and speed with which the firms or entity is able identify and acquire a free external knowledge that defines the firm's acquisition capabilities (Zahra & George, 2002). In a competitive business environment, acquisition capability is critical as the gains of knowledge spillovers are dependent on the speed with which an entity acquires the knowledge. Beyond the acquisition of knowledge, knowledge assimilation is critical to making gains from knowledge spillover. Assimilating knowledge is what an entity does to bring understanding of the external knowledge. This involves interpretation, comprehension and learning from the knowledge to make sense of the knowledge (Zahra & George, 2002). A key ingredient to doing this is the learning capabilities of the beneficiary entity which hinges more on the R&D effort of an entity hoping to benefit from knowledge spillover.

Transformation dimension of knowledge spillover explains the capability of a knowledge spillover beneficiary entity to internalize and convert knowledge externality to a usable form (Dodgson, 1993). It has been argued that transformation dimension requires beneficiary entities to adapt to the new knowledge (Zahra & George, 2002) as a way to deal with the deal with the adjustment cost of bringing new and unknown knowledge to the knowledge production fold (Amendola, 2024). The extent to which an entity can transform the new knowledge into a usable form depends on how well the receiving entity understands the new knowledge and is equipped with the skill to be able to use it. Learning is an imperative in the transformation of knowledge, however, it is dependent on the experience and the knowledge base of the receiving entity. Zahra and George (2002) explained that in transforming knowledge, the process require combining knowledge externality which is new and normally unknown with an entity's own knowledge resource. The transformation of external knowledge requires that receiving entity has the capacity to determine the complementarity or otherwise between the external knowledge and the entity's own knowledge resources. It is known from the prior literature that knowledge from the two sources be technologically proximate (Nooteboom, 2000). Cognitive distance is known to be solved through high absorptive capacity. The more interactive a receiving entity is, the higher the chances that such cognitive distance that limits transformation of external knowledge is reduced. Cohen and Levinthal (1990) make the argument that beside human capital as a source of knowledge in the knowledge production function, an important source of knowledge to the knowledge production function is the absorptive capacity of the entrepreneur. The authors argue that absorptive capacity allows an entity to learn new knowledge from external entities and gives the ability to deal with the challenges to combining external sources of knowledge with internal knowledge sources.

Knowledge exploitation is the ability of an entity that has received new knowledge to be able to put the knowledge into use (Cohen & Levinthal, 1990). This requires competences that allow firms to leverage external and home-grown knowledge resources to create newer and more useful knowledge (Zahra & George, 2002). Exploitation requires that beneficiary firms or entities are able incorporate the different knowledge resources, both internal and external, into its operations (Tiemessen, Lane, Crossan, & Inkpen, 1997). Taking advantage of external knowledge requires high level absorptive capacity which in the view of (Volberda, Foss, & Lyles, 2010) is a consequence of individual cognition, motivation and interaction. The quality of human resources is therefore a critical part of absorptive capacity needed to ensure knowledge spillover.

Absorptive Capacity, Knowledge Spillover and R&D

The size of R&D determines the extent of innovation and learning that is done within an organization or a country. It is empirically proven that the size of a firm's R&D determines the firm's innovation but not just that, it also determines the capacity of the firm to assimilate external knowledge (Nonnis et al., 2023). It is known that external knowledge through the knowledge spillover channel is accessible to every one and at all times, but the ability to identify, assimilate and to exploit the knowledge is dependent on the absorptive capacity of the firm (Nonnis et al., 2023; Roper et al., 2008, Chesbrough, 2003). An important challenge in ensuring complementarity between internal R&D and external R&D rests with how firms are better able to deal with the problems of bringing the different sources of knowedge with diverse characteristics and making it possible for these resources to work together for suatained innovation (Davila et al., 2005; Zahra & George, 2002). From prior literature, knowledge spillover is sensitive to R&D (Nonnis et al., 2023). This shows that firms with high R&D are more able to access knowledge spillover and improve the possibility of infussing higher knowledge spillover resources into its knowledge production function.

The size of R&D has generally been a measure of absorptive capacity (Griliches, 1979). The position of the literature concerning absorptive capacity is that firms engage in R&D investment to increase their absorbtive capacity in the long term (Audretsch & Belitski, 2020). This, in the view of the prior literature is important in assimilating external knowledge (Zahra & George, 2002) and allow the firm to be able to exploit both external and internal knowledge for innovation (Davila, Epstein, & Shelton, 2005; Zahra & George, 2002). This makes absorptive capacity a binder that brings different sources of R&D together for exploitation (Aldieri, Sena, & Vinci, 2018). Given that European countries are among the highest in terms of R&D intensity, European countries have benefited from inter-industry knowledge spillover (Harris et al., 2021). European firms have developed competencies that has enabled them to assimilate and exploit external knowledge from variety of industries (Aldieri et al., 2018). However, the knowledge spillover these firms have attracted does not translate into innovation in firms of some countries in Europe. It has been explained that within Europe there has been substantial differences between the Western European countries and the Eastern European countries interms of the effect of absorbtive capacity on R&D and innovation (Aldieri et al., 2018). One possible consequence is that the complementarity between R&D and knowledge spillover is compromised because of the varied effect of absorptive capacity in these countries.

1.11 Knowledge Spillover and its associated Policies

Knowledge spillover, being an incentive to beneficiary firms, has garnered a lot of attention from state governments and regional authorities as well as firms. In terms of policies, there are two streams of ideas that the extant literature presents. One stream of policy considers knowledge spillover as a public good and therefore believes that knowledge, once created must be allowed to benefit the entire society. This section of policy makers encourage knowledge spillovers and faction policies to encourage knowledge spillovers. There is another group of thinkers or policy makers who are of the view that knowledge created as an investment and therefore must be fully appropriated by the investor. Policies that affect knowledge spillovers are therefore on two wave lengths, one to encourage knowledge spillovers and another to appropriate knowledge spillovers.

1.11.1 R&D Incentives

The failure of market forces to provide the needed incentives for R&D predisposes firms and organisations involved in R&D because the non-rivalry nature of their R&D outcome, to attempt to fully appropriate their R&D outcomes in a way to block knowledge spillovers (Feldman & Kelley, 2006; Harhoff, 1996). Incentives for R&D are shaped by industry specific factors such as level of competition, appropriability conditions, demand and technological opportunities existing in the industry. Firms are predisposed to reduce their investment in R&D is they are unable to appropriate the outcome of their R&D. One of the policy initiatives by governments has been to provide support to firms whose knowledge creation has high potentials of knowledge spillover by way of R&D subsidies (Feldman & Kelley, 2006). The decision on which R&D project to support is made prior to the outcome of the R&D outcome. Feldman and Kelley (2006) make the argument that the challenging part of R&D subsidy is determining the R&D project with potential for knowledge spillovers. One strategy is to determine an R&D project that will not be undertaken without government subsidies to avoid firms substituting their own investment for government subsidies. There is evidence that indicates political interference and distorted incentives have resulted in wrong R&D project selection (Klette, Moen, & Griliches, 2000)

The literature presents mixed findings on the effectiveness of R&D subsidies. The effectiveness of R&D subsidies is so dependent on identifying the right R&D project to support. The social rate of returns is high for R&D projects that have higher R&D or knowledge spillovers than R&D projects whose outcomes are appropriated by their originators. One of the important ways to determine the potential of knowledge spillovers of a firm's R&D outcomes is to examine the network ties of firms. The extant literature has shown that when government R&D support goes to R&D projects of firms which have network ties the results has been good for knowledge spillovers (Powell, Koput, & Smith-Doerr, 1996). This position is consistent with the theory of network as captured by (Granovetter, 1994). The author argues that when a firm has a lot of connection within the network, it becomes a central node or a source of knowledge spillover. Universities being an important source knowledge spillovers (Feldman & Kelley, 2006), it has been an important candidate for receiving government's knowledge spillover subsidies (Gittelman & Kogut, 2003). Spence (1984) in his study argued that subsidied have been effective in dealing with incentive problems when there is knowledge spillover than other means of support such as collaboration in executing R&D projects. The idea of R&D sunsidies is to incentivise firms to make public their private R&D outcome for the benefit of society.

The motive of demand side R&D incentuives such as R&D subsidies is to make public private technology and to increase assess and use of knowledge from other firms. Even though the general position of prior literature shows that R&D subsidies have been effective in improving knowledge spillover and making knowledge assessible (Nemet, 2012), the cost to the exchequer has always been the contention.

An alternative to R&D subsidy is the R&D tax credit. R&D tax credit differ from R&D subsidies only in form and not substance. In both cases originator of knowledge is resourced to make the knowledge public or treat private knowledge as public good. Both R&D tax credit and R&D subsidies have been aimed at inducing additional private investment in R&D reducing cost and risk of R&D investment (Dimos et al., 2022). One of the main difference between R&D tax credit and R&D subsidies is that R&D tax credit is ex post whilst in the case of R&D subsidies it is ex ante or when the private R&D is undertaken(Dimos et al., 2022). This striking differences give an indication of the relative effectiveness of the two policy options for knowledge spillovers. In the case of R&D tax credit, the private firms engaged in R&D do not have the benefit of the external resources from government to inject R&D at the point the investment is being made. The disadvantage of this policy instrument is that it does not help reduce the risk of R&D to the private sector. This is likely to reduce R&D investment and knowledge spillover. However, the advantage is that it make the selection of R&D projects to be supported easily because government agencies are able to assess the contribution of the R&D project before the support is given ex ante. In case of subsidies, private R&D investment benefit from government financial support at the point of R&D investment which helps take away the risk of R&D and potentially increase R&D and knowledge spillover. The down side to this policy instrument is that government commit resources before the R&D investment. This could result in wasting resources in case the R&D investment fails to yield the expected knowledge externality.

Both instruments have implications for additionality and ecventaully knowledge spillover. R&D tax credit may have a dead weight loss because the intervention happens after private R&D has already taken place and the chances that the instrument may not have effect on R&D and knowledge spillover is high (David, Hall, & Toole, 2000). On the other hand, subsidies could be fraught with crowding out because the support is given ex ante (Dimos & Pugh, 2016). Firms have the choice of substituting firm’s own contribution to R&D for government subsidies. This will potentially reduce R&D and knowledge spillover.

1.11.2 Intellectual Property Protection and Knowledge Spillovers

Both empirical and theroretical literture acknowledge the importance of knowledge spillovers to innovation and growth of economies. The endogenous growth theory (Romer, 1990), assumes that knowledge spillover is endogenous and automatic agaist the empirical liteature position that there are filters that block the spread and disemination of knowledge (Xu, Wang, Zhou, & Zhang, 2019;Acs, Audretsch, Braunerhjelm & Carlsson, 2012). One of these filters that is known to block knowledge spillovers is intellectual property protection. Even though Romer (1990) in his endogenous growth theory suggested that knowledge spillover is automatic, he also admits that institutions play an important role in knowledge spillover.

Samaniego (2013), in his study explained th e role of institutions in innovation as an enforcer of Intellectual Prorperty Rights (IPR). Samaniego (2013) stated that when intellectual property rights are enforced, then the appropritability of knowledge is high but if IPR are not enforced well, then appropritability is weak. IPR is therefore considered as one of the filters to knowledge spillovers. Contrary to the thinking that treating knowledge spillover as public good is ideal (Stiglitz,1995), some theoretical and empirical literature suggests knowledge as a public good is a disincentive to knowledge creation (Kim & Marschke, 2005). Intellectual property protection has therefore been used a policy response to direct and influence innovation by firms and countries.

Samaniego (2013) in a study showed that IPR discourages open innovation and compells firms and countries to rely on their own R&D effort. This is a challenging situation especially for countries that are not resourceful enough enough to be self reliant in terms of technology. Besides, open innovation goes beyond the ability to be self reliant, for innovation purposes cross fertlised R&D is normally considered a better option that relying on only inhouse R&D. The idea of intellectual property right is that intangible assets of a firm or country must accrue gains to the owner of the assets rather than a competitor accessing the asset without any gains to the originator (Samaniego, 2013). This position limits the gains firms can make through knowledge spillovers and as a consequence adversely affect innovation. The effect of intellectual property right such as patenting on innovation shows a tricky outcome. For example in (Acs & Sanders, 2012), the authors revealed that initially firms cope with intellectual property righ by injecting more resources into R&D which immediately increase innovation. However, firms are unable to sustain their investment for a long time, hence a fall in innovation eventually.

Intellectual property right focuses on fostering new knowledge generation and improving innovation. Because R&D renains an expensive enterprise, what intellectual property right seeks to achive is to ensure the investor gets maximum benefit from its knowledge assets to encourage increased amount of R&D investments. There is a good case for IPR for innovation. Authors have agreed by consensus that IPR gives firms the confidence that their R&D investment is protected. This would naturally encourage appropriation of knowledge. However, in a study by (Adomako & Tran, 2024), the authors found a positive effect of IPR on knowledge transfer. The extent of knowledge spillover has long been considered a measure of weakness in IPR of countries (Žigić, 1998). Countries with strong IPR observe less kowledge spillover relative to countries with weak intellectual capital. This is an indication that IPR does not foster knowledge spillover. IPR appropriate knowledge and allows for knowledge transfers rather than knowledge spillovers.

2 Gap, Aim and Hypotheses Development

2.1 Research Gaps Identified in Literature

The large number of studies on knowledge spillovers are partly because of its relevance to the growth and productivity of economies. Generally, studies that evolve around knowledge spillover have focused on the effect of knowledge spillovers (Xu, Wang, Zhou, & Zhang, 2019; Trachuk & Linder, 2019). The particular attention of these studies have been on how knowledge spillovers have affected growth and productivity (Trachuk & Linder, 2019). The outcome of these studies have by consensus shown that knowledge spillover is an important cartalyst for growth and productivity of firms and countries (Maity & Sinha, 2021;Mukhamediyev & Spankulova, 2020;Silajdzic & Mehic, 2015). From the studies of knowledge spillovers and their effect on productivity and growth, authors acknowledge two types of knowledge, endogenously determined knowledge which is the firm or country's own investments to achieving innovation and exogenous knowledge which defines knowledge spillover which is exogenously determined outside the economic system.

Modern economic thinking and recent empirical findings tout the important role of knowledge spillover in the growth and productivity(Xu, Wang, Zhou, & Zhang, 2019; Trachuk & Linder, 2019). However, vestiges of endogenous growth models have explained the possibility of firms and countries relying on internal R&D and economic activities for innovation, growth and enhanced productivity (Romer, 1990; Jaffe, 1986). Empirical studies have disputed the endogenous models' position and have suggested that knowledge spillover can be exogenous. In this case firms and countries have the benefit of combining own R&D which is endogenous and exogenous knowledge spillovers. The literature as yet, has not investigated the additionality effect of knowledge spillover which is necessary to determine whether beneficiaries of exogenous knowledge spillovers are substituting exogenous knowledge spillover for own R&D or they are complementary in improving economic growth. The adjustment cost of external knowledge resources such as knowledge spillover is also yet to be given the needed attention in the empirical literature. An important aspect of the knowledge spillover that has engaged the attention of the innovation literature is the measurement of knowledge spillovers. The invinsible nature of knowledge complicates the measurement of knowledge and the literature highlights these as challenges of measuring knowledge spillover (Kaiser, 2002). A good assessment of knowledge spillover effect rests with a good measure of knowledge spillover. The varied methods of measuring knowledge spillover brings different dynamics into the computation resulting in different outcomes (Kaiser, 2002). Other studies have also shown that besides the methods of measurement, the input measures such as citation, both literature and patent introduce biases in the measurement of knowledge spillovers (Nelson, 2009).

What the literature is yet to uncover is measuring the covergence or otherwise of knowledge spillover measures presented in the literature and how effective these measures have been able to actually measure knowledge spillover. The offshoot of the challenges of measuring knowledge spillover is the inability to fully and adequately determine the effect of knowledge spillover. Besides the challenges of measuring knowledge spillover, there are still important grey areas in analysing the effect of knowledge spillover. Approaches the literature have adopted in determining the effect of knowledge spillover seem to assume that any increase in economic growth or innovation associated with an increase in knowledge spillover is an addition to the existing R&D processes. However, averting our minds to the concept of additionality as used in the innovation literature, the extent to which an R&D input generates genuine additional R&D that would not have taken place in its absence (Czarnitzki & Hussinger, 2018), could be undermined if recepient of knowledge spillover substitute it for own R&D inputs. In the context of knowledge spillover effect, knowledge in the form of externality is received initially as an R&D input that must be translated into an R&D output by a combination of own R&D and knowledge spillover as a way of some positive gains to the economy. Additionality of knowledge spillover is input addionality and output additionality and these represent the true contribution of knowledge spillover to R&D input and output. These two sets of knowledge spillover additionality has not been accounted for by existing studies in the innovation literature. The adjustment cost of receiving foreign knowledge and how that affect innovation and innovation outcomes have also not been fully account for the existing empirical studies. This therefore blurs the actual contribution of knowledge spillover to innovation and economic growth.

2.2 Aim of Study

To abreast the innovation literature with current ideas on the knowledge spillover effects and methods of their measurements, the proposed study is aimed at understanding the role of knowledge spillover- assessing the additionality effect of knowledge spilllover, determine whether countries continue to investment in R&D even in the presence of knowledge externality from abroad or spillover rather substitutes country own R&D investment. The study also aims to account for the adjustment cost of knowledge spillover on innovation and innovation outcomes in the receiving country as well as investigate the various approaches of measuring knowledge spillovers, determine their validity and reliability in capturing knowledge spillover from abroad and determine the potential biases in their measurement. In this study, the role of absorptive capacity in influencing the relationship between knowledge spillover from abroad and innovation performance is assessed.

Specifically, the proposed study is aimed at achieving the following:

1. Assess the validity and reliability of selected measures of knowledge spillover.
2. Assess the complementarity between knowledge spillover and R&D to improving high technology export among selected countries in Europe.
3. Evaluate the joint effect of country's own R&D and knowledge spillover from abroad on high technology export among selected countries in Europe.
4. Examine the role of absorptive capacity in the relationship between knowledge spillovers and innovation performance

2.3 Hypothesis Development

This section of the study presents hypothesis development for the study. The study discusses three main hypotheses in agreement with the three objectives of the study.

2.3.1 Validity and Reliability of Knowledge Spillover Measures

The literature on knowledge spillovers is inundated with empirical studies focusing on the effect of knowledge spillover on innovation and innovation output variables. However, the literature presents several measures of knowledge spillover and authors have used these measures of knowledge spillover (Keller, 2000; Kaiser, 2002; Keller, 2021) without recourse to their validity and reliability as measures of knowledge spillover. In studies that investigate the effect of knowledge spillover, the choice of knowledge spillover measures used have influenced the outcome and the choice of these measures in empirical studies have been done arbitrarily because there are no empirical studies that have evaluated the validity and reliability of these knowledge spillover measures. The literature accounts show that in the computation of knowledge spillover measures there are several input variables that are required, ranging from the selection of variable to capture technology and most importantly technology distance and physical distance which have been an important part of most of the notable knowledge spillover measures to determine technological location in a knowledge spillover plane (Zhu, Hagedoom, Zhang, & Liu, 2021). The selection of these input variables and measures of distance between firms and entities in the knowledge spillover plane or space have been done almost arbitrarily and has been the major source of biasness in the computation of knowledge spillover (Zhu, Hagedoom, Zhang, & Liu, 2021; Diestre & Rajagopalan, 2012; Rothaermel & Boeker, 2008).

However, there are plethora of distance matrixes that have been used by different authors to capture the distance between firms in a knowledge spillover space and these choices have been made without recourse to any baseline information and remains the source of biasness in the estimation of knowledge spillover. Evaluating the validity and reliability of knowledge spillover to give direction to which approach fits for different scenarios is therefore critical to enhancing the knowledge spillover literature. The study therefore tests the hypothesis on the validity and reliability of three of the most used knowledge spillover measures, the uncentered correlation approach, the Euclidean distance approach and the Branstetter approach.

H_1a: The uncentered correlation Knowledge spillover measure is a valid measure of knowledge spillover.

H_1b: The Euclidean distance Knowledge spillover measure is a valid measure of knowledge spillover.

H_1c: The Branstetter Knowledge spillover measure is a valid measure of knowledge spillover.

H_1d: The uncentered correlation Knowledge spillover measure is a reliable measure of knowledge spillover.

H_1e: The Euclidean distance Knowledge spillover measure is a reliable measure of knowledge spillover.

H_1f: The Branstetter Knowledge spillover measure is a reliable measure of knowledge spillover.

2.3.2 Knowledge Spillover, Innovation and Country's Own R&D

It is the usual thinking in modern economic and policy analysis to assume that firms and countries do not only rely on just their own R&D for innovation. One of the main sources of knowledge for innovation is knowledge externality from abroad. This knowledge from abroad, which constitutes knowledge spillover has become one of the main sources of innovation for firms and countries. Knowledge spillovers are rich source of external R&D which complements the R&D efforts of countries to improve innovation (Verdolini & Galeotti, 2011). It has been shown that Internal and external knowledge must be complementary in order that to generate new technological knowledge for innovation (Antonelli, Patrucco, & Quatraro, 2011).The complementarity between knowledge spillover and country's own R&D is something that economists and policy makers will naturally wish will be the case, but this cannot be assumed to be automatic. Anselin et al.(2000) suggests that some knowledge spillovers may not be complementary if the knowledge is not related to R&D in the destination. External knowledge coming from abroad are normally new to firms in the destination and therefore imposes some adjustment cost and a set back to innovation activities in the destination (Amendola, 2023). Failures in innovation policies that attract spillover knowledge from abroad as a way to positively influence innovation could be a pointer to the fact that spillover knowledge is not complemenatry to internal R&D efforts. However, the literature is yet to investigate such complementarities between internal R&D and knowledge spillover and their effect on innovation. To address this important policy concern, the study hypothesises the following:

H_2: Knowledge spillover complements the country's own R&D to improve high technology export among selected countries in Europe.

2.3.3 Joint effect of knowledge spillover and country's own R&D on innovation

The position of the knowledge spillover literature undoubtedly sees knowledge externality as an important input to enhance innovation performance of firms. This known fact has swayed policy direction and the thinking of policy makers into believing that once there is knowledge externality, the recipient firm is bound to experience improvement in its innovation performance. This position suggests that researchers and policy makers have not averted their minds to the role of adjustment cost imposed by knowledge externality. The literature shows that even though knowledge externality reduces cost of knowledge adoption, knowledge spillover from FDI and other external channels can have a negative effect on innovation (Ali, Cantner, & Roy, 2016). This, in the view of the authors, is accounted for by insufficient absorptive capacity to deal with adjustment cost associated with using external and unfamiliar knowledge. This position is contrary to the widely held view that knowledge spillover has a positive effect on innovation. A section of empirical literature admits that the joint effect of knowledge spillover and own R&D on innovation is nonlinearly complex (Kathuria, 2002). The question as to why such knowledge sources will have other effects on innovation rather than positive has still not been answered. However, knowing that external knowledge sources impose cost on the recipient due to the high adjustment cost (Amendola, 2023) initially but diminishes with time as firms become conversant with the external knowledge, it is expected that the negative effect of knowledge spillover could change as the adjustment cost diminishes. This complex relationship between knowledge spillover and innovation performance is yet to be investigated.

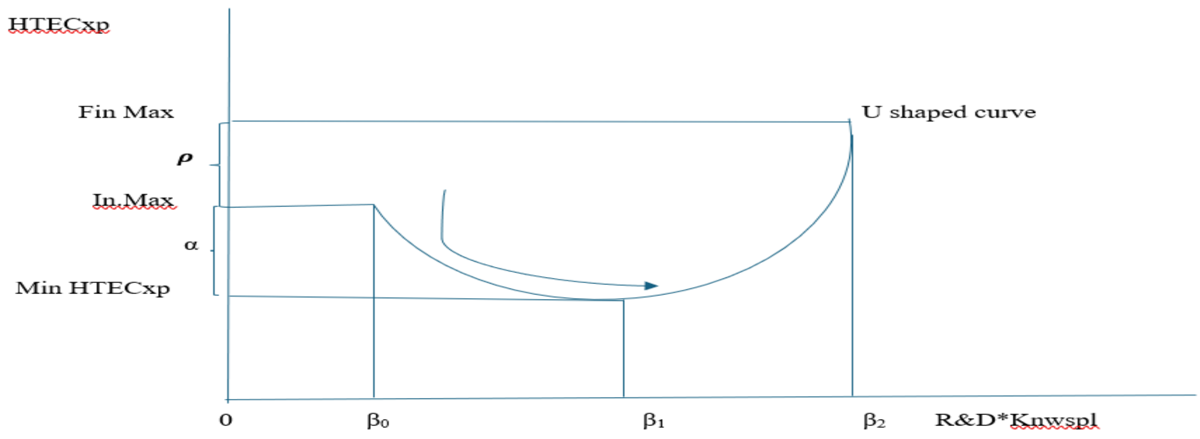

Figure 1 U-shaped Relationship between Knowledge Spillover and Innovation

Figure 1 explains the expected U-shaped relationship between the joint R&D and knowledge spillover. Figure 1 shows that countries experience initial maximum (In.Max) high technology export attributable to only R&D at R&D level β_0. However, the introduction of knowledge spillover and its combination with R&D increase R&D efforts from β_0 to β_1. This increase in R&D inputs also introduces some R&D adjustment cost (Amendola, 2023) and therefore becomes disruptive to innovation reducing high technology export. This is shown by the falling part of the curve at α. The fall in innovation terminates at R&D and knowledge spillover combination at β_2. After this point, the firms of countries must have fully adjusted and can therefore reap the benefits of the knowledge spillover from abroad leading to a rise in innovation as the combination of knowedge spillover and knowledge spillover reach β_2. ρ represent the increase in innovation result from the combined effect of R&D and knowledge spillover from abroad. This is the difference between the initial maximum high technology max (In.max) which is the result of just own R&D and the final maximum high technology export (Fin.max) resulting from the combination of the two R&D resources.

The study aims to influence the empirical literature by investigating this complex relationship between knowledge spillover and innovation through the following hypothesis:

H_3: The joint effect of R&D and knowledge spillover on high technology exports among selected countries in Europe is U shaped.

2.3.4 Absorptive Capacity, Knowledge Spillover and Innovation Performance

The literature accounts on absorptive capacity is multidisciplinary ranging from the fields of strategic management, organizational economics to international business, each of which twerk the meaning to suit the context of the study. It is in this view that Zahra and George (2002) admit that the concept of absorptive capacity is both ambiguous and diverse. Context and clarity are therefore essential in conceptualizing absorptive capacity for effective analysis, an issue that has generally eluded the knowledge spillover and technology management literature.

Studies on the importance of absorptive capacity in the field of technological management date to a study by Schilling (1998). In this study, Schilling (1998) investigated the role of absorptive capacity in driving technological success and failure and relied heavily on the resource-based view which recounts the importance of organisational learning in innovation and renewing its core competences. In most studies, absorptive capacity has been restricted to organisational learning. This can be understood in the context of the studies these authors have conducted, especially where space and interaction among parties are not important in determining absorptive capacity. In this study, the central theme being knowledge spillover hinges on space and interactions among dyad, learning parties and knowledge ownwers. I therefore, define absorptive capacity in its broad sense to means any advantage a country can leverage to learn another country's technology. This include invisble assets as explained in (Itami & Roehl, 1987) and in line with absorptive capacity of technology adopters in a geo-economic space requiring the inclusion in the construct of absorptive capacity, spatial advantages and core competencies (Coccia, 2008) dimensions as well as already accumulated knowledge or the R&D of a country (Nonnis et al., 2023). I recognise that absorptive capacity is path dependent for which reason investment in country's own R&D remains an important element to be able to absorp external knowledge.

In contrast with prior literture, the complexity of the interaction between parties is also recognised as a geo-economic phenomenon that cannot be overlooked in the construct of absorptive capacity within a knowledge spillover space (Lane & Lubatkin, 1998). This is inculcated in the study's perspective of absorptive capacity relative to the restricted view of absorptive capacity which does not take into account the complex web of interaction and interdepence in a knowledge spillover space that influence international learning of new technologies. The study, based of the spatial dimension of absorptive capacity postulate the following hypothesis for testing:

H_4: Absorptive capacity of countries positively and significantly influence the effect of knowledge spillover on innovation performance of countries

3 Research Methodology

3.1 Introduction

Chapter four of the study presents the research methodology of the study. The chapter presents research design, data and sample, measurement of variables and model estimation.

3.2 Research Design

The study executes and tests four hypotheses, the validity and reliability of knowledge spillover measures, the complementarity between international knowledge spillovers and country's own R&D, the joint effect of knowledge spillovers and country's own R&D and the effect of absorptive capacity in the relationship between knowledge spillovers and innovation performance. The broad range of objectives has influenced the research design of the study. Consistent with prior studies that have investigated related objectives (Nan, 2024; Paci, Marrocu, & Usai, 2014; Noseleit & de Faria, 2013), the current study is an explanatory study seeking to explain the statistical relationship between knowledge spillover and innovation. The study also used explanatory approaches to assess the validity and reliability of knowledge spillover measures.

The study involves measurements of knowledge spillovers, estimation of effect and relationship that exist between variables. Inspired by prior literature such as (Aldieri, Sena, & Vinci, 2018) and (Ali, Cantner, & Roy, 2016), both of which investigated the role of some economic variables on innovation performance. These and other related studies acknowledge that in examining the effect of such economic variables, the most suitable approach is a quantitative one which allows for the use of quantitative data and estimation techniques. Beyond the inspiration from prior empirical literature, the choice of quantitative study over qualitative or a mixed method is bourne out of the search for precision. All the aspects of this study require quantification in the collection and analysis of data. In this study, knowledge spillovers which are considered as a difficult variable to trace (Kaiser, 2002) is being measured. This is an indication that the current study involves measurement of variables and therefore can only adopt a quantitative approach. The study, based on the objectives, is either quantifying or estimating a relationship or quantifying the effect of knowledge spillover on innovation. This study is, therefore naturally, within the domain of quantitative study.

The study also employs a longitudinal approach to execute the objectives of the study, following knowledge spillover behaviour of sixteen countries over a period between 2011 and 2022 and its effect on innovation within the same period. The study also employs network analysis to explain the knowledge spillovers within networks and clusters. To this end, the study is also descriptive in nature. The use of network analysis in this study helps to account for the characteristics of knowledge spillovers within clusters. This is clearly in sync with the tenets of descriptive research which state that descriptive research accounts for the characteristics of individuals, groups and situation (Jack & Clarke, 1998). The study is therefore a multifaceted research design based using different approaches, depending on the dictates of the different aspects of the study objectives.

The study design is consistent with prior studies cited in innovation and knowledge spillover studies. A notable study in the innovation and knowledge spillover literature that has focused on testing the efficacy of knowledge spillover measures (Keller, 1998), has adopted explanatory study design. This study therefore takes inspiration from Keller (1998) to adopt an explanatory approach to examining the efficacy of knowledge spillover measures. In this study, the focus has been on investigating the effect of knowledge spillovers on innovation performance. The dominant approach the prior literature adopts in this area has been explanatory. For example, the study choice of explanatory approach is also inspired by authors such as Ali, Cantner and Roy(2016) and Audretsch and Belitski, (2020) who addopted similar explanatory approaches to investigate the effect of knowledge spillover on some economic variables. As part of examining the efficacy of knowledge spillover measures, the study tests the reliability of knowledge spillover measures. One approach adopted requires comparing different knowledge spillover measures. The study therefore used networks analysis to determine knowledge spillovers in clusters to allow for comparison between geographic distance-based measures and technology technological distance based measured. This is consistent with (Zacchia, 2020), who also investigated knowledge spillover in clusters using descriptive approaches including network analysis. In summary, the current study adopts a quantitative, descriptive and longitudinal study design.

3.3 Data, Sample and Measures

Four separate but related hypotheses are tested in this study. In testing the hypotheses of the study, the analysis is restricted to the high technology industry made up of the Information Communication Technology Industry and the Biotechnology industry of selected countries in Europe. This premises the study on the widely held view that knowledge spillover is dependent on technological proximity (Jaffe, 1986). The empirical literature suggests that firm innovation is a function of industry specific externalities (Nieto & Quevedo, 2005) for which reason the study is premised on the assumption that knowledge spillover only occur between firms with the same technological base. Besides technological proximity as a basis for recombination innovation, the high technology industry in Europe is a technology intensive industry (Hashi & Stojcic, 2003) which makes the industry suceptible to knowledge spillovers. Data for the study is sourced from the OECD database on countries in Europe. Countries sampled for the study are sixteen including Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Italy, Lithuania, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia and Spain. The span of the data is twelve years from 2000 to 2023. The choice of the data span of 25 years is based on data availability. It is however, important to stress that some countries in the sample could not producce the full complement of the data set which therefore makes it an unbalanced panel culminating into a panel data points of 384.

This section of the methodology is split into two, measuring knowledge spillover and measuring the other other variables used in the study.

Three knowledge spillover measures are considered in this study for the test of reliability and efficacy of knowledge spillover measures, the uncentered correlation approach, the Euclidean distance approach and the Branstetter approach to measuring knowledge spillover. However, in testing for the complementarity between country's' own R&D and knowledge spillover and their effect on innovation performance, the geography-based measure of knowledge spillover is also introduced.

In the estimation of the uncentered correlation approach to knowledge spillover, equation (10) is used as follows:

$$S_i = \sum_{j \neq i}^{N} \omega ij \; k_j \tag{10}$$

where

S_i	the uncentered correlation knowledge spillover measure of country i,
ωij	the weight or the technological distance between country i and all other countries in the sample j,
k_j	the knowledge stock of countries j that country i can prey on for spillover. This stock of knowledge does not include knowledge stock of country i. In this study, k is the patent application by residents in each country.

$$\omega ij = \frac{f_i f_j'}{[(f_i f_i')(f_j f_j')]^{\frac{1}{2}}} \tag{11}$$

where

S_i in equation 10 is the knowledge spillover between countries using the uncentered correlation approach.

The uncentered correlation adopts the cosine similarity where f_i *and* fj are vector points in a plane representing patent application of domestic country i and other countries j. The Uncentered correlation measures the angle the vectors, f_i *and* fj form in relation to the origin. The vectors are R&D expenditure in two technology areas, forming the high technology export sectors, ICT and Pharmacy. The choice of sector is based on data availability of the study.

In measuring the knowledge spillover using the Branstetter approach, the study applied the formular in equation (12).

$$S_{fi} = \sum P_{ij} R_j \qquad (12)$$

where

P_{ij} the weight or the technological distance in the uncentered correlation as in e quation (12),

R_j the knowledge stock measured by R&D intensity of the individual countries j.

The Euclidean distance approach to measuring knowledge spillover follows the approach described by Inkmann and Pohlmeier (1995). Where the distance between the units of analysis ranges from zero where the unit of analysis (country) are the same to infinity where they are totally different.

$$\omega_{ij} = \sum_{p=1}^{p} \sqrt{\left(\frac{x_{ip}-x_{jp}}{SD.(x_p)}\right)^2} \qquad (13)$$

where

ωij the weight or the technological distance between countries,

x_{ip} R&D of country i,

x_{jp} the mean R&D of countries that contribute to the R&D pool with the exception of country i,

$SD.(x_p)$ the standard deviation of R&D across all countries.

In computing knowledge spillover in all the three approaches two key knowledge pools are indentified, the knowledge pool of the individual countries and that of the entire countries that are suceptible to knowledge spillover. It is important to state that knowledge spillover must necessarily be an externality and therefore knowledge pool suceptible to knowledge spillover must not include knowledge of country i when it is country i that is accessing knowledge from the knowledge pool.

This is achieved in this study by assigning zero to each country knowledge contribution so that each country accesses knowledge from other countries except its own.

In computing knowledge spillover in all the three approaches two key knowledge pools are indentified, the knowledge pool of the individual countries and that of the entire countries that are suceptible to knowledge spillover. It is important to state that knowledge spillover must necessarily be an externality and therefore knowledge pool suceptible to knowledge spillover must not include knowledge of country i when it is country i that is accessing knowledge from the knowledge pool.

This is achieved in this study by assigning zero to each country knowledge contribution so that each country accesses knowledge from the pool but does not access its own contribution in the pool.

Table 1 Knowledge Spillover Pool Computation

Country	**A**	**B**	**C**	**Knowledge Stock**
A1	0	X	X	0+X+X
A2	0	X	X	0+X+X
A3	0	X	X	0+X+X
A4	0	X	X	0+X+X
B1	X	0	X	X+0+X
B2	X	0	X	X+0+X
B3	X	0	X	X+0+X
B4	X	0	X	X+0+X
C1	X	X	0	X+X+0
C2	X	X	0	X+X+0
C3	X	X	0	X+X+0
C4	X	X	0	X+X+0

Source: Author’s own (2025)

Table 1 presents a sketch of how knowledge pool is computed to make knowledge spillover reflect externality. In the first row are contries A, B and C. In the first column we have same countries at different times, 1,2,3 and 4. In column 5 of the Table there is a computation of knowledge stock accessible to each country by way of knowledge spillover. Table 1 shows that for each country the computation is without the country's own contribution. So for example the knowledge stock available to country A by way of knowledge spillover is 0+X+X where 0 is A contribution to the knowledge stock. From Table 1 one observes that countries at any point in time have access to knowledge spillover pool but withouot its own contribution to the pool. This therefore reflects the fact that international knowledge spillovers are externalities and without the contribution of the beneficiary country.

In this study the geography based measures of knowledge spillovers is also used. The geographic based knowledge spillover measure is inspired by empirical studies such as (Greunz, 2003) who used both geographical and technological knowledge spillover in a study that sought to understand the knowledge spillover in Europe regions.

In measuring knowledge spillover geography based measure is used

$$S_i = \sum_{j \neq i}^{N} \omega ij \; k_j \tag{14}$$

where

S_i the knolwedge spillover in country i from all other countries in Europe (j),

k_j the knowledge stock of countries j that country i can prey on for spillover. This stock of knowledge does not include knowledge stock of country i. In this study, k is high technology export of a country.

In computing the R&D input of the geographic neighbour and its contribution to an entities R&D output, the study adopts the approach by Greunz (2003). The geographic neighbour's R&D efforts are weighted by row standardised square inverse of distance weight matrix. This reflects the theoretical notion that knowledge spillover falls with distance.

The geographical distance weight is computed as follows in equation (15).

$$W_{ij} = \frac{d_{ij}^{-2}}{\sum d_{ij}^{-2}} \quad = d \tag{15}$$

where

W the weight or neighbourliness and d is the disance between the capital cities of the countries i and j.

The final stage of computing the geographic distance based knowledge spillover is computed by applying equation (16).

$$S_i = W_{ij} * K_j \qquad (16)$$

In equation (16) knowledge spillover in country i is S_i, W_{ij} is as explained in equation (15) and K_j is the R&D of other countries that are the subject for knowledge spillover.

Measuring other Variables

Data for the study is secondary data and quantitative in nature. It is a World Bank data sourced from the global economy database.

In this study, the efficacy of knowledge spillover measures is assessed. It is important to state that because knowledge spillover is not measured directly but measured by the impact it makes, the study, in assessing the efficacy of knowledge spillover measures does that through the effect knowledge spillover measures exert on innovation. This therefore requires that other influencing factors that determine innovation are included in the innovation equation alongside the knowledge spillover measures to reduce biasness.

From Table 2, it is shown that the knowledge spillover variables, uncentered correlation, Branstetter, Euclidean distance and geographic distance-based measure are latent variables. These measures are computed based on the variables sourced from the World Bank as discussed earlier under knowledge spillover measures.

In this study, innovation is measured by high technology export. The basis of this measure is empirical studies that have shown a close association between innovation and high technology export. For example, the literature shows a close association between high technology export of European countries such as Germany, Nerherland, France and UK and innovation performance between rising high technology export (Sandu & Ciocanel, 2014). The notion of high technology export is product embedded with high R&D intensity (Sandu & Ciocanel, 2014). It is also known from empirical studies that innovation is a positive function of R&D intensity. The challenges of having a direct measure of innovation have led researchers to proxy innovation by variables that are highly correlated with R&D intensity and in some cases R&D intensity itself. Patent is one of the most used measures of innovation in empirical studies (Coy & Lu, 2015; Tidd & Bessant, 2014). However, patent as a measure of innovation is saddled with some challenges that bias patent as a measure of innovation. For example, not all innovations are patented and therefore using patent as a measure of innovation could bias innovation downwards.

Table 2 Variables and Measures

Measure	Symbol	Variable
Knowledge spillover variables		
Uncentered correlation knowledge spillover	Knw_SpvrR1	Latent variable
Branstetter knowledge spillover	Knw_SpvrR2	Latent variable
Euclidean distance knowledge spillover	Knw_SpvrR3	Latent variable
Geographic distance knowledge spillover	Geod_Spill	Latent variable
Innovation variable		
Innovation	HTECxp	High technology export
Main determinants of innovation		
Intellectual capital	RDint	R&D intensity
Physical capital	Cpinvt	Capital investment
Human capital	PuBspedugdp	Public spending on education as a percentage of GDP
	lTer_enrlElig	Tertiary enrolment as a percentage of eligible people
Control variables		
Economic growth	RGDPgr	Real GDP growth rate
Globalisation	Glindx	Globalisation index
Trade openness	lTrd_openness	(Import+export)/GDP
Internet access	INTupop	Internet usage per population
International capital inflow	Wld_FDI	FDI inflow to domestic economy
Productivity	Lab_Prod	Labour productivity

Source: Author’s own (2025)

To address these potential biases in the measure of innovation authors have found alternative measures such as high technology export. The current study takes inspiration from authors such as Meral (2019) who argued in a study that the high technology is synonymous with innovation. This has been confirmed in other studies that have measured innovation. For example, the literature account shows that innovation has been measured by high technology export (Charutawephonnukoon, Jermsittiparsert, & Chienwattanasook, 2021). “High technology exports are considered products that are designed and developed with high intensity of R&D” (Charutawephonnukoon, Jermsittiparsert, & Chienwattanasook, 2021, p. 440; Durmaz & Yıldız, 2020) and a good proxy for innovation as argued and used in (Maradana, et al., 2017). The choice of high technology export as a measure for innovation is also consistent with empirical studies as an unbiased measure of innovation (Hollanders & Celikel-Esser, 2007; Moon & Lee, 2005; Geisler, 1995).

In measuring intellectual capital, the study is guided by prior literature. The literature on intellectual capital conceptualizes intellectual capital as an intangible resource that generate future value (Chahal & Bakshi, 2015). These intangible resources are made up of three main organizational resources, human capital, organizational capital and relational capital (Jurczak, 2008). Innovation studies have generally measured intellectual capital by the intensity of investment a firm or a country commits towards improving these intangible resources that generate future value. In the innovation literature, contrary to what is presented in the general management literature such as (Chahal & Bakshi, 2015), human capital is considered distinct of intellectual capital. For example, in the innovation-based theory of growth, a clear distinction is made between physical capital, human capital and intellectual capital (Romer, 1990). This study is guided by the innovation-based theory of growth which is an endogenous growth theory and draws a line between these capital inputs for innovation. Based on the innovation-based theory, three key variables, intellectual capital measured by R&D intensity, physical capital measured by capital investment and human capital measured by spending on education and tertiary enrollment are included in the innovation model. The importance of making these distinct in an innovation study of this kind is grounded in (Romer, 1990) endogenous growth theory. Per the endogenous growth theory intellectual capital, which is measured by R&D investment is the source of technological progress and is accrued by innovation, but physical capital and human capital are accumulated by savings and education respectively. These inputs play different roles in innovation process and keeping them distinct in tandem with innovation studies is to allow the study to assess the separate role each plays in the innovation process.

The important role of economic growth in innovation cannot be over emphasized. Innovation is an expensive enterprise that requires that countries must be resourceful, in terms of both intangible and tangible resources. Financial resources are required in the innovation processes of countries for which the rate at which an economy is expanding is a critical component in determining innovation and innovation outcomes of countries. Studies on determinants of innovation. In the innovation literature, the size and growth of an economy is considered important influencers of innovation. The innovation literature shows a bidirectional causality between economic growth and innovation (Maradana, et al., 2017). It is in this light that economic growth measured by the rate of change in Gross Domestic Product is considered a determinant of innovation and therefore included in the model to reduce biasness in assessing the efficacy of knowledge spillover measures. Even though studies that have investigated the effect of economic growth on other economic variables such as innovation have measured economic growth either by per capita GDP growth rate or real GDP growth rate and even sometime nominal GDP growth rate, the current study measure economic growth by real GDP growth rate. The reason for this choice is that among all the measures real GDP growth rate is the least biased measure of economic growth and especially so when the study is a panel study of countries with different economic circumstances. For example, using per capita GDP growth rate could be problematic in a particular country income distribution is concentrated. Per capita GDP growth rate will not in that sense reflect the general performance of the economy as the figure is average and could be affected by extreme abnormal values. The preferred measure of economic growth is the GDP growth rate in real terms not in nominal terms. This is because in this study, data is drawn from different countries with different levels of incomes distributions. Using GDP growth rate avoids the problem of the growth measure being adversely affected by the different income distributions that exist in the different countries in the panel. Beyond the GDP growth rate, the study chose real GDP growth rate over the nominal because in a panel study such as in this study, the different panels (countries in this case) have have different levels of inflation which can bias the study outcome. To deal with this problem real GDP is used to deal with inflated GDP growth rate problems.

In the innovation literature, globalization is featured prominently as one of the variables determining knowledge spillover and innovation. Empirical literature recounts the importance of globalization for innovation. It is generally known that globalization creates the opportunity for interaction among people, firms and countries that creates the opportunity for knowledge spillovers and transfers which are important recipe for innovation (Tee, Saini, & Ibrahim, 2018). Globalisation, in this study is used as a control variable to help reduce biasness in the model. There are several measures of globalization used in empirical studies. This is because globalization is multidimensional construct, and authors have used the different aspects of the variable’s dimension as proxies. For example, in a study by (Archibugi & Iammarino, 1999) the author measured technological globalization using three dimensions of globalization as three different constructs of international exploitation, global generation and international collaboration. Other studies have measured globalization in a more comprehensive way where individual dimensions of globalization are formed into one composite index. This study adopts a broad-based measure of globalization called the KOF globalization index that looks at globalization from economic, social and political dimensions (Gygli, Haelg, Potrafke, & Sturm, 2019). The choice of this measure is informed by the fact that it is more representative of the construct globalization than mere measures of globalisation (Potrafke, 2015).

The literature on innovation highlights the importance of trade openness on innovation performance of countries. The empirical literature shows that opening the economy to international trade stimulates innovation (Dotta & Munyo, 2019). This is because an open economy stimulates interaction among economic agents and ensures knowledge spillovers and transfers. Several authors who have investigated trade openness in the innovation literature and as a determinant of innovation (Arshad, Shabbir, & Niazi, 2019). Consistent with the empirical literature that has measured trade openness by the sum of import and export as a share of GDP (Chen, Zhang, & Wang, 2022; Pilinkiene, 2016; Karras, 2003), the current study follow suit by measuring trade opennes as the the sum of import and export as a share of GDP.

Internet access remains one of the key variables that influence innovation performance of firms and countries. In the innovation literature internet access is seen as a channel for reducing discovery cost and thereby leading to increased innovation performance (Xu, Watts, & Reed, 2019). In Xu et al.(2019), internet access was measured by the percentage of the population with a given internet download speed. An equivalent measure has been used in this study, the individuals who have used internet in the last three months of a given year. This is the Wold Bank measure of internet access. This measure has been used in emprical studies as a proxy for internet access (Haighta, Quan-Haase, & Corbett, 2014; Emmanouilides & Hammond, 2000).

The innovation literature has shown that innovation of a country is the sum total of internal and external factor or resource inflow. One of the external sources of innovation inputs is Foreign Direct Investment (Erdal & Göçer, 2015). In this study, international capital inflow is recognised as an important influencer of innovation and therefore included in the model as a control against model biasness. A widely used proxy for international capital inflow is foreign direct investment. For example, in a study by Tille and Van Wincoop (2010) where the authors investigated international capital flows, foreign direct investment inflows was used as a proxy. Other studies that have used Foreign Direct Investment as a measure of international capital flow in the innovation literature have stressed that FDI is an important variable that explains innovation performance of countries (Branstetter, 2006; Branstetter, 2000). This justifies the inclusion of FDI in an innovation model that using the determinants of innovation to determine the efficiacy of knowledge spillovers.

The relationship between innovation and productivity levels with in the economy has been studies variously by different authors. The importance of productivity in innovation is well explained in the innovation literature. The relationship between innovation and productivity has long been known (Lee, 2008; Lööf, 2004; Griliches, 2000). However, these studies have observed the relationship in the reverse order with labour productivity being dependent on innovation. However, in this study labour productivity is considered an influencer of innovation. This is consistent with authors who have argued that the changing conditions of the labour market (labour flexibilities) influence innovation performance (Preenen et al., 2017). This is the basis for the inclusion of labour productivity measured by the average number of hours worked by a worker in the scope of one year based on the World Bank measure. This measure reflects the changing labour market conditions and labour flexibility (Preenen et al., 2017).

Table 3 Measuring Absorptive Capacity

Measure	**Symbol**	**Variable**
Absorptive capacity		
R&D intensity	R&D	R&D expenditure as a percentage of GDP
Contiguity	Cont	Number of countries sharing border with the focal country
Centrality	Cent	Inverse of mean distance between focal country and other countries

Source: Author's own (2025)

In the innovation literature, absorptive capacity of firms and countries have generally followed the views of (Cohen & Levinthal, 1990) who argue that absorptive capacity defines the ability to identify, assimilate, transform and exploit new technological ideas. The spatial nature of innovation and its associated knowledge spillover is not in sync with the definition of knowledge spillover given by Cohen and Levinthal (1990). To the extent that innovation and knowledge spillovers are spatial in nature, defining absorptive capacity in the context of Cohen and Levinthal (1990) where the construct is only measured by the size of R&D is restrictive. Absorptive capacity in the context of innovation is multidimensional and beyond the size of

R&D (Tang et al., 2020). Tang et al.(2020) identified seven dimensions of absorptive capacity in relation to innovation studies as R&D capabilities, economic level, human capital openness, infrastructure, distance from the source of knowledge and governance. In this study, these dimensions of absorptive capacity have been groups into two, R&D and spatial factors.

I make the argument based on empirical studies (Neves & Branco, 2020; Wang, 2010) that R&D of a country is a function of the performance of the economy, human capital, infrastructure and governance. In this study therefore these dimensions of absorptive capacity are represented by the R&D of the countries. Using R&D as a measure of absorptive capacity is conventional and consistent with emprical studies in the innovation literature. What is novel is the spatial dimension of measuring absorptive capacity. Empirical evidence suggests that there is a spatial dimension in the measurement of absorptive capacity when dealing with innovation (Tang et al.,2020). Tang et al.(2020) based their argument on studies that emphasise the importance of geographic distance to absorbing knowledge spillovers. Space is therefore an important variable in absorbing external knowledge for innovation. Geographic proximity allows for easier interaction and reduction in transaction cost (Jaffe, Trajtenberg, & Henderson, 1993). In testing the role of absorptive capacity in the relationship between knowledge spillover and innovation, the spatial dimension of absorptive capacity should be considered since knowledge spillovers have spatial effect. In this study therefore two spatial dimensions of absorptive capacity are considerd, centrality which measured average physical distance from a country to all other countries in te data set. The shorter the average distance the more central the country is and the higher the interaction with other countries. The other measure of absorptive capacity is contiguity. This is a measure of the number of countries bordering a country. The more countries a focal country shares border with the higher interaction and therefore higher absorption of knowledge spillover and innovation. These two measures of absorptive capacity are consistent with spatial dimensions of absorptive capacity explained in (Tang, Chen, Wang, Xu, & Yi, 2020) and based on the ideas of (Jaffe, Trajtenberg, & Henderson, 1993).

3.4 Estimation Techniques

In this section of the methodology, the techniques employed in testing the four hypotheses are explained in accordance with the different hypotheses. This section first presents the estimation of the knowledge spillover models to test the efficacy of the three knowledge spillover measures. This is followed by testing the complementarity between international knowledge spillover and country's own R&D. This section follows this with the estimation of the joint effect of knowledge spillover and country's own R&D on innovation performance and then the role of absorptive capacity in the relationship between knowledge spillover and innovation performance.

Estimating the Knowledge Spillover Effect Model

There is a consensus among authors that knowledge and knowledge spillovers are intangible and can therefore not be observed directly but only through the impact they make. This means that to measure the extent of knowledge spillover the impact knowledge spillover makes is important to estimate.

To test the efficacy of knowledge spillover measures, the study estimates the effect of knowleege spillover on innovation output variables

$$ks_{it} = \alpha_0 + \beta_1 \Sigma hmc_{it} + \beta_2 \Sigma lntC_{it} + \beta_3 \Sigma phC_{it} + \beta_4 \Sigma Con_{it} + \sum \beta_5 knw + e_{it} \tag{17}$$

Equation (17) is modelled on the ideas of the endogenous growth theory also knowln as the innovation-based theory that recognised that intellectual capital, which is the source of technological progress is distict from human and physical capital. So in equation (18) innovation output variable *ks* is a function of a vector of human capital (*hmc*), intellectual capital (*Intc*), physical capital (*phc)* and a vector of control variables (*con*) and the variable of interest, knowledge spillover(knw). Equation 18 is pooled OLS which does not take into consideration that panel structure. A fixed effect model which takes into account the panel structure is modelled in equation (18):

$$ks_{it} = \alpha_0 + \beta_1 \Sigma hmc_{it} + \beta_2 \Sigma lntC_{it} + \beta_3 \Sigma phC_{it} + \beta_4 \Sigma Con_{it} + \sum \beta_5 knw + \omega_{it} + e_{it} \tag{18}$$

where

ω the unobserved individual effect.

The study as part of assessing the reliability of the knowledge spillover measures modelled the long run knowledge spillover. Equation (19) is a dynamic model based on the fixed effect model.

$$ks_{it} = \alpha_0 + \rho ks_{it-1} + \beta_1 \Sigma hmc_{it} + \beta_2 \Sigma lntC_{it} + \beta_3 \Sigma phC_{it} + \beta_4 \Sigma Con_{it} + \sum \beta_5 knw + \omega_{it} + e_{it} \tag{19}$$

Model (19) tests the presence of dynamic process in the model to allow the estimate of long run knowledge spillover effect on the innovation output variable. For the model to have dynamic process ρ must be positive less than 1.

$$longrunKnw = \frac{1}{1-\rho} \tag{20}$$

Equation (20) is applied to attain the long run knowledge spillover. This figure must be close to the fixed effect static model knowledge spillover for a stable measure of knowledge spillover.

Criteria for Accessing Efficacy of Knowledge Spillover Measure

Reliability and validity are the standard psychometric criteria for ascertaining measurement adequacy (Nunnally & Bernstein, 1994). A reliable measure in this study is defined as the ability of a measure to produce the same results when the measure is reapplied to the same group. This will mean that a knowledge spillover measure is reliable when it shows consistency in its outcomes. In terms of validity of knowledge spillover, the study adopts Price et al (2015) definition which suggests that a measure is valid by the extent to which it represents what it intends to measure. This is operationalised consistent with Cronbach and Meehl (1955) who showed that validity of measure is determined by establishing a theoretical relationship between the measure of a given construct and another variable. In simple terms if there is a theoretical relationship between A and B then a measure of A is valid if the measure retains the relationship A has with B.

Reliability Test

In testing the reliability knowledge spillover measures, the study sort to determine the consistency of the measure. Three methods are adopted in this study, the consistency of the measure overtime or the stability of the measure. This is done by examining the long run effect and comparing with the short run effect of the measure has on innovation outcome variables. Consistent with Griffiths and Murrells (2010) who who argues that reliability is the extent to which a measures produces the same results. In (Polit & Beck, 2008), the authors used equivalence assessment to measure reliability of a measure. In both Griffiths and Murrells (2010) and Polit and Beck (2008) correlation analysis of outcomes have been used to test for reliabilty of a construct. This study is inspired by these study and adopt correlation analysis in testing for reliability of knowledge spillover measures. The study estimates both pooled OLS and fixed effect models for eight sub samples made of Australia and Belgium, Czech Republic and Denmark, Finland and France, Germany and Italy, Lithuania and Netherland, Norway and

Poland, Portugal and Slovakia and the slovenia and Spain as well as the full sample. An intraclass correlation analysis is conducted to determine the consistency between the pooled OLS and the fixed effect model estimation of knowledge spillover. Most studies cited in the literature have either employed pooled OLS or fixed effect or both. If a knowledge spillover approach is consistent the expectation is that the intraclass correlation coefficient will be high 0.8 or higher (Wooldridge, 2009).

The intraclass correlation coefficient is computed based on the pearson correlation coefficient in equation (21):

$$r = \frac{\sum(x_i - \bar{x}_i)(y_i - \bar{y}_i)}{\sqrt{\sum(x_i - \bar{x})^2 \Sigma(y_i - \bar{y})^2}} \qquad (21)$$

where

r the intraclass correlation coefficient,

x the individual knowledge spillover coefficients in the pooled OLS modle,

$\bar{x}$ value of pooled OLS knowledge spillover coefficients,

y the individual knowledge spillover coefficients in the fixed effect models,

$\bar{y}$ the mean value of the fixed effect model kowledge spillover coefficient.

Theoretically the best estimates of reliability test is an equvilance of two forms of test for comparison (Kuder & Richardson, 1937). This has influenced the comparison between the OLS and the fixed effect estimate for test of reliability.

The study also conducts a test of reliability of knowledge spillover by way of test-retest analysis. However, this test is usually testing same sample after time. In this study the base for comparison is the full sample and the test units are the sub sample. This is a test of equality which compares knowledge spillover estimates between the full samples and the sub samples. The analysis is conducted under the null hypothesis: H_0: β = 0 or there is no significant difference between the full sample knowledge spillover coefficient and the subsample knowledge spillover coefficient. A significant chi square statistic rejects the null hypothesis for the alternative which suggest the sub sample coefficients are significantly different from the full sample coefficient. This will indicate the measure for knowledge spillover is not reliable.

Validity Test for Knowledge Spillover Measures

From Cronbach and Meehl (1955) who explained that validity of a measure requires that a construct retains its theoretical relationship with other variables, this study falls on the engenous growth models that stipulated innovation output variables as an increasing function of knowledge spillover. Given this background, a knowledge spillover measure is valid if it has a positive and significant effect on innovation output variable. This will require that β_5 in equations 17, 18 and 19 be positive and significant. Again the longrun knowledge spillover coefficient estimated using equation 20 must be positive and significant.

Complementarity Between International Knowledge Spillover and Country's Own R&D

In conceptualizing complementarity and its measurement, the study follows strictly the definition and measurement by Schmiedeberg, (2008). Complementarity represents where the use of one input or strategy pays off more if the complementary input or strategy is presents (Schmiedeberg, 2008). In this study therefore, countries' own R&D being complementary with international knowledge spillover means that countries' own R&D ensures high innovation if if at the same time countries have access to international kowledge spillover and vise versa.

In estimating the complementarity between international knowledge spillovers and countries' own R&D, the Griliches (1978) production function provides a guide as to the variables that enters the knowledge production model specified. In view of Griliches (1978), the production function connects some measures of output *Y* at the micro or macro level to inputs *X*, *K* and u. Where X represents conventional inputs in production such as labour and capital whilst K measures the current state of technology determined partly by R&D expenditure and u is the idiosyncratic error term that captures errors of measurement and variables that are not explicitly captured in the model but have some minimal effect on the output. The Griliches (1978) production function is therefore captured in the following form in equation (22).

$$Y = F(X, K, u) \tag{22}$$

Prior studies on complementarity estimation have adopted two variants of the production function approach to estimating complementarity between economic variables. In a study to determine the complementarity between internal and external innovation strategies, two approaches have been used, productivity and adoption approached (Schmiedeberg, 2008).

Productivity Approach to Measuring Complementarity

The knowledge productivity approach measures the outcome of innovation to innovation input activities. It is a direct test of supermodularity through an innovation regression model where an innovation measure is regressed on innovation input variables for which complementarity is being determined. Based on Schmiedeberg (2008), equation (23) is specified to test the complementarity between international knowledge spillover and countries' own R&D for innovation performance

$$Inno_{it} = \alpha_0 + \beta_1 R\&D_{it} + \beta_2 knw_{it} + \beta_3 (R\&D_{it} * knw_{it}) + \beta_4 \Sigma Con_{it} + \omega_i + e_{it} \qquad (23)$$

Equation (23) estimates the complementarity between internal R&D (R&D) of country i, in Europe and international knowledge spillover from countries j also in Europe. β_4 measures the effect of a vector of control variables on innovation. The study adopts panel regression analysis that accounts for the unobserved variables (ω_i) and the random error term is e_{it}. The coefficient of interest β_3 .which needs to be significant and positive for a conclusion of complementarity (Schmiedeberg, 2008).

Adoption Approach to Measuring Complementarity

In the adoption approach, there is a rationality assumption that countries and firms will use both innovation production inputs (Schmiedeberg, 2008). In this study, the rationality assumption being made is that firms and countries will rely on both international knowledge spillovers and the individual countries' own R&D or will not employ any of these inputs. Being a profit maximizing firm or countries with the aspiration to improve innovation, the expectation is that countries will combine their own R&D efforts and free flowing international knowledge spillovers. Once these countries are using these resources or inputs together the positive correlation could be misleading and misinterpreted to mean complementarity (Athey, 1998). The solution is to regress one of the variables on the other and introduce control variables to deal with the biases (Athey, 1998). Consistent with Schmiedeberg (2008) who investigated the complementarity between internal and external innovation inputs, the current study specified equation (24) to test complementarity between countries' own R&D investments and international knowledge spillovers.

$$R\&D_{it} = \alpha_0 + \beta_1 knw_{it} + \beta_2 \Sigma Con_{it} + \omega_i + e_{it} \qquad (24)$$

In Equation (23) R&D is the own R&D of country i whilst knw is knowledge spillover from countries j. ΣCon is a vector of control variables. The coefficient of interest is β_1 and is expected to be positive and significant to confirm that R&D and knowledge spillover are complementary.

Joint Effect of International Knowledge Spillover and Countries' Own R&D innovation

In testing the hypothesis on the joint effect of knowledge spillover and country's own R&D on innovation, the study is guided by the innovation-based theory popularly known as the endogenous growth theory. The endogenous growth theory splits the components of growth into human capital, physical capital and intellectual capital. The model for the estmating the effect of these two innovation inputs on innovation will follow the endogenous growth theory that has been the dominant approach adopted in estimating innovation performance. Equation 25 presents the model for estimating the joint effect of international knowledge spillover and countries' own R&D on innovation performance.

$$HTECxp_{it} = \alpha_0 + \beta_1 R\&Dint_{it} * knw + \beta_2 (R\&Dint_{it} * knw)^2 + \beta_3 knw + \beta_4 R\&Dint_{it} + \beta_6 \Sigma phC_{it} + \beta_7 \Sigma Con_{it} + \omega_i + e_{it} \quad (25)$$

Where $HTECxp$ is high technology export of countries. The analysis is conducted using the fixed effect model. The long run effect of the knowledge spillover variable and its interaction with country's own R&D is fitted as a quadratic to assess whether the effect of the joint effect between R&D and knowledge spillover switch at a point because of adjustment cost.

In equation (24), the study acknowledges the heterogeneity introduced in the knowledge production function when combining two different knowledge sources, countries' own R&D and international knowledge spillovers. Here in equation 24, heterogeneity is not seen as a problem to deal with but the knowledge production function is modelled to reflect the heterogeneity from combining own R&D and international knowledge spillover.

The Role of Absorptive Capacity in the Complementarity between International Knowledge Spillover and Countries' Own R&D

In assessing the role of absorptive capacity in the complementarity between international knowledge spillovers and countries' own R&D, the study recognise the importance of the different sources of absorptive capacity for international knowledge spillover. Prior literature on innovation and knowledge spillovers has generally linked absorptive capacity to prior knowledge, basically R&D. Another source of absorptive capacity that the prior literature mentions is links with basic research (Veugelers, 1997). The literature is in sync with the thinking that technologies must be familiar for complementarity to occur. This is important in conceptualizing absorptive capacity in this study. Given that knowledge spillovers and its absorption are spatial phenomenon, absorptive capacity is conceptualized also to include spatial dimension. Contiguity and centrality are considered measures of absorptive capacity alongside the traditional measure of absorptive capacity, R&D expenditure.

$$Inno_{it} = \alpha_0 + \beta_1 R\&D_{it} + \beta_2 knw_{it} + \beta_3 (ac_{it} * knw_{it}) + \beta_4 ac_{it}$$
$$\beta_5 \Sigma Con_{it} + \omega_i + e_{it} \qquad (26)$$

where

ac absorptive capacity measured by R&D, contiguity and centrality of a country.

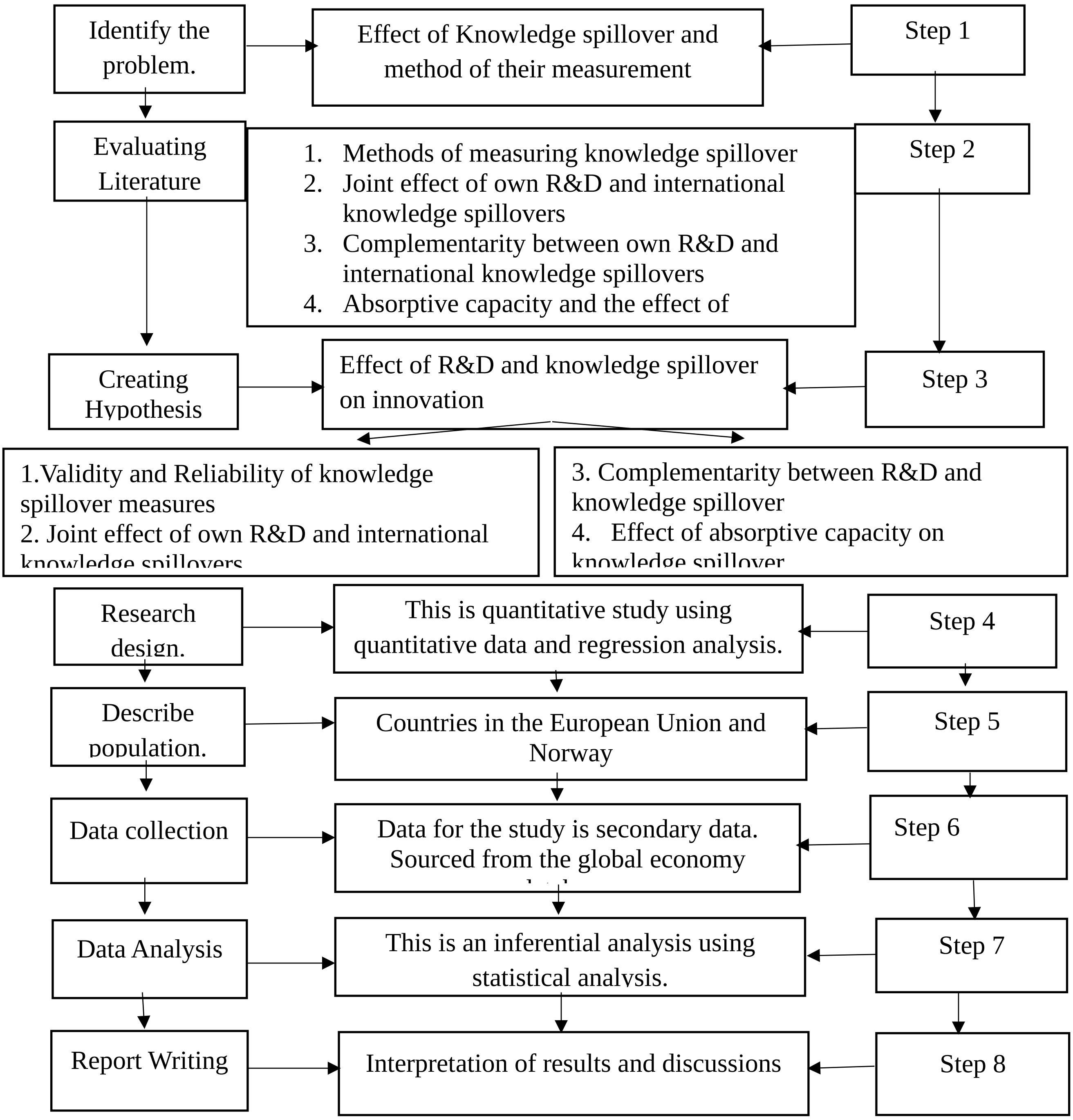

Figure 2 Research Process
Source: Author's Own (2025)

4 Results and Discussions

4.1 Results

This section of the study presents results and discussions of the study. The study in this section first presents results on the data analysis. The results section first presents descriptive statistics of the data to give an idea of the data used in the analysis. This is followed by the specific results of the study based on the hypothesis set to be tested. The study presents first, the results and discussions on the validity and reliability of selected measures of knowledge spillovers. Second, the study presents results and discussions on the complementarity between knowledge spillover and high technology export as a measure of innovation. Thirdly, the study presents results and discussions on the joint effect of a country's own R&D and knowledge spillover from abroad on technology export as a measure of innovation. Fourth, the chapter presents results and discussions on the role of absorptive capacity in the relationship between knowledge spillover and innovation performance.

4.1.1 Descriptive Statistics

Table in appendix A presents the descriptive analysis of the variables used in the analysis. Specifically, Table 4 presents correlation analysis, the means of the variables and the associated standard deviations as well as the minimum and maximum values of the variables. The correlation analysis shows that the variables are generally not highly correlated with each other. However, correlation between patent application by residents and high technology export is high at 0.9. This does not presents a problem because these variables are not part of the same regression model. All other correlation coefficients are below threshold of 0.8 and therefore the variables are not candidates for multicollinearity.

The descriptive statistics in appendix A shows that the mean R&D intensity is 1.78 with a high standard deviation of 0.77 with a range of minimum value of 0.45 and a maximum of 3.7. This is a clear indication of high differences in the countries' innovation activities. This reflect in the high differences of countries' high technology exports which is one of the measures of innovation adopted in the study. High technology export shows high difference among countries as the standard deviation is high and the value ranges between as low as 961.43 million to as high as 223370 million.

Table 4 Stationarity Test

Variables	Stationary at level	Remarks
Cpinvt	I(0)	Stationary
GOVTspgdp	I(0)	Stationary
INTupop	I(0)	Stationary
INNdx	I(1)	Stationary
RDint	I(1)	Stationary
INFtecxtox	I(0)	Stationary
HTECxp	I(1)	Stationary
PUBspedugdp	I(0)	Stationary
Glindx	I(0)	Stationary
Lab_Prod	I(1)	Stationary
Lab_Prate	I(1)	Stationary
Trd_Opness	I(1)	Stationary
Pub_spEduPsp	I(1)	Stationary
Ter_enrlElig	I(0)	Stationary
wld_FDI	I(1)	Stationary
PATappres	I(1)	Stationary
KnwSlver	I(0)	Stationary
Man_knwstock	I(0)	Stationary

Source: Author's Own (2025)

Table 4 is a pesentation of the stationarity test of the variables and first difference as a way to stationarise variables that are not stationary at level. At level variables that are stationary include capital investment, government spending as a percentage of GDP, internet users as a percentage of population, information technology export as a percentage of total export, public spending on education as a percentage of GDP, globalisation index and percentage of world FDI. Variables that are stationary only after first differencing include innovation index, R&D intensity, high technology export, labour productivity, labour force participation rate, trade openess and public spending on education as a percentage of public spending proportion of world FDI and Patent application by residence.

Table 5 Descriptive Analysis at Country Level

Ctry	Cont	Centrality	Knowledge spillover	R&D	Abs. capacity	Innovation (Patent_App)	High_Tech Export
BE	3	995.338	1244.7188	9716.722	91941.81	712.2857	30964.99
CZ	4	865.732	188.11878	2711.713	24017.02	721.6364	28553.92
DK	1	1022.817	416.983566	7285.774	10865.36	1532.545	10704.99
DE	7	879.0847	5625.48489	80478.69	119780.9	47366.36	197272.5
ES	2	1809.29	598.194553	13111.13	25289.7	2719.773	15392.86
FR	4	1099.487	2122.97073	44987.2	504895.5	14163.09	105533
IT	3	1314.311	474.699374	20378.28	223769.8	8651.515	31954.74
LT	1	1312.045	12.1055229	323.4186	2783.008	87.80237	2054.148
NL	2	1042.054	1147.08498	13429.7	139781.6	2260.125	81966.46
AT	5	935.4033	1172.8279	8985.305	89940.55	2437.739	5323.684
PL	4	1128411	222.069683	3920.838	30506.51	3252	15351.81
PT	1	2293.116	77.2672317	2326.555	23026.77	465.1364	2688.479
SL	2	1043.114	36.0826987	741.7142	7324.328	348.1667	1879.076
SK	3	1034.97	59.6253733	531.7499	4477.568	200.625	6611.946
FL	1	1445.71	172.534733	6314.624	73238.14	1729.773	6643.266
NO	1	1348.335	160.084051	5725.044	59148.71	1105.25	4869.088

Source: Author’s own (2025)

Table 5 presents descriptive statistics of the main variable used in the study at the country level. The results shows that the first order contiguity, number of immediate countries bordering a country shows values ranging from seven (7) for Germany and one (1) for countries like Denmark, Lithuania, Portugal, Finland and Norway. This variable gives an indication of the extent of interaction between countries. Noting that interaction between countries is distance decay, the expectation is that the number of a country’s immediately bordering it determines the extent of interaction with the outside world. The centrality variable measures the location of the country within the study area. This determines the distance between a country and all other countries within the study area. The shorter the distance, the more central the country is. The most central country within the study area is the Czech Republic with an average distance of 865.732 Km whereas the most isolated country is Spain with an average distance of 1809.29 Km. Knowledge spillover gains of countries show that on the average the highest knowledge spillover gains of 5625.485 accrue to Germany whilst the lowest of 12.11 accrue to Lithuania. In terms of R&D expenditure, the averages suggests that Germany is the highest with 80478.7

Euros whilst the lowest is Lithuania with 323.4 Euros. The results also show that the absorptive capacity of countries vary with the France leading with an average figure of 504895.5 Euros and Lithuania with the least of 2783 Euros over the study period. Innovation measured by patent application by residents varies across countries and over time. The average patent application by residents is highest in Germany with a value of 47366 and the lowest of 88 for Lithuania. In measuring innovation, the study also used High technology export. The variable records the highest average figure of 197272.5 whilst the lowest is Slovenia with value of 1879.

Table 6 Descriptive Analysis at Country Level Continuation

Country/Variables	R&Dint	INFtecx/tox	HTECxp	PATappres	INNdx	RGDPgr
Austria	2.09	1.40	5362.19	2541.61	51.33	2.81
Belgium	2.27	2.90	22544.46	710.17	54.82	1.70
Czechia	1.61	13.28	28913.12	713.78	49.17	2.58
Denmark	2.72	4.50	10459.37	1513.30	57.59	1.52
Finland	3.19	9.57	7943.22	1722.26	59.43	1.52
France	2.17	5.14	105722.6	14129.3	40.34	1.31
Germany	2.74	5.84	197519.8	47038.35	55.46	1.24
Italy	1.28	2.46	31886.52	9518.35	48.90	0.49
Lithuania	0.88	3.78	2074.86	576.88	46.66	4.04
Netherland	1.92	12.90	81351.78	2636.81	51.45	1.64
Norway	1.72	1.84	4842.39	1516.55	49.04	1.70
Poland	0.87	6.40	14941.86	3628.43	42.25	3.80
Portugal	1.20	4.94	2622.55	921.42	44.71	0.98
Slovakia	0.71	12.92	6780.23	203	42.56	3.46
Slovenia	1.83	1.87	1861.0	962.50	45.89	2.44
Spain	1.21	2.39	15164.73	2700.38	46.97	1.65

Source: Author’s own (2025)

In Table 6 the means of R&D intensity and all the innovation output variables for the individual countries in the panel are presented. From the results in Table 6 what is observed is that countries with high R&D intensity (R&Dint) are generally countries with high innovation output. For example, Finland, Australia, Belgium, Denmark, France and Germany are the countries with the highest R&D intensity and are the same countries that occupy the top tier in terms of innovation index (INNdx). Lithuania, Poland, Portugal and Slovakia which are among the countries with the least R&D intensity are among the countries that occupy the lowest tier in terms of innovation index. It is however, important to recognise some outliers such as France with the least innovation performance index even though it has an appreciable high level of R&D intensity. This trend is almost the same for all other innovation output variables except for patent application by residents (PATappres) which does not seem to show any discernible relationship with R&D intensity.

4.1.1.1 Distribution of International Knowledge Spillover Inflows to Countries

The literature on knowledge spillovers is generally thorn between two polar arguments, one that suggests knowledge spillovers are localized or occur in a network of clusters and the opposing view that suggests that technological proximity is critical to knowledge spillovers. This section of the descriptive analysis presents the network analysis of knowledge spillover within the study panel and an associated map that shows the distribution of knowledge spillover inflows within the study panel.

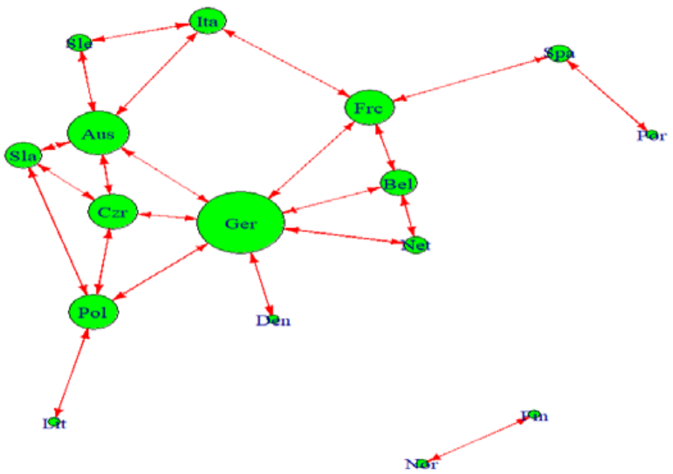

Figure 3 Network Analysis on International Knowledge Spillovers
Source: Author's own (2025)

In analysing the distribution of international knowledge spillovers, the principal idea adopted is that knowledge spillovers are localized and occur in clusters (Murata et al., 2014; Jaffe et al., 1993). Figure 3 presents a network analysis of international knowledge spillovers within some sixteen selected countries in Europe. The size of the nodes (green circles) represents inward knowledge spillovers received by countries and the vertices (red arrows) represent the direction of flow of knowledge spillovers. From figure 3, two things are apparently clear, nodes at the center of the network are larger relative to nodes far away from the center of the network. For example, Figure 2 shows that visually Germany (Ger) is more centrally placed than countries such as Spain (Spa), Portugal (Por) and Lithuania (Lit) among others. The central position of Germany relative to these other peripheral countries accounts for the high knowledge spillover inflow to Germany relative to these periphery countries. As countries move away from the periphery towards the center knowledge spillover inflows to countries increase. This is evident from Figure 3. A comparison between the most periphery countries of Lithuania (Lit), Norway (Nor), Finland (Fin), Portugal (Por) and countries that are closer to the center such as France (Frc), Austria (Aus) and Poland (Pol) shows that France, Austria and Poland have larger node size relative to the most periphery countries. This confirms the ideas espoused in prior literature that knowledge spillovers are localized and as one move away from the center knowledge spillover reduce (Jaffe, Trajtenberg, & Henderson, 1993). A critical evaluation of Figure 3 shows that apart from centrality, there is another factor that determines the size of the nodes (Knowledge spillover inflows). Slovenia, Italy, Spain and Portugal are all periphery countries. The question is: how do these countries have different node sizes when they are all periphery countries (Ita>(Slo=Spa)>Por)? This leads us to a very important aspect of international knowledge spillovers, contiguity. Contiguity is the number of countries immediately bordering a focal country. Knowledge spillover is a function of interaction and other soft factors such as culture. Neighbouring countries have a lot of things in common are able to interact among themselves through trade, education and other channels that non neighbouring countries. From Figure 2 Italy, even though a periphery country in the same class as Slovenia, Spain and Portugal, Italy has a contiguity of 3. It shares borders with Austria, Slovenia and France. It is natural to expect that Italy will interact with these countries and gain some level of knowledge spillover inflows than it can do with countries it does not share borders with. Slovenia and Spain has the same node size visually but bigger than Portugal. The same principle applies here. Spain and Slovenia share borders with two countries each whereas Portugal shares border with only Spain. From the network analysis in Figure 2, location of a country influence knowledge spillover inflows into a country. The size of knowledge spillover inflows is determined by two spatial factors consistent with the localized or cluster-based thinking of knowledge spillovers (Huber, 2012; Jaffe, Trajtenberg, & Henderson, 1993). In agreement with Huber (2012), from the network analysis, I contend that clusters are important factors in determining kowledge spillovers even at the international level.

Table 7 Centrality and Contiguity

Country	Contiguity	Centrality	Country	Contiguity	Centrality
Czech R.	4	865.732	Germany	7	879.0847
Germany	7	879.0847	Austria	5	935.4033
Austria	5	935.4033	Czech R.	4	865.732
Belgium	3	995.338	France	4	1099.487
Denmark	1	1022.732	Poland	4	1128411
Slovakia	3	1034.97	Belgium	3	995.338
Netherland	2	1042.054	Italy	3	1314.311
Slovenia	2	1043.114	Slovakia	3	1034.97
France	4	1099.487	Spain	2	1809.29
Lithuania	1	1312.045	Netherland	2	1042.054
Italy	3	1314.311	Slovenia	2	1043.114
Norway	1	1348.355	Denmark	1	1022.732
Finland	1	1445.71	Lithuania	1	1312.045
Spain	2	1809.29	Portugal	1	2293.116
Portugal	1	2293.116	Finland	1	1445.71
Finland	1	1445.71	Norway	1	1348.335

Source: Author’s own (2025)

Table 7 provides a descriptive analysis to support the network analysis in informing which of the two dominant factors, centrality and contiguity is at play in determing international knowledge spillover inflows. Tables 7 compared the role of centrality and contiguity to determine which of the two factors is reflected mostly by figure 2. The first three columnsTable 8 is sorted based on centrality with the most centrally located countries first in decending order. Whilst the next three columns is sorted based on contiguity with countries with the highest contiguity first in a decending order. Comparing Figure 2 with Table 7, it can be noticed that the network analysis typifies the first three columns of Table 7 where the countries with the highest contigity are the ones with the biggest node size. Countries such as Lithuania, Denmark, Portugal, Norway and Poland with contiguity values of 1 have the smallest node size and therefore gains least from international knowledge spillovers.

4.1.2 Validity and reliability of selected measures of knowledge spillover

This section of the study explores the alternative ways of measuring knowledge spillovers. The literature review shows that different authors have used varied approaches to measure knowledge spillovers. At this stage of the study, these approaches to measuring knowledge spillovers is applied to the same data to determine the consistencies or reliability, stability biasness, uniqueness of the measure and the variance of the different approaches as well as the extent to which they are able to measure knowledge spillovers. Three measures of knowledge spillovers are considered in this study, Jaffe's uncentered correlation, Branstetter approach and the Euclidean distance approach to knowledge spillovers.

4.1.2.1 Uncentered Correlation Approach

The validity and relaibility of the uncentered correlation approach to measuring knowledge spillover is investigated. The validity of a knowledge spillover measure, from Cronbach and Meehl (1955) will require that the measure retains its theoretical relationship with other variables. Based on the endogenous growth models, the expectation is that a valid knowledge spillover variable will have a positive and signficant relationship with innovation output, in this case high technology export. The results as shown in Table 8, model 1 presents the results of other variables on high technology export without the uncentered correlation estimate of knowledge spillover (Knw_SpveR1) based on OLS.

Model 2 includes Knw_SpveR1 which is uncentered correlation measure of knowledge spillover. The variable is positive and significant, indicating that the measure has established its theoretical relationship with an innovation output variable. This confirms the hypothesis that the uncentered correlation measure of knowledge spillover is valid with an explanatory power of 0.1116 (difference in adjusted R square). In model 3 of Table 9 and 4 of Table 10, the fixed effect model is used. Model 3 is without Knw_SpveR1. The explanatory power of model 3 measured by the adjusted R squared is 0.0815 comparing this with an explanatory power of 0.0870 in model 4 of 10 which includes Knw_SpveR1 indicates that Knw_SpveR1 has an explanatory power of 0.0055. In testing the validity of Knw_SpveR1 in the fixed effect model, the analysis shows that Knw_SpveR1 is positive and significantly related to high technology export. This establishes the theoretical relationship between knowledge spillover and innovation output variable and confirms the hypothesis of a valid knowledge spillover measure.

Table 8 Uncentered Correlation and High Technology Export

Variable	Model 1	Model 2	Model 3
lg_HTECxp	n/a	n/a	n/a
RGDPgr	0.043627 (0.072763)	0.0405985 (0.0595634)	0.0200906 0.032543
Cpinvt	-0.398979 (0.3424554)	0.5114084* (0.2907084)	0.1578962 (0.1985641)
GOVTspgdp	2.53613*** (0.4872553)	2.202921*** (0.3998549)	0.7460527*** (0.378665)
RDint	0.4085754** (0.1822323)	0.2671688* (0.1496515)	0.1293* (0.0796043)
PUBspedugdp	-2.594261*** (0.3179334)	-1.25346 (0.2838817)	0.4389379 (0.3058193)
lTrd_Opness	-.0116152 (0.1356531)	0.718243*** (0.1270432)	1.134348*** (0.2017847)
lTer_enrlElig	-0.7680962*** (0.1288675)	-0.5572313*** (0.1069857)	-0.1071087 (0.0796008)
wld_FDI	0.4295311*** (0.0373355)	0.2458556*** (0.0342827)	0.0485446 (0.0302167)
Knw_SpverR1		0.4819283*** (0.0407533)	
_cons	12.72584*** (1.870012)	-0.154215 (1.878711)	0.9748091 (1.993663)
R-Squared: Within: Between:	0.6710	0.7803	0.0032 0.1544 0.0034
Adj. R-Squared	0.6617	0.7733	0.0815
Dif Adj R-sq		0.1116	
F-statistics	71.89	110.90	
Probability		0.0000	

Source: Author's Own (2025) **** p<0.01; **p<0.05; *p<0.10. Standard errors in parenthesis. ++placebo p>0.8 All variable are in their logarithmic transformation.*

Table 9 Uncentered Correlation and High Technology Export (Continuation)

Variable	Model 4	Model 5	Model 6	Placebo Anal.
lg_HTECxp	n/a	0.0000223*** (3.00e-06)	n/a	n/a
RGDPgr	0.0248405 (0.0325788)	0.0167521 (0.0297975)	0.0624385 (0.0437984)	0.0434981 (0.0728936)
Cpinvt	0.1906254 (0.199006)	0.0715253 (0.1833207)	0.0661219 (0.0488663)	-0.4010903 (0.3433045)
GOVTspgdp	0.8733542** (0.3856841)	0.9232338** (0.3623194)	0.7997338 (3.923609)	2.531511*** (0.4889593)
RDint	0.1340035** (0.0794196)	0.1003983 (0.1080688)	0.0682441 (0.0489706)	0.4093713*** (0.1826163)
PUBspedugdp	0.5676522* (0.3151622)	0.4398351 (0.3047466)	0.1095973 (0.1067336)	-2.586564*** (0.3221263)
lTrd_Opness	1.058622** (0.2065802)	0.9519754*** (0.1969546)	1.278355 (5.115187)	-0.0116078 (0.1358882)
lTer_enrlElig	-0.0994976 (0.0795027)	-0.2024948*** (0.0758683)	0.0510543 (0.03599)	-0.7695874*** (0.1294296)
wld_FDI	0.0431733 (0.0303096)	0.0475454 (0.0283525)	0.0644572 (0.0448409)	0.4298704*** (0.0374607)
Knw_SpverR1	0.0761872* (0.0472065)	0.0613925 (0.0428545)	0.0654081 (0.0486439)	-0.0265658++ (0.1667196)
_cons	-0.0834127 (2.093053)	0.7448961 (1.96618)		12.74723 (1.878056)
R-Squared: Within: Between:	0.0193 0.1626 0.0195	0.6514 0.3105 0.6793		0.6710
Adj. R-Squared	0.0870	0.2415		0.6605
Dif Adj R-sq	0.0055			
F-statistics	5.74	11.26		63.68
Probability	0.0000	0.0000		0.0000

Source: Author’s Own (2025) *** *p<0.01; **p<0.05; *p<0.10*

Models 5 and 6 of Table 9 presents results on the long run effect of the uncentered correlation measure of knowledge spillover (Knw_SpveR1). The results show that, even though, model 5 show signs of dynamic process in the model, model 6 shows that Knw_SpveR1 has no long run effect on high technology export. The long run analysis rejects the hypothesis that Knw_SpveR1 is a reliable measure of knowledge spillover. A placebo analysis conducted in Table 10 shows that if a variable made up of random numbers is substituted for Knw_SpveR1 in the fixed effect model, the random variable is unable to replicate Knw_SpveR1. This means that Knw_SpveR1 is unique and a valid measure of knowledge spillover as suggested by Keller (1998).

Table 10 Intraclass Correlation Analysis of Uncentred Correlation Approach

Number	Sample	OLS	FE
1	Full sample	0.4819283*** (0.0407533)	0.0761872* (0.0472065)
2	Austria and Belgium	0.3563926 (0.5512255)	-0.141757 (0.6220615)
3	Czech Republic and Denmark	-0.6880528 (0.3452218)	-0.3055993 (0.3957934)
4	Finland and France	1.490992*** (0.1886812)	2.201758** (0.9137403)
5	Germany and Italy	0.8809777*** (0.1524349)	0.0586962 (0.1650396)
6	Lithuania and Netherland	0.1375474 (0.1624522)	-0.7835046*** (0.2370753)
7	Norway and Poland	0.0207011 (0.2043355)	-0.0860679 (0.2226163)
8	Portugal and Slovakia	-0.1091869 (0.0965034)	-0.1934976* (0.1071179)
9	Slovenia and Spain	0.1213075 (0.0851544)	0.0442893 (0.0647016)
	Interclass correl. coef.		0.7721**

Source: Author’s own (2025) **** p<0.01; **p<0.05; *p<0.10*

In testing the reliability or consistency of the uncentered correlation approach, intraclass correlation analysis between OLS estimates and fixed effect estimates of uncentered correlation measure for sub samples of two countries and the full sample.

Table 11 Test of Equality of Uncentred Correlation Approach

Number	Sample	Hypothesis	Chi sq st	P value
1	Full sample	H_0: $\beta_0 = 0$ H_1: $\beta_0 \neq 0$		
2	Austria and Belgium	Full sample is not significantly different from Austria and Belgium subsample	1.67	0.1961
3	Czech Rep. and Denmark	Full sample is not significantly different from Czech and Denmark subsample	13.79	0.0002***
4	Finland and France	Full sample is not significantly different from Finland and France subsample	86.66	0.0000***
5	Germany and Italy	Full sample is not significantly different from Germany and Italy subsample	53.02	0.0000***
6	Lithuania and Netherland	Full sample is not significantly different from Lithuania and Netherland subsample	0.11	0.7390
7	Norway and Poland	Full sample is not significantly different from Norway and Poland subsample	5.92	0.0150***
8	Portugal and Slovakia	Full sample is not significantly different from Portugal and Slovakia subsample	51.01	0.0000***
9	Slovenia and Spain	Full sample is not significantly different from Slovenia and Spain subsample	1.05	0.3062

Source: Author's Own (2025) *** *p<0.01; **p<0.05; *p<0*

Table 10 and 11 present a test of reliability of the uncentered correlation approach to measuring knowledge spillovers. Two tests are conducted to assess reliability, intraclass correlation analysis and test of equality of coefficients across samples are presented on Table 10 and 11. Table 10 tests the hypothesis that the uncentered correlation approach is reliable (consistent) across samples for the two dominant estimation techniques used in the literature, pooled OLS and fixed effect models. The intraclass correlation analysis in Table 10a shows a correlation coefficient of 0.77 significant at 5% significant level. This confirms the hypothesis that the uncentered correlation approach to measuring knowledge spillover is a reliable approach across pooled OLS and fixed effect models.

The intraclass correlation analysis in Table 10 shows a correlation coefficient of 0.77 significant at 5% significant level. This confirms the hypothesis that the uncentered correlation approach to measuring knowledge spillover is a reliable approach across pooled OLS and fixed effect models. Table 11 presents the test of equality between uncentered correlation estimates of knowledge spillover between the full study sample and the sub samples. The results indicate that uncentered correlation knowledge spillover measures for the full sample is not significantly different from sub samples of Australia and Belgium, Lithuania and Netherlands, and Slovenia and Spain. However, in the case of sub samples of Czech Republic and Denmark, Finland and France, Germany and Italy, Norway and Poland and Portugal and Slovakia, the results show that the uncentered correlation approach to measuring knowledge spillover is not reliable as the measures could not produce consistent results with the full sample.

4.1.2.2 Branstetter Approach

Table 12 presents results on the test of validity of the Branstetter approach to measuring knowledge spillovers. Model 1 and 2 of Table 12 presents a pooled OLS analysis of the effect of the Branstetter knowledge spillover measure on high technology exports. Model 1 is without the Branstetter knowledge spillover variable but model 2 has the Branstetter knowledge spillover variable. In testing the validity of the Branstetter approach the study seeks to determine whether the Branstetter approach retains the theoretically positive and significant relationship that exist between knowledge spillover and high technology export as an output of innovation. In model 2 the hypothesis of a positive and significant relationship between the Branstetter knowledge spillover measure (Knw_SpverR2) and high technology export is confirmed. Comparing the adjusted R squared values in model 1 and 2, it is observed that in model 2 the adjusted R squared increased by 0.0247. This represents the explanatory power of the Branstetter knowledge spillover measure confirming the validity of this approach to measuring knowledge spillover. Models 3 and 4 of Table 12 presents fixed effect estimation of the effect of Branstetter knowledge spillover measure on high technology export. Model 3 does not have Knw_SpverR2 but model 4 has the Branstetter knowledge spillover variable (Knw_SpverR2).

In model 4, Knw_SpverR2 is positive and significant at 1% significant level confirming the hypothesis that the Branstetter knowledge spillover is a valid measure of knowledge spillover.

This is because the theoretical positive and significant relationship between the knowledge spillover variable and innovation output is established. Comparing the adjusted R square values of model 3 and 4, it is observed that in model 4 the adjusted R Square value increased by 0.0826. This is the explanatory power of Knw_SpverR2 in the model. This further confirms the validity of Knw_SpverR2 as a knowledge spillover measure.

Table 13 Models 5 and 6 test the long run effect of Knw_SpverR2. Model 5 shows that the lag dependent variable, the lag of high technology export (lgHTECxp) is positive less than one. This suggests the presence of a dynamic process in the model. Model 6 shows that Knw_SpverR2 is significant at 1% confirming study hypothesis that in the long run the Branstetter knowledge spillover is reliable and stable. In model 7 of Table 13, the placebo analysis suggests that the variable made up of random numbers is not statistically significant. This indicates that the Branstetter knowledge spillover measure is unique and cannot be replicated by other variables.

Table 12 Effect of Branstetter's Knowledge Spillover on High Technology Export

	Model 1	Model 2	Model 3	Model 4
lgHTECxp	n/a	n/a	n/a	n/a
RGDPgr	0.0473312*** (0.0154416)	0.0397025*** (0.0148799)	0.0222849 (0.0327461)	0.0134727 (0.0311951)
Cpinvt	-0.0088415 (0.0126098)	-0.0250671*** (0.0124442)	0.3926639* (0.203726)	0.2460159 (0.1956307)
GOVTspgdp	0.2601313*** (0.0274407)	0.1981008*** (0.0285814)	0.626393* (0.4315773)	-0.3313597 (0.4456631)
RDint	0.3536286*** (0.0802994)	0.3857895*** (0.0772664)	0.3756817** (0.1503864)	0.218348* (0.1458804)
PUBspedugdp	-0.8244877 (0.062825)	-0.7554002*** (0.0615421)	0.6995696** (0.318614)	0.691379** (0.3031304)
Glindx	0.0921021 *** (0.0182127)	0.1074651*** (0.0176916)	-3.866583*** (1.512765)	-3.291797** (1.442984)
Lab_Prod	.0078382*** (0.0030596)	0.0038019 (0.0030236)	0.2232025 (0.3864964)	-0.231262 (0.3767898)
Trd_Opness	-0.0087966*** (0.0012573)	-0.0097342*** (0.0012181)	1.427691*** (0.3581385)	0.8356635** (0.3571683)
Ter_enrlElig	-0.0264692*** (0.002598)	-0.0281061*** (0.0025101)	-0.1232883* (0.082094)	-0.1339221* (0.0781272)
wld_FDI	0.0154808 (0.010895)	0.0214123*** (0.0105082)	-0.004715 (0.0058007)	-0.0000245 (0.0055836)
INTupop	0.0001361 (0.0029773)	-0.0086776*** (0.0032645)	0.1239547 (0.1017422)	0.0492435 (0.0977359)
Knw_SpverR2	n/a	0.0002046*** (0.0000367)	n/a	0.0001602*** (0.000029)
_cons	2.282218* (1.313417)	2.198587* (1.260375)	14.13974** (6.277846)	19.09567*** (6.039616)
R-Squared: Within: Between:	0.6971	0.7219	0.0333 0.2034 0.0552	0.0639 0.2815 0.1220
Adj. R-Squared	0.6876	0.7123	0.1299	0.2125
Dif Adj R-sq	n/a	0.0247	n/a	0.0826
F-statistics	73.23	75.50	6.54	9.17
Probability	0.0000	0.0000	0.0000	0.0000

Table 13 Effect of Branstetter's Knowledge Spillover on High Technology Export(cont)

	Model 5	Model 6	Model 7
lgHTECxp	0.7166313*** (0.0400908)	Longrun	Placebo Analysis
RGDPgr	-0.0047997 (0.021155)	-0.0169381 (0.0747576)	0.0220337 (0.0328108)
Cpinvt	-0.1341317 (0.1338674)	-0.4733468 (0.4877295)	0.3927996* (0.2040583)
GOVTspgdp	0.0751354 (0.3026733)	0.2651505 (1.070887)	0.6250516* (0.4323049)
RDint	-0.0053463 (0.0993065)	-0.018867 (0.3508184)	0.3748778*** (0.1506569)
PUBspedugdp	0.0790131 (0.2229874)	0.278835 (0.7821454)	0.6995492** (0.3191328)
Glindx	-3.031404*** (1.021909)	-10.69774*** (3.82729)	-3.876854*** (1.515644)
Lab_Prod	0.0227296 (0.2594458)	0.080212 (0.9162521)	0.2373009 (0.3901763)
Trd_Opness	0.406047* (0.2472145)	1.432928 (0.8765235)	1.419756*** (0.3597672)
Ter_enrlElig	-0.065113 (0.0539974)	-0.2297819 (0.1910566)	-0.1226541 (0.0822568)
wld_FDI	0.000957 (0.0037407)	0.0033771 (0.013211)	-0.0048414 (0.0058265)
R-Squared: Within: Between:	0.9275 0.6769 0.9570		0.0328 0.2036 0.0547
F-statistics	42.55		5.99
Probability	0.0000		0.0000

Source: Author's own 2025 *** *p<0.01; **p<0.05; *p<0;* n/a not applicable

Table 14 presents result on the reliability test of Branstetter approach as a measure of knowledge spillovers. The results shown in columns 3 and 4 Table 14 is a reliability test based on the dominant estimation approaches, pooled OLS and fixed effect models. The intraclass correlation analysis shows a positive correlation coefficient of 0.898 significant at 1%. This indicates that there is a close association between the Branstetter knowledge spillover estimates in both the pooled OLS and the fixed effect estimation strategies. This confirms the hypothesis that the Branstetter approach to measuring knowledge spillover is reliable.

Table 14 Intraclass correlation Analysis of Branstetter Approach

No.	Sample	OLS	FE
1	Full sample	0.0002046*** (0.0000367)	0.0001602*** (0.000029)
2	Austria and Belgium	5.805664*** (1.433017)	6.884182*** (0.9141173)
3	Czech Republic and Denmark	4.704446*** (1.044734)	2.372055*** (0.5647655)
4	Finland and France	0.0005896*** (0.0001803)	0.000119** (0.0000536)
5	Germany and Italy	0.0002047 (0.0001825)	3.981786** (2.235886)
6	Lithuania and Netherland	0.0008069*** (0.0001314)	0.0000637*** (0.0000284)
7	Norway and Poland	-0.00012 (0.0000462)	0.0001757*** (0.0000401)
8	Portugal and Slovakia	0.0002266*** (0.000067)	0.0001349*** (0.0000407)
9	Slovenia and Spain	-0.0000355 (0.0001883)	0.000204*** (0.0000329)
	Intraclass correlation coefficient		0.897617***

Source: Author’s own (2025) **** p<0.01; **p<0.05; *p<0*

Table 15 also tests the reliability of the Branstetter knowledge spillover measures based on test of equality between full sample Branstetter coefficients and sub sample coefficients. The results suggest all subsamples deviate from the full samples. None of the subsamples Branstetter knowledge spillover values is statistically the same as the full sample Branstetter knowledge spillover measure. The study therefore finds evidence to suggest that there is no consistency between Branstetter estimates of knowledge spillover between the full sample and all the sub samples. The results reject the study hypothesis that the Branstetter knowledge spillover measure is reliable.

Table 15 Test of Equality Analysis of Branstetter Approach

No.	Sample	Hypothesis	Chi sq	P value
1	Full sample	H_0: $\beta_0 = 0$ H_1: $\beta_0 \neq 0$		
2	Austria and Belgium	Full sample is not significantly different from Austria and Belgium subsample	10.21	0.0014***
3	Czech Rep. and Denmark	Full sample is not significantly different from Czech and Denmark subsample	23.88	0.0000***
4	Finland and France	Full sample is not significantly different from Finland and France subsample	194.83	0.0000***
5	Germany and Italy	Full sample is not significantly different from Germany and Italy subsample	43.97	0.0000***
6	Lithuania and Netherland	Full sample is not significantly different from Lithuania and Netherland subsample	8.15	0.0043***
7	Norway and Poland	Full sample is not significantly different from Norway and Poland subsample	9.53	0.0020***
8	Portugal and Slovakia	Full sample is not significantly different from Portugal and Slovakia subsample	11.04	0.0009***
9	Slovenia and Spain	Full sample is not significantly different from Slovenia and Spain subsample	8.63	0.0033***

Source: Author's own (2025) *** *p<0.01; **p<0.05; *p<0*

4.1.2.3 Euclidean Distance Approach

Tables 16 and 17 presents results on the validity test on the Euclidean distance approach to measuring knowledge spillover. Models 1 and 2 of Table 16 presents an OLS estimation of determinants of high technology export as an innovation output. Model 1 is without the Euclidean distance measure of knowledge spillover.

Table 16 Effect of Euclidean distance Knowledge Spillover on High Technology Export

Variable	Model 1	Model 2	Model 3
lgHTECxp			
Cpinvt	0.0155158 ** (0.0079286)	0.019362*** (0.0073971)	-0.003855 (0.005198)
RDint	0.0810992*** (0.0139462)	0.09965*** (0.0132156)	0.0439489*** (0.0125076)
Pub_spEduPsp	0.7263908*** (0.2040431)	0.9424866*** (0.1920974)	-0.0250961 (0.2016536)
Glindx	0.0767779*** (0.0099001)	0.0740102*** (0.0092215)	-0.0155519 (0.0117375)
Trd_Opness	-0.0043834*** (0.0007421)	-0.0041646*** (0.0006913)	0.0070814*** (0.0016852)
Ter_enrlElig	-0.0009939 (0.0019138)	0.0011572 (0.0018043)	0.0005291 (0.0012979)
INTupop	0.0061305*** (0.0019652)	0.0013537 (0.0019378)	0.0059164*** (0.0016014)
Knw_SpverR3		3.50e-08*** (4.69e-09)	
_Cons	-8.347775*** (0.9049367)	-9.150035*** (0.8490552)	1.182386 (1.080111)
R-Squared: Within: Between:	0.5540	0.6147	0.0325 0.3808 0.0325
Adj. R-sq	0.5452	0.6060	0.3406
Dif Adj R-sq		0.052	
F-statistics		70.41	29.79
Probability		0.0000	0.0000

Source: Author's own (2025) *** p<0.01; **p<0.05; *p<0*

However, in model 2 the Euclidean distance measure is added. Model 2 of Table 16 shows that the Euclidean distance measure of knowledge spillover (Knw_SpverR3) is positive and significant at 1% significant level. This establishes the theoretical relationship between knowledge spillover and innovation out variables confirming the study hypothesis and validity of the Euclidean knowledge spillover variable. Comparing the adjusted R square of model 1 and 2, it is seen that the adjusted R squared in model 2 increased by 0.052. This represents the explanatory power of Knw_SpverR3 further confirming the validity of Knw_SpverR3 as a measure of knowledge spillover.

Table 17 Effect of Euclidean distance Knowledge Spillover on High Technology Export

Variable	Model 4	Model 5	Model 6	Model 7
lgHTECxp	n/a	0.8175466*** (0.0504648)	n/a	n/a
Cpinvt	-0.0050086 (0.0051789)	0.0008545 (0.0039895)	0.8182458*** (0.050902)	-0.0057937* (0.0030373)
RDint	0.0425529*** (0.0124246)	0.020337** (0.0096337)	0.8345182*** (0.0509247)	0.0203182*** (0.0073081)
Pub_spEduPsp	0.0100651 (0.2006071)	0.2711749* (0.1653208)	1.121732*** (0.266074)	-0.3553294*** (0.1185706)
Glindx	-0.0124525 (0.0117137)	0.0189038** (0.0097625)	0.8332992*** (0.0535806)	-0.0000761 (0.0068579)
Trd_Opness	0.0065108*** (0.0016878)	-0.0018148 (0.0013957)	0.8160656*** (0.0499774)	0.0049748*** (0.0009852)
Ter_enrlElig	-0.0010756*** (0.0014393)	-0.0000223 (0.0011106)	0.8175284*** (0.0505191)	-0.0008739 (0.0007584)
INTupop	0.0048589*** (0.0016446)	0.0009784 (0.001439)	0.8183473*** (0.0503)	0.0031235*** (0.0009376)
Knw_SpverR3	1.11e-08** (4.44e-09)	4.33e-11 (3.57e-09)	0.8175466*** (0.0504648)	0.0307005++ (0.0272143)
_Cons	1.073026 (1.072751)	-2.225063** (0.9048822)		0.3956735 (0.6322403)
R-Squared: Within: Between:	0.0538 0.3921 0.0145	0.9331 0.6567 0.9828		0.0310 0.4975 0.0007
Adj. R-sq	0.3507	0.63097		
Dif Adj R-sq	0.0101			
F-statistics	27.25	68.21		41.83
Probability	0.0000	0.0000		0.0000

Source: Author's own (2025) **** p<0.01; **p<0.05; *p<0,* n/a not applicable

In model 3 of Table 16 and model 4 of Table 17 the fixed effect estimation of the determinants of high technology export is presented. Model 3 is without the Euclidean distance measure of knowledge spillover but in model 4 of Table 17, the knowledge spillover measure is added. The results in model 4 Table 17 shows a positive and significant Knw_SpverR3 at 5% significant level. This established the theoretical relationship between knowledge spillover and innovation and confirms the hypothesis that the knowledge spillover measure (Knw_SpverR3) is a valid measure of knowledge spillover. Model 5 and 6 of Table 17 present the long run effect of Knw_SpverR3 on high technology export. In model 5 the lag dependent variable has coefficient of positive lower than 1 indicating the existence of a dynamic process in the model.

Model 6 of Table 17 shows that in the long run the Knw_SpverR3 coefficient is 0.816. This indicates that a 1% change in knowledge spillover leads to 0.8% change in high technology export in the same direction. This establishes the theoretical relationship between knowledge spillover and high technology export in the long run and confirms the study hypothesis of reliability of Knw_SpverR3. Model 7 of Table 17 presents the placebo experiment where the Euclidean distance knowledge spillover variable is replaced with a placebo. The results show that the placebo could not replicate Knw_SpverR3. This suggests Knw_SpverR3 is unique and a valid measure of knowledge spillover.

Table 18 presents results on the test of reliability of the Euclidean distance approach to measuring knowledge spillovers based on the intraclass correlation analysis. Table 18 present test of reliability by assessing the consistency between pooled OLS and fixed effect models which are the dominant techniques used in assessing the effect of knowledge spillovers. The intraclass correlation coefficient shows a value of 0.37 which is not significant. This suggests no association between the knowledge spillover estimation by the pooled OLS and the fixed effect models. This rejects the null hypothesis that the Euclidean distance approach to measuring knowledge spillover is reliable. The test of reliability is also conducted using equality test between Euclidean estimates knowledge spillover based on the full sample and the sub samples is presented on Table 19.

Table 18 Intraclass correlation Analysis of Euclidean Distance Approach

Number	Sample	OLS	FE
1	Full sample	3.50e-08*** (4.69e-09)	1.11e-08** (4.44e-09)
2	Austria and Belgium	7.38e-08** (2.89e-08)	9.00e-08*** (2.69e-08)
3	Czech Republic and Denmark	3.53e-08** (1.56e-08)	3.39e-08** (1.55e-08)
4	Finland and France	1.24e-08** (5.99e-09)	1.53e-08* (1.03e-08)
5	Germany and Italy	5.19e-10 (4.25e-09)	2.68e-09 (2.43e-09)
6	Lithuania and Netherland	1.18e-08 (1.08e-08)	3.28e-08 (1.07e-08)
7	Norway and Poland	-4.39e-08 (3.38e-08)	-6.68e-09 (2.05e-08)
8	Portugal and Slovakia	9.45e-08*** (2.19e-08)	9.07e-09 (3.51e-08)
9	Slovenia and Spain	9.45e-08*** (2.19e-08)	9.07e-09 (3.51e-08)
	Interclass correlation coefficient	n/a	0.37145

*Source: Author's own (2025)   *** p<0.01; **p<0.05; *p<0*

The results as shown in Table 19 compared the estimates of the full sample and the subsamples. The results are a mixed one. Whereas sub samples of Austria and Belgium, Czech Republic and Denmark and Portugal and Slovakia confirm the study hypothesis and show that there is no significant difference between the full sample and sub sample knowledge spillover coefficients, the case of Finland and France, Germany and Italy, Lithuania and Netherland, Norway and Poland as well as Slovenia and Spain indicate that there is a significant difference between the full sample knowledge spillover coefficient and the sub sample coefficients. This therefore rejects the hypothesis that the Euclidean distance measure of knowledge spillover is reliable.

Table 19 Test of Equality Analysis of Euclidean Distance Approach

Number	Sample	Hypothesis	Chi sq statistic	P value
1	Full sample	H_0: $\beta_0 = 0$ H_1: $\beta_0 \neq 0$		
2	Austria and Belgium	Full sample is not significantly different from Austria and Belgium subsample	2.06	0.1507
3	Czech Rep. and Denmark	Full sample is not significantly different from Czech and Denmark subsample	1.06	0.3029
4	Finland and France	Full sample is not significantly different from Finland and France subsample	2.26	0.1327*
5	Germany and Italy	Full sample is not significantly different from Germany and Italy subsample	3.41	0.0648*
6	Lithuania and Netherland	Full sample is not significantly different from Lithuania and Netherland subsample	2.47	0.1163*
7	Norway and Poland	Full sample is not significantly different from Norway and Poland subsample	4.93	0.0265**
8	Portugal and Slovakia	Full sample is not significantly different from Portugal and Slovakia subsample	1.11	0.2928
9	Slovenia and Spain	Full sample is not significantly different from Slovenia and Spain subsample	7.09	0.0077**

Source: Author's own (2025) *** $p<0.01$; ** $p<0.05$; * $p<0$

In Table 20, the results show that based on the OLS and fixed effect model, all three measures of knowledge spillover are valid. However, the uncentered correlation shows the largest effect size and explanatory power for the OLS. The Branstetter approach shows an effect size smaller than the uncentered correlation but higher than the Euclidean distance. The situation is similar in the case of the fixed effect model with the only difference being that the effect sizes are lower for all the knowledge spillover measures but their position remains unchanged. In terms of their explanatory power (*figures in brackets*), in the OLS model the uncentered correlation explains 10% of the variation in innovation whilst it is 2% for Branstetter and 5% for the Euclidean distance. In the fixed effect model, the Branstetter approach has the largest explanatory power of 8%, followed by the Euclidean distance approach with an explanatory power of 1%. The uncentered correlation lags with an explanatory power of 0.5%.

Table 20 Performance of Knowledge Spillover Measures

Measures	OLS	Fixed Effect	Long run	Intraclass correlation	Test of equality
Uncentered correlation	0.4819*** (0.1116)	0.0762*** (0.0055)	n/a	0.7721**	3/8
Branstetter Approach	0.0002046*** (0.0247)	0.00001602*** (0.0826)	0.00002618***	0.897617***	n/a
Euclidean distance	3.50e-08*** (0.052)	1.11e-08*** (0.0101)	0.8175***	0.37145	3/8

Source: Author's Own (2025) **** p<0.01; **p<0.05; *p<0.10.* Explanatory power of measure in bracket, n/a not applicable.

Table 20 also shows that the uncentered correlation has no long run effect. However, in the long run the Euclidean distance approach makes the greatest knowledge spillover impact, even though still below unitary elastic. The Branstetter approach also makes significant impact in the long run but with a small effect size. Based on the intraclass correlation analysis, only the uncentered correlation and the Branstetter approaches are reliable but not the Euclidean distance approach. However, using the test of equality, the uncentered correlation and the Euclidean distance approaches show that 3 out of the 8 sub samples show consistent knowledge spillover effect with the full sample. In the case of the Branstetter approach none of the sub samples showed consistent results with the full sample casting doubts on its reliability. Table 21 presents a summary of the hypothesis test on the validity and reliability of the three selected knowledge spillover measures.

In testing the validity of the knowledge spillover measures, the estimation techniques used are OLS and the fixed effect models. Both estimation techniques confirm the hypothesis that all three knowledge spillover measures are valid measures of knowledge spillover. In evaluating the hypothesis that the measures of knowledge spillover are reliable, three approaches are used. The results from the intraclass correlation approach show that the hypothesis is supported in the case of uncentered correlation and the Branstetter approach to measuring knowledge spillover but not in the case of Euclidean distance approach to measuring knowledge spillover.

Table 21 Summary of Hypothesis Test

Knowledge spillover measures	Evaluation of validity of knowledge spillover hypothesis		Evaluation of reliability of knowledge spillover measures hypothesis		
	OLS	Fixed effect	Intraclass Correlation	Test of Equality	Test Retest (Long run)
Uncentered Correlation	Supported	Supported	Supported	3/8 Supported	Not Supported
Branstetter Approach	Supported	Supported	Supported	Not Supported	Supported
Euclidean Distance	Supported	Supported	Not Supported	3/8 Supported	Supported

Source: Author’s Own (2025)

The test of equality shows that in the case of uncentered correlation approach to measuring knowledge spillover, three out of the eight sub sample are consistent with the full samples and therefore three sub samples support the hypothesis. It is the same in the same in the case of the Euclidean distance approach to measuring knowledge spillover. However, in the case of the Branstetter approach to measuring knowledge spillover, the hypothesis is not supported. Based on the test-retest approach to testing the reliability of knowledge spillover measures, the evaluation of the hypotheses shows that the uncentered correlation approach to measuring knowledge spillover is not supported. However, the Branstetter approach and the Euclidean distance support the hypothesis.

4.1.3 Complementarity in Knowledge Spillover and Country’s Own R&D

This section of the study presents results and discussions on the complementarity between international knowledge spillovers and R&D of countries. Two approaches have been used to execute and test the hypothesis of complementarity, the adoption approach and the productivity approaches.

4.1.3.1 Complementarity between Knowledge Spillover and Own R&D

Table 22 presents analysis on the complementarity between countries' own R&D investment and knowledge spillover among selected countries in Europe.

Table 22 Complementarity between R&D and International Knowledge Spillover

Variable	Full sample Analysis		Subsample Analysis	
RD_exp	DVLS	DVLS-IV	IV (R&D<13810)	IV (R&D>13810)
Constant	-3.911868e+05*** (8.968009e+04)	-5.210700e+05*** (1.051431e+05)	-1.845e+05*** (3.842e+04)	5.951e+04 (3.111e+05)
dist_Kn_Spill	4.201498e-01*** (6.853391e-02)	7.110512e-01*** (1.297515e-01)	1.845e-01*** (4.741e-02)	6.240e+00*** (8.747e-01)
AC(-1)	9.936247e-03** (4.605642e-03)	1.032752e-03 (5.829684e-03)	2.431e-02*** (6.483e-03)	-7.746e-02*** (1.044e-02)
Cpinvt	3.675533e+02*** (1.085386e+02)	5.812293e+02*** (1.382066e+02)	2.258e+02*** (4.429e+01)	-2.057e+01 (5.431e+02)
log(GOVTsp_gdp)	1.421916e+04*** (4.300767e+03)	1.528657e+04*** (4.494172e+03)	4.262e+03** (1.564e+03)	-5.365e+04* (2.383e+04)
RGDPgr	-6.478419e+01 (9.259858e+01)	-1.517180e+02* (1.016798e+02)	-8.542e+01** (2.828e+01)	-4.104e+02 (3.123e+02)
lnGlindx	8.464678e+04*** (2.211159e+04)	1.121108e+05*** (2.518742e+04)	3.866e+04*** (8.466e+03)	4.595e+04 (9.274e+04)
Lab_Prod	-1.002884e+03*** (2.618836e+02)	-1.039352e+03*** (2.729253e+02)	-1.150e+02 (7.315e+01)	-2.320e+03 (2.617e+03)
Lab Prod^2	6.608608e+00*** (1.611351e+00)	6.564870e+00*** (1.677287e+00)	8.324e-01 (4.497e-01)	9.486e+00 (1.426e+01)
Per_WFDI	1.628544e+02*** (5.847270e+01)	2.108670e+02*** (6.343687e+01)	8.024e+00 (1.762e+01)	-3.746e+02* (2.174e+02)
Country	Yes	Yes	Yes	Yes
R-squared	0.9758	0.9737	0.9678	0.9909
Adj R-squared	0.9733	0.9711	0.9642	0.9883
F-st (Prob)	395.4 (0.0000)			
Wald_Test (Prob)		364.7(0.0000)	278.1(0.0000)	370.9 (0.0000)

Source: Own *** *p<0.01; **p<0.05; *p<0.10*. Explanatory power of measure in bracket. Note: For Subsample Analysis - Countries with mean R&D < , > mean of sample=13,810.

The first column of Table 22 presents the variables. The first variable which is the explained variable, RD_exp is R&D investments undertaken by a country. Other variables in the first column are the explanatory variables.

In the second and third columns, the study presents the results based on full sample. The second column tests the complementarity between R&D and knowledge spillover (dist_Know_Spill) based on dummy variable least square to preserve time invariant variables in the model whilst controlling for unobserved heterogeneity. The results show that the knowledge spillover variable is positive and significant, indicating complementarity between R&D investment of countries and knowledge spillovers, confirming the hypothesis of complementarity between R&D and knowledge spillover. Variables such as the lag of absorptive capacity (AC-1), capital investment (Cpinvt) and the log of government spending have the expected sign. Log of globalization index and percentage foreign direct investment also takes on the expected behaviour in the model. The results show that the relationship between labour productivity and R&D changes from negative initially at lower levels of productivity to positive as labour productivity increases.

In column 3 of Table 22, the study presents results on the second stage of instrumental variable analysis where the instrument is a measure of centrality of a country (aggregate distance from a country to all other countries). The study assumes that the variable knowledge spillover is endogenous and therefore used the centrality of a country as an instrument to address the endogeneity concerns of the model. The results confirm the hypothesis that knowledge spillover and country's own R&D are complementary in improving innovation performance as the knowledge spillover variable is positive and significant.

Columns 4 and 5 present a subsample analysis based instrumental variable analysis. The sample is split based on R&D expenditure of countries. Column 4 results pertain to less R&D intensive countries whose R&D investment falls below the full sample average of 13810 in million Euros whilst column 5 present results of high R&D intensive countries with R&D investment above the full sample average. For both low and high R&D intensive countries, the hypothesis of complementarity between R&D and knowledge spillover is confirmed. However, the extent of complementarity is strongest in high intensive R&D countries compared with the low R&D intensive countries and the full sample. It is, however, important to stress that the high R&D intensive model in column 5 is the least efficient model as most of the variables are insignificant, reducing degrees of freedom and contributing less to the model. This is attributed to the small number of countries in the model compared with the less R&D intensive and the full sample models.

4.1.3.2 Complementarity between Knowledge Spillover and Own R&D

Figure 4 is a scatter plot of knowledge spillover and innovation measured by high technology export. The plot shows a systematic pattern, a cone like relationship in the plot. This is an indication that knowledge spillover is an important source heteroscedasticity in a model that has innovation measured by high technology export as a dependent variable and knowledge spillover as an independent variable.

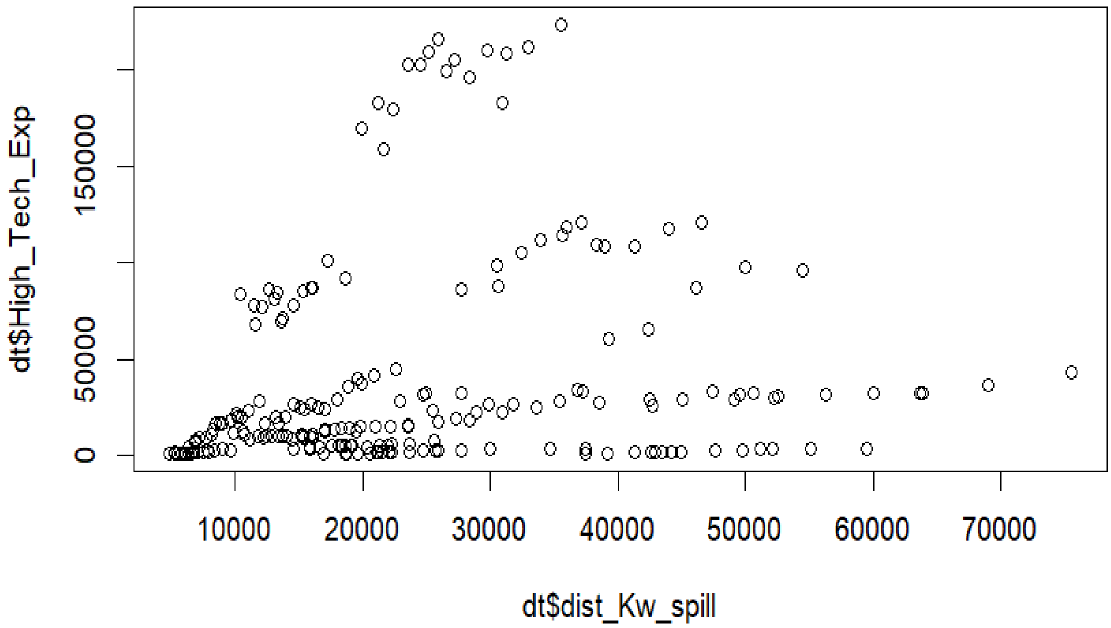

Figure 4 Scatter Plot between High Technology Export & knowledge Spillover
Source: Author's own, (2025)

Table 24 present results on the test of complementarity based on the productivity approach and the effect of combining knowledge spillover and country own R&D on innovation. Column 1 presents variables with the first variable being the dependent variable, high technology export (High_tech_Exp) as a measure of innovation. Table 24 presents full sample analysis in columns 2 and 3 using panel least square and weighted panel least square respectively. Table 25 presents the subsample analysis based on R&D investment below the full sample average in columns 2 and 3 and R&D investments above the full sample average in columns 4 and 5.

Column 2 of Table 23 presents results of the analysis based on panel least squares, ignoring the possibility of the model being heteroscedastic. The results show that the log of the interaction term which is an interaction between R&D investment of countries (RD_exp) and knowledge spillover (dist_Kn_Spill) is positive and significant. This is confirmation of the hypothesis that country's own R&D and knowledge spillover are complementary. Interpreting the log of the interaction and its square together tests the curvilinear relationship between combining RD_exp and dist_Kn_Spill as regressors and innovation measured by high technology export (High_tech_Exp) as dependent variable. The results in column 2 show that the combined effect of R&D investment of countries and knowledge spillover on innovation is an inverted U-shaped contrary to the hypothesized inverted U-shaped relationship. The Breusch Pagan test of homoscedasticity shows a significant test statistic indicating that the model in column 2 is heteroscedastic that compromises hypothesis testing. Based on the scatter plot of the relationship between knowledge spillover and innovation in figure 1, the source of heteroscedasticity is knowledge spillover. Using weighted least squares based on knowledge spillover variable as the weight, column 3 of Table 23 presents a weighted least square model which is homoscedastic. The full sample panel least square, column 2 of Table 23, is not a reliable source for testing hypothesis because of heteroscedasticity. However, the model in the third column, the weighted panel least square shows that the log of the interaction term is negative and significant whilst its squared counterpart is positive and significant. This confirms the hypothesis that the combined effect of own country's R&D and knowledge spillover form a U-shaped relationship with innovation performance. However, the negative sign means that there is no complementarity between knowledge spillover and R&D based on the full sample using the weighted least square.

The subsample analysis in Table 23 based on data from low R&D intensive countries with mean of R&D below the full sample average of 13,810 in million Euros is presented in column 2 and 3 and 4 and 5 respectively of Table 24. Both the panel least square and the weighted least squares approaches in the low R&D intensive subsample failed to confirm the hypothesis of complementarity between own country R&D and knowledge spillover. However, both models confirm the hypothesis that the combined effect of Country's own R&D and knowledge spillover form a U-shaped relationship with innovation performance. The results of the study, based on high R&D intensive countries with R&D above the full sample average of 13,810 in million Euros, in Table 24 columns 4 and 5 confirm the hypothesis of complementarity between own country's R&D and knowledge spillover. This is true for both the panel least squares and the weighted panel least squares. It is important to state that the strength of complementarity is highest in high R&D intensive countries and highest in the weighted least square approach in column 5 of Table 24.

Table 23 Product Approach to Measuring Complementarity

Variable	Full sample Analysis	
High_tech_Exp	Panel LS	Panel WLS
Constant	2.818e+06*** (3.472e+05)	3.338e+01** (1.163e+01)
AC	2.479e-02*** (6.120e-03)	-8.634e-08 (2.720e-07)
RD_exp	9.116e-01*** (1.021e-01)	-1.730e-06 (4.658e-06)
Ln_ dist_Kn_Spill	-9.185e-02 (1.928e-01)	3.894e-05*** (9.159e-06)
Ln_Interaction	6.061e+04*** (8.983e+03)	-1.311e+00*** (3.490e-01)
Ln_Interaction^2	-2.745e+04*** (4.298e+03)	9.190e-01*** (1.691e-01)
lag_High_tech_Exp	5.917e-02* (2.283e-02)	8.870e-07* (9.007e-07)
Distance	-6.391e+01*** (6.428e+00)	-7.658e-04*** (2.031e-04)
RGDPgr	3.421e+02* (1.424e+02)	1.339e-02* (5.206e-03)
First_cont	6.149e+03*** (8.790e+02)	4.138e-01*** (2.963e-02)
Second_cont	-6.252e+03*** (8.749e+02)	1.445e-02 (2.595e-02)
Year	Yes	Yes
Country	Yes	Yes
R-squared	0.9827	0.962
Adj R-squared	0.9812	0.9587
Breusch Pagan	105.64***	0.01027
F-stats (Prob)	664.1(0.0000)	295.9(0.0000)

Source: Author’s Own **** $p<0.01$; **$p<0.05$; *$p<0.10$.*

Table 24 Product Approach to Measuring Complementarity (cont)

Variable	Subsample Analysis (low R&D)		Subsample Analysis (High R&D)	
High_tech_Exp	Panel LS	Panel WLS	Panel LS	Panel WLS
Constant	-7.143e+01** (2.554e+01)	-6.958e+01* (2.799e+01)	1.741e+01*** (2.343e+00)	1.036e+02* (4.690e+01)
AC	-4.304e-06*** (8.734e-07)	-4.694e-06*** (9.229e-07)	2.323e-09 (1.124e-07)	3.525e-07 (3.702e-07)
RD_exp	-3.501e-05* (1.662e-05)	-3.877e-05* (1.899e-05)	1.469e-05** (5.145e-06)	2.705e-05* (1.226e-05)
Ln_ dist_Kn_Spill	3.025e-05*** (5.186e-06)	2.883e-05*** (6.856e-06)	-5.435e-05*** (1.317e-05)	-8.332e-05* (3.493e-05)
Ln_Interaction	-2.854e+00*** (6.490e-01)	-2.880e+00*** (7.090e-01)	4.660e+00*** (9.978e-01)	6.656e+00** (2.262e+00)
Ln_Interaction^2	1.638e+00*** (3.030e-01)	1.650e+00*** (3.319e-01)	-3.031e+00*** (7.030e-01)	-3.913e+00* (1.508e+00)
lag_High_tech_Exp	3.459e-05*** (2.514e-06)	4.535e-05*** (2.951e-06)	7.094e-06*** (5.267e-07)	-1.377e-07 (5.069e-07)
Distance	1.038e-03 (5.651e-04)	1.091e-03 (6.015e-04)	-5.343e-03*** (5.222e-04)	-9.587e-04 (3.792e-03)
RGDPgr	6.265e-03 (3.617e-03)	6.307e-03 (3.776e-03)	3.538e-03* (1.728e-03)	1.012e-02** (3.693e-03)
First_cont	2.676e-01*** (3.718e-02)	2.123e-01*** (3.911e-02)	-3.456e-01*** (2.746e-02)	1.042e-02 (1.999e-01)
Second_cont	1.491e-01* (6.876e-02)	1.425e-01 (7.232e-02)	2.9430e+02 (1.9323e+02)	2.9822e+02 (1.8012e+02)
Year	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
R-squared	0.9816	0.9736	0.9985	0.9932
Adj R-squared	0.9797	0.9709	0.9981	0.9913
Breusch Pagan	44.186***	0.0043046	23.182***	0.001457
F-stats (Prob)	527.6(0.0000)	364.3(0.0000)	2773 (0.0000)	524.2(0.0000)

Source: Author's Own(2025) *** *p<0.01; **p<0.05; *p<0*

4.1.4 Combined Effect of International Knowledge Spillover and Own R&D

The test of combined effect of knowledge spillover and R&D on innovation, based on the high intensive R&D sub sample is also confirmed. The squared log of the interaction term is negative and significant whilst it is positive for the interaction term itself. This is an indication that the effect of combining knowledge spillover and country's own R&D on innovation is an inverted U relationship in the case of the full sample. If the data is split into low R&D countries and high R&D countries the results is very insightful.

For low R&D intensity countries the weighted least square estimates show a U-shaped relationship in agreement with the stated hypothesis whilst in the case of high R&D intensity sample it is agreement with the full sample case where the relationship is inverted U shape. This suggests that in the case of low R&D intensity countries the adverse effect of heterogeneity of combining internal and external knowledge resources on the knowledge production function weighs down on innovation. However, in high R&D countries learning and coping with external knowledge is easier and adaptation to knowledge spillover from abroad is not a challenge because of the high investment in R&D. The results is therefore a mixed one, where the U-shaped relationship is only confirmed in situation where the sample is a low R&D investment country but in the case of high R&D country sample the hypothesis is not confirmed.

4.1.5 Absorptive Capacity, Knowledge Spillover and Countries' Own R&D

In this section of the study, an analysis and results of the effect of absorptive capacity in the complementarity between international knowledge spillovers and country's own R&D. The study at this point considers three measures of absorptive capacity, two of which are based on spatial measures and one based on R&D intensity. The spatial based measures of absorptive capacity are centrality and contiguity. In Table 25, the study presents an analysis on the effect of the selected absorptive capacity measures in the relationship between knowledge spillovers and two innovation measures. This is to test the robustness and aid in selecting innovation measures and the validity of the absorptive capacity measures. Table 25 assesses the effect of absorptive capacity measured by R&D intensity in the relationship between international knowledge spillovers and innovation performance measured by high technology exports (HTEX) and Patent count measured by patent application by residents. The results of the analysis show that the absorptive capacity measured by R&D intensity is only able to influence knowledge spillover measures by the logarithmic transformation of high technology export in model 2 of Table 25. A similar analysis that used patent count as a measure of innovation in model 4 of Table 25 showed that R&D intensity as a measure of absorptive capacity has no effect on the relationship between knowledge spillover and innovation measured by patent count.

Table 25 Absorptive Capacity, Knowledge Spillover and Innovation

lnHTEX/ lnPat	Model 1 HTEX	Model 2 HTEX	Model 3 Patent	Model 4 Patent
laglnHTEX/ laglnPAT	6.12e-07 (5.86e-07)	7.02e-07 (5.64e-07)	0.323277*** (0.1155791)	0.3260625*** (0.1150449)
lnknw_spill	28.32152*** (4.057997)	23.53705*** (4.262347)	-5.561401* (3.033047)	-8.270909** (3.666309)
lnknw_spill^2	-1.073895*** (0.1541051)	-0.916444*** (0.1589513)	0.2087143* (0.1149885)	0.3029459** 0.1354017
lag_lnCpinvt	0.11189 (0.1723685)	0.0455277 (0.1672716)	0.292573* (0.1900903)	0.2970464* (0.1892102)
Trd_opn	0.0053793*** (0.0013866)	0.0046672* (0.0029877)	0.0015629 (0.002179)	0.0016256 (0.0021691)
Ped	0.0244842 (0.03459)	-0.017174 (0.035929)	0.1031912*** (0.023738)	0.0913663*** (0.0253097)
RD_exp	-0.0000241*** (8.21e-06)	-.0000258*** (7.95e-06)	-1.07e-06 (6.18e-06)	-7.23e-07 (6.15e-06)
lnknw_spill* Abs_cap (R&D intensity)		0.6392793*** (0.2077245)		0.2223489 (0.1707696)
Cons	-177.194*** (26.78363)	-149.8642*** (27.57421)	38.13329*** (19.88518)	54.38318** (23.39651)
R-squared :within :Overall	0.4362 0,4232	0.4807 0.3907	0.3367 0.9852	0.3521 0.9824
F-statistics	9.50	9.72	5.22	4.82
Probability	0.0000	0.0000	0.0000	0.0000

Source: Author's Own (2025) *** *p<0.01; **p<0.05; *p<0.10*

A further analysis on the two measures of innovation has shown that whereas high technology export is very responsive to international knowledge spillovers (lnknw_spill) and its quadratic term (lnknw_spill^2) in models 1 and 2, the results show that the response is sluggish in the case Patent count in model 3 and 4.

Again R&D expenditure, a well-known determinant of innovation significantly influence innovation measured by high technology export even though negative, the results indicate that that patent count is not responsive to this variable. Knowing that innovation is a function of how an economy is open, the expectation is that trade openness will influence innovation performance. The results of the analysis shown that Trade Openess (Trd_opn) only influenced innovation performance measured by high technology export but not patent count. Some other key influencers of innovation capital investment (lag_lnCpinvt) in its lag and Public spending on education (Ped) as a measure of human capital influence Patent count but not high technology export.

In analysing the role of absorptive capacity in the complementarity between international knowledge spillover and own R&D, the study adopted the adoption approach to assessing complementarity. Table 26 presents the analysis that tests the hypothesis that absorptive capacity positively and significantly influences the relationship between knowledge spillover (lnKnw_spill) in its logarithmic form and own R&D countries.

The results as presented in Table 26 model 1 shows the complementarity between international knowledge spillover and the country's own R&D. The results show that the knowledge spillovers variable (lknwspill) is positive and significant. This is an indication that increasing knowledge spillover from abroad solicits an increased amount of country's own R&D. This confirms complementarity between international knowledge spillovers and the country's own R&D. After controlling for innovation measured by high technology export (HTEX) which has the expected positive sign and significant and human capital, measured by public expenditure on education as a percentage of public spending (Pedp), the knowledge spillover variable remains positive and significant. The effect of Pedp shows that public spending on education is not perpetual, the relationship turns negative after a point. Trade openness behaves in a similar way. After observing a positive relationship with the country's own R&D, there is a saturation point after which the relationship turns negative.

In model 2 of Table 26, the study presents the test of the hypothesis that absorptive capacity measured by R&D intensity has positive effect on the complementarity between international knowledge spillover and country's own R&D.

Table 26 Absorptive Capacity and Complementarity

R&D Investment	Model 1	Model 2 R&D int	Model 3 Contiguity	Model 4 Centrality
Pedp	0.2055288* (0.1116196)	0.2847488*** (0.09026)	-0.0595581** (0.0228397)	0.1181408* (0.1457119)
Pedp^2	-0.0101261** (0.0047082)	-0.0125027*** (0.0037943)		-0.0067072* (0.0061312)
lknwspill	0.0463962* (0.0254616)	-1.152246*** (0.2088702)	0.05286 (0.1949431)	1.358254*** (0.3091732)
lnHTEX	0.2093144*** (0.0503591)	0.2035646*** (0.040452)	0.4145452*** (0.0705575)	0.2848759*** (0.0682044)
Trd_opn	0.02499*** (0.005736)	0.0164628*** (0.0047503)	0.0067736* (0.0045617)	0.0075403* (0.0042356)
Trd_opn^2	-0.0000829*** (0.0000205)	-0.0000535*** (0.0000169)	-0.0000339* (0.0000215)	-0.0000329* (0.0000196)
lnknw_spill* Abs_cap		-3.17e-07*** (9.26e-08)	5.25e-08 (2.96e-07)	-3.14e-09*** (8.03e-10)
lnknw_spill* Abs_cap^2		0.0537295*** (0.0078625)	-1.08e-14 (4.34e-14)	7.04e-19*** (2.00e-19)
Abs_cap		-0.0658611 (0.1140926)	0.2686628*** (0.0744425)	0.4303699*** (0.0565633)
Cons	2.530358*** (0.8936809)	9.715914*** (1.683315)	4.121793* (2.363326)	-11.85343*** (3.765317)
R-squared : Within Between Overall	0.7563 0.2729 0.2768	0.8472 0.3648 0.3683	0.9959	0.9967
F-statistics	39.02	52.99	982.08	1160.19
Probability	0.0000	0.0000	0.0000	0.0000

Source: Author's Own (2025) **** p<0.01; **p<0.05; *p<0.10*

The results confirm the hypothesis that absorptive capacity positively influences the complementarity between international knowledge spillovers and the country's own R&D.

However, the results are a bit more complicated. The complementarity is a bit sluggish in responding to the absorptive capacity of countries. Initially the response of the complementarity is negative but turns positive as absorptive capacity increases to an appreciable level.

The results of the analysis presented in model 3 indicate that contrary to where absorptive capacity is measured by R&D intensity, measuring absorptive capacity by contiguity shows no effect on the complementarity between international knowledge spillovers and own R&D of countries. The results is realized after controlling all the important variables that determine the country's own R&D as in the case of models 1 and 2.

In model 4 the results of the effect of absorptive capacity measured by centrality of a country in the network of countries influencing the complementarity between international knowledge spillovers and country's own R&D in presented. The results confirm the study hypothesis that absorptive capacity positively influences the complementarity between international knowledge spillovers and the country's own R&D. However, the role of absorptive capacity is a bit complicated. There is inertia in the complementarity, but as absorptive capacity increases the complementarity gains momentum.

4.1.6 Robustness Checks

In this study, several additional tests are carried out to ensure the study results are reliable and that the results of the data analysis are stable. These tests are conducted for each study objective and are therefore organized here based on the different study objectives.

In assessing the efficacy of knowledge spillover measures, the focus of the study centered on validity and reliability of knowledge spillover measures. The challenge that confronts such an endeavor is that model misspecification could provide feedback that would affect the validity and reliability of the knowledge spillover measures when in fact these measures in themselves are independent of these validity and reliability problems. To avert these challenges, the selection of variables into the validity and reliability models for knowledge spillover was based on the Least Absolute Shrinkage and Selection Operator. LASSO is a model selector that exhibits the tradeoff between model biasness and overfitting. In assessing the validity and reliability of knowledge spillover measures, the regression model is confronted with a problem of having a tradeoff between unbiasedness and overfitting which may inadvertently feed into the validity and reliability of knowledge spillover measures. Unbiasedness will mean introducing a lot of the explanatory variables that explain the dependent variable on board and following the nonlinear patterns in the model. This could, however, introduce over fitting into the model that could possibly affect the validity and reliability of knowledge spillover measures. To isolate the knowledge spillover measures' validity and reliability from model specification biases, LASSO has been used to reduce the model specification biases. Thus, all variables in the regression model that test the validity and reliability of knowledge spillover are based on LASSO.

The analysis has generally been based on panel analysis. This is an important step to deal with heterogeneity in the data set, accounting for differences within countries, In this study, the data is drawn from many countries making it necessary to deal with the within country effect, hence the panel analysis estimation technique. To avoid spurious regression, all variable used in the study had to go through stationarity test and remedial actions taken where necessary to ensure stationarity. The first difference is adopted in cases where a variable is found to be nonstationary.

The focus of validity and reliability test of knowledge spillover has been on technology-based measures of knowledge spillovers. However, to test for the validity and reliability, an associated measure of knowledge spillover that rival the technology-based measures, the geographic based measures was also analysed using the same data set.

In testing for the complementarity between knowledge spillover and country's own R&D based on the adoption approach required regressing R&D on knowledge spillover. This predisposes the model to endogeneity considering the relationship between knowledge spillover and R&D of countries. To address the possible endogeneity problem, an instrument variable analysis is used using centrality as an instrument for knowledge spillover. The choice of centrality as an instrument is influenced by the fact that it meets the two main criteria of a good instrument. First, centrality is closely associated with increasing knowledge spillovers. Knowledge spillover is generally known to be a function of interaction between economic actors. The literature on knowledge spillover and innovation by consensus indicates that the location of an actor determines the extent of knowledge spillover. Actor near the source of knowledge benefit more from knowledge spillover. In this study, what is under consideration is international knowledge spillover and centrality here measures the inverse of aggregate distance it takes to travel from a country to all other countries in the network of countries. This is important in selecting an instrument in instrumental variable analysis. The instrument should be closely associated with the endogenous variable to be able to represent it. Second, the instrument should not be related to the dependent variable but only through the endogenous variable in this case knowledge spillover. Proximity between countries per the extant literature has no relationship with innovation but only through innovation. This qualifies centrality as an instrument for knowledge spillover by the second criterion for selecting an instrument.

The study also as part of robustness checks conducted subsample analysis. This splits that data into subunits and the same analysis is conducted and compared with the full sample analysis. In this study, the data is split based on R&D. This allows the study to assess the role of different R&D level and its effect on the results. This is important to the extent that R&D is the main determinant of innovation so splitting the data based on R&D is a way of controlling for the effect of R&D and comparing the results between the different subsample and the full sample.

In analysing the complementarity between knowledge spillover and country's own R&D, the study adopts two different approaches, the productivity and adoption approaches. This allows the study to compare the results of the two approaches as way to improve the robustness of the results. Besides, the productivity approach tested the presence of heteroscedasticity and remedied it using weighted least square. This allowed the study to improve hypothesis testing other than relying on the panel least square alone with heteroscedastic error term.

Even though polynomial regression analysis comes with the possible problems of over fitting, this study exploited it to improve robustness of the study outcomes. In accessing the joint effect of knowledge spillover and country's own R&D on innovation performance, the curvilinear relationship between the combined inputs and innovation is exploited through a quadratic regression analysis. This brings out the complex relationship which is normally hidden when linear models are assumed.

4.2 Discussions

This section of chapter six presents the discussions of the results on the four hypotheses tested in this study. The section presents discussions on the measures of knowledge spillovers. This is followed by discussions on the complementarity between international knowledge spillovers and a country's own R&D after which discussions on the joint effect of international knowledge spillover and country's own R&D are presented. The last part of the discussion is on the role of absorptive capacity in the complementarity between international knowledge spillovers and country's own R&D.

4.2.1 Validity and Reliability of Knowledge Spillover Measures

In this study, the validity and reliability of three knowledge spillover measures have been assessed and the outcome of the study suggests somewhat inconclusive results. The study has shown mixed results, whereas all three measures of knowledge spillovers, Euclidean distance, uncentered correlation and Branstetter approach show evidence of valid measures of knowledge spillovers, their reliability as measures of knowledge spillovers show mixed results. The different tests of reliability give different verdicts. The study confirms the hypotheses that all the three measures of knowledge spillovers are valid measures of knowledge spillovers. However, in terms of reliability, the results are inconsistent. Based on the intraclass correlation analysis, the findings of the study indicate that the uncentered correlation and the Branstetter approaches are reliable measures of knowledge spillover but not the Euclidean distance approach. The test of equality shows that the Branstetter approach shows no evidence of reliability but the Euclidean distance and the Uncentered correlation show some semblance of reliability whereas the test-retest approach to testing the reliability of knowledge spillover measures showed that the Branstetter and the Euclidean distance approaches are reliable measures of knowledge spillovers but not the uncentered correlation approach.

To situate the study findings of this study in the prior literature, one would first recognize that these measures of knowledge spillovers investigated belong to one of the knowledge spillover paradigms, technological related knowledge spillover measures estimated based on the knowledge production function as opposed to geographic proximate knowledge-based measure of knowledge spillover. The Euclidean, Uncentered correlation and the Branstetter approaches of measuring knowledge spillovers depart from the geographic proximate measure of knowledge spillovers as revealed in this study. Whereas the geographic proximate approach think of knowledge spillovers as localized and influenced by network of relationships and therefore clustered Audretsch and Feldman (1996), the three main approaches investigated follow the ideas of Jaffe, Trajtenberg and Henderson (1993) who argue that knowledge spillover occur because the technologies of agents in a spillover space are related. These polar views remain the source of inconsistency and for that matter reliability problems in measuring knowledge spillovers. **From the findings of the study, all the three measures of knowledge spillovers investigated are valid but same cannot be said about their reliability.** The issue of reliability has to do with consistency, measured by comparing measures or following the behaviour of a knowledge spillover measure over time and under changing conditions. Having polar measures of knowledge spillovers as the literature has suggested predisposes knowledge spillover measures to such inconsistencies and reliability problems.

By consensus, the literature on knowledge spillovers indicates that one of the important drivers of knowledge spillovers is interaction between actors in a knowledge spillovers plane (Zacchia, 2020; Cropanzano & Mitchell, 2005)**.** One would expect that whatever measure of knowledge spillover there is would inculcate into it the level of interaction between actors. **Unfortunately, technology related based measures of knowledge spillovers such as the Euclidean distance, Uncenterd correlation and the Branstetter approaches do not pay attention to interactivity in measuring knowledge spillovers**. However, interactivity is at the center of geographic proximity based measures of knowledge spillover executed through network analysis. This contributes to the reliability problems of knowledge spillovers, especially if the test of reliability does a cross comparison of different knowledge spillover measures. On the otherhand, geographic based measures of knowledge spillover based on the networks analysis also over simplify the measurement of knowledge spillovers. It assumes that once there is colocation there is interaction between actors and knowledge spillovers occurs automatically. However, prior literature makes it clear that there are filters that block knowledge spillovers (Xu, Wang, Zhou, & Zhang, 2019;Acs, Audretsch, Braunerhjelm & Carlsson, 2012), colocation will therefore not necessarily mean that there is knowledge spillover. This is however, addressed by the technology related based measures of knowledge spillovers. For example in all three technology relatedness measures of knowledge spillovers investigated in this study, the assumption that knowledge spillover is automatic is difused. All the measures have weights in their computations. **These weights are based on the entity's own R&D which is a measure of absorptive capacity**. Comparing these measures with spatial based measure which assumes knowledge spillovers have no filters that blocks its diffusion, it is argued in this study that the spatial or geographic proximity based measure, through its network work analysis and the emphasis on clusters over simplify the process of knowledge spillovers and renders the measure unreliable. The assuption that underpins the various measures of knowledge spillovers, some of which are only theoretical without any practical implications is what compromise their reliability and practicality.

To the extent that knowledge spillovers are intangible and cannot be measured directly, the strategy adopted largely by authors in prior literature has been to measure knowledge spillovers by the impact they make on an innovation variable. Griliches (1979) knowledge production function has been a very useful tool in measuring knowledge spillovers. This allows the researcher to measure knowledge spillovers by assessing the size and behaviours of beta coefficients associated with the external R&D. In this study, even though all three knowledge spillover variables were found to be valid, any model specification biases could have affected the validity and reliability of the knowledge spillover measures. In the test of reliability, dynamic and longrun analysis holds the potential of introducing biases into the knowledge production function as posited by (Lee, 2006) which reflects in the knowledge spillover measure and cause validity and reliability reliability problems. Relative to spatial based or geographic based measures of knowledge spillover meansures such as those derived through network analysis, the **technological related measures estimated through econometric approaches become so complicated and in the end intoduces biasness that affect the validity and reliability of knowledge spillover measures**. Theoretical considerations dominates the technology relatedness measures of knowledge spillover which make them lose their practical touch and relevance in the real world analysis. However, the spatial based or geographic proximity based measure have also been overly simplifies with an extreme attention to colocation and interaction with very little or no attention to absorptive capacity. Aggregation bias could explain a portion of reliabiliy problems in knowledge spillover measures as revealed by the findings of the current study. Breschi, Lissoni and Montobbio (2005) asserts that the impact of percuniary knowledge spillovers are insignificant and therefore a split between percuniary knowledge spillovers and pure knowledge spillovers in estimating their impact is needless. However, Lee (2006) and (Griliches, 1979) have suggested that failure to split these two knowledge spillovers into their different domains is an important source of bias that can affect the validity and reliability of knowledge spillover measures.

Authors who have spent time over the years to find estimates of knowledge spillovers such as Kaiser (2002); Branstetter (2006); Fritsch and Franke (2004); Encaoua et al.(2000); Griliches (1979); Jaffe (1988, 1986); Inkmann & Pohlmeier (1995) have been confronted with the complex issue of spliting between the different knowledge pools. **This complicates the estimation of knowledge spillovers and have the tendency of introducing errors and reliability problems**. For example, the three measures of technology relatedness measures of knowledge spillovers considered in this study treats knowledge spillover pools differently (Kaiser, 2002). This puts to question convergence and consistency among the measures of knowledge spillovers making these measures susceptible to reliability problems. Again, the computation of technological distance is another source of problem that could be distortions in the estimates of knowledge spillovers. The variants of the colocation in the spatial or geographic distance measure in the technological distance measure of knowledge spillovers remains an important source of distortion that could explain the reliability problems associated with the three technological distance-based measures of knowledge spillovers. The study finds that there is no consistency in the computation of technological distance. Whereas the uncentered correlation and the Branstetter approaches use cosine similarity (Encaoua et al.2000; Jaffe, 1988,1986) the Euclidean distance approach, adopts, as the name implies Euclidean distance (Inkmann and Pohlmeier,1995). **These two measures of distances are just mathematical approaches but their implications for knowledge spillovers estimates have not been assessed, therefore unclear what these distance measurements import into the knowledge spillover computations.** These could be sources of distortion and could adversely affect the reliability of knowledge spillovers as the current study has revealed. This is consistent with the view expressed by Kaiser (2002) who expressed that technological distance measures adopted by the technology proximity based measures of estimating knowledge spillovers have been a source of reliability problems.

4.2.2 Complementarity between Country's Own R&D and knowledge Spillover

The findings of the study pertaining to the complementarity between countries' own R&D and knowledge spillovers are mixed, with the study outcome hugely influenced by the level of R&D investment committed by the country. The study confirms hypothesis based on the adoption approach that there is a complementarity between a country's own R&D and international knowledge spillover. The details of the results indicate that the models with the endogenous problem show complementarity between own R&D and international knowledge spillover, but the extent of complementarity is lower than in the instrumental variable-based models. However, based on the productivity approach, the study only found evidence in support of the hypothesis for full sample panel least square and for both high R&D intensive and low R&D intensive countries. The results confirm the importance of R&D size in the complementarity between knowledge spillovers and countries own R&D. The results of the study has shown that using the adoption approach, countries with high R&D investment have higher complementarity between own R&D and international knowledge spillovers.

From the findings of the study, there is evidence of complementarity between own R&D and international knowledge spillover. What is important to highlight is that R&D intensity is important in the complementarity between own R&D and international knowledge spillovers. Countries with high R&D intensity show evidence of higher complementarity than countries with low R&D. The findings of the study make clear that the complementarity between a country's own R&D and international knowledge spillovers is not automatic, it requires that countries have high R&D intensity. This is consistent with the idea that absorptive capacity is important in learning external knowledge (Choi & Lee, 2021; Cohen & Levinthal, 1986). R&D

has been found to be everything in innovation and all other factors are secondary but relevant. Lin (2014) has shown that the intensity of countries R&D is important to imitate what others do. Complementarity requires that countries can learn from others. This is mainly based on R&D intensity which gives the learning ability to be able to learn other countries' technology. The findings and the importance of R&D to the complementarity between countries' own R&D and knowledge spillover is at variance with the endogenous growth theory that assumes that knowledge spillover is automatic. The role of R&D size in the complementarity between countries' own R&D and knowledge spillover is a recognition that learning ability of countries is important in the countries' ability to easily combine internal and external knowledge source for innovation. This is a clear departure from collocation or knowledge spillover clusters principle. The assumption that knowledge spillovers are localized is diffused by the findings of the study. Countries can combine international knowledge spillovers with their own R&D resources easily if their R&D resources are high enough to allow countries learn from international knowledge spillovers. This is in conformity with literature findings that suggest that there are channels of international knowledge spillovers. However, combining these external knowledge resources with internal resources as the findings have revealed is a function of countries' R&D resources. The study findings even though highlight the importance of learning ability of countries through investment in R&D, it is important to stress the role of interaction among actors or countries as explained in social exchange theory (Cropanzano & Mitchell, 2005). The a high R&D may be important but that alone will not be enough. The channels of knowledge spillovers that transport external knowledge between countries such as foreign direct investment, trade and scientific publication and meetings of scientists (Harabi, 1997) and their effectiveness are important sources of complementarity between countries' own R&D and knowledge spillover from abroad. It is worth mentioning that the important role of countries R&D identified in this study in the complementarity between countries' own R&D and knowledge spillover from abroad agrees with Harabi (1997) proposition that the most effective channels of knowledge spillover is own R&D. There is therefore a good reason to believe that clustering could be a good reason why there should be complementarity between R&D and knowledge spillovers, at least within the cluster.

The thinking that clusters are a source of learning and encourages knowledge spillovers (Audretsch &Feldman, 1996) may be a simplistic assumption to make given the findings of this study. It could well be that clustering is not an influential enough factor in knowledge spillover but rather the level of investment these economic agents in knowledge spillover space have committed to R&D as complement knowledge spillover. Knowledge spillovers are not complete if firms are unable to complement it with their own R&D to improve innovation. Firms and countries will have to be able to use this external knowledge by combining this external resource with its own R&D resources. The inability to ensure such complementarity will mean that knowledge spillover has not occurred.

The combination of own R&D and international knowledge spillover is a technology intensive activity that requires high knowledge capacity to execute (Zahra and George, 2002). Some have even argued that technologies must be related to ensuring complementarity. However, the findings of the study, in agreement with Cohen and Levinthal (1990) indicate that this technology distance caveat is surmounted if the receiving country has the absorptive capacity. This is in sync with the position of the prior literature that knowledge spillover and complementarity with own R&D is sensitive to the size of R&D (Nonnis et al., 2023; Roper et al., 2008, Chesbrough, 2003). It is however important to state that even in the presence of R&D investments, complementarity could be hard to achieve if the technological distance is huge. This makes a good case for technological proximity which suggests that knowledge spillover takes place because the external knowledge is either known or related to technology used by the technologies of the receiving econmic agents than just being in geographic proximate or in close network. It is clear from the fimdings of the study that complementarity between knowledge spillover and countries' own R&D is made possible because the receiving country understands or is able to learn the external technology.

It is known that, eventhough both R&D and knowledge spillovers are both technology based resources, the focus and effect have not been the same and therefore assuming automatic complemantarity may not give a whollistic picture. Whereas countries' own R&D are geared towards innovation and productivity, knowledge spillovers are not fit for purpose because the originator of the knowledge produced such knowledge based on a country specific objective which is generally different from the objective of the beneficiary country. It will therefore take a country or firms with high knowledge capabilities to be able to identify, assimilate and to combine such external knowledge sources within house R&D for commercialization (Cohen & Levinthal,1990). This proposition is in agreement with the important role of R&D size in the complementarity between knowledge spillovers and countries' own R&D as revealed in this study. The study is not oblivious of the fact that access to such external knowledge sources could be explained by other factors beyond the size of R&D. Credence is therefore given to spatial consideration such as clusters and geographic proximity. However, it is my contention based on the findings of this study that these aid countries to access knowledge but the R&D of countries is what allows countries to be able to combine external knowledge with own R&D resources for utilization. The notion that the location of an economic agent within a cluster of knowledge spillover or in a knowledge spillovers space determines the extent of absorption (Malmberg & Power, 2005), cannot be wholly accurate. This at best gives acces to the knowledge but the size and the extent of incvestment in R&D is what determines ability to combine external R&D resources and and countries' own R&D resources. The proposition in prior literature to the effect that centrality is what determines gains from knowledge spillovers (Gilbert et al.,2008) is not supported by by the findings of this study. What the findings of this study indicates is that there is knowledge spillover between countries only when the country finds the external knowledge complementary with its own R&D resources and is able to combine them for utilisation. Such complementarity is enherently dependent on the extent of investment a country has commited to R&D.

4.2.3 Combined Effect of Own R&D and International Knowledge Spillovers

The study has shown that the combined effect of countries' own R&D and knowledge spillover on innovation is mixed. Whereas the hypothesis of U-shaped relationship is confirmed for low R&D intensive countries, in the case of high R&D intensive countries the relationship is an inverted U-shaped. The hypothesized relationship suggests that countries upon receiving knowledge spillovers from abroad must go through a period of adaptation and to get familiar with the external knowledge sourced freely from abroad. This is because such external knowledge is new and unfamiliar to the country. The process of adaptation drains the countries resources and momentarily will set back the innovation process of the country (see figure 1 for explanation). After the adaptation period, the country becomes familiar with external knowledge, reduces the heterogeneity of combining the different knowledge resources and so it becomes easier to integrate the external knowledge very well into its knowledge production function. It is at this point that the combination of countries' own R&D resources and knowledge spillover from abroad begin to have a positive effect on innovation. The hypothesis only holds, for low R&D intensive countries. In high R&D intensive countries, knowledge spillovers combine effectively with countries' own R&D resources to improve innovation initially, but at a latter period innovation performance fall as the size of combined internal and external knowledge resources rises. This defines the inverted U-shaped relationship observed in the case of high R&D intensive countries.

In this study knowledge spillover has a positive effect on innovation at a point, in both low R&D intensive and high R&D intensive countries consistent with prior literature (Vujanovic et al., 2022; VuMontoro-Sanchez et al.,2011). Thus, in the case of high R&D countries the combined effect of own R&D and knowledge spillover is realized immediately but in the case of low R&D countries the positive effect of combining own R&D and knowledge spillover is sluggish and takes place at a latter period, after the challenges of combining the two resources are surmounted.

The literature on innovation performance and their determinants have shown an inconsistent relationship between knowledge spillovers and innovation, especially between developed and emerging economies (Vujanovic et al., 2022). The findings of the study address this inconsistency and explain the dynamics that cause this inconsistency. Most of the studies cited in the literature have assumed, contrary to what the current study has uncovered that knowledge spillover is applied in the knowledge production process in isolation without any other knowledge source. This study has revealed that this assumption is simplistic and requires a second thought. The findings of the study have shown that knowledge spillover effect on innovation does not happen in isolation but in combination with own R&D, a process that introduces heterogeneity into the knowledge production function and therefore alters the relationship which would be established if knowledge spillovers were the only knowledge input in the knowledge production function.

Contrary to the empirical literature that has generally shown a positive relationship between knowledge spillover and innovation (Montoro-Sanchez et al., 2011), the findings of the current study reveal a more complicated and realistic relationship that reflects the fact that knowledge spillover works with own country resource to affect innovation. It is clear from the outcome of this study that high R&D intensive countries and their low R&D intensive counterparts behave differently in terms of the relationship between knowledge spillover and innovation performance. Whereas in low R&D intensive countries the effect of knowledge spillover on innovation is sluggish, allowing for adaptation period to effectively work in combination with countries' own R&D, in the case of high R&D intensive countries the positive impact of knowledge spillover on innovation is immediate and countries do not require time to adapt to the use of knowledge spillovers. The findings of this study has shown that when knowledge spillovers from abroad find its way into a knowledge production function, the possibility of the spillover from abroad introducing heterogeneity into the knowledge production function when combined with the country's own R&D exists and cannot be ignored. This heterogeneity, which is the consequence of combining knowledge inputs from different sources and home-grown knowledge resource alters the behaviour of these inputs from their usual. In fact, knowledge spillover from abroad itself is a product of multiple R&D investment from different sources and therefore has a diverse background (Griliches, 1992). This, even though means combining these inputs with country's own R&D resources produces a more fertile input for innovation performance, the study finds that this also presents a challenge to the knowledge production function. Combining different R&D input sources requires coping strategy (Perri &Peruffo, 2016) that countries may not have and could set back their innovation drive depending on the strength of their R&D.

The important role of countries' own R&D resources to the effect of knowledge spillovers in affecting innovation has been one of the highlights of the currents study. Consistent with prior literature on innovation that highlights that countries that have invested in R&D (Zahra and George, 2002), this study has shown that countries with high R&D intensity and those of low R&D intensity show marked differences in their response to the heterogeneity introduced into knowledge production function by combining knowledge spillovers and country's own R&D. R&D intensity has been shown to be the reason for the differences in the effect of knowledge spillovers on innovation. R&D intensity has been found to develop countries' capacity to identify and to exploit knowledge spillover for innovation performance. This agrees with Zahra and George (2002) who has argued that R&D is the source of absorptive capacity that allows firms to be able to utilise knowledge spillover effectively. This is further explained by the findings of the study which has shown that in countries with high R&D intensity adapting to knowledge spillover is more effective than when the country's R&D intensity is not high. The findings of the study has shown that the relationship between knowledge spillover and innovation is not a linear one as large portions of the innovation literature have suggested. A clear departure from this paradigm as revealed in this study is that in high R&D intensive countries, firms are able to adapt to knowledge spillover from abroad faster than in low R&D intensive countries. Thus, countries can leverage their R&D for learning other countries' innovation and to improve their own innovation. This is contrasted with what pertains in low R&D intensive countries where the study reveals that the effect of knowledge spillover on innovation remains sluggish in the adaptation period which takes a long time and sets innovations performance back and only has positive effect on innovation after firms fully adjust to the new external knowledge resources from abroad.

A country's ability to learn from another country's R&D requires that the receiving country have what it takes to identify, access and exploit external knowledge (Zahra and George, 2002). This is what serves as the capital for countries with high R&D intensity allowing them to learn faster, the knowledge emanating from other countries with features and characteristics that are usually unknown to the beneficiary country. As explained by Dodgson (1993), countries after receiving knowledge spillovers must internalize these knowledge externalities and convert them to useable forms relevant for innovation. This is what countries with low R&D are unable to do with ease, hence the initial inverse relationship between the combining knowledge spillover with own R&D on innovation performance. However, in countries with high R&D intensity, the high R&D intensity enables such countries to effectively transform knowledge spillover into useable forms to enhance innovation performance. Countries with high R&D intensity are therefore able to surmount the challenges of combining knowledge spillover from abroad and their own R&D inputs to ensure that the combined effect has positive effect on innovation immediately but in the case of low R&D intensity countries, the learning process is slow setting back innovation performance initially but as countries become accustomed to the external knowledge the positive impact is realized.

4.2.4 Absorptive capacity, Knowledge Spillovers and Country's Own R&D

The findings of the study where absorptive capacity is measured by the R&D intensity and the centrality of a country in the network of countries confirms the important role of absorptive capacity as alluded to by the literature (Qian & Acs, 2013). Even though the literature on knowledge spillovers and innovation recognises the importance of absorptive capacity, the findings of the current study bring new insights. The role of absorptive capacity brings some complexities in the complementarity between international knowledge spillovers and country's own R&D. Even though prior literature highlight that absorptive capacity is important in helping countries identify, access and exploit external knowledge (Zahra & George, 2002), the findings of the current study has shown that absorptive capacity is important but the other twist is that there is inertia in the complementarity but this is overcome as absorptive capacity increases and then the complementarity is given momentum. This feature of the complementarity means that countries have to invest in human and intellectual capital to be able to effectively combine their own R&D inputs and that coming by way of externality from abroad.

In this study, the use of different measures of absorptive capacity to reflect the spatial and cognitive dimensions of knowledge spillovers brings to bear in the current study the advantage of understanding the different aspects of absorptive capacity and their role in the complementarity between R&D of countries and external knowledge sources in particular knowledge spillovers. For example, Zahra and George (2002) in their explanation of absorptive capacity stated that an important aspect of absorptive capacity allows countries to identify external knowledge. This brings to bear the need to measure absorptive capacity based on spatial dimensions such as centrality and contiguity as has been done in this study. These measures of knowledge spillover, even though different from the known measures such as cognitive measures of knowledge feed into the transformation dimension of absorptive capacity that allows firms the ability to combine its own R&D inputs with international knowledge spillover (Dodgson, 1993). Centrality and contiguity are locational measures that indicate the extent to which a country within a network of countries is close to the other. These measures of absorptive capacity suggest that countries are close to the source of external knowledge and the proximity allows countries to interact and allow countries to learn from each other enhancing complementarity.

On the other hand, technological proximity is important in the complementarity between knowledge spillover and country's own R&D (Nooteboom, 2000). However spatial measures of absorptive capacity may not suffice to ensure complementarity between international knowledge spillovers and the country's own R&D. This may explain why cognitive measures of absorptive capacity could not influence the complementarity between international knowledge spillovers and country's own R&D. To assume that spatial measure of absorptive capacity. The argument that absorptive capacity is an enabler that allows learning external knowledge and being able to combine external knowledge with own R&D resources for innovation is very much confirmed by the findings of the current study. It is argued in this study that the explanation by authors that human capita is the only source of absorptive capacity (Cohen and Levinthal,1990) is simplistic. As has been revealed by the findings of the current study, other dimensions of absorptive capacity such as centrality and contiguity that foster interaction and learning not captured necessarily by cognitive measures such as R&D intensity have significant and positive influence on the complementarity between knowledge spillovers and country's own R&D.

Volberda et al. (2010), in their study gave a broad definition of what absorptive capacity when they stated that it encapsulates cognition, motivation and interaction. The measures of absorptive capacity in this study have shown that both cognitive measured by R&D intensity and interactive measured by centrality of countries in the network of countries are important is soliciting complementarity between international knowledge spillovers and countries ‘own R&D.

Literature on innovation acknowledges an important obstacle to the complementarity between internal knowledge inputs and external knowledge inputs. Because knowledge spillover is a product of varied R&D projects from different countries or regions (Davila et al., 2005; Zahra & George, 2002), combining this knowledge with internal knowledge sources is cumbosome. This require a clear understanding of the external knowledge. This findings of the study has shown that both cognitive and spatial dimensions of absorptive capacity provide antedote to dealing with the conundrum. Centrality allows proximity and fosters interaction among countries and creates the necessary platforms for cointries to learn and shares technological knowledge efficiently. Cognitive measures of absorptive capacity such as a countries investment in R&D have been shown to foster such learnings that allows countries to understand external knowledge sources for innovation.

5 Conclusions and Recommendations

5.1 Summary of Main Findings

The study investigates knowledge spillover effect and the methods of their measurement with the specific aim of assessing the different approaches that have been employed in measuring knowledge spillovers. The study also investigates the effect of spillovers of international knowledge, its complementarity with country's own R&D and how in combination, international knowledge spillovers and country's own R&D affect innovation performance of countries. The study also investigates the role of absorptive capacity in the complementarity between international knowledge spillovers and country's own R&D to influence innovation performance.

In investigating the methods of measuring knowledge spillovers, the focus of the study has been on assessing the validity and reliability of these knowledge spillover measures focusing on three measures of knowledge spillovers including the Euclidean distance, uncentered correlation and the Branstetter approaches of measuring knowledge spillovers. As part of assessing the validity and reliability of knowledge spillover measures, the study also presents an analysis on geographic proximity-based measures using network analysis and contrasts that with technology proximity measures of uncentered correlation, Euclidean distance and the Branstetter approaches to assess the validity and reliability of knowledge spillover measures. The focus of this study, beyond the assessment of knowledge spillover measures, is to investigate the effect of knowledge spillovers. This is conducted on two wave lengths. First the study assesses the complementarity between international knowledge spillovers and country's own R&D and second an evaluation of the combined effect of knowledge spillover from abroad and Country's own R&D. To achieve this, the study employs the two dominant approaches to establishing complementarity in the economics literature and specifically in the innovation literature, the adoption and the productivity approaches. In this study, it is acknowledged that in as much as the complementarity between knowledge spillover and country's own R&D are important, the final goal for innovation performance of countries is the ability to combine these two important knowledge production inputs for enhanced innovation performance. The study's approach has been the recognition that knowledge spillover, even though a cross product of several R&D products and therefore, a rich source of knowledge input, it also comes with some heterogeneity that could be inimical to the knowledge production function of beneficiary countries. The study therefore develops a methodology that recognizes this heterogeneity in the knowledge production function not as a problem but a feature that needs to be modeled as part of analysing the combined effect of international knowledge spillover and country's own R&D on innovation. The study therefore modeled this relationship using a quadratic relationship to reflect the possible switch in the relationship between combining internal and external resources and their influence on innovation performance. This accounts for the effect of adaptation of external knowledge into the knowledge production function of countries. Contrary to the tenets of the endogenous growth theory, which is the main theory the anchors this study, the study deviated a bit from these tenets to assume that knowledge spillover is not an automatic source of innovation. This is based on empirical findings that have proven that there are filters that prevent the transmission of international knowledge spillover to innovation. In recognition of the role of such filters that prevents the transmission of knowledge spillovers into innovation, the study presents an investigation into the role of absorptive capacity in the complementarity between international knowledge spillovers and country's own R&D.

5.1.1. Objective 1: Validity and Reliability of Knowledge Spillover Measures

The study has shown that there is a wide disparity between geographic proximity-based measures of knowledge spillovers and technology proximity-based measures of knowledge spillovers. In this study, it is revealed that the proximity-based knowledge spillover measure, based on network analysis has shown that centrality and contiguity are the main determinants international knowledge spillovers. Countries that are centrally located in the network of countries are the ones that benefit more from international knowledge spillovers. Contiguity defined by the number of countries that immediately border a country influences the gains of knowledge spillover that accrue to a country. Peripheral countries benefit very little from international knowledge spillovers. The critical issue that determines knowledge spillovers in interaction among actors and that is the focus of geographic proximity-based measures of knowledge spillovers. In contrast, the Euclidean distance, uncentered correlation and Branstetter approaches to knowledge spillovers are technology proximity-based measures of knowledge spillovers. These measures accrue gains of knowledge spillover based on the extent of similarity between technologies of the knowledge spillover pool and the focal country's technology.

Validity estimates have shown that all the three measures of knowledge spillovers, Euclidean distance, the uncentered correlation and Branstetter approaches are valid measures of knowledge spillover to the extent that they retain their theoretical relationship with innovation performance. The study has shown that these measures of knowledge spillover exhibit the characteristics of knowledge spillover. An increasing positive change in these measures, for example, reflects a positive change in innovation performance outcomes. A placebo test shows that replacing these knowledge spillover measures with random numbers cannot replicate the expected bahaviour of the knowledge spillover measures. In terms of reliability, the findings of the study has shown that the different reliability test reveals different outcomes for the different knowledge spillover measures. The study used the intra class correlation analysis, the test of equality and the test-retest analysis to test for the reliability of these knowledge spillover measures. The study finds that the uncentered correlation and the Branstetter approach are reliable measures of knowledge spillover based on the intraclass correlation analysis but no evidence of reliability for the Euclidean distance approach. but the test of equality only finds reliability for some of the samples for uncentered correlation and Euclidean distance approach but found no evidence of reliability for the Branstetter approach. The test-retest analysis finds evidence to support the reliability for both the Branstetter and the Euclidean distance approaches but not the uncentered correlation approach.

5.1.2 Objective 2: Complementarity between Knowledge Spillovers and R&D

In this study, two approaches have been used to assess the complementarity between international knowledge spillover and country's own R&D. These approaches are the adoption and productivity approaches. Both approaches have shown that there is complementarity between international knowledge spillovers and country's own. The adoption approach employed least square dummy variables and instrumental variable analysis to allow the inclusion of time invariant centrality measures and deal with the potential endogeneity in the model respectively. The results of the study reveals that there is complementarity between country's own R&D and international knowledge spillovers. This is the same in the case of productivity approach where the weighted least square approach is used to surmount the challenges of heteroscedasticity. The study finds that complementarity is influenced by the intensity of R&D. A split of the data between high and low R&D intensity samples shows that in samples with high R&D intensity the complementarity is higher than in samples with low R&D intensity. The productivity approach to measuring complementarity between knowledge spillover and country own R&D to an extent mimics the results expressed by the adoption approach. However, there are some marked differences that need to be highlighted. Based on the full sample analysis, there is inertia in the complementarity. Upon the receipt of knowledge spillover from abroad, combining such knowledge resources with the country's own R&D set the country's innovation process back but bounces back to improve innovation performance as the level of the combine R&D resources increase. Comparing the split sample between high

R&D intensity countries and low R&D intensity reveals some interesting outcomes. Whereas the low R&D intensive countries mimic the full sample, exhibiting a setback to their innovation process initially and improving after higher level of the input combination, high R&D countries do not face such a challenge. Countries with high R&D intensity are immediately able to surmount the challenges that come with combining the two knowledge inputs to have increased innovation.

5.1.3 Objective 3: Combined Effect of Knowledge Spillover and Own R&D

The combined effect of international knowledge spillover and country's own R&D has been found to exhibit a curvilinear relationship as the study hypothesized. However, the study has shown that whether the effect of combining knowledge spillover and country's own R&D on innovation with be U-shape or inverted U-shaped will be dependent on the extent of R&D investment made. It has been shown in this study and related prior studies that R&D intensity of countries is what drives innovation through learning from external sources. This study has shown that a country's own R&D is what is necessary when it comes to combining a country's own internal R&D resources with knowledge spillover from abroad. The question as to why the size and intensity of R&D matter is that it increases the absorptive capacity which allows the countries learn external knowledge. The findings of the study bring an important contrast between high R&D intensity countries and low R&D intensity. The study has shown that in low R&D intensity countries combining countries own R&D with knowledge spillover pose a challenge for countries as their meager R&D does not allow them to easily learn and effectively integrate external knowledge into their knowledge production function. However, in high R&D countries, R&D increases their absorptive capacity which allows these countries to learn and adopt external knowledge. This is partly the reason why the study observes an inverted U-shaped relationship signifying early adopting and use of knowledge spillover for innovation, but the reverse is the case for low R&D intensity countries.

5.1.4 Objective 4 Absorptive Capacity, R&D, Knowledge Spillover Complementarity

An important area of the innovation literature that the current study has investigated is the role of absorptive capacity in influencing the complementarity between international knowledge spillovers and country's own R&D. In this study, the concept of absorptive capacity has been defined to reflect its relevance in knowledge spillover to include relational absorptive capacity. Rather than restricting the definition to only cognitive ability of a country, its people and their organizational process, the study acknowledges the fact that knowledge spillovers are spatial phenomenon. This means that spatial advantage countries enjoy such as the location of countries gives some level of absorptive capacity. Apart from cognitive absorptive capacity that is measured in prior studies by intensity of R&D, the study also included in spatial measures of absorptive capacity, contiguity and centrality of a country in a network of countries. The study has shown that both cognitive and spatial dimensions of absorptive capacity are important influencers of complementarity between knowledge spillovers and country's own R&D. Whereas the contiguity is unable to explain the complementarity between international knowledge spillovers and country's own R&D, measures such as R&D intensity and centrality of a country in the network of countries are good predicters of the complementarity between country's own R&D and international knowledge spillovers.

5.2 Significance of the Study Findings

The literature on knowledge spillovers, their effects and measurements present a large array of ideas that have been cited in prior studies of innovation and knowledge. However, the literature in its current form presents some gaps that the current study has provided answers to and given further guidance to influence policies and future studies.

Measuring knowledge spillover remains one of the most challenging areas of the innovation literature. For this reason, different authors have devised different approaches to measuring the phenomenon, knowledge spillovers. Even though several authors have, to some extent, appraised the different measures of knowledge spillovers, this study is among the few that have formerly assessed the efficacy of knowledge spillover measures. In this study, the parameters for assessing the reliability and validity of knowledge spillover measure are clearly spelt out and the expectation is that future studies that attempt and appraisal of knowledge spillover measure can emulate. The criteria for assessing the validity and reliability of knowledge spillover measures set in this study which forms part of the novel contribution of this paper is expected to arouse debate in the scholarly literature and fill an important gap in the knowledge spillover literature.

The study recognises that the intangible nature of knowledge is part of the reason why there are challenges in the measurement of knowledge spillovers. The study therefore posits that authors may make do with the available measures the literature presents with all the challenges that come with these measures. What the current study has done in this regard is to contribute the literature is to assess the validity and reliability of the existing measures to serve as a guide on how and under what circumstances the existing knowledge spillover measures are valid and reliable. This is important to the extent that most authors have used these measures of knowledge spillovers merely because of need to use them because of non-availability of better measures of knowledge spillovers. To such authors, a guide such what has been provided in this study, indicating the strength and weakness of the various measures of knowledge spillovers will be an important guide in selecting which of the measures to use.

The practical use of knowledge spillover measures is one of the important challenges policy makers faces. The dilemma of choosing between geographic proximity and technological proximity measures of knowledge spillover clouds policy making and effectiveness of innovation policy that integrate into itself knowledge spillover dependence. This study has clearly shown that most of the technology proximity measures of knowledge spillover are just theoretical without very little practical touch. In this study, I have critiqued the different approaches of assessing technological similarity and conclude that these are mere theoretical dispositions. The study has shown that there exist a disparity between spatial measures of knowledge spillover based on network analysis that reflect reality than the use of technological proximity measures that serve theoretical purpose. For practical application of knowledge spillover measures, the findings of the study has shown that treating knowledge spillover as a spatial rather than use of technological relation mapping is ideal.

In this study the social exchange theory and its relevance has come to bear. Knowledge spillover has been revealed more of a phenomenon of interaction between actors in a network apart from being a phenomenon transmitted between actors of similar technological knowledge. Knowledge spillovers have both technological proximity as well as a spatial dimension. **Contrary to some aspects of prior literature that have suggested that technological proximity weighs higher in knowledge spillover than spatial dimension, this study concludes by rejecting such a proposition**. This study largely puts to rest the opposing argument that knowledge spillovers are localized or not. It is concluded based on the findings that knowledge spillovers are a function two capacities, inability to fully appropriate knowledge generated and the capacity on the part of the recipient to absorb external knowledge. Knowledge spillover is therefore not a local phenomenon but only a function of absorptive capacity which can be defined as including local factors. The issues of geographic distance in explaining knowledge spillovers is a mute argument. What is actually at play in the relationship between geographic distance and knowledge spillovers is access to technology which is not actually a function of distance but how well actors are integrated into the network of technological interdependence. If actors are well connected distance cannot be a hindrance top knowledge spillovers.

5.3 Practical Implication of the Study Findings

Based on the findings of the study some important issues can be distilled to aid policy makers in their attempt at functioning out policies for innovation purposes especially within Europe.

First the thinking among some policy makers that knowledge spillovers are local without international cross-border channels may be outmoded. From the findings of the current study, international knowledge spillover is an important source of innovation performance input resources. Policies on innovation should be anchored on among other external sources international knowledge spillovers. This presents a rich source of innovation input as it is a cross product between different R&D projects internationally. This calls for a concerted effort among countries to improve the environment to encourage information sharing, collaboration and learning among firms and their employees. To achieve this, countries and firms must promote a learning culture where firms in countries vigorously pursue learning from other firms' knowledge. International conferences and mentorship are important channels through which such learning can be achieved. Other channels that can be explored include workshops and the use of online learning resources. To improve knowledge spillovers, countries must adopt both formal and informal approaches. However, it should be noted that knowledge spillovers are in all instances externalities and therefore the onus is on the beneficiary countries to make the effort to improve on their ability to be draw on these external knowledge sources.

The findings of the study have shown that collaboration and interactions between countries is an important source of knowledge spillovers. This means that collaborations and interaction between countries in the form of trading and international capital mobility by way of Foreign Direct Investment and joint R&D projects are important channels of encouraging knowledge spillovers. Within the European region, trade and international capital mobility, even though high, efforts to ensure strengthening these channels especially between the high R&D intensive and low R&D intensive countries will be important to ensure transmission of knowledge spillover from abroad. Coupled with this, R&D of countries have been shown to be important for knowledge spillovers and innovation. The implication of these findings for policy is to first exploit the existing channels of interaction between these countries which are a major source of knowledge spillover transmission between countries. This requires capacity on the part of countries to be able learn other country's technologies through reverse engineering. This requires countries to invest a bit more in R&D to build the absorptive capacity of countries, especially low R&D intensive countries, to be able to learn the technologies of high R&D intensive countries. Foreign direct investments are also channels that can be exploited to improve the flow of knowledge spillover across countries. However, in this study it is acknowledged that such capital mobility requires some fundamentals to occur. If countries can put right the macroeconomic fundamentals to attract foreign direct investments, it will be possible to learn from knowledge of multinational companies which remain one of the richest and cheapest sources of technology which include access to new technologies, managerial practices and other organizational practices to enhance innovation in the domestic economy. Technologies from multinational companies, even though generally considered as good can have some adverse consequences on the innovation of domestic country, these challenges are surmounted if there is the capacity to deal with the adverse effect of such new and complicated technologies.

It is known from the findings of the study that new technologies from external sources may pose complementarity problems for the receiving countries. However, the findings of the study also reveal that where countries have high investments in R&D the problem is assuaged making it possible to use rich external sources of knowledge in combination with home generated sources of knowledge. Absorptive capacity, both relational and cognitive as revealed by the findings of this study are cardinal to ensuring the international knowledge spillovers are beneficial to domestic economy. Thus, whilst countries invest in R&D it easier to understand and use international knowledge spillovers, it is also important to be in close touch with the source of international knowledge spillover as a way to make adaptation to the technologies easier. In most cases relational capacity afford the receiving country the benefit of receiving coaching on how to apply these technologies to enhance innovation.

On the part of the originators of the knowledge, which in most cases are the high R&D intensive countries, interventions from government are required to improve knowledge spillovers. Bearing in mind that treating knowledge as public good inure to the benefit of all parties in a knowledge spillover network, it is the contention of this study that this is only true in the case of the originators of knowledge if there are incentives that cushions their R&D investments. The originator of knowledge, knowing very well that their R&D investment cannot be fully appropriated, will be discouraged from investing more in R&D to serve the public good. The role of government is therefore inevitable if R&D investments and knowledge spillover will increase. Governments of the various countries individually and jointly must step in to incentivize R&D investment. This will deal with the adverse effect of knowledge as a public good and optimize its benefits simultaneously. One of the well-known incentive packages that work well is the R&D tax credit. R&D tax credit gives tax cuts to firms of the domestic economy that have engaged in R&D investment as a way a disincentive to R&D investment and knowledge spillovers. Knowing that R&D investment is expensive and may have a lagged effect on innovation, it becomes a high-risk enterprise for firms to engage in. R&D tax credit therefore becomes a way that government absorbs part of the cost and risk to encourage knowledge production and spillover for the public good.

Contrary to the endogenous growth theory that suggests that knowledge spillovers are automatic source of innovation performance, the findings of the currents study cautions policy makers to be weary of this proposition. The findings of the study make a clear statement that contradicts this proposition. It has been found that there are filters that block the transmission of knowledge spillovers into innovation performance. Knowledge spillovers are just the pool of knowledge external sources that can be learnt into the knowledge production function of others for innovation purposes. Learning this external knowledge is not automatic. This study has shown that **complementarity between external knowledge and countries' own R&D as well as absorptive capacity of countries and their firms** are conditions for exploiting these external knowledge sources. It is therefore important that countries seeking to leverage knowledge spillovers for innovation boost their capacity. This will require not just cognitive but also relational capacity. Practically social interaction is the main source of knowledge spillover. Getting involved in networks is encouraged. This can be done through conferences, exchange programs between firms and learning institutions.

In as much as relational capacity building is being advocated as key to leveraging knowledge spillover, it is important to underscore the need to build the cognitive capacity of countries. This will involve conscious efforts to increase investment in research and development of countries. The findings of the study have shown that countries with high R&D investment or high R&D intensity countries are able to identify and adopt and use international knowledge spillovers. Coupling R&D investment with integration into the networks of technological interdependence, through conferences, trade and foreign direct investment and the use of digital platforms is the catch for a new, robust and effective innovation policy.

The findings of the current study put a lot of currency on centrality of a country in the network of countries for the gains of knowledge spillover. Countries that are centrally placed in the network of countries can learn more from their peers relative to countries isolated in the network. The theory diverges a bit from practice. The colocation argument, even though theoretically sound, practically digital tools change the dynamics a bit. Relational absorptive capacity being a critical ingredient in exploiting knowledge spillover is in no doubt a must if countries can improve their innovation. However, colocation or being centrally located in the network of countries in practical terms is not the only channels or route to achieving success. In this era of digitalization other options include investing in the use of digital platforms. Digital platforms are high technology communication tools that allow for communication across country borders. This is a clear substitute to central location within the network of countries. This will not mean that a combination of the two, being centrally located and use of digital tools, is not doable. For practical purposes therefore, the findings of the current study encourage investment in digital tools as a way to encourage knowledge spillovers.

Measuring knowledge spillover has been done using various approaches. However, based on the findings of the current study, I contend that most of these measures are theory focus and very little focus is given to the practical relevance of these measures. The practical implication of the findings therefore is that policy makers must be very selective in which of the measures to adopt for practical purposes. Technology related based measures such as the Euclidean distance and the Uncentered correlation approaches make a lot of intuitive sense as a measure of knowledge spillover. However, how these measures determine related technologies has only theoretical appeal making them less relevant for practical use and purposes. However, the geographic proximity based measures are more practical inclined but also have serious gaps that compromises its practical relevance.

Direction for Future Studies

An important gap in the knowledge spillover literature is the lack of good measure of knowledge spillover. By consensus, prior literature suggests two main categories of measuring knowledge spillover measures, technology proximity-based measures and geographic proximity-based measures. Researchers agree that the knowledge pool created by countries' investment in R&D become susceptible to spillovers only for countries that can access the knowledge and have the cognitive ability to exploit the knowledge for innovation purposes. This brings to the fore three parameters for a good measure of knowledge spillover: (1) Knowledge pool, (2) relational capacity and (3) cognitive capacity. Forming a composite index using these parameters and computing the relevant weights for these parameters should suffice a good enough measure of knowledge spillover that will have practical relevance in future studies.

Teaching Contributions

Throughout the authors' PhD studies, he has participated in pedagogical activities including handling seminars in microeconomic and macroeconomics, managerial informatics, current issues in economics and economic and financial aspects of innovation. In these activities, the author has applied several of the theories and principles underlying the study. Endogenous growth theory, which is the main theory underlying the thesis, has been applied in seminars to explain the role of knowledge spillovers in innovation. In macroeconomics and microeconomics, the symbiosis between handling seminars and the thesis is felt. Many of the principles of public economics such as externalities and public goods that are taught during the seminars are applied in the thesis. For example, knowledge spillovers by its nature is considered public good and the externalities that come with it are issues that the author of the thesis has explained to his students during seminars.

References

[1] Acs, Z. J., Audretsch, D. B., & Lehmann, E. E. (2013). The knowledge spillover theory of entrepreneurship. *Small Business Economics, 41*(4), 757–774.

[2] Acs, Z. J., Audretsch, D. B., Braunerhjelm, P., & Carlsson, B. (2009). The knowledge spillover theory of entrepreneurship. *Small Business Economics, 32*, 15–30.

[3] Acs, Z. J., Audretsch, D. B., Braunerhjelm, P., & Carlsson, B. (2012). Growth and entrepreneurship. *Small Business Economics, 39*(2), 289–300.

[4] Acs, Z., & Audretsch, D. (1988). Innovation in large and small firms: an empirical analysis. *American Economic Review, 78*(4), 678–690.

[5] Acs, Z., & Sanders, M. (2012). Patents, knowledge spillovers, and entrepreneurship. *Small Business Economics, 39*(2012), 801–817.

[6] Adomako, S., & Tran, M. D. (2024). Intellectual property rights protection and sustainable innovation performance: The mediating role of technology spillover. *Sustainable Development*, 1-13.

[7] Aghion, P., & Jaravel, X. (2015). Knowledge spillovers, innovation and growth. *The Economic Journal, 125*(583), 533-573.

[8] Alavi, M., & Leidner, D. (2001). Knowledge management and knowledge management systems: conceptual foundations and research issues. *MIS Quarterly, 25*(1), 107–136.

[9] Aldieri, L., Sena, V., & Vinci, C. P. (2018). Domestic R&D spillovers and absorptive capacity: Some evidence for US, Europe and Japan. *International Journal of Production Economics, 198,* 38-49.

[10] Ali, M., Cantner, U., & Roy, I. (2016). Knowledge spillovers through FDI and trade: the moderating role of quality-adjusted human capital. *Journal of Evolutionary Economics, 26*(4), 837-868.

[11] Amendola, M. (2024). Input additionality of R&D tax reliefs: results from a panel LP-IV approach. *Economics of Innovation and New Technology, 33*(5), 736-753.

[12] Antonelli, C., Patrucco, P. P., & Quatraro, F. (2011). Productivity growth and pecuniary knowledge externalities: an empirical analysis of agglomeration economies in European regions. *Economic Geography, 87*(1), 23-50.

[13] Archibugi, D., & Iammarino, S. (1999). The policy implications of the globalisation of innovation. *Research policy,, 28*(2-3), 317-336.

[14] Arrow, J. (1962). Economic welfare and the allocation of resources for invention. In R. Nelson, *The Rate and direction of inventive activities* (pp. 609–625). Princeton: Princeton University Press.

[15] Arshad, M. U., Shabbir, M. N., & Niazi, M. (2019). Trade openness and public innovation: a causality analysis. *SAGE Open, 13*(3).

[16] Athey, S. S. (1998). *An empirical framework for testing theories about complementarity in organizational design.* Cambridge,: NATIONAL BUREAU OF ECONOMIC RESEARCH.

[17] Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *The American economic review, 86*(3), 630-640.

[18] Audretsch, D., & Belitski, M. (2020). The role of R&D and knowledge spillovers in innovation and Productivity. *European Economic Review, 123*(2020).

[19] Audretsch, D., & Lehmann, E. (2005). Does the Knowledge Spillover Theory of Entrepreneurship hold for regions? *Research Policy, 34*(2005), 1191–1202.

[20] Audretsch, D., Keilbach, M., & Lehmann, E. (2006). *Entrepreneurship and Economic Growth.* Oxford: Oxford University Press.

[21] Autant-Bernard, C. (2001). The Geography Of Knowledge Spillovers And Technological Proximity. *Economics of Innovation and new Technology, 10*(4), 237-254.

[22] Autio, E., Nambisan, S., Thomas, L. D., & Wright, M. (2018). Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. *Strategic Entrepreneurship Journal, 12*(1), 72-95.

[23] Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191-215.

[24] Bandura, A. (1986). *A social cognitive theory.* New Jessy: Prentice-Hall.

[25] Bandura, A. (2001). Social Cognitive Theory of Mass Media. *Mediapsychology, 3*, 265–299.

[26] Becker, G. (1964). *Human Capital.* Chicago, Illinois: University of Chicago Press.

[27] Belitski, M., & Desai, S. (2016). What drives ICT clustering in European cities? *The Journal of Technology Transfer, 41*(3), 430-450.

[28] Bell, G. (2005). Clusters, networks, and firm innovativeness. *Strategic Management Journal, 26*, 287–295.

[29] Blau, P. M. (1964). *Exchange and power in social life.* New York: John Wiley.

[30] Bloom, N., Griffith, R., & Reenen, J. (2002). Do R&D tax credits work? Evidence from a panel of countries 1979–1997. *Journal of Public Economics, 85*(2002), 1-31.

[31] Bock, G., Zmud, R., Kim, Y., & Lee, J. (2005). Behavioral intention formation in knowledge sharing: examining the roles of extrinsic motivators, social–psychological forces and organisational climate. *MIS quarterly*, 87-111.

[32] Branstetter, L. (2006). Is foreign direct investment a channel of knowledge spillovers? Evidence from Japan's FDI in the United States. *Journal of International economics, 68*(2), 325-344.

[33] Branstetter, L. (2000). *Is Foreign Direct Investment a Channel of Knowledge Spillovers?: Evidence from Japan's FDI in the US* . Davis: Institute of Governmental Affairs, University of California, Davis.

[34] Breschi, S., & Lissoni, F. (2005). Cross-Firm" inventors and social networks: Localized knowledge spillovers revisited. *Annales d'Economie et de Statistique*, 189-209.

[35] Breschi, S., Lissoni, F., & Montobbio, F. (2005). The geography of knowledge spillovers Conceptual issues and measurement problems. In S. Breschi, & F. Malerba, *Clusters, Networks and Innovation* . Oxford: Oxford University Press.

[36] Caniëls, M. C. (2000, March 20). Knowledge spillovers and economic growth: regional growth differentials across Europe. pp. 1-5.

[37] Caniëls, M. C., & Verspagen, B. (2001). Barriers to knowledge spillovers and regional convergence in an evolutionary model. *Journal of evolutionary economics, 11*, 307-329.

[38] Caragliu, A., & Del Bo, C. (2011). Determinants of spatial knowledge spillovers in Italian provinces. *Socio-Economic Planning Sciences, 45*(1), 28-37.

[39] Cartillo, V., Garone, L., Maffioli, A., Rojo, S., & Stucchi, R. (2020). Knowledge Spillover through Labour Mobility. *The Journal of Development Studies, 56*(3), 469-488.

[40] Castellacci, F., & Archibugi, D. (2008). The technology clubs: The distribution of knowledge across nations. *Research Policy, 37*, 1659–1673.

[41] Chahal, H., & Bakshi, P. (2015). Examining intellectual capital and competitive advantage relationship: Role of innovation and organizational learning. *International Journal of Bank Marketing, 33*(3), 376-399.

[42] Charlot, S., Crescenzi, R., & Musolesi, A. (2015). Econometric modelling of the regional knowledge production function in Europe. *Journal of Economic Geography, 15*, 1227–1259.

[43] Charutawephonnukoon, P., Jermsittiparsert, K., & Chienwattanasook, K. (2021). Impact of high technology exports, patent applications and research and development expenditure on economic growth: evidence from ASEAN countries. *Psychology and Education, 58*(2).

[44] Chen, S., Zhang, H., & Wang, S. (2022). Trade openness, economic growth, and energy intensity in China. *Technological Forecasting and Social Change, 179*, 1-10.

[45] Chen, W., Boase, J., & Wellman, B. (2002). The global villagers: Comparing Internet users and uses around the world. *The Internet in everyday life*, 74-113.

[46] Chia, K. C., Hsu, C. C., Lin, L. T., & Tseng, H. H. (2021). The identification of ideal social media influencers: Integrating the social capital, social exchange, and social learning theories. *Journal of Electronic Commerce Research, 22*(1), 4-21.

[47] Choi, M., & Lee, C. Y. (2021). Technological diversification and R&D productivity: The moderating effects of knowledge spillovers and core-technology competence. *Technovation, 104*(102249).

[48] Cincera, M. (2005). Firms' productivity growth and R&D spillovers: An analysis of alternative technological proximity measures. *Economics of Innovation and New Technology, 14*(8), 657-682.

[49] Coccia, M. (2008). Spatial mobility of knowledge transfer and absorptive capacity: analysis and measurement of the impact within the geoeconomic space. *The Journal of Technology Transfer, 33*, 105-122.

[50] Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128–152.

[51] Coy, P., & Lu, W. (2015). The Bloomberg Innovation Index.

[52] Crevoisier, O. (2016). The Economic Value of Knowledge: Embodied in Goods or Embedded in Cultures? *Regional Studies, 50*(2), 189-201.

[53] Cropanzano, R., & Mitchell, M. S. (2005). Social exchange theory: An interdisciplinary review. *Journal of management, 31*(6), 874-900.

[54] Cuervo-Cazurra, A., Nieto, M. J., & Rodríguez, A. (2018). The impact of R&D sources on new product development: Sources of funds and the diversity versus control of knowledge debate. *Long Range Planning, 51*, 649–665.

[55] Czarnitzki, D., & Hussinger, K. (2018). Input and output additionality of R&D subsidies. *Applied Economics, 50*(12), 1324-1341.

[56] Dalkir, K. (2011). *Knowledge Management in Theory and Practice.* Massachusetts: The MIT Press.

[57] Dalrymple, D. (2003). Scientific knowledge as a global public good: Contributions to innovation and the economy. In M. Julie, & F. Paul, *The role of scientific and technical data and information in the public domain: proceedings of a symposium* (pp. 35-49). Washington: National academic press.

[58] David, P., Hall, B., & Toole, A. (2000). Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research Policy, 4-5*, 497-529.

[59] Delmar, F., Wennberg, K., & Hellerstedt, K. (2011). Endogenous growth through Knowledge spillover entrepreneaurship: An empirical test. *Strategic Entrepreneurship Journal, 5*(2011), 199–226.

[60] Dimos, C., & Pugh, G. (2016). The effectiveness of R&D subsidies: a meta-regression analysis of the evaluation literature. *Research Policy, 45*(4), 797–815.

[61] Dimos, C., Pugh, G., Hisarciklilar, M., Talam, E., & Jackson, I. (2022). The relative effectiveness of R&D tax credits and R&D subsidies: A comparative meta-regression analysis. *Technovation, 115*(102450).

[62] Dodgson, M. (1993). Organizational learning: A review of som literature. *Organization Studies, 14*, 375-394.

[63] Doring, T., & Schnellenbach, J. (2006). What do we know about geographical knowledge spillovers and regional growth?: a survey of the literature. *Regional Studies*, *40*(3), 375-395.

[64] Dotta, V., & Munyo, I. (2019). Trade openness and innovation. *The Innovation Journal, 24*(2), 1-13.

[65] Drahos, P. (2004). The regulation of public goods. *Journal of International Economic Law, 7*(2), 321-339.

[66] Durmaz, A., & Yıldız, Ü. (2020). Uluslararası İktisadi ve İdari İncelemeler Dergisi. *The impact of innovation in the process of high technology exports: an analysis on BRICS countries., 28*, 193-202.

[67] Eapen, A., Yeo, J., & Sasidharan, S. (2019). Finance constraints and technology spillovers from foreign to domestic firms. *Economic Modelling, 76*(2019), 50-62.

[68] Easterby-Smith, M., Crossan, M., & Nicolini, D. (2000). *Journal of Management Studies, 37*(6), 783–796.

[69] Emerson, R. M. (1976). Social exchange theory. *Annual Review of Sociology, 2*, 335-362.

[70] Emmanouilides, C., & Hammond, K. (2000). Internet usage: Predictors of active users and frequency of use. *Journal of Interactive Marketing, 14*(2), 17-32.

[71] Erdal, L., & Göçer, İ. (2015). The effects of foreign direct investment on R&D and innovations: Panel data analysis for developing Asian countries. *Procedia-Social and Behavioral Sciences, 195*(2015), 749-758.

[72] Evans, G. L. (2019). Emergence of a digital cluster in east London: Birth of a new hybrid firm. Competitiveness Review. *An International Business Journal, 29*(3), 253–266.

[73] Fang, Y., Wade, M., Delios, A., & Beamish, P. (2013). An exploration of multinational enterprise knowledge resources and foreign subsidiary performance. *Journal of World Business*, 30-38.

[74] Feldman, M. P., & Audretsch, D. B. (1999). Innovation in cities:: Science-based diversity, specialization and localized competition. *European economic review, 43*(2), 409-429.

[75] Feldman, M. P., & Kelley, M. R. (2006). The ex ante assessment of knowledge spillovers: Government R&D policy, economic incentives and private firm behavior. *Research policy*, *35*(10), 1509-1521.

[76] Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies, 41*(5), 685-697.

[77] Fritsch, M. (2002). Measuring the quality of regional innovation systems: A knowledge production function approach. *International regional science review, 25*(1), 86-101.

[78] Frost, J., & Morner, M. (2010). Overcoming knowledge dilemmas: Governing the creation, sharing and use of knowledge resources. *International Journal of Strategic Change Management, 2*(2/3).

[79] Garcia, R., Araujo, V., Mascarini, S., Gomes, E., Santos, D., & Costa, A. (2008). Is cognitive proximity a driver of geographical distance. *Area Development and Policy, 3*(3), 349-367.

[80] Gehringer, A. (2011). Pecuniary knowledge externalities and innovation: Intersectoral linkages and their effects beyond technological spillovers. *Economics of Innovation and New Technology, 20*(5), 495-515.

[81] Geisler, E. (1995). An integrated cost-performance model of research and development evaluation. *Omega, 23*(3), 281–294.

[82] Ghio, N., Guerini, M., Lehmann, E., & Rossi-Lamastra, C. (2015). The emergence of the knowledge spillover theory of entrepreneurship. *Small Business Economics , 44*, 1-18.

[83] Gilbert, B. A., McDougall, P. P., & Audretsch, D. B. (2008). Clusters, knowledge spillovers and new venture performance: An empirical examination. *Journal of business venturing, 23*(4), 405-422.

[84] Gittelman, M., & Kogut, B. (2003). Does good science lead to valuable knowledge? Biotechnology firms and the evolutionary logic of citation patterns. *Management Science, 49*(4), 366–382.

[85] Goren, E. (2022). Genetic, cultural and historical department of knowledge creation. *Macroeconomic Dynamics, 26*, 1833–1890.

[86] Granovetter, M. (1994). The Handbook of Economic Sociology. In N. Smelser, & R. Swedberg, *Business groups.* Princeton: Princeton University Press.

[87] Grant, R. (1996). Toward a Knowledge Base Theory of the Firm. *Strategic Management Journal, 17*, 109-122.

[88] Greunz, L. (. (2003). Geographically and technologically mediated knowledge spillovers between European regions. *The Annals of Regional Science, 37*(2003), 657-680.

[89] Grigorescu, A., Zamfir, A. M., & Mocanu, C. (2020). Emerging trends and drivers for knowledge-intensive economy. *Management & Marketing-Challenges for the Knowledge Society, 15*(2), 172-185.

[90] Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *Bell Journal of Economics, 10*(1), 92-116.

[91] Griliches, Z. (1992). The Search for R&D Spillovers. *Scandinavian Journal of Economics, 94*, 29-47.

[92] Griliches, Z. (2000). *R&D, Education, and Productivity.* Cambridge, MA: Harvard University Press.

[93] Gupta, G., & Bose, I. (2019). Strategic learning for digital market pioneering: Examining the transformation of Wishberry's crowdfunding model. *Technological Forecasting and Social Change, 146*, 865–876.

[94] Gygli, S., Haelg, F., Potrafke, N., & Sturm, J. E. (2019). The KOF globalisation index–revisited. *The Review of International Organizations,, 14*, 543-574.

[95] Haighta, M., Quan-Haase, A., & Corbett, B. (2014). Revisiting the digital divide in Canada: the impact of demographic factors on access to the internet, level of online activity, and social networking site usage . *Information, Communication & Society, 13*(1), 503–519.

[96] Hall, R., & Andriani, P. (2002). Managing Knowledge for innovation. *Long Range Planning , 35*, 29-48.

[96] Harabi, N. (1997). Channels of R&D spillovers: An empirical investigation of Swiss Firms. *Technovation, 17(11/12) (1997), 17*(11/12), 627--635.

[98] Harhoff, D. (1996). Strategic spillovers and incentives for research and development. *Management Science, 42*(6), 907-925.

[99] Hashi, I., & Stojcic, N. (2003). Knowledge spillovers, innovation activities, and competitiveness of industries in EU member and candidate countries. *Economic annals, 58*(198), 7-34.

[100] Henderson, J. V. (2007). Understanding knowledge spillovers. *Regional Science and Urban Economics, 37*, 497–508.

[101] Heng-Li, Y., & Ted, C. W. (2008). Knowledge sharing in an organisation. *Technological forcasting and social change, 75*, 1128 – 1156.

[102] Hicks, D. (1995). Published papers, tacit competencies and corporate management of the public/private character of knowledge. *Industrial and Corporate Change, 4*, 401-424.

[103] Hinings, B., Gegenhuber, T., & Greenwood, R. (2018). Digital innovation and transformation: An institutional perspective. *Information and Organization, 28*(1), 52–61.

[104] Hollanders, H., & Celikel-Esser, F. (2007). *Measuring innovation efficiency INNO Metrics 2007 report.* Brussels: European Commission, DG Enterprise.

[105] Huber, F. (2012). Do clusters really matter for innovation practices in Information Technology? Questioning the significance of technological knowledge spillovers. *Journal of economic geography,, 12*(1), 107-126.

[106] Inkmann, J., & Pohlmeier, W. (1995). *R&D Spillovers, Technological Distance and Innovation Success.*

[107] Isaksson, O. H., Simeth, M., & Seifert, R. W. (2016). Knowledge spillovers in the supply chain: Evidence from the high tech sectors. *Research Policy,, 45*(3), 699-706.

[108] Itami, H., & Roehl, T. (1987). *Mobilizing invisible assets.* . Cambridge MA: Harvard University Press.

[109] Jack, B., & Clarke, A. M. (1998). *The value of quantitative research in nursing.* London: Professional Nurse.

[110] Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents profits, and market. *American Economic Review, 76*(5), 984–1001.

[111] Jaffe, A. B. (1989). Real effects of academic research. *American Economic Review, 79*(5), 957-970.

[112] Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly journal of Economics, 103*(3), 577-598.

[113] Jones, C. I. (2019). Paul Romer: Ideas, nonrivalry, and endogenous growth. *The Scandinavian Journal of Economics, 121*(3), 859-883.

[114] Jordão, R. V., & Almeida, V. R. (2017). Performance measurement, intellectual capital and financial sustainability. *Journal of intellectual capital, 18*(3), 643-666.

[115] Jurczak, J. (2008). Intellectual capital measurement methods. *Economics and organization of enterprise, 1*(1), 37-45.

[116] Kaiser, U. (2002). Measuring knowledge spillovers in manufacturing and services: an empirical assessment of alternative approaches. *Research Policy 31 (2002), 31*, 125–144.

[117] Kanea, A., Argote, L., & Levine, J. (2005). Knowledge transfer between groups via personnel rotation:Effects of social identity and knowledge quality. *Organizational Behavior and Human Decision Processes, 96* (2005), 56–71.

[118] Kankanhalli, A., Tan, B., & Wei, K. (2005). Contributing knowledge to electronic knowledge repositories: an empirical investigation,. *MIS Quarterly, 29*, 113–143.

[119] Karras, G. (2003). Trade openness and economic growth can we estimate the precise effect? *Applied econometrics and international development*, *3*(1).

[120] Kathuria, V. (2002). Liberalisation, FDI, and productivity spillovers—an analysis of Indian manufacturing firms. *Oxford Economic Papers, 54*(2), 688-718.

[121] Keller, W. (1998). Are international R&D spillovers trade-related?: Analyzing spillovers among randomly matched trade partners. *European Economic Review, 42*(8), 1469-1481.

[122] Klette, J., Moen, J., & Griliches, Z. (2000). Do subsidies to commercial R&D reduce market failures? Microeconometric evaluation studies. *Research Policy, 29*, 471–95.

[123] Kraus, S., Palmer, C., Kailer, N., Kallinger, F. L., & Spitzer, J. (2019). Digital entrepreneurship: A research agenda on new business models for the twenty-first century. *International Journal of Entrepreneurial Behaviour and Research, 25*(2), 353–375.

[124] Kuder, G., & Richardson, M. (1937). The theory of the estimation of test reliability. *Psychometrika 2, , 2*, 151–160.

[125] Lahari, N. (2010). Geographic distribution of R&D activity: how does it affect innovation quality? *The Academy of Management Journal, 53*(5), 1194-1209.

[126] Lane, P. J., & Lubatkin, M. (1998). Relative absorptive capacity and interorganizational learning. *Strategic management journal, 19*(5), 461-477.

[127] Laursen, B., & Hartup, W. W. (2002). The origins of reciprocity and social exchange in friendships. *New Directions for Child & Adolescent Development, 95*(2002).

[128] Lee, C. (2008). The Relationship Between Innovation, Productivity and Exports: Some Preliminary Evidence from Malaysian Manufacturing Sector. *Economics Bulletin, 12*(31), 1-13.

[129] Lee, Y., Hsieh, Y., & Hsu, C. (2011). Adding Innovation Diffusion Theory to the Technology Acceptance Model: Supporting Employees' Intentions to use E-Learning Systems. *Education Technology & Society, 14*(4), 124-137.

[130] Lemos, N. (2007). *Introduction to the Theory of Knowledge.* New York: Cambridge University Press.

[131] Lemos, N. (2020). *An introduction to the theory of knowledge.* Cambridge: Cambridge University Press.

[132] Leshed, G., Haber, E. M., Matthews, T., & Lau, T. (2008). CoScripter: automating & sharing how-to knowledge in the enterprise. *Human Factors in Computing Systems*, (pp. 1719-1728).

[133] Li, Y., & Bosworth, D. (2020). R&D spillovers in a supply chain and productivity performance in British firms. *Journal of Technology Transfer, 45*, 177-204.

[134] Loebbecke, C., & Picot, A. (2015). Reflections on societal and business model transformation arising from digitization and big data analytics: a research agenda. *Journal of Strategic Information Systems, 24*(3), 149–157.

[135] Lööf, H. (2004). *A Comparative Perspective on Innovation and Productivity in Manufacturing and Services.* CESIS: Electronic Working Paper Series, paper.

[136] Lucas, R. E. (1989). On the Mechanics of Economic Development. *Journal of Monetary Economics, 22*(1), 3-42.

[137] Malmberg, A., & Power, D. (2005). (How) do (firms in) clusters create knowledge? *Industry and innovation, 12*(4), 409-431.

[138] Maradana, R. P., Pradhan, R. P., Dash, S., Gaurav, K., Jayakumar, M., & Chatterjee, D. (2017). Does innovation promote economic growth? Evidence from European countries. *Journal of Innovation and Entrepreneurship, 6*, 1-23.

[139] Mariotti, S., Piscitello, L., & Elia, S. (2010). Spatial agglomeration of multinational enterprises: the role of information externalities and knowledge spillover. *Journal of Economie Geography, 10*, 519-538.

[140] Marshall, A. (1920). *Principles of Economics* (8th ed.). London: Macmillan.

[141] Martinez-Brawley, E., & Zorita, P. M. (2007). Tacit and Codified Knowledge in Social Work: A Critique of Standardization in Education and Practice. *Families in Society, 88*(4), 534-542.

[142] Martínez-Climent, C., Mastrangelo, L., & Ribeiro-Soriano, D. (2021). The knowledge spillover effect of crowdfunding. *Knowledge Management Research & Practice, 19*(1), 106-116.

[143] Mclnerney, C. (2002). Knowledge management and dynamic. *Journal of the American society of information science and technology, 53*(12), 1009-1018.

[144] Meral, Y. (2019). High technology export and high technology export impact on growth. *International Journal of Business Ecosystem & Strategy, 1*(3), 32-38.

[145] Mezirow, J. (1995). Transformation theory of adult learning. In M. Welton, *defense of the lifeworld: critical perspectives on adult learning.* Albany, New York, USA: State University of New York Press.

[146] Molm, L. D. (1994). Dependence and risk: Transforming the structure of social exchange. *Social Psychology Quarterly, 57*, 163-176.

[147] Montoro-Sánchez, A., Ortiz-de-Urbina-Criado, M., & Mora-Valentín, E. M. (2011). Effects of knowledge spillovers on innovation and collaboration in science and technology parks. *Journal of knowledge management, 15*(6), 948-970.

[148]Moon, H., & Lee, J. (2005). A fuzzy set theory approach to national composite S&T indices. *Scientometrics, 64*(2), 67–83.

[149]Mowery, D., & Ziedonis, A. (2015). Markets versus spillovers in outflows of university research. *Research Policy, 44*(2015), 50–66.

[150] Murata, Y., Nakajima, R., Okamoto, R., & Tamura, R. (2014). Localized knowledge spillovers and patent citations: A distance-based approach. *Review of Economics and Statistics, 96*(5), 967-985.

[151] Nan, D. (2024). The influence of proximity and knowledge base on recombination innovation in R&D collaboration. *Plos one, 2*.

[152]Nelson, A. (2009). Measuring knowledge spillovers: What patents, licenses and publications reveal about innovation. *Research Policy , 38*, 994–1005.

[153] Nemet, G. F. (2012). Subsidies for new technologies and knowledge spillovers from learning by doing. *Journal of Policy Analysis and Management, 31*(3), 601-622.

[154] Neves, M., & Branco, J. (2020). Determinants of R&D on European high technology industry: panel data evidence. *Journal of the Iberoamerican Academy of Management, 18*(3), 285-305.

[155] Nico, S. (2020). Knowledge as a Public Good and Knowledge as a Commodity. *Epistemology & Philosophy of Science, 57*(4), 40-51.

[156] Nieto, M., & Quevedo, P. (2005). Absorptive capacity, technological opportunity, knowledge spillovers, and innovative effort. *Technovation, 25*(10), 1141–1157.

[157] Noorderhaven, N., & Harzing, A. (2009). Knowledge-sharing and social interaction within MNEs. *Journal of International Business Studies, 40*(2009), 719–741.

[158] Nooteboom, B. (2000). *Learning and Innovation in Organizations and Economies.* Oxford: Oxford University Press.

[159] Nooteboom, B. (2000). Learning by interaction: Absorptive capacity, cognitive distance and governance. *Journal of Management and Governance, 4,* 69–92.

[160] Noseleit, F., & de Faria, P. (2013). Complementarities of internal R&D and alliances with different partner types. *Journal of Business Research 66 (2013), 66*(2013), 2000–2006.

[161] Paci, R., Marrocu, E., & Usai, S. (2014). The Complementary Effects of Proximity Dimensions on Knowledge Spillovers. *Spatial Economic Analysis, 9*(1), 9-30.

[162] Padilla-Meléndez, A., Fuster, E., Lockett, N., & del-Aguila-Obra, A. R. (2021). Knowledge spillovers, knowledge filters and entrepreneurial university ecosystems. Emerging role of University-focused venture capital firms. *Knowledge Management Research & Practice, 19*(1), 94-105.

[163] Pahl-Wostl, C., Mostert, E., & Tàbara, D. (2008). The growing importance of social learning in water resources management and sustainability science. *Ecology and Society, 13*(1).

[164] Peri, G. (2005). Determinants of knowledge flows and their effect on innovation. *Review of economics and Statistics, 87*(2), 308-322.

[165]Perri, A., & Peruffo, E. (2016). Knowledge spillovers from FDI: a critical review from the international business perspective. *International Journal of Management Reviews, 18*(1), 3-27.

[166] Petruzzelli, A., Albino, V., & Carbonara, N. (2007). Technology districts: proximity and Knowledge Access. *Journal of Knowledge Management, 11*(5), 98-114.

[167] Pilinkiene, V. (2016). Trade openness, economic growth and competitiveness: The case of the central and eastern European countries. *Inžinerinė ekonomika, 27*(2), 185-194.

[168] Plaskoff, J. (2003). Intersubjectivity and community building: Learning to learn organizationally. In M. Easterby-Smith, & M. Lyles, *The Blackwell handbook of organizational learning and knowledge management* (pp. 161–184). Malden, MA: Blackwell.

[169] Polanyi, M. (1958). *Personal Knowledge: Towards a Post-Critical Philosophy.* Chicago: University of Chicago Press.

[170] Polit, D., & Beck, C. (2008). *Generating and Assessing Evidence for Nursing Practice.* Lippincott Williams & Wilkins.

[171] Porter, M. (1998). *On Competition.* Boston: Harvard Business School Publishing.

[172] Potrafke, N. (2015). The evidence on globalisation. *The World Economy, 38*(3), 509-552.

[173] Powell, W., Koput, K., & Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: networks of learning in biotechnology. *Administrative Science Quarterly, 41*, 116–145.

[174] Preenen, P. T., Vergeer, R., Kraan, K., & Dhondt, S. (2017). Labour productivity and innovation performance: The importance of internal labour flexibility practices. *Economic and Industrial Democracy, 38*(2), 271-293.

[175] Proeger, T., & Runst, P. (2020). Digitization and knowledge spillover effectiveness—Evidence from the “German Mittelstand. *Journal of the Knowledge Economy, 11*(4), 1509-1528.

[176] Qian, H., & Acs, Z. J. (2013). An absorptive capacity theory of knowledge spillover entrepreneurship. *Small Business Economics, 40*, 185-197.

[177] Rice, R. E., Heinz, M., & Van Zoonen, W. (2019). A public goods model of outcomes from online knowledge sharing mediated by mental model processing. *Journal of Knowledge Management, 23*(1), 1-22.

[178] Rigby, D. (2015). Technological Relatedness and Knowledge Space: Entry and Exit of US Cities from Patent Classes. , *Regional Studies, 49*(11), 1922-1937.

[179] Rippa, P., & Secundo, G. (2019). Digital academic entrepreneurship: The potential of digital technologies on academic ntrepreneurship. *Technological Forecasting and Social Change, 146*, 900–911.

[180] Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy, 98*(5), S71–S102.

[181] Samaniego, R. M. (2013). Knowledge spillovers and intellectual property rights. *International Journal of Industrial Organization, 31*(1), 50-63.

[182] Sandu, S., & Ciocanel, B. (2014). Impact of R&D and innovation on high-tech export. *Procedia Economics and finance, 15*, 80-90.

[183] Schilling, M. (1998). Technological lockout: An integrative model of the economic and strategic factors driving technology success and failure. *Academy of Management Review, 23*, 267-284.

[184] Schmiedeberg, C. (2008). Complementarities of innovation activities: An empirical analysis of the German manufacturing sector. *Reseach Policy, 37*(2008), 1492-1503.

[185] Shaw, M. E. (1981). *Group Dynamics: The Psychology of Smnall Group Behavior.* New York: McGraw-Hill.

[186] Shope, R. (1983). *The Analysis of Knowing: A Decade of Research.* Princeton, NJ: Princeton University Press.

[187] Simonen, J., & McCann, P. (2008). Innovation, R&D cooperation and labor recruitment: evidence from Finland. *Small Business Economics, 31*, 181-94.

[188] Spence, M. (1984). Cost reduction, competition, and industry performance. *Econometrica, 52*(1), 101-121.

[189] Stephan, A., Bening, C. R., Schmidt, T. S., Schwarz, M., & Hoffmann, V. H. (2019). The role of inter-sectoral knowledge spillovers in technological innovations: The case of lithium batteries. *Technological Forecasting and Social Change, 148*(119718).

[190] Stiglitz, J. (1999). *On Liberty, the right to know, and Public Discourse: The Role of Transparency in Public Life*. Retrieved March 24, 2023, from https://documents1.worldbank.org/curated/en/436941546609601734/pdf/WP-Stiglitz-right-to-know-OUO-9.pdf

[191] Stiglitz, J. E. (1999). *Knowledge as a global public good. Global public goods: International cooperation in the 21st century.* Oxford: Oxford University press.

[192] Stover, M. (2004). Making tacit knowledge explicit: The ready reference database as codified knowledge. *Reference services review, 32*(2), 164-173.

[193] Sussan, F., & Acs, Z. J. (2017). *Small Business Economics, 49*(1), 55–73.

[194] Tang, Y., Chen, Y., Wang, K., Xu, H., & Yi, X. (2020). An analysis on the spatial effect of absorptive capacity on regional innovation ability based on empirical research in China. *Sustainability, 12*(7), 1-23.

[195] Tee, C. L., Saini, A., & Ibrahim, S. (2018). Globalisation and innovation activity in developing countries. *Institutions and economies, 10*(4), 1-18.

[196] Tidd, J., & Bessant, J. (2014). *Strategic innovation management.* Chichester, West Sussex: Willey.

[197] Tiemessen, I., Lane, H. W., Crossan, M., & Inkpen, A. C. (1997). Knowledge management in international joint ventures. In P. Beamish, & J. Killing, *Cooperative*

strategies: North American perspective: (pp. 370-399). San Francisco: New Lexington Press.

[198] Tille, C., & Van Wincoop, E. (2010). International capital flows. *Journal of international Economics, 80*(2), 157-175.

[199] Trachuk, A., & Linder, N. (2019). Knowledge spillover effects: Impact of export learning effects on companies' innovative activities. *Current issues in knowledge management*.

[200] Tsai, W. (2001). Knowledge transfer in intraorganizational networks: effects of network position and absorptive capacity on business unit innovation and performance. *Academy of Management Journal , 44*(5), 996–1004.

[201] Turner, S., Higginson, J., Oborne, A., Thomas, R., Ramsay, A., & Fulop, N. (2014). Codifying knowledge to improve patient safety: A qualitative study of practice-based interventions. *Social Science and Medicine, 113,* 169-176.

[202] Verdolini, E., & Galeotti, M. (2011). At home and abroad: An empirical analysis of innovation and diffusion in energy technologies. *Journal of environmental economics and management, 61*(2), 119-134.

[203] Vertesy, D., & Van Roy, V. (2013). *Update on the Composite Indicators of Structural Change towards a More Knowledge-Intensive Economy.* Reference Report by the Joint Research Centre of the European Commission,.

[204] Veugelers, R. (1997). Internal R&D expenditures and external technology sourcing. *Research Policy, 26,* 303–315.

[205] Volberda, H., Foss, N., & Lyles, M. (2010). Perspective-Absorbing the concept of absorptive capacity: how to realize Its potential in the organization field. *Organisational Science*, *21*, 931-951.

[206] Wang, C. C., & Lin, G. C. (2013). Dynamics of innovation in a globalizing china: Regional Environment, Inter-firm relations and firm attribute. *Journal of Economic Geography, 13*(3), 397-418.

[207] Wang, E. C. (2010). Determinants of R&D investment: The Extreme-Bounds-Analysis approach applied to 26 OECD countries. *Research Policy,, 39*(1), 103-116.

[208] Wooldridge, J. M. (2009). *Econometrics: Panel Data Methods.*

[209] Wuestman, M. L., Hoekman, J., & Frenken, K. (2019). The geography of scientific citations. *Research Policy, 48*(7), 1771–1780.

[210] Wuyts, S., Colombo, M., Dutta, S., & Nooteboom, B. (2005). Empirical tests of optimal cognitive distance. *Journal of Economic Behavior & Organization, 58*(2005), 277-302.

[211] Xu, X., Wang, Z., Zhou, B., & Zhang, Z. (2019). The empirical analysis of knowledge spillover effect measurement. *Knowledge Management Research & Practice, 17*(1), 83–95.

[212] Xu, X., Watts, A., & Reed, M. (2019). Does access to internet promote innovation? A look at the US broadband industry. *Growth and Change, 50*(4), 1423-1440.

[213] Yan, Z., Wang, T., Chen, Y., & Zhang, H. (2016). Knowledge sharing in online health communities: A social exchange perspective. *Information and Management, 53*(2016), 643-653.

[214] Zacchia, P. (2020). Knowledge spillovers through networks of scientists. *The Review of economic studies, 87*(4), 1989-2018.

[215] Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review, 27*(2), 185–203.

[216] Zhu, S., Hagedoom, J., Zhang, S., & Liu, F. (2021). Effects of technological distance on innovation performance under heterogenous technological orientations. *Technovation, 106*(2021).

[217] Žigić, K. (1998). Intellectual property rights violations and spillovers in North–South trade. *European Economic Review, 42*(9), 1779-1799.

Appendix A

Descriptive Analysis for Panel of Countries

Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**
1.RGDPgr	1.00																		
2.Cpinvt	0.34	1.00																	
3.GOVTsp	-0.30	-0.08	1.00																
4.INTup	-0.17	-0.16	0.40	1.00															
5.INNdx	-0.05	0.08	0.36	0.25	1.00														
6.R&Dint	-0.21	-0.03	0.58	0.51	0.52	1.00													
7.INFtecx	0.01	0.06	0.07	0.06	-0.02	-0.01	1.00												
8.HTECxp	-0.10	-0.17	0.15	0.10	0.08	0.37	0.03	1.00											
9.PATapp	-0.11	-0.20	-0.07	0.03	0.18	0.33	-0.02	0.90	1.00										
10.PUBse	-0.17	-0.05	0.68	0.34	0.36	0.54	0.06	0.39	-0.19	1.00									
11.Glindx	-0.23	-0.14	0.59	0.68	0.36	0.65	0.09	0.30	0.23	0.37	1.00								
12.Labpr	-0.19	-0.04	0.54	0.50	0.33	0.59	0.07	-0.30	0.22	0.55	0.72	1.00							
13.LabP	0.05	0.17	0.21	0.38	0.14	0.24	-0.05	-0.05	-0.12	0.36	0.17	0.25	1.00						
14.Trdop	0.17	0.06	0.08	0.22	-0.01	-0.08	0.13	-0.11	-0.26	-0.08	0.15	-0.16	0.00	1.00					
15.Pseps	0.24	0.15	-0.08	-0.13	0.06	-006	-0.01	-0.42	-0.41	0.26	-0.37	-0.22	0.40	0.00	1.00				
16.Tenel	-0.03	0.02	0.15	0.37	0.21	0.21	0.03	-0.50	-0.49	0.35	0.05	0.11	0.26	-0.11	0.44	1.00			
17.PwFDI	-0.01	-0.06	0.06	-0.01	-0.02	0.08	-0.04	0.33	0.27	-0.08	0.17	0.18	0.00	-0.87	-0.11	-0.19	1.00		
18.RDtax	-0.15	-0.02	0.36	0.29	0.21	0.41	0.01	0.20	0.18	0.35	0.39	0.60	0.19	-0.16	-0.13	0.11	0.06	1.00	
19.Knstock	-0.14	-0.26	-0.26	-0.25	-0.05	-0.17	-0.29	-0.30	-0.17	-0.10	-0.29	-0.24	0.15	-0.13	0.23	-0.19	-0.13	-0.13	1.00
Obs	368	368	368	368	368	368	366	368	368	363	362	368	368	368	368	368	368	368	
Mean	2.05	23.04	20.69	68.46	49.16	1.78	91.23	33749	5689	5.308	83.32	78.85	59.12	96.99	11.48	69.93	1.60	0.71	
Std.dev	3.04	3.56	2.52	22.62	7.34	0.77	1635	51649	11362	1.09	4.75	23.71	4.43	40.46	2.01	19.53	4.04	0.43	
Min	-14.84	12.66	16.3	6.43	24.66	0.45	0.74	961.34	62	3.52	65.57	31.38	48.13	37.01	7.1	4.99	-39.17	0.21	
Max	11.11	33.05	27.93	99	63.4	3.73	31294	223370	51736	8.56	91.31	176.88	67.46	204.12	19.18	119	23.98	6.88	

Source: Author’s own (2025)