Gordon Institute of Business Science
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An investigation of the relationship between open innovation and business financial performance in South Africa: a firm-level analysis based on accounting data

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A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Philosophy (Corporate Strategy).

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Abstract

The objective of this thesis is to investigate the relationship between open innovation practices and financial performance for public companies in South Africa. Despite the growing number of theoretical and empirical studies on open innovation and performance, the results on open innovation and performance, the results have been mixed. Employing a quantitative approach and drawing from financial data, this research assesses measures of openness, inbound and outbound innovation alongside the financial performance indicator, Return on Assets.

Keywords

Open innovation, openness, inbound open innovation, outbound open innovation, financial performance, public companies.

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Philosophy in Corporate Strategy at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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1. Introduction

It has become generally accepted that for a firm to be competitive, it must be innovative (Brunswicker & Chesbrough, 2018; Moore & Seedat, 2020; Zhu et al., 2019). Innovation has often been a critical driver of economic growth by improving productivity, leading to growth in the Gross Domestic Product (GDP) and ultimately an improved standard of living (World Intellectual Property Organization [WIPO], 2022). The importance of innovation cannot be overstated in the current turbulent environment. However, it must also be highlighted that not all innovation has been successful. In some developed economies, productivity has been slowing down despite high levels of innovation (WIPO, 2022). It is essential to measure levels of innovation, its impact on a firm's competitiveness and value creation (Organisation for Economic Co-operation and Development & Statistical Office of the European Communities [OECD/Eurostat], 2018). Measuring provides data for determining how effective innovation is.

Innovation has traditionally been the stronghold of the northern hemisphere, with the United States of America being seen as the hotbed of innovation. In recent years, nations in Europe have increased their innovation levels and capacity, with Switzerland named the most innovative in 2022 (WIPO, 2022). However, developing economies are still lagging (WIPO, 2022). Moreover, the proportion of GDP income spent on innovation in Africa falls far below their Western counterparts, with most expenditure spent on the public sector (African Union Development Agency [AUDA], 2019).

South Africa was ranked 69th in the Global Innovation Index (WIPO, 2022) innovation inputs and 61st in innovation outputs. South Africa fell in the Innovation Inputs ranking from 49th in 2020 to 69th in 2022. However, the trend was reversed for innovation output, with South Africa moving from 68th in 2020 to 61st in 2022 (WIPO, 2022). This trend indicates that South Africa has produced more innovation outputs than inputs. Overall, South Africa's innovation levels are not consistent, and it appears to be falling below the levels expected of it.

COVID-19 affected every country worldwide, one of the first genuinely global pandemics, and no continent was spared. As the pandemic spread, businesses began to suffer as the movement of people was restricted. However, very few companies had planned for restricted movement and operating hours, and to survive, they had to innovate. This brought innovation to the forefront of every business.

1.1. Background to the research problem

There has been increased growth in research on innovation in the past decade (Dilrukshi et al., 2022; Feng et al., 2021; Lu & Chesbrough, 2022). The Open Innovation (OI) concept was introduced in Chesbrough (2003)'s seminal book, Open Innovation: The New Imperative for Creating and Profiting from Technology. Chesbrough and Bogers (2014) defined OI as "an innovation model that emphasizes purposive inflows and outflows of knowledge across the boundary of a firm to leverage external sources of knowledge and commercialization paths, respectively" (p. 10). While innovation is expected to give firms a competitive edge, OI looks explicitly at how externally acquired knowledge and tools allow a firm to prosper (Bogers, Burcharth et al., 2019; Bogers, Chesbrough et al., 2019; Zhu et al., 2019). While it is not a new concept, Chesbrough (2003) was the first scholar to define it as a strategy clearly.

1.1.1. Open Innovation and firm financial performance

Numerous studies have shown how OI can give a firm a competitive edge and impact performance (Brunswicker & Chesbrough, 2018; Dahlander et al., 2021; Gao et al., 2020). The consensus from practitioners and scholars is that there is a positive relationship between OI and firm performance as it improves the time to market for products, among other things (Bogers, Burcharth & Chesbrough, 2019; Dahlander et al., 2021; Zhang et al., 2018; Zhou et al., 2019). However, there have been mixed reviews on how much of an effect, if any, it has (Gao et al., 2020; Lu & Chesbrough, 2022), e.g., Laursen and Salter's (2006) research postulated an inverse relationship between OI and financial performance, while Bogers, Burcharth and Chesbrough (2019) found support for a positive relationship between openness and firm performance. Chesbrough et al. (2018) highlighted the need to understand the relationship between OI and value creation.

OI's impact on value creation and performance has not been sufficiently addressed in the current literature. Therefore, there has been an ask for further research in this area to clarify the position of OI and firm performance (Lu & Chesbrough, 2022; Singh et al., 2021). Moreover, the majority of research has concentrated on developed Western countries or sizable developing nations like China and India (Bogers, Burcharth & Chesbrough, 2019; Scaliza et al., 2022). Therefore, there is a shortage of knowledge on OI impact in developing markets such as Africa (Bogers, Burcharth & Chesbrough, 2019; Gao et al., 2020).

1.1.2. South Africa's innovation environment

South Africa is considered one of the most developed countries in the African continent, with advanced financial institutions and industries. Its economy is mainly commodity-driven, with a rising number of firms that rely on innovation (Department of Science and Innovation [DSI], 2022). Government expenditure on Research and Development (R&D) had risen to over R19 billion by 2020. However, this only represented about 0.62% of the GDP (DSI, 2022), well below the target of 1% (AUDA, 2019). In addition, only 7% of companies in South Africa were considered innovative (Moore & Seedat, 2020). According to the National Development Plan (NDP) Vision 2030, introduced in 2011, productivity improvements should be driven by innovation, which would be the main focus for the second phase from 2018-2023 (Department of Science and Technology [DST], 2019).

South Africa's digital competitiveness ranking was 60 out of 63 countries in 2020 (DSI, 2022). It had the lowest National Entrepreneurship Context Index of the BRICS nations in 2019 (DSI, 2022). This indicated that the South African environment was not conducive to entrepreneurship and innovation. This was supported by the article by Moore and Seedat (2020), which showed that 85% of South African companies were at risk of future disruption and needed to improve their innovation capabilities. Work has been done to encourage OI through open innovation hubs. However, these have been mainly aimed at small and medium enterprises (DSI, 2022). Large firms are working to increase their innovation budgets (Moore & Seedat, 2020).

Business expenditure on R&D to develop new technologies, processes or knowledge in South Africa stood at 0.32% of GDP in 2022 compared to Europe, which was expected to be 2% of GDP (AUDA, 2019). This indicates that a small proportion of businesses performed R&D activities or had limited investment in innovative activities.

1.2. Definition of the Research problem and research aims

As observed by Lu and Chesbrough (2022), "there is not sufficient research investigating the relationship between nuanced open innovation practices and firm financial performance" (p. 13). While there has been extensive research on this topic, very few studies have been carried out in Africa (Dilrukshi et al., 2022). According to Bogers, Burcharth and Chesbrough (2019), the innovation landscape has undergone a transformation facilitated by globalisation, which has enabled the widespread dissemination of technologies. Notably, influential players are now emerging from developing nations in the innovation field, and this warrants further investigation into their innovation performance. Therefore, there needs to be more research in an African context.

Africa is characterised by developing economies with different resources and constraints than the West and the East. As a result, there are expected differences between the openness of firms in developed countries and those in developing countries (Wang & Jiang, 2020). The Business Innovation Survey (Centre for Science, Technology and Innovation Indicators [CeSTII], 2020) highlighted that most South African businesses rate internal sources as the most important for innovation. The same survey showed that OI is utilised primarily on value chains. However, only 20% of innovative businesses used collaboration as part of their innovation activities (CeSTII, 2020). South Africa's experience of OI is impacted by its unique environment. As such, it is a significant research gap to be addressed, providing empirical context due to weak institutions and cultural differences. Nevertheless, there are lessons to be learnt from this opportunity. The ability of a firm to generate unique value from innovation is an important research area (Felin & Zenger, 2020). Therefore, this paper seeks to answer the call from Lu and Chesbrough (2022) and will investigate how OI affects financial performance using evidence from South African firms.

As previously highlighted, there has been considerable research into the impact of OI and firm performance, with mixed results (Dilrukshi et al., 2022; Lu & Chesbrough, 2022). OI is complex, and with different variations and applications, it can be challenging to determine the relationship with profitability or performance. Generally, many scholars agree that there is a positive impact on performance (Lu & Chesbrough, 2022; Zhang et al., 2018). However, some purport that the effect is limited and difficult to measure, with some scholars identifying a negative relationship between the two (Lu & Chesbrough, 2022; Wang & Jiang, 2020). Other researchers identified an S-shaped relationship (Schäper et al., 2023) and an inverted U-shaped relationship between firm performance and OI (Laursen & Salter, 2006; Zhang et al., 2018). Given that results have been mixed, there is room for more studies on the relationship. The scholarly debate on OI and firm performance is ongoing and requires further studies to be carried out.

Most of the studies have looked at one form of OI in relation to performance. However, recent researchers have highlighted that most firms employ at least two types of OI. Therefore, they should be looking at how the different combinations of OI, in concert, affect firm performance and identifying how the different forms of OI impact. Unfortunately, there has been insufficient research on the relationship between OI and firm performance in developing economies (Singh et al., 2021), especially in Africa. However, it must be acknowledged that several theses and papers have been produced in South Africa on OI, with the majority centred around Small and Medium enterprises (SMEs). In addition, the majority of the papers were qualitative.

Understanding how to measure innovation, innovation performance, and its impact on business performance is essential. A lot of capital is invested in innovation, and it's vital to compute its effect on value creation and determine whether its return on capital is sufficient. Schäper et al. (2023) highlighted the need for determining the financial drawbacks of OI as well as understanding its cost-benefit implications. This was supported by Dahlander et al. (2021), who advocated for a cost-benefit analysis to determine how much value is achieved from openness. The challenge is that innovation can span many years, so attributing income or value to it can be tricky (Dahlander et al., 2021).

While previous studies have explored the relationship between OI and business performance using mainly qualitative methods, there is a need for further research that utilises secondary data to investigate this relationship. This study aims to address this gap by conducting a secondary data analysis of firm-level data to examine the relationship between OI and business performance.

OI research on South African firms is limited, it is crucial to understand if South African firms are gaining value from implementing OI practices. In their bibliometric analysis, Gao et al. (2020) highlighted that more quantitative studies needed to be conducted in Asia and South Africa. The research question is:

What is the relationship between open innovation practices and a firm's financial performance?

The sub-research questions will be as follows:

1. Does openness have a positive impact on a firm's financial performance?
2. Does inbound open innovation have a positive impact on a firm's financial performance?
3. Does outbound open innovation have a positive impact on a firm's financial performance?

The scope of the research question is limited to firms in South Africa that have evidence of implementing OI practices. This study is expected to contribute to the literature on OI and firm performance by using secondary data to better understand the relationship between OI adoption and business performance in South Africa.

1.3. Conclusion

This chapter sets out the background and business needs for this research. There has been an explosion in the amount of research relating to OI in the past decade (Dilrukshi et al., 2022). However, studies have often arrived at different conclusions regarding the relationship between OI and firm performance. Furthermore, studies in Africa have been very limited. Therefore, there is a theoretical and business need to understand how OI activities impact firms in South Africa. The following section will outline the literature review of the current OI literature, trends in research and hypotheses.

2. Literature Review

This section looks at the current conversation on OI and firm performance by investigating the relevance of the research question and identifying research gaps. The first section discusses OI in-depth, covering its definition, benefits and disadvantages. The second section looks at firm performance, and the last section looks at research into both OI and firm performance.

2.1. Innovation

Innovation is universally regarded as integral to business success and wealth creation (Andrade et al., 2020; Chesbrough, 2020; Felin & Zenger, 2020). Gault (2018) described innovation as “the implementation of a new or significantly changed product or process” (p. 619). It is a complex concept with many different aspects and layers (Felin & Zenger, 2014). There are a multitude of definitions of what innovation is. The Oslo Manual (OECD/Eurostat, 2018) defined innovation as:

> *An innovation is a new or improved product or process (or combination thereof) that differs significantly from the unit’s previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)*. (p. 60)

Innovation refers to improving existing products or creating new products, processes and services (Chesbrough & Bogers, 2014; Hameed et al., 2021; Teece, 2020). In the business sense, innovation requires revamped knowledge to generate new products or processes and leads towards better commercials for the business.

Traditionally, innovation was internally focused, i.e., firms generated, developed, financed and implemented ideas independently in a closed innovation process (Andrade et al., 2020; Felin & Zenger, 2014; Schäper et al., 2023). There was a strong focus on utilising internal resources, and this was usually supported by having a Research and Development (R&D) department with large companies having large R&D budgets to support innovation. Closed innovation led to the discovery and development of many new technologies and products, however, it was touted as slow and expensive. Knowledge was hidden and protected as it would grant competitive advantages (Noh, 2015).

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As the world evolved and became more competitive, there has been an increased need for speed when it comes to innovation. If internal skills or knowledge were insufficient to give a competitive edge, firms would have to look externally for more innovative ideas. To augment internal innovation resources, firms often turn to collaborations with external partners or technology acquisition (Ogink et al., 2023; Schäper et al., 2023; Teece, 2020). One of the options would be to incorporate external ideas into a firm through Mergers and Acquisitions (M&A) (Teece, 2020). This involves an independent firm joining with or taking over one or more independent firms to create a new entity. Traditionally, M&A has facilitated growth and entry into new markets (Teece, 2020). However, another critical component would be to gain access to knowledge and technology that would allow the firm to be more competitive (Bogers, Chesbrough et al., 2019). Through M&A, firms can gain access to firms with the required technology, processes or products to make them more innovative and competitive, bringing in-house external knowledge (Teece, 2020). Firms could have access to other technologies or processes which they could utilise to improve existing processes. Nevertheless, mergers and acquisitions may not be a feasible choice for every firm, considering the time, cost and regulatory impacts involved in such transactions. Furthermore, this requires the presence of a sufficiently valuable firm for acquiring or merging with. M&A transactions are not always successful and may be detrimental to the firm. Therefore, other ways to gain external knowledge have to be employed. To stay abreast, firms need to innovate and collaborate more and more.

The closed innovation approach is no longer suitable in today's volatile and complex environment, where the best skills might not be found internally (Bogers, Chesbrough et al., 2019). The world economy has been characterised by recessions and pandemics in the past decade (Wang & Jiang, 2020) and relying on closed innovation alone is not a viable option. The speed at which technology, markets, and customer needs have changed has been exponential due to rapid globalisation.

Innovation must be dynamic, constantly evolving, and at every level of the economy (OECD/Eurostat, 2018). Therefore, innovation can take many forms. Using external sources of information to feed through the innovation process is not a new concept but has been around for decades (Cohen & Levinthal, 1990). Many scholars have highlighted how firms should use external knowledge sources and partners to increase their innovativeness and competitiveness (Bogers, Burcharth & Chesbrough, 2019; Chesbrough, 2020; Chesbrough et al., 2018; Cohen & Levinthal, 1990; Laursen & Salter, 2006). While many firms are exposed to external knowledge, they can only benefit if they can assimilate it and utilise it to improve some internal workings. There has been an increased focus on incorporating external knowledge into internal innovation processes. Chesbrough and Bogers (2014) identified this concept as open innovation and concluded that firms must have a permeable knowledge boundary allowing for internal and external knowledge flows for their innovation processes. Based on their research, this would allow firms to be more competitive and stay relevant.

2.1.1. Innovation Types

The Oslo Guide identifies four main categories of innovation, i.e., Product, which includes goods and services, Marketing, Organisational and Process (OECD/Eurostat, 2018). The categories are briefly summarised below:

Product- Goods and Service Innovation: relates to delivering new or significantly changed offerings to customers (Gault, 2018; OECD/Eurostat, 2018). These include ”new to market” and new to firm type innovations. It refers to applying new concepts and technologies to improve product or service quality and efficiency (Feng et al., 2021; Gault, 2018). Traditionally, most innovation has been in the goods and services sector as competition is rife, and innovation is essential to stay ahead. This has covered such things as bringing new to market goods or changing/improving existing ones. Hameed et al. (2021) posited that service innovation would be a key driver to enhance business performance.

Marketing Innovation: relates to changes in marketing activities, including sales and after-sales support (OECD/Eurostat, 2018). This may include the use of new media or techniques for promotional activities, changes to packaging and so on. This type of innovation is usually not carried out in isolation but in line with another form of innovation.

Organisational Innovation: this alludes to the improvement or introduction of new ways of knowledge management, systems for information exchange, quality management and business engineering (OECD/Eurostat, 2018).

Process innovation: refers to new or significantly improved methods for the supply and/or production of goods and services (OECD/Eurostat, 2018)**.**

2.1.2. Innovation in developing economies

Numerous innovation studies have been carried out in developed regions like Europe, North America and the United Kingdom (Dilrukshi et al., 2022). In developing regions, the studies have mainly focused on countries like India, China and Latin America. However, studies in developing economies have been limited (Dilrukshi et al., 2022). Furthermore, they have shown that innovation is lagging in developing markets (Bogers, Burcharth et al., 2019; Krammer & Kafouros, 2022). There is often a strong focus on exploiting natural resources, concentrating mainly on basic industries like mining and agriculture (Krammer & Kafouros, 2022). Most innovation in Africa centred around buying equipment and technology (AUDA, 2019). The majority of firms were more interested in innovation for improving the quality of goods and services rather than producing radical innovations (AUDA, 2019; Krammer & Kafouros, 2022; CeSTII, 2020).

That is not to say that there are no radical innovations, but the type of innovation differs greatly from developed nations (Barasa et al., 2017). Firms in developing nations often have lower input costs and generally compete on price rather than innovativeness (Krammer & Kafouros, 2022). Therefore, there is a focus on more cost-effective, radical innovation based on the limited resources available (Krammer & Kafouros, 2022). There have even been instances of reverse innovation, where innovations from developing countries are successfully implemented in developed countries (Krammer & Kafouros, 2022). While innovation is limited in developing regions, it is still beneficial and may have applications beyond its original purpose.

It has been noted that developing economies often suffer from barriers to entry, trust deficits, low skill levels, and limited intellectual property rights, which all contribute to making innovation a struggle in such settings (Bogers, Burcharth, et al., 2019). Strong institutions are required to provide an environment in which innovation can thrive, with weak institutions leading to inefficient business conduct (Barasa et al., 2017; Krammer & Kafouros, 2022). Institutional factors, such as regulations and legislation, as well as weak IP rights, were also blockers to innovation in Africa (Barasa et al., 2017; CeSTII, 2020). Such an environment negatively affects the value that a firm can get from performing innovation activities such as R&D (Barasa et al., 2017).

In South Africa, only a fifth of businesses engaged in collaboration as part of their innovation activities, with most businesses valuing internal sources of information (CeSTII, 2020). Furthermore, the macroeconomic and societal setting has an important impact on the success of any innovation activities (Barasa et al., 2017; Bogers, Burcharth, et al., 2019). Financial barriers, including lack of internal funds for innovation as well as the excessive cost of innovation, were cited as blockers to innovation (CeSTII, 2020; AUDA, 2019). Consequently, there are a few challenges to innovation in South Africa.

2.2. Open Innovation

Chesbrough and Bogers (2014) defined OI as "an innovation model that emphasizes purposive inflows and outflows of knowledge across the boundary of a firm to leverage external sources of knowledge and commercialization paths, respectively" (p. 10). Thus, OI relates to how a firm utilises internal and external knowledge resources to improve its competitiveness, produce new or improved products and monetise underutilised internal resources (Chesbrough & Bogers, 2014; Chesbrough et al., 2018; Dahlander et al., 2021; Gao et al., 2020). In this globalised age, no firm can genuinely have a monopoly on knowledge, and as such, it requires firms to be more interactive with their stakeholders and environment (Chesbrough et al., 2018). This would require a mindset change, concentrating on getting the most out of available knowledge and assets in the market.

2.2.1. Openness

According to Laursen and Salter (2006), the openness in OI relates to search breadth and depth, where breadth relates to the number of external resources a firm depends on for innovation and depth relates to the level of dependence on these firms. It can also be represented by how easily information and knowledge flow in and out of an organisation, and can be utilised by a firm (Ovuakporie et al., 2021; Zhu et al., 2019). No firm works in isolation and knowledge flow is shaped by its operating environment, i.e., the technological opportunities and competition from other firms (Hutton et al., 2021; Laursen & Salter, 2006) as well as organisational culture (Scaliza et al., 2022). Previous research has shown the use of OI in such diverse strategies as R&D, knowledge creation and innovation performance leading to faster product development (Zhu et al., 2019).

West and Bogers (2014) stated that the OI process had three stages: acquisition, integration and commercialisation. First, knowledge must be acquired and integrated into the existing business structure, products and processes. Only when commercialised as an improved process, product or entirely new offering can it create value successfully (Ovuakporie et al., 2021; Singh et al., 2021; Teece, 2020). Dahlander and Gann (2010) identified four types of openness: sourcing, acquiring, selling, and revealing. These concepts align with West and Bogers' (2014) categorisation as it broadly follows the same process. However, it must be noted that openness is generally seen as a subjective measure as it is self-reported in most studies and bias cannot be discounted (Lu & Chesbrough, 2022). Studies have looked at various methods and constructs for measuring openness including surveys (Zhu et al., 2019), meta-analysis (Feng et al., 2021) and the use of secondary data such as financial accounts and other publicly available data (Fu et al., 2019; Schäper et al., 2023).

Dahlander and Gann (2010) defined different forms of openness based on whether they were pecuniary or non-pecuniary and related to inbound or outbound innovation. Table 1 below outlines the forms of openness:

Table 1: Forms of Openness

	Inbound Innovation	**Outbound innovation**
Pecuniary	Acquiring	Selling
Non-Pecuniary	Sourcing	Revealing

Source: *Dahlander and Gann (2010)*

Revealing was set as a non-pecuniary outbound innovation where internal resources are shared with external parties, often without financial reward (Dahlander & Gann, 2010). This allows firms to build on each other's work, leading to the industry's rapid advancement, e.g., the boost to the electric car industry due to Tesla sharing its electric vehicle technology (Dahlander et al., 2021).

Selling relates to pecuniary outbound innovation wherein the internal knowledge of the firm is sold in the market. Firms benefit from selling or licensing their resources through tools such as patents (Dahlander & Gann, 2010). This allows firms to benefit from resources that might otherwise have been idle. However, a challenge with this approach is the need to disclose information before the deal is finalised, putting the firm at a disadvantage to the buyer (Schäper et al., 2023).

Sourcing relates to how firms can search out and use external information sources, like suppliers, customers, competitors, consultants, etc., to gain ideas or knowledge that they can use to innovate (Dahlander & Gann, 2010). This subjects the firm to a wide range of information and ideas (Feng et al., 2021).

Acquiring relates to gaining access to external ideas and knowledge by purchasing technology or knowledge (Dahlander & Gann, 2010). This may be an expensive exercise depending on the type of purchase, as it may include payment of licence fees or royalties (Yuan & Li, 2019).

OI can take multiple forms and can be used to increase innovativeness, competitiveness or even production levels. Chesbrough (2020) highlighted how openness accelerated the development of COVID-19 vaccines during the pandemic due to the mobilisation of data from many different sources. Furthermore, firms that are more open to collaboration innovate better than those that focus only on their internal innovation resources (Andrade et al., 2020; Scaliza et al., 2022). This supports the position that for a firm to be competitive, it cannot rely only on closed innovation (Bogers, Burcharth & Chesbrough, 2019).

Bogers, Burcharth and Chesbrough (2019) posited that there would be varying degrees of openness in firms as they pick and choose what can be brought in, retained and shared externally. Such decisions would have to be made in light of the environment in which a firm operates, its internal processes as well as the challenges it seeks to address (Felin & Zenger, 2020). Thus, choices must be made about how open a firm can be, what resources to seek externally and what it wants to share in its external operating environment. Furthermore, OI is not without its challenges. Yuan and Li (2019) identified that OI activity would involve costs from coordinating the activities, competing costs as well as costs for protecting Intellectual Property (IP). These and other challenges are discussed more in the section outlining the challenges of OI.

2.2.2. Forms of open innovation

Bogers, Chesbrough et al. (2019) highlighted that OI could be thought of as a dynamic capability as it involves “leveraging and enhancing internal capabilities, either to enhance one’s business model (Outside-In open innovation) or to explore a new business model (Inside-Out open innovation)” (p. 84). The dynamic capabilities framework shows how a firm could create a sustainable competitive advantage by utilising internal and external resources (Teece, 2020). According to Hutton et al. (2021), firms can use OI to exploit knowledge resources and build dynamic capabilities. OI seeks to utilise external knowledge to build internal resilience and monetise its internal Intellectual Property (IP). The process of OI requires a firm to learn and use new capabilities continually.

OI can relate to a new or improved process, product platform, or service (Bogers, Burcharth & Chesbrough, 2019; Scaliza et al., 2022; Singh et al., 2021). Multiple external groups can also participate in OI, including but not limited to educational institutions, industry bodies, customers, suppliers, and competitors (Brunswicker & Chesbrough, 2018; Hameed et al., 2021). Activities can range from open-source software development and licensing to inter-firm, industry and university collaborations (Bogers, Burcharth & Chesbrough, 2019). In today's digital world, every firm utilises OI, whether it is reviewing industry publications or using open-access tools. The very nature of technological and digital innovation requires collaboration with multiple partners as a firm must interact with and learn from its environment to capitalise on new knowledge (Chaudhary et al., 2022; Hameed et al., 2021).

However, it is a very broad concept and studies have split it into separate components to understand it better. Chesbrough and Bogers (2014) identified three types of OI based on the direction of the knowledge flows; outside-in (Inbound), inside-out (Outbound), and Coupled. These concepts will be discussed more below.

2.2.2.1. Inbound Open Innovation

With Inbound OI, firms internalise externally developed technologies, ideas and processes from customers, competitors, suppliers and other external stakeholders (Chesbrough et al., 2018; Scaliza et al., 2022). Such collaboration can assist in gaining knowledge on such topics as market needs and customer preferences. Inbound OI involves identifying, selecting and internalising ideas from the external environment (Singh et al., 2021). Furthermore, the knowledge flow can be pecuniary, such as the purchase of IP or non-pecuniary, like customer feedback (Yuan & Li, 2019). According to Bogers, Chesbrough et al. (2019), there has been a sustained decline in many firms' internal R&D budgets as it becomes cheaper to collaborate externally. Ideas can be gathered through collaboration and research initiatives with external actors, but the success of OI can only come through when they are operationalised and commercialised (Gao et al., 2020). Firms look for and leverage valuable sources of knowledge in their environment from other players (Bogers, Chesbrough et al., 2019) as they cannot rely purely on their internal resources given the ever-evolving competitive landscape. The objective of this process is to enhance the firm's knowledge base by internalising knowledge, skills, and technologies acquired externally. As a result, Inbound OI has received the most scholarly attention in the past decade as it is usually the first mode of OI to be employed by a business (Dilrukshi et al., 2022). It must be noted that such approaches are not without problems. When an idea is gathered from a customer through a feedback process and successfully monetised, the origination of ideas may be questioned as it might not be clear who owns the idea (Dahlander et al., 2021). Therefore, legal issues of ownership are still an issue in inbound innovation, and costs will be incurred in clarifying such issues (Dahlander et al., 2021).

There are different types of inbound OI. Sourcing open innovation is classified as non-pecuniary as some knowledge can be freely gathered from the external environment, such as open source software or feedback from customers (Dahlander et al., 2021; Dahlander & Gann, 2010). This enables a company to obtain external resources without incurring any costs. Open-source software might be free to access, but there will still be some restrictions on how the technology can be used and requirements to share modifications (Dahlander et al., 2021; Yuan & Li, 2019). Thus, there may also be a risk of being required to expose the firm's IP based on the use of open source material.

Furthermore, while the information might be free, there are still costs involved in gathering and integrating the information into the organisation (Andrade et al., 2020). Chaudhary et al. (2022) highlighted that the time and cost required to make sense of the collected data might exceed the benefits of the OI process. The amount of data produced through OI activities may be beyond the firm's capabilities to utilise effectively (Dahlander et al., 2021). There is a risk of over-search beyond which the costs of acquiring the knowledge outweigh the benefits (Audretsch & Belitski, 2023; Laursen & Salter, 2006). Large volumes of information can be gathered through sourcing and then they have to be sifted through to try and identify valuable and viable suggestions. Furthermore, there are also non-pecuniary costs involved with inbound OI, such as the time spent reviewing the information as well as the tensions that may arise through the process, causing friction (Andrade et al., 2020). The process does not guarantee that anything worthwhile will be discovered or created.

Acquiring is the pecuniary form of inbound innovation as it involves purchasing valuable knowledge or technologies such as the acquiring of IP (Dahlander et al., 2021). Studies have shown that coordination costs could actually outweigh the benefits of inbound innovation (Andrade et al., 2020; Audretsch & Belitski, 2023). The costs of acquiring IP can be very high and may be prohibitive for firms that cannot afford them. According to Felin and Zenger (2020), companies might pay more than necessary for assets and overestimate their capacity to derive value from the acquired knowledge. It is difficult to determine if the cost of inbound innovation is appropriate and if further development is required to capture value, the costing becomes more complex. Thus, it is imperative to be able to correctly value any knowledge bought and to also determine how to monetise it profitably. If there are royalties or licence fees to be paid, there will be a continued cost that will reduce profits in the future. Therefore, the particular practice of inbound OI that a firm can implement may be limited by its financial resources. Furthermore, given the high initial cost, it may take time for a firm to claw back its initial outlay, therefore, some inbound OI activities' benefits are only experienced in the long term.

2.2.2.2. Outbound Open Innovation

Outbound OI is where internally developed resources such as ideas and knowledge are taken outside the firm and may be utilised by others in the environment (Scaliza et al., 2022; Singh et al., 2021). This may be through pecuniary processes such as selling IP rights or licensing out (Bogers, Chesbrough et al., 2019; Teece, 2020). There are also non-pecuniary initiatives, such as offering free use of products to the public (Yuan & Li, 2019). Thus, a firm may enjoy income through licensing its technologies and also ensure that its technology becomes integral to a market or industry.

However, not all outbound practices are financially beneficial to the firm. Therefore, there may not be an incentive to participate in such practices. Revealing innovation involves collaboration and sharing information and IP with external parties such as customers and other firms (Yuan & Li, 2019). This may lead to indirect benefits, such as generating demand for the offering, thereby expanding the market for various products (Dahlander et al., 2021). As demand grows, the value of the IP increases. As internal firm knowledge is freely shared, competitors could also use this information to their advantage and the detriment of the revealing firm (Schäper et al., 2023; Yuan & Li, 2019). Through this process, a firm's proprietary knowledge may become public and be used by competitors without monetary compensation (Bogers, Chesbrough et al., 2019; Ovuakporie et al., 2021). Such activities may work against the strategy of the firm to retain its competitive edge as revealing OI could lead to stronger competitors. An argument could be made that this leads to a more innovative environment, which would benefit both customers and the impacted industry.

Disposing of idle assets through selling IP may raise money to invest in and develop new technologies (Bogers, Chesbrough et al., 2019; Teece, 2020). As selling OI involves disposing of internal IP, the firm gives up the opportunity to develop new products based on the IP sold. This form of OI allows for the monetisation of underutilised ideas by granting access to external parties (Chaudhary et al., 2022). This could be an advantage when non-core technology or knowledge is sold, as it would allow the selling firm to concentrate on its core business (Zhou et al., 2019). This allows a firm to be more flexible and efficient in the future, and also under-utilisation of firm assets is reduced (Filiou, 2021). However, outbound OI can be a very complex process, given the intangible nature of the products. There are multiple costs and challenges involved in this OI process.

The selling firm may not fully appreciate the value of the technology, so there is a risk of undervaluing their IP and losing out on future profits and benefits (Filiou, 2021). Furthermore, there are costs involved in this process, as selling can be a resource-intensive process requiring specialised personnel and controls to be in place (Audretsch & Belitski, 2023; Yuan & Li, 2019). Appropriate partners/buyers have to be identified and verified, contracts put in place, and so on (Filiou, 2021). There may be short-term financial gains from selling. However, these must be compared to the potential future uplift that would be given away by not developing the same technology. Furthermore, there is a real risk that the firm's future competitive advantage is reduced or lost through revealing or selling.

2.2.2.3. Coupled Open Innovation

OI is a diverse concept with many facets. The concept of coupled OI entails mingled knowledge inflows and outflows between partners in the innovation process (Chesbrough & Bogers, 2014; Ovuakporie et al., 2021; Teece, 2020). Inbound and Outbound OI are seen as generally flowing in one direction (internally or externally), unlike Coupled OI, where the firm boundary allows an inflow and outflow of knowledge and technology (Chaudhary et al., 2022). Therefore, coupled innovation could be thought of as a combination of inbound and outbound innovation. It involves interaction mechanisms such as feedback loops, inter-firm collaboration, co-creation with partners and integration into external networks (West & Bogers, 2014). Studies on coupled innovation have been very limited compared to those on outbound and inbound OI (Gao et al., 2020). The challenges of coupled OI would include those encountered under both inbound and outbound OI.

2.2.3. Challenges of Open Innovation

According to Chaudhary et al. (2022), due to OI's complexity, it may encounter failure due to environmental, inter and intra-firm level challenges and individual issues related to the cost of openness. OI has managerial and organisational implications as it requires a certain mindset and operational models to be successful (Teece, 2020). Dahlander et al. (2021) posited that not everyone benefits from OI as the costs might outweigh the benefits. OI may be hampered by strategic factors such as resource constraints, process factors such as coordination constraints and community factors such as knowledge barriers and community readiness (Chaudhary et al., 2022; Lu & Chesbrough, 2022). In addition, cognitive differences among the actors involved can complicate the process (Lu & Chesbrough, 2022). This aligns with Dahlander et al. (2021), who acknowledged that while OI had benefits, it also had costs.

While it can be beneficial, increasing levels of OI may reach a point of diminishing returns (Laursen & Salter, 2006). The organisational environment may also hamper OI, including hierarchical cultural structures, bureaucracy, inflexibility and challenges with external knowledge exploitation challenges, among other issues (Bogers, Burcharth & Chesbrough, 2019; Lu & Chesbrough, 2022). It has been argued that closed innovation would be generally easy to manage compared to OI as all the resources, skills, and financing are all internal and are believed to be able to provide superior performance when dealing with complex problems (Felin & Zenger, 2014). On the other hand, OI requires engagement with external parties who may not be aligned with the firm. Therefore, there is a need for strong oversight and management of the collaboration process to ensure it aligns with the firm's goals.

There are also internal challenges, including staff resistance to change which has been named the Not Invented Here (NIH) syndrome (Bogers, Burcharth & Chesbrough, 2019; Chaudhary et al., 2022; Laursen & Salter, 2006; Teece, 2020) leadership and governance challenges (Chaudhary et al., 2022) and unsuitable or rigid organisational cultures and business models (Chaudhary et al., 2022; Scaliza et al., 2022). These hurdles would have to be overcome to benefit fully from OI and may require changes in organisational culture, business models, and buy-in from stakeholders. They also add additional costs to the OI process as training and change management become a requirement to ensure the success of the initiative.

OI cannot work in situations where technology does not yet exist or is limited (Bogers, Chesbrough et al., 2019). This means it's not a magic bullet for all problems but a valuable tool in the appropriate context. Zhou et al. (2019) highlighted that OI effectiveness depends on a firm's OI strategy and implementation, leading to widely different results on the impact of OI. Their study also established that processes that could strengthen inbound innovation tended to weaken outbound innovation. This implies that some OI strategies may be counter-productive, and it is imperative to ensure that a firm has a balanced mix of OI (Zhou et al., 2019). Selecting the wrong type of OI, and not ensuring that the internal structures and resources are suitable, may work against a firm's innovation and financial performance. Therefore, it is important to be able to measure innovation to be able to determine its value addition to an organisation.

2.2.4. Open Innovation measurement

Research has shown that there are challenges in measuring or quantifying innovation outcomes, often resorting to using R&D expenditure as a proxy measure (Coluccia et al., 2020). As more research has been carried out, various measures have been identified or developed to quantify innovation. Openness or OI has also been measured using different mechanisms including pecuniary and non-pecuniary measures such as intellectual property rights, levels and types of collaboration, new products and services and sources of knowledge, etc. (Fu et al., 2019; Laursen & Salter, 2006; Liao et al., 2020; Lu & Chesbrough, 2022; Michelino et al., 2015). Most of these measurements have been derived from survey data

(Audretsch & Belitski, 2023; Oltra et al., 2018; Wang & Jiang, 2020) and others through the interrogation of secondary data (Caputo et al., 2016; Fu et al., 2019; Lu & Chesbrough, 2022; Michelino et al., 2015). The availability of data often determines the choice of how to calculate the value of OI.

2.2.4.1. Innovation surveys

Multiple studies have utilised individual surveys or institutional surveys such as Community Innovation Surveys (CIS), the World Bank Enterprise Survey and the Innovation Follow-up Survey (Barasa et al., 2017; Ovuakporie et al., 2021). The CIS methodology was originally based on the OECD Oslo Manual 2005 (Ovuakporie et al., 2021; Ozturk-Kose et al., 2023). Over time, the CIS has become more comprehensive, covering more regions and being performed regularly, e.g., every two years in EU member states (Ovuakporie et al., 2021). Such surveys have been adopted to different geographical regions and even carried out in South Africa (CeSTII, 2020). Therefore, a multitude of survey data has built up over time and has been made available to researchers for different analyses. Furthermore, there is a large body of survey questions that may be adopted for different questionnaires in future studies. However, the South African surveys are still in their infancy, and the third survey results covering 2019-2021 are still to be published. Consequently, the community survey data is still limited in South Africa.

Individual research surveys are usually carried out with senior managers or executives in the innovation and R&D fields or managers in emerging or high-technology businesses (Bagherzadeh et al., 2020; Liao et al., 2020; Wang & Jiang, 2020). Such surveys are based on or adapted from already pre-existing surveys, such as the one by Atos Consulting (Bagherzadeh et al., 2020) or the CIS (Laursen & Salter, 2006; Ovuakporie et al., 2021; Ozturk-Kose et al., 2023). Different surveys have concentrated on different aspects of innovation, with some researchers having to use multiple surveys to build up their data for analysis (Ozturk-Kose et al., 2023). Therefore, survey data might not always address all the questions that need to be raised. Both qualitative and quantitative analyses have been used to measure innovative activities and outputs.

However, there has been a decline in survey research as it has its challenges. Surveys have been criticised for sample and variable bias (Faems, 2020). Due to the nature of surveys, it is likely that the people who respond to the surveys are those who are more invested in the topic (Faems, 2020). Most surveys are cross-sectional, and consequently, they lack evidence of causality (Ebersberger et al., 2021; Faems, 2020). Furthermore, there is a limit to the number of questions and variables that can be included in a survey, so some important information might likely be missed, as seen in innovation surveys which concentrated on one form of openness (inbound) and neglected others (coupled), (Faems, 2020; Schäper et al., 2023). This may be overcome by having multiple waves of the survey to the same organisation, with different respondents (Faems, 2020). A major criticism of survey data is that it is subjective as it is dependent on the respondents' understanding of the question as well as their particular situation (Faems, 2020; Leavy, 2017). Surveys, by nature, provide an individual's views based on their attitude and beliefs; two people in the same situation might very well arrive at different conclusions when asked the same question.

2.2.4.2. Secondary data

Secondary data sources have also been used in multiple studies to analyse OI. Such studies have utilised information such as patent data, R&D disclosures and financial accounts to determine relationships between OI and various performance measures (Coluccia et al., 2020; Filiou, 2021; Fu et al., 2019; Wang & Jiang, 2020; Zhang et al., 2018). The use of secondary data has been lauded as it addresses some of the shortcomings identified with using survey data, as it is generally standardised and can be used to analyse longer periods (Faems, 2020). However, utilising secondary data is not without challenges. It frequently requires extensive processing before being suitable for specific analyses and may not offer insights into underlying mechanisms (Faems, 2020). Innovation studies have used secondary data in a number of ways and two of them are outlined below:

2.2.4.2.1. Content analysis

A recent trend in measuring innovation has been the use of data mining on secondary data, such as annual firm reports (Schäper et al., 2023). Language and text-based methods have been used to come up with innovation measures or scores based on assessing text input. This has involved building innovation keyword baskets or dictionaries that can be used to comb through business reports and identify words and phrases related to innovation practices (Lu & Chesbrough, 2022; Schäper et al., 2023). The construction of the innovation dictionary may also include some subjectiveness as there was some human intervention (Lu & Chesbrough, 2022; Schäper et al., 2023). After the analysis, the result would be an open innovation score, which measures the openness of a firm and inbound or outbound measures. This method has been further augmented with machine learning methods such as topic modelling to better identify open innovation practices (Lu & Chesbrough, 2022). Text-based measures of OI have been used in longitudinal studies and hence are seen as an improvement on surveys, which are generally cross-sectional (Schäper et al., 2023).

As a relatively new field in innovation studies, there is a scarcity of guidance on how to conduct such research(Schäper et al., 2023). Therefore, there is a need for more studies of this nature to be carried out to build more support for these methods. It must be noted that such research methods require copious amounts of data and the use of very powerful computers to analyse the information (Schäper et al., 2023). This might be a deterrent to more studies, however, as computing power improves and becomes cheaper, it might be a viable option in the future.

2.2.4.2.2. Accounting methods

The use of accounting information to calculate OI values is not a recent development. Such studies have calculated the values of OI processes by identifying specific financial transactions linked to OI practises such as R&D expenditure, technology purchases, royalties, patents and more (Zhang et al., 2018). This is similar to text-mining, except the actual monetary value is the target variable.

Michelino et al. (2015) developed a framework for the measurement of OI based on accounting transactions in the pharmaceutical industry. This methodology examined OI activities through costs, revenues, new investments and disinvestment linked to innovation (Caputo et al., 2016; Michelino et al., 2015). Michelino et al. (2015) measured OI forms through accounting information by looking at the R&D expenditure and measures of intangible assets. The framework identified four dimensions of OI covering inbound processes (costs and additions) and outbound processes (revenues and disposals) under financial and economic transactions (Fu et al., 2019; Michelino et al., 2015). Costs and revenues characterised economic or operational transactions, while financial transactions covered additions and disposals (Caputo et al., 2016; Fu et al., 2019; Michelino et al., 2015). The diagram below sets out the relationship between the dimensions and the transactions considered:

Figure 1: Four dimensions of Open innovation practises

	Economic transaction		
Inbound	• Collaborative development • Outsourcing of R&D services • In-licencing • Technical services fees **Costs**	• Collaborative development • Outsourcing of R&D services • Rendering of services **Revenues**	**Outbound**
	Additions • Patents • Technology • Licences • Trademarks	**Disposals** • Patents • Technology • Licences • Trademarks	
	Financial transactions		

Source: (Fu et al., 2019)

Subsequent studies adopted the framework to research specific OI activities in biopharmaceuticals (Fu et al., 2019). Financial transactions were identified as having an impact on firm assets, and economic transactions as having an impact on the operating transactions of the firm (Fu et al., 2019). Thus, each innovation measure is based on a combination of financial and economic transactions. The use of accounting information is more objective given its standardisation, furthermore, it is monitored by regulators and investors, enhancing its reliability as a source of information (Zhang et al., 2018). The data should also be readily available in the public domain, allowing for replicability. Given that the data is created to present the financial position of a firm, it does take time to go through the accounts and identify the required OI transactions. Furthermore, this type of analysis disregards non-pecuniary forms of OI (Fu et al., 2019).

2.2.4.3. Section conclusion

There are multiple ways of measuring OI, from using existing and new surveys to determine metrics to utilising data from publicly available sources such as patent databases and financial accounts. It is important to be able to measure levels of OI as it then allows firms to be able to determine how effective their OI activities by looking at how those activities have impacted their innovation and firm performance.

2.2.5. Innovation performance

Innovation measurement and performance play a crucial role in determining organisational success and can signify how well a company's innovation activities align with its strategy (Scaliza et al., 2022). Innovation performance relies on the two-way process of knowledge transfer to expedite innovation (Hameed et al., 2021). It can be measured in multiple ways and is often seen as the output or profit from any innovative activity (Wang & Jiang, 2020). It has been measured as the percentage of product sales which are new to the market or new to the world, new products launched, firm size as well as R&D activities and expenditure (Bagherzadeh et al., 2020; Ebersberger et al., 2021; Laursen & Salter, 2006). Other measures have looked at incremental innovation, such as sales relating to significantly improved products or new products (Coluccia et al., 2020). Alternative studies have assessed it using metrics such as patent counts, applications or citations, innovation awards, or expenditures on research and development (R&D) (Wang & Jiang, 2020). Survey-based measures have also been created to formulate open innovation metrics (Lu & Chesbrough, 2022; Mazzola et al., 2016). Recent studies have also moved to using subjective and qualitative measures such as cultural intelligence and innovative work behaviour (Coluccia et al., 2020).

The measurement of innovation performance is a broad subject, and usually, the metrics chosen depend on the particular focus of the study as well as the availability of information.

There is no consensus on what measures should be utilised, and the results differed based on the form of OI being studied, leading to conflicting results. Some studies indicated a curvilinear relationship, characterised by an inverted U-shape, between openness and innovation performance (Laursen & Salter, 2006). This was based on the dimensions of search breadth and depth, with the argument that at elevated levels of openness, there was an increased risk of knowledge loss. Others observed a positive relationship when using turnover from improved products (Ebersberger et al., 2021). Other researchers discovered a negative relationship (Wang & Jiang, 2020) or no relationship at all (Caputo et al., 2016) with openness. Some scholars identified a positive correlation between innovation performance and both coupled and inbound OI strategies (Ovuakporie et al., 2021; Wang & Jiang, 2020; Zhou et al., 2019), while others observed that inbound OI had an inverted U-shaped relationship with performance (Ebersberger et al., 2021). Outbound OI was also found to have an inverted U-shaped relationship, as there is a point beyond which the cost of outbound OI exceeds the benefits due to empowering competitors and the cost of managing external relationships (Zhou et al., 2019).

Scholars have suggested that the mixed results come about due to different internal organisation processes, technological capabilities and practises for OI (Liao et al., 2020). The studies have been carried out across a variety of firm types with various results, including public companies (Caputo et al., 2016; Lu & Chesbrough, 2022; Michelino et al., 2015; Schäper et al., 2023), large firms (Brunswicker & Chesbrough, 2018), small and medium enterprises (Andrade et al., 2020; Singh et al., 2021; Tsai et al., 2022) and other types of firms (García-Vidales et al., 2019). Bagherzadeh et al. (2020) ascertained that determining a more accurate relationship between outbound OI and innovation performance required that internal practices were accounted for as they had a mediating effect on OI practices. These would be different depending on the type of firm as well as the resources at its disposal.

Different studies arrived at different conclusions using different measurement metrics. Therefore, there is no consensus on the subject of OI and its impact on innovation performance. These contradictions merit further study into the relationship between OI practises and performance. More importantly, firms need to be able to determine how OI practises impact their firm performance to ascertain the effectiveness and value they would have realised from those activities.

2.3. Firm Performance

Firm performance is predicated on creating and delivering value to customers with positive consequences (Hameed et al., 2021; OECD/Eurostat, 2018). Therefore, performance measurement is crucial for the firm's effective management as it serves as an indicator of its success. The question of how firm performance can be measured has been debated for decades (Dahlander et al., 2021; Gao et al., 2020). Both financial and non-financial measures can be used to determine performance (Chesbrough et al., 2018; Hameed et al., 2021). Depending on the scholar, firm performance can be measured by the customer's willingness to pay, market performance, number of employees, share price and return on investment, as well as other accounting measures (Chesbrough et al., 2018; Hameed et al., 2021; Lu & Chesbrough, 2022).

Financial performance measurement usually looks at accounting measures such as Return on Equity (ROE), Return on Assets (ROA), turnover, profit, liquidity ratios, earnings before interest and tax as well as market performance information such as share prices (Feng et al., 2021; Zhang et al., 2018). On the other hand, non-financial measures look more at factors such as customer satisfaction, relationships with suppliers, employees and other stakeholders, as well as operating efficiency (Feng et al., 2021). As a result, these may be perceived as more subjective measures. However, both types of measures have been successfully used to measure the impact of OI on firm performance.

2.3.1. Open innovation and firm performance

Many studies have been conducted to determine the impact of OI on firm performance, both from a financial and non-financial perspective. These performance measures have been made at the firm, product and project levels. A key construct in previous studies is that OI does not affect performance in isolation, but there may be other factors that also affect the outcome. These factors include firm age, firm size, and industry, amongst other measures (Andries & Stephan, 2019; Caputo et al., 2016; Fu et al., 2019; Hameed et al., 2021; Mazzola et al., 2016).

2.3.1.1. Open innovation and firm non-financial performance

Studies have shown that OI could create value and improve organisational effectiveness and efficiency (Zhang et al., 2018; Zhou et al., 2019). Innovation can be measured not just by financial means but also by its impact on processes and other stakeholders, including employees and customers. By increasing the level of technology, employee performance and organisational output can be increased significantly. Increased creativity in an organisation also means an increased ability to innovate continuously, leading to customer satisfaction and, therefore, brand recognition and awareness. This would allow firms to be more competitive.

2.3.1.2. Open innovation and firm financial performance

The relationship between firm performance and OI has been widely studied with varying results (Laursen & Salter, 2006; Lu & Chesbrough, 2022; Singh et al., 2021). Several studies have been carried out with multiple authors supporting the view that there is a positive relationship between openness and firm performance (Bogers, Burcharth & Chesbrough, 2019; Ovuakporie et al., 2021; Singh et al., 2021). It is generally accepted that OI encourages growth and high-growth companies are valued highly (Lu & Chesbrough, 2022). Those companies that can establish genuine connections with external actors are likely to see the economic benefits of OI (Singh et al., 2021).

OI success hinges on a firm's ability to create and capture value (Bogers, Chesbrough et al., 2019; Chesbrough et al., 2018; Teece, 2020). Value creation is related to the ability to generate new resources through the OI process and value capture would be the crystallisation of the value created through that process (Chaudhary et al., 2022; Teece, 2020). However, Chesbrough et al. (2018) highlighted that the definitions of value creation and capture needed further clarification in the OI research. Ogink et al. (2023) posited that OI influenced firm value through its impact on firm capabilities. However, it is still unclear how value creation in OI can be defined and measured due to the multitude of constructs in the research.

OI is a broad concept, covering several constructs with differing impacts on performance (Lu & Chesbrough, 2022; Ovuakporie et al., 2021). Various constructs have been used to determine the relationship between OI and financial performance. The constructs cover topics ranging from crowdsourcing venture capital to collaborations with customers or suppliers. While the consensus has been that OI positively impacts performance (Dahlander et al., 2021), the degree to which firm performance is attributed to OI varies greatly depending on the study. For example, Laursen and Salter (2006) observed an inverted U-shaped relationship between OI and innovation performance, indicating that there is a point beyond which increased OI does not provide commensurate benefits. On the other hand, Schäper et al.'s (2023) investigation revealed an S-shaped relationship between OI and financial performance based on an analysis of over 9,000 firms in the United States.

Commented [II2]: Explain why its s-shaped

Innovation has been linked to greater firm performance through increased sales and services and reduced operational costs (Chesbrough et al., 2018). OI benefits come through resource acquisition, organisational adaption and learning (Ovuakporie et al., 2021).

Therefore, there is still uncertainty about the value derived from OI and its effect on business performance. Overall, the position would be that OI positively impacts firm profitability or financial performance. However, some studies have discovered the opposite to be true, with a negative relationship between OI and performance or no relationship at all. This has been attributed to the different measures utilised to analyse the relationship. Nevertheless, studies have shown that firms that adopt OI practise are more innovative (Laursen & Salter, 2006; Ovuakporie et al., 2021) and the expectation is that this would improve performance. In view of this position, this study hypothesises that :

Hypothesis 1: Openness has a positive relationship with financial performance.

The relationship between openness and performance can be broken down into inbound and outbound innovation to take a closer look at how the subcomponents also relate to performance. Multiple studies have taken a closer look at the components of inbound innovation to determine their specific impact on performance. It has been established that not all activities affect performance in the same way.

2.3.1.2.1. Inbound innovation and firm financial performance

Researchers have posited that inbound innovation practices positively influence financial performance (Mazzola et al., 2016; Oltra et al., 2018). However, other scholars observed that inbound OI had a negative relationship with performance (Fu et al., 2019); others noted that it positively impacted performance, and some established that it had no impact at all (Lu & Chesbrough., 2022; Mazzola et al., 2016). Other researchers have highlighted that the relationship is non-linear, with some finding an inverted U-shaped relationship with performance (Caputo et al., 2016; Fu et al., 2019; Zhang et al., 2018) and even an S-shaped relationship (Schäper et al., 2023). Thus, there is an expectation that increasing levels of inbound OI will not continue to have a positive relationship with performance into perpetuity. At some point, there will be diminishing returns from additional OI activities and costs will increase, leading to a negative impact on performance.

Some studies have even shown that inbound OI activities may have a discordant impact on innovation and financial performance, i.e., one practice may positively impact innovation performance but would negatively impact financial performance (Mazzola et al., 2016). The purchase and selling of certain IPs, as well as involvement in joint ventures, was found to not have an impact on performance (Mazzola et al., 2016). In contrast, Lu and Chesbrough (2022) ascertained that contracting and IP-related activities actually had a weak positive association with performance. Furthermore, partnerships and joint-venture activities had a significantly negative association with performance (Lu & Chesbrough, 2022). The relationship between openness and financial performance may very well depend on the performance measure used, as well as the open innovation metric (Caputo et al., 2016).

Different measures of financial performance may give different results for the same innovation measures in different studies. This reflects how different open innovation practices will have different impacts on different financial performance measures. However, it can be argued that given the costs incurred in implementing OI activities, the benefits of OI cannot outweigh the costs forever due to diminishing returns as levels increase. Therefore, there are benefits to implementing inbound OI, however, there should be a point beyond which the costs incurred might very well exceed returns from further increases in open innovation practices. Therefore, this research postulates that:

Hypothesis 2: Inbound OI has an inverted U-shaped relationship with financial performance.

2.3.1.2.2. Outbound innovation and firm financial performance

Studies on outbound innovation have also had mixed results on its relationship with firm financial performance. Oltra et al. (2018) concluded that outbound OI had a positive effect on performance. Selling idle IPs can quickly raise funds for a firm. This supports the view that outbound activities can be financially beneficial to the firm through licensing activities. In contrast, some research discerned a negative linear relationship when performance was measured based on patent activities (Caputo et al., 2016). Patenting takes time and involves many costs from idea generation to formulation before a viable IP is produced and this still has to be legally protected. Therefore, it is expected that there may be a negative impact on performance due to the nature of the activity. Furthermore, outbound OI has been criticised for strengthening competitors as they would now have access to valuable internal IP (Zhou et al., 2019). However, in the same study, Caputo et al. (2016) also observed that outbound innovation had a quadratic or U-shaped association with performance based on sales growth and asset turnover. Initially the costs of engaging in OI activities would outweigh the benefits, however as outbound OI activities increased, more benefits would accrue to the firm. This is supported by revealing OI, which has shown that relationships that have been built over time can be exploited and monetised.

The initial costs of revealing and selling might be high hence, low levels of outbound OI might negatively affect performance. However, as more benefits accrue to the firm, the trend might be reversed. The following hypothesis is derived from this perspective:

Hypothesis 3: Outbound OI has a U-shaped relationship with financial performance.

2.3.1.2.3. Measuring firm financial performance

There are multiple measures of financial performance that can be split into accounting and economic measures. Both types of measures have been used to determine the impact of OI activities on financial performance.

Return on Equity (ROE) is an accounting measure of efficiency that measures how well a firm has utilised its resources (Zhang et al., 2018). Other studies have used Return on Assets (ROA), asset turnover ratios and sales growth, all of which measure operating performance (Caputo et al., 2016; Noh, 2015). While it has become more accepted that accounting metrics do not fully show firm value as they ignore the impact of intangibles (Coluccia et al., 2020), they do provide a holistic view of firm performance by providing a historical view of performance (Nyeadi et al., 2018).

2.4. Summary

This section explored literature on innovation, OI and its relationship with firm financial performance or value creation. The literature review identified research gaps relating to the various OI measures and their bearing on firm financial and non-financial performance. Most studies supported the position that OI practises positively impacted financial performance. However, the extent and nature of the impact is still being debated. The following section will set out the research questions with the hypothesis to be analysed, followed by the methodology the researcher proposes to follow to conduct the research and investigate the hypothesis.

3. Research questions and hypothesis

3.1. Introduction

This section outlines the research questions and associated hypotheses that will be investigated. The thesis covers a primary research question along with its sub-questions and the resulting hypotheses.

3.2. Research question

Multiple studies have explored the relationship between Inbound Open Innovation (OI) and firm performance in South African firms. Numerous empirical studies have produced mixed results (Caputo et al., 2016; Lu & Chesbrough, 2022; Oltra et al., 2018; Wang & Jiang., 2020; Zhang et al., 2018). There is no congruence, so more studies are required to add to the existing body of literature. Therefore, by working to add to this body of work, this thesis tested previously identified relationships, which falls under theory testing (Bell et al., 2019). The research question below was formulated based on the information available in the existing literature set out in Chapter 1:

RQ1:What is the relationship between open innovation practices and a firm's financial performance?

The sub-research questions will be as follows:

The hypothesis derived from the sub-research questions are set out below:

1. Does openness have a positive impact on a firm's financial performance?

H1 – Open innovation positively impacts a firm's financial performance, i.e., using open innovation practises leads to increased performance. The more open a firm is, the better its financial performance.

The researcher expects to find a linear relationship between openness and financial performance, given that the South African firms' innovation levels are low.

2. Does inbound open innovation have a positive impact on a firm's financial performance?

The researcher expects to find an inverted U-shaped relationship between OI and firm financial performance based on the available research.

H2 – Inbound Open Innovation has an inverted U-shaped relationship with a firm's financial performance. As open innovation practises increase, there is a positive impact on performance until a point beyond which there will be diminishing returns from increased open innovation practises.

3. Does outbound open innovation have a positive impact on a firm's financial performance?

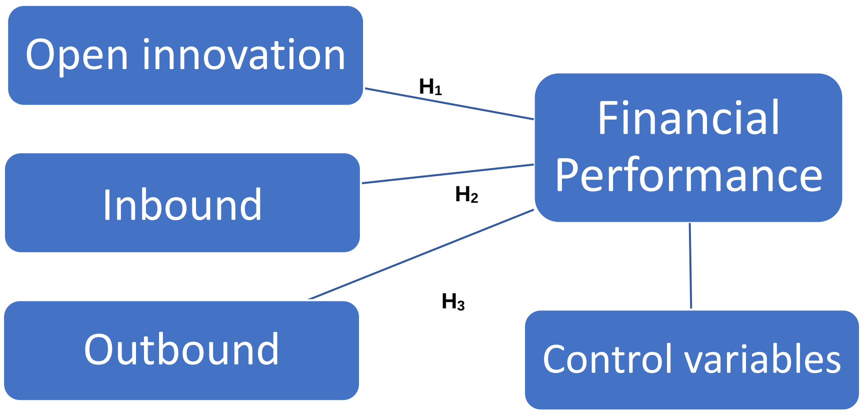
The researcher expects to find a U-shaped relationship between outbound OI and firm financial performance.

H_3 – Outbound Open Innovation has a U-shaped relationship with a firm's financial performance. When outbound innovation is at a low level, the costs surpass the benefits, leading to a negative impact on performance. Yet, with increasing levels of activity, the benefits from open innovation also rise, suggesting that performance should experience a positive impact beyond a certain tipping point

3.3. Conceptual framework

The conceptual framework presented below elucidates the principal constructs of this study, specifically focusing on open innovation activities and firm financial performance, along with the associated hypotheses.

Figure 2: Model of investigation



3.4. Conclusion

This study seeks to explore the connection between open innovation practices and the performance of public companies in South Africa. By addressing this, it aims to fill the research gap regarding the impact of open innovation on firm performance in developing nations (Bogers, Burcharth & Chesbrough, 2019; Lu & Chesbrough, 2022). The next chapter covers the research methodology that was used to test the hypotheses above.

4. Methodology

This section focuses on the research philosophy, methodology, design, research variables, population, sample, data collection and analysis methods that will be applied to address the research questions from Chapter 3. This research employed a deductive, positivist methodology to investigate the relationships of various quantifiable variables through statistical analysis (Bell et al., 2019; Leavy, 2017). This section also covers the methodology limitations and ethical considerations of this study.

4.1. Research philosophy

Research philosophy is a system of assumptions or beliefs on the nature of things, how they work and how that knowledge can be gained (Leavy, 2017). As one of the main research building blocks, it has three main elements: paradigm, ontology and epistemology (Bell et al., 2019; Leavy, 2017). A paradigm is a "worldview or framework through which knowledge is filtered" (Leavy, 2017, p. 11). Thus, there can be multiple views through which research can be carried out. Ontology refers to studying the nature of existence, reality and how the world is categorised and understood (Leavy, 2017). According to Leavy (2017), epistemology is a "philosophical belief system about how research proceeds and what counts as knowledge" (p. 12). Thus, it is imperative to understand the epistemology of research as it informs how research should be conducted to understand the phenomenon being studied. This research was based on quantitative data, therefore, from an epistemological view a quantitative analysis (descriptive and inferential) was appropriate (Scherbaum & Shockley, 2015).

Positivism is an epistemological stance that supports using the methodologies employed in the natural sciences to examine social reality (Bell et al., 2019). It perceives the world through the lens of a natural scientist, therefore, it involves collecting observable data and testing causal relationships (Leavy, 2017). Therefore, it could be said it is an objective position. This research utilises data collected from secondary sources to objectively test the hypothesis through statistical methods. Consequently, the positivist research philosophy was adopted for this research.

Understanding a researcher's philosophy helps recognise the assumptions underlying their work, as this impacts how the research is done. It contributes to forming the research design by taking into account the required data. Furthermore, it supports researchers in choosing the design that is most suitable for the specific study. Finally, it enables researchers to formulate research designs that extend beyond the confines of their prior expertise.

4.1.1. Research design

Praxis is the practice of research and sets out the tools used to conduct research, including methods and theories (Leavy, 2017). The research design answers the questions on how the study will be conducted (Leavy, 2017). Multiple research designs can be utilised, and the choice of research design depends on the research philosophy (Bell et al., 2019) and alignment with the research question. It outlines the research process from data collection to analysis and findings (Bell et al., 2019).

The thesis adopted a desktop research design involving the analysis of secondary data spanning the years 2016 to 2018. Despite the data being collected over a three-year timeframe, it would not qualify as a longitudinal study. Hence, it was appropriate to approach the research as a cross-sectional study. It must be noted that cross-sectional research designs are commonly employed in studies investigating the relationship between open innovation and firm financial performance, as indicated in prior research (Caputo et al., 2016; Fu et al., 2019; Michelino et al., 2015). Hence, the chosen research design aligns with the prevailing methodology observed in existing literature.

4.1.2. Choice of Methodology

The research method is the actual tool for data collection (Leavy, 2017) and relates to how data can be collected in different ways (Bell et al., 2019). Based on the research question on how OI affects business financial performance, the aim was to perform an objective assessment based on secondary data. The research used public non-human data from credible databases, including Refinitiv Workspace and ABI/INFORM Complete. This data was augmented with data collected from trusted websites. As this research looked over a period of time, primary data collection would not be suitable. Secondary data allows for the analysis of data over different time periods, which is important when considering that the impacts of OI are delayed. As per similar research, it lags between one and three years (Fu et al., 2019; Michelino et al., 2015; Ozturk-Kose et al., 2023). This study accounted for a lag of 2 years from the observation of OI practises in 2016 to measuring effects in 2018. Furthermore, secondary data is cost-efficient and also saves time (Saunders et al., 2007). Unfortunately, secondary data also requires a significant amount of cleaning to be suitable for a particular research need, as it may have been collected for different purposes (Faems, 2020; Saunders et al., 2007).

A positivist statistical approach was applied, utilising a quantitative research design. The quantitative research method allows for an objective study of research phenomena, i.e., theory testing (Lock & Seele, 2015). The study will explore the relationship between firm performance (dependent variable) and OI (independent variable), so a quantitative approach is suitable to investigate the relationship. This research will use regression analysis to analyse the relationship between OI and firm financial performance. However, quantitative methods are not without their drawbacks. It has been noted that assumptions (like normality) may have to be made on the distribution of the dependent or independent variables (Scherbaum & Shockley, 2015).

This thesis explored the relationship between Inbound Open Innovation (OI) and firm performance in South African firms. Multiple empirical studies have produced mixed results (Lu & Chesbrough, 2022; Zhang et al., 2018). There is no congruence, so more studies are required to add to the existing body of literature. Therefore, by working to add to this body of work, this thesis tested previously identified relationships, which falls under theory testing (Bell et al., 2019).

4.1.3. Population

A population is the total number of units from which a segment will be selected for research purposes (Bell et al., 2019). The study was conducted in South Africa, a developing nation, to address the research gap highlighted by Lu and Chesbrough (2022), who emphasised the need for increased research activities in developing countries.

Based on the research questions, the population was the pool of JSE-listed companies. Initially, the population was identified as 331 firms that were active on the stock exchange in 2016. This population was selected due to the availability of data as well as the data quality. The Johannesburg Stock Exchange (JSE) requires all public companies to submit annual financial statements prepared in accordance with International Financial Reporting Standards (IFRS) and IAS requirements. Each listed company is expected to publicly publish certain financial information in terms of the Companies Act of South Africa. This allows investors access to information to make informed business decisions and allows for comparative views, given that all companies would use the same standard. Therefore, this information would be readily available in the public space for research purposes. Additionally, its consistency and reliability are confirmed due to the strict guidelines and requirements on published financial accounts. Furthermore, public companies are more likely to have formalised research and innovation processes and hence, information on these activities would be used to identify OI activities.

4.1.4. Sampling

A population segment is a sample representative of the entire research population (Bell et al., 2019). Purposive, non-probability sampling was utilised as the sample was chosen based on meeting certain characteristics specific to the study (Bell et al., 2019). With non-probability sampling, the chance of selecting a specific firm is unknown (Scherbaum & Shockley, 2015).

The sampling frame comprised all firms JSE listed as active between 2016 and 2018, non-equity entities were disregarded. The initial data on all JSE firms was extracted, giving 331 companies. The sample was restricted by removing all firms whose incorporation date was after 2012 and who did not have figures for 2016, leaving 190 firms in the sample. This would ensure that all firms in the model would be at least four years old and was done to remove startups or new firms who might not have built sufficient experience in their relevant industries. The sample was further restricted by removing all firms with neither R&D expenditure nor acquisition cashflows in 2016 and 2017. This was used to identify firms that had engaged in at least one innovation practice in that period. R&D expenditure has been identified as one of a firm's leading indicators of innovativeness (Coluccia et al., 2020; Wang & Jiang, 2020). Thus, it was used as the primary determinant to identify the sample for analysis. Furthermore, collaborative activities such as joint ventures often feature in OI practises. Thus, a combination of firms with R&D expenditure and Joint venture (JV) activity in any of the years from 2016 to 2018 were identified. This gave a total sample size of 132 firms. Another 19 firms were dropped for not having any open innovation metrics based on the method applied (i.e., all three measures of Openness, Inbound and Outbound OI were zero), leaving a final sample of 105 firms in the analysis.

4.1.5. Level and Unit of analysis

According to Bell et al. (2019), there are various sampling units, including individuals, groups, organisations, cities, etc. According to Leavy (2017), "Units of analysis can be thought of as chunks of data" (p. 147). The scope and unit of analysis for this study were at the firm level, with the thesis examining financial data on a firm level (individual company) basis.

4.2. Data Gathering process and research instrument.

The research used secondary financial data from credible databases, including Refinitiv Workspace and ABI/INFORM Complete, for the identified sample of South African firms. The data covered transactions relating to R&D, costs and income related to intangible assets, purchase and sale of intangible assets, consulting and contracting activity, joint venture expenditure and income, as well the transactions relating to calculations ROA. The research utilised published information, including annual financial statements, presentations and announcements. This data was augmented with data collected from trusted websites. As this research looked over a period of time, primary data collection would not be suitable. Due to the use of public secondary data, the investigation posed no significant ethical risk. As required by the University of Pretoria, all the data collected as part of the research was stored in a personal cloud account and would be held for at least ten years.

4.2.1. Variables to be investigated

Three main types of variables will be utilised for this research, i.e., independent, dependent and control. An independent variable has a causal effect on another variable, on the other hand, a dependent variable is influenced by another variable (Bell et al., 2019).

4.2.1.1. Independent Variable

The independent variables were identified as OI practices: openness, inbound OI and outbound OI. Data was sourced from financial accounts and disclosures for the targeted firms in the research period. This thesis was based on a pecuniary approach to OI transactions. Thus, only those activities that had been quantified in the financial accounts were used. They were measured through expenditure (and income from) on intangible assets such as Intellectual Property, licences, collaboration activities, patents and non-patented technology from published annual reports and other company reports for 2016.

Figure 3: Four dimensions of open innovation practises

Economic transaction

	Inbound	**Outbound**
Economic transaction	• R& D expenditure • Technical services, consulting fees • Amortisation of intangible assets acquired **Costs**	• Revenue from Intellectual Property, e.g., royalties, licence fees • Revenue from Associated Companies & Joint Ventures • Outsourcing of R&D services **Revenues**
Financial transactions	**Additions** • Purchase of intangible assets • Software development costs - expenditure • Increase in value of Brands, Patents, Trademarks, Marketing & Artistic Intangibles	**Disposals** • Sale of intangible assets • Software development costs - income • Decrease in value of Brands, Patents, Trademarks, Marketing & Artistic Intangibles

Financial transactions

Adopted from Michelino et al. (2015)

Once the financial transactions set out in the table above were identified, the formulas below from Michelino et al. (2015)'s research were used to calculate the OI variables:

$$Openess\ ratio = \frac{\sqrt{costs\ ratio^2 + revenues\ ratio^2 + additions\ ratio^2 + disposal\ ratio^2}}{4}$$

$$Inbound\ OI\ ratio = \frac{\sqrt{costs\ ratio^2 + additions\ ratio^2}}{2}$$

$$Outbound\ ratio = \frac{\sqrt{revenues\ ratio^2 + disposals\ ratio^2}}{2}$$

Where the subcomponents of the ratios were calculated as follows as per Michelino et al. (2015):

$$\textbf{Costs ratio} = \frac{\text{Cost from OI}}{\text{Total R\&D}} \qquad \textbf{Revenues ratio} = \frac{\text{Revenues from OI}}{\text{Total R\&D}}$$

$$\textbf{Disposals ratio} = \frac{\text{Disposals from OI}}{\text{Intangibles related to OI}} \qquad \textbf{Additions ratio} = \frac{\text{Additions from OI}}{\text{Intangibles related to OI}}$$

To identify inbound OI-related activities, only the costs related to OI activities were used and this covered collaboration costs, costs from outsourcing or purchase of R&D activities and in-licences and royalty fees. For outbound OI-related expenditure, this included mainly IP related transactions bringing in income as well as consulting and JV related activities. The study concentrated on the investments and disinvestments of intangible assets related to innovation, including licences, patents, trademarks, technology and goodwill. The JSE requires all public companies to submit annual financial statements prepared in accordance with International Financial Reporting Standards (IFRS) and IAS requirements. However, the level of detail available differed, therefore, some assumptions had to be made where transactions could not be clearly identified as one thing, e.g., where joint-venture activity was grouped with transactions from associated companies, the figures were taken as if they fully applied to joint-ventures only. R&D expenditure was taken as the 'R&D expense – supplemental' from the Refinitiv database. Where it was not available for a particular firm, then the 'R&D expenditure' variable was utilised. Intangibles related to OI were calculated based on the difference between Intangible assets (excluding goodwill) and other intangible assets, where this figure was negative or not available, the Intangibles Assets-Gross value was used.

4.2.1.2. Dependent Variable – firm financial performance

Firm financial performance measures were determined by extant literature. There are multiple measures of financial performance that can be split into accounting and economic measures. Accounting measures depend on historical financial information supplied by the firm and may be susceptible to manipulation. On the other hand, economic measures may be subject to market fluctuations. The use of both measures provides a more holistic view of firm performance. The financial measures were determined based on the 2018 accounts.

As the study looks at the impact of OI on firm performance, the Return on Assets (ROA) was used to measure performance. ROA is an accounting ratio that shows the asset efficiency, i.e., how profitable it is based on its total assets. This ratio considers a firm's debt level and thus provides a view of profitability, including any capital from borrowing. The higher the percentage, the better the firm efficiency and performance. Data for the calculation of ROA was collected from the Refinitiv database, and the following formula was used:

$$Return\ on\ Assets = \frac{\text{Net Income}}{\text{Total Assets}}$$

All values were sourced from the Refinitiv database. Any gaps in the data were plugged by data from actual firm annual accounts. The financial performance data was also sourced from the Refinitiv databases and annual financial reports. As the impact of OI practises does not lead to immediate benefits, the financial information will be tracked for three years after the end of the research period to 2018. This should be an adequate period for OI practises' impact to filter through to firm performance.

4.2.1.3. Control Variables

The last variable type to be considered was control variables, which Nielsen and Raswant (2018) defined as empirically essential but not central to the research question. The purpose of control variables is to increase the precision of the relationship between the dependent and independent variables by addressing spuriousness, which helps improve research rigour (Cuervo-Cazurra et al., 2016; Nielsen & Raswant, 2018). Therefore, they will assist in eliminating firm-specific influences from the study and support the validity of the inferences made in the research (Nielsen & Raswant, 2018). Including appropriate control variables is essential in research (Cuervo-Cazurra et al., 2016).

However, utilising control variables has its shortcomings. They may distort the research findings if not identified or used correctly (Nielsen & Raswant, 2018). This may call into question the validity of the results (Cuervo-Cazurra et al., 2016)

The selection of the control variables was based on satisfying the criteria of spuriousness established in previous research (Cuervo-Cazurra et al., 2016). Previous OI studies identified the following control variables: firm size, age, and industry.

4.2.1.3.1. Research and development

As only a quarter of the sample had R&D values, rather than determine the R&D intensity, the researcher chose to create a dummy variable to represent whether or not a firm had disclosed any R&D expenditure. Firms that spend on R&D were expected to be more innovative.

4.2.1.3.2. Industry

The industry in which a firm operates impacts innovation from the nature of the work, how competitive it is, the opportunities available, and the industry's knowledge bases (Oltra et al., 2018). Generally, the primary commodities industry exhibits low levels of innovation compared to knowledge-intensive industries such as pharmaceuticals (Laursen & Salter, 2006). The business innovation survey split the business sectors into two based on how their innovation performance was perceived: Industry comprising of mining manufacturing and utility firms and Services which covered wholesale and trade, finance, transport, communication, engineering and tech (CeSTII, 2020). Based on this, a decision was made to create a dummy variable (DIndustry) with firms that fell within the “Industry” classification from the survey being assigned a 1 and a 0 for all other firms. For purposes of this research, the ‘industry’ sector comprised of firms from Basic materials, Consumer Staples, Energy and Industrials. All other sectors were classified as 0.

4.2.1.3.3. Firm size

Firm size goes to the resources and capabilities of the organisation, with the expectation that larger firms will have more resources and are, therefore, able to take advantage of opportunities than smaller firms (Coluccia et al., 2020; Ovuakporie et al., 2021; Schäper et al., 2023). It is generally accepted that economies of scale apply to larger firms, and small firms suffer from the liability of smallness. On the other hand, large firms may be hampered by bureaucracy and unable to take advantage of the opportunities available due to a lack of flexibility. Thus, firm size could have a positive or negative impact. The firm size variable was based on the natural logarithm of the previous three-year average annual income to eliminate large variances (Fu et al., 2019).

4.2.1.3.4. Firm age

Older firms are more established and have considerable resources for innovative activity (Coluccia et al., 2020). They also tend to be larger and garner the benefits of size. Studies have also shown that younger firms tend to be more innovative, as older firms may have entrenchment issues (Zhang et al., 2018). Firm age was measured as the time from incorporation to the year 2016.

The table below outlines the variables used in the model:

Table 2: Variables used in this investigation

Variables	Description	Value
Independent Variables – Open Innovation measures		
Openness	Combination of the inbound and outbound innovation measures	Continuous and a percentage
Inbound	Square root of calculated variables $Costs^2$ and $Additions^2$	Continuous and a percentage
Outbound	Square root of calculated variables $Disposals^2$ and $Revenues^2$	Continuous and a percentage
Dependant Variables - Firm Financial Performance		
ROA	Net profit after tax divided by total income	Continuous
Control Variables		
DResearch	A dummy variable with 1 for those firms who have disclosed R&D expenditure and 0 for those who did not have any.	1 or 0
DIndustry	Industry of the listed firm - Dummy (1=the company belongs to the focal industries; 0=the company does not belong to the focal industries)	1 or 0
Firm Size	Natural logarithm of the average of the past 3 years' turnover	Continuous
Firm Age	Number of years from the year of establishment to reference year	Discrete

4.3. Data analysis

A multivariate and hierarchical regression approach was employed to examine the correlation between different open innovation practices and firm performance. H2 and H3 state that there is an inverse U-shaped and U-shaped relationship between OI and firm performance respectively, the model was expected to take a polynomial form. As H1 postulates, there is a linear relationship, the squared term will fall off.

$$X_i = \alpha_0 + \alpha_1 OI_i + \alpha_2 OI^2_i + \sigma_1 \beta_i + \varepsilon_i$$

Where:

- X_i measure of firm financial performance
- α_0 constant
- OI_i is the OI score based on the type of OI being measured.

- β_i measure of the control variables
- ε_i error variable

4.3.1. Independence of observations

Multiple regression requires the assumption of independence to be met, i.e., the observations should not be related. The Durbin-Watson statistic was used to test for independence as it tests for 1st-order correlation. The test statistic can range from 0 to 4. If the value is close to 2, then it is accepted that the residuals are independent.

4.3.2. Test for Linearity and Homoscedasticity

Multiple regression also assumes that the independent variables are collectively linearly related to the dependent variable and that each independent variable is also linearly related to the dependent variable (Saunders et al., 2007). A visual check of the scatterplot between studentised residuals and the predicted values was conducted to test for the linear relationship between the dependent and independent variables (Saunders et al., 2007). To test for the linear relationship between the dependent variable and each independent variable, a partial regression plot between each independent variable and the dependent variable (Laerd Statistics, 2015). If the relationship between the dependent variable and an independent variable does not follow a straight line, then the data would have failed the assumption of linearity (Laerd Statistics, 2015).

Homoscedasticity posits that the variance remains uniform across all values of the predicted independent variables (Laerd Statistics, 2015; Saunders et al., 2007). The conditions for homoscedasticity are met when the scatter plot of the studentised residual and the unstandardised predicted value do not take a particular shape.

A crucial condition for a linear regression model is the existence of a linear relationship between the predictor variables and the dependent variable. To verify this, plots of the studentised residuals against each predictor variable, known as partial plots, are produced. These plots would assist in pinpointing any variables that might contribute to heteroskedasticity (non-linearity) in the residuals within the data. These scatterplots show the relationship between a specific predictor variable and the dependent variable while holding the effects of the other predictor variables constant (Laerd Statistics, 2015).

4.3.3. Test for multicollinearity

Multicollinearity occurs when two or more independent variables are highly correlated (Laerd Statistics, 2015). This negatively impacts the results as it becomes difficult to identify which variables contribute to the variance in the model. Pearson's *r* assesses the strength and direction of the linear relationship existing between the variables being studied (Bell et al., 2019). Thus, it can be used to test for multicollinearity. The statistic takes values between zero and ±1 depending on the direction of the relationship (Bell et al., 2019). If the absolute values are close to one, this indicates a robust relationship and values closer to zero indicate a weaker relationship (Bell et al., 2019; Saunders et al., 2007).

Multicollinearity can be identified by examining correlation coefficients or Variable Inflation Factor (VIF) values. When testing using correlation coefficients, multicollinearity is present if any independent variables have correlations greater than 0.9 (Saunders et al., 2007). If using the VIF variable, all the values must be below 10 for multicollinearity to not be a threat (Saunders et al., 2007). The lower the VIF, the better for the model.

4.3.4. Outliers

The data may contain ‘unusual points’ that may not fit the multiple regression model, including outliers. Bell et al. (2019) described an outlier as an extreme value in a dataset. An outlier is a data point that does not follow the usual pattern of points. For research purposes, there should be no significant outliers to perform multiple regression analysis as they negatively affect the accuracy of the model (Plonsky & Ghanbar, 2018). The standardised or studentised deleted residuals may be used to test for outliers. The Casewise Diagnostics table highlighted cases with outliers, i.e., the standardised residual was greater than ±3 standard deviations.

For the studentised deleted residual, any residuals greater than ±3 standard deviations would be classified as potential outliers (Laerd Statistics, 2015). This would be done via a visual inspection of the variable in the Data View window in SPSS. The data would be sorted ascending or descending and inspected for residuals greater than the three standard deviations.

4.3.5. Checking for Normality

Inferential statistics require the residuals to be normally distributed. Two methods were used to test for normality: A histogram with a superimposed normal plot and a *P-P* plot of the studentised residuals. The points will align to the diagonal line if residuals are normally distributed. Multiple regression analysis is relatively robust against deviations from normality, so the results must only be approximately normal to avoid violating the normality assumption (Laerd Statistics, 2015). Furthermore, given that residuals are not simple random variables, their behaviour is not expected to follow a normal distribution. Therefore, the normality assumption is not deemed crucial.

4.3.6. Checking for a non-linear association

To explore a non-linear connection (specifically, an inverted U-shaped relationship), it is essential to have a meaningful and positive coefficient for the independent variable and a significant and negative coefficient for its squared term (Lu & Chesbrough).

4.3.7. Hypothesis testing

To probe the hypothesis further, confidence intervals were also used to test the hypothesis. The null hypothesis states that there is no relationship or association with the variable in question (Scherbaum & Shockley, 2015). The decision to accept or reject the null hypothesis is based on calculating the probabilities of obtaining the observed result if the null hypothesis is accurate (Scherbaum & Shockley, 2015). The prevailing practice sets the standard for rejecting a null hypothesis at 5% or less (Scherbaum & Shockley, 2015). Therefore, if the probability is above the 5% significance level, the null hypothesis cannot be rejected.

Confidence intervals offer interval-based estimates, unlike point coefficients, which provide point estimation of the study parameter. If the null hypothesis, i.e., H_0 =0, falls in the confidence interval, H_0 fails to be rejected (Scherbaum & Shockley, 2015). Alternatively, if H_0 falls outside the confidence interval, the null hypothesis can be rejected.

The null hypothesis is tested in order to avoid Type I errors, where the null hypothesis may be rejected when it is, in fact, true (Leavy, 2017; Scherbaum & Shockley, 2015; Wooldridge et al., 2016). A Type II error occurs when you reject a relationship that actually exists (Leavy, 2017; Wooldridge et al., 2016).

4.4. Research Rigour

In research, the significance of identifying the correct relationships and mechanisms is of the highest importance so that the research results can be trusted (Cuervo-Cazurra et al., 2016). Therefore, the data sample will be firms listed on the JSE for this research. As the JSE has standard reporting requirements, this allows for comparing similar metrics. Furthermore, only companies with complete data sets will be utilised. According to Bell et al. (2019), the higher the heterogeneity in a sample, the bigger the required sample size. Therefore, taking companies from the JSE will allow for a large enough sample and using control variables will ensure that the analysis is valid for South Africa (Cuervo-Cazurra et al., 2016; Teagarden et al., 2018).

Furthermore, Faems (2020) stressed, "deductive quantitative research can provide substantial added value to test the importance of current innovation policies and practices" (p. 360). This supports the use of a deductive method in this study. Secondary data is usually standardised, allowing for comparisons over a period of time and is great for testing for relationships between variables (Faems, 2020). Financial information is published every year in a standardised format per the requirements of the JSE.

In this research, various quality control measures were implemented to guarantee the credibility of the results, and these procedures are set out in Chapter 5.

4.4.1. Validity

According to Bell et al. (2019), validity refers to the extent to which an identified indicator measures a concept. Furthermore, validity is an important requirement in research methodology as it ensures that the results of a study are meaningful and can be confidently used to draw conclusions or make inferences (Bell et al., 2019; Sürücü & Maslakci, 2020). If a study lacks validity, its findings may not accurately represent the phenomenon under investigation, rendering the research ineffective and potentially misleading.

Measurement, or construct, validity refers to the degree to which a measure accurately measures the concept it is designed to measure (Bell et al., 2019). When there are questions as to the validity of a construct, reference to other researchers who have dealt with similar contexts can assist in determining the suitability of measures (Saunders et al., 2007). This procedure was followed to ensure the measures in this study had credibility based on studies that had also used financial transactions to determine OI measures (Caputo et al., 2016; Fu et al., 2019; Michelino et al., 2015). Content validity refers to the confirmation of the validity of a measure by subject experts and was established by using measures which had been used by multiple researchers in other studies (Leavy, 2017). Statistical validity alludes to the appropriateness of the statistical analysis chosen, as well as the results of the analysis being consistent with statistical requirements (Leavy, 2017). There were statistical tests used to test validity. Pearson's correlation determines the strength and direction of a relationship between two variables (Leavy 2017). For multiple regression, the correlation coefficient, *R,* can also be used (Leavy, 2017). Both of these measures were used to test for validity.

4.4.2. Reliability

Reliability pertains to the precision or consistency of the instrument in delivering comparable results when employed consistently across different instances (Sürücü & Maslakci, 2020). According to Leavy (2017), it "refers to the consistency of results" (p. 114). To test the robustness of the results, a third performance measure, Return on Equity (ROE), was used to test the three hypotheses. The results of this regression were set out in Annexure 3.

4.5. Research Limitations

It must be noted that a quantitative approach has its critics. Scholars have noted that it gives a spurious sense of accuracy and lacks flexibility (Bell et al., 2019). Scholars have also noted that it gives a spurious sense of accuracy and lacks flexibility (Bell et al., 2019). Another criticism is that it does not give insight into the why of the matter, i.e., the motivation behind certain behaviours (Goertzen, 2017). These should be noted as some of the limitations of the study.

The use of secondary data also has challenges, as data is usually collected for general purposes and requires heavy manipulation and processing to be applied in a specific study (Faems, 2020). This can be a cumbersome and time-consuming process. Also, secondary data may not contain all the information required in a study, necessitating several different sources of data (Goertzen, 2017) or qualitative research to complement the data. Innovation scholars have identified numerous variables that can impact such studies, and it is unlikely that any data set will account for all variables, leading to potential gaps in the data (Faems, 2020). The fact that secondary data is available to all means scholars have access to the same dataset and may work on similar research, posing a risk for future publications (Faems, 2020).

- The final sample of 105 firms was small, limiting the ability to generalise results.
- The sample covered 10 different industry classifications, which meant the sample was heterogeneous. Ideally, the study should have concentrated on one industry and have a homogenous sample. However, this would have severely constrained the sample size.
- Not all firm accounts had sufficient details in their disclosure to accurately identify open innovation-related activities, so assumptions had to be made. If different assumptions are made, then it is likely that different results will be obtained. This impacts the ability to generalise the study.
- The time horizon was limited to firm activities between 2016 and 2018. If the time horizon had been extended, likely different results would have been obtained.
- Firm performance was measured using ROA. However, there is no consensus on what measure is best. Other financial measures could have been selected and could have yielded different results.

4.6. Summary

This section outlined the rationale for the research design and methodology to be applied in this research. It covered the variables to be considered based on previous studies from scholars within the field as well as the limitations of the study.

5. Results

5.1. Introduction

This chapter sets out the results of the statistical analysis following the methodology in Chapter 4. A more detailed analysis of the results will be done in Chapter 6.

5.2. Sample descriptive statistics

This section covers the descriptive statistics, providing an overview of the data used in the research. From the initial 132 companies identified for the research, the final sample had 105 firms with open innovation information in 2016. Further descriptive statistics are set out in Annexure 1.

5.2.1. Industry analysis

Figure 4 shows the split of the 105 firms by their industry classification. Industrials had the highest number of firms in the sample, with 24, followed by Financials with 21 firms. The energy sector only contributed two firms, the lowest number in the sample.

Figure 4: Number of firms per industry classification

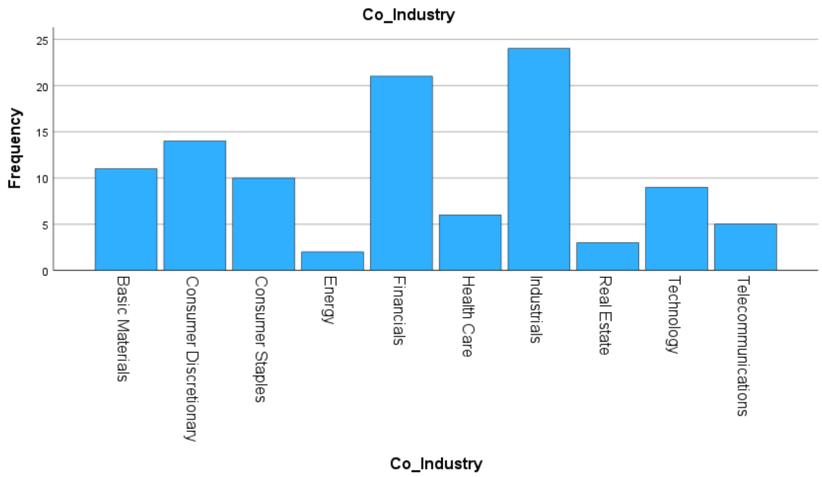


Figure 5 shows a pie chart with the split of the sample by percentages, with Industrials contributing 23% of the sample size, closely followed by Financials contributing 20%. Energy and Real Estate contributed the least, with 2% and 3% of the sample, respectively.

Figure 5: Split of the sample by industry classification

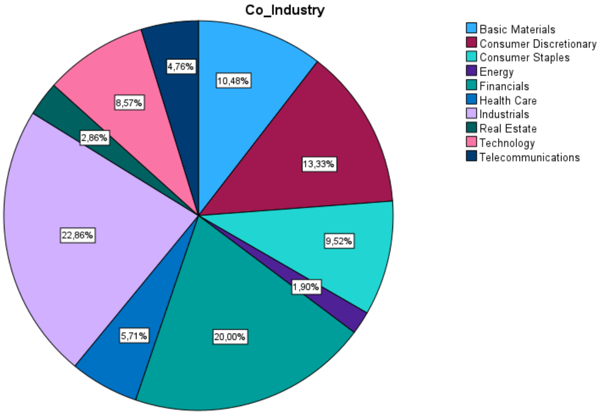
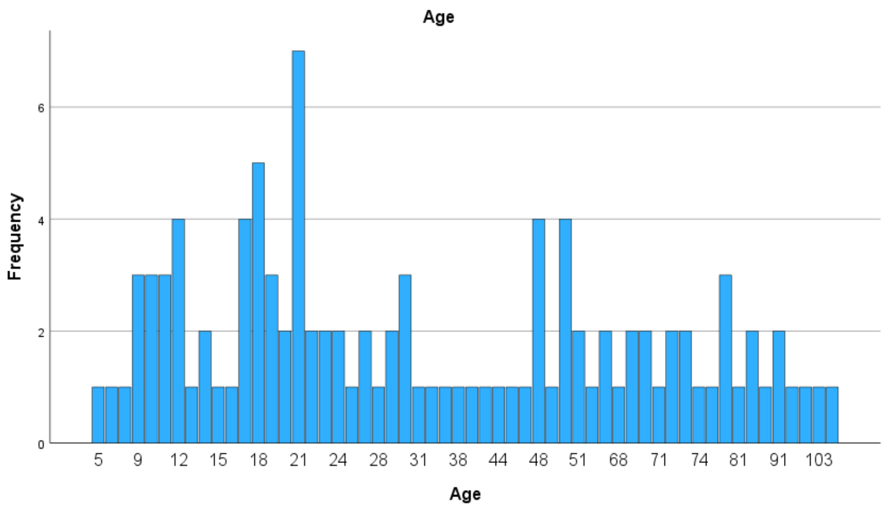


Figure 6 outlines the age distribution of the sample firms based on the years from incorporation to 2016. The sample had an average firm age of 39 years, and the modal age was 21 years.

Figure 6: Age distribution of the sample



5.2.2. Descriptive statistics – model variables

The table below outlines the descriptive statistics that apply to the variables used in this research. The mean of a sample is a central measure of tendency and is measured as a singular point estimate representing the distribution of the data (Saunders et al., 2007). The standard deviation shows the extent to which the data is spread about the mean (Bell et al., 2019; Saunders et al., 2007). The mean was 5.21% for ROA. The firms were 39 years old on average, and firm size, represented as the natural logarithm of the average of three years' revenue, was 22.70.

***Table 3*: Variable statistics**

		Openness	**InboundOI**	**OutboundOI**	**Age**	**Size**	**ROA**
N	Valid	105	105	105	105	105	105
	Missing	0	0	0	0	0	0
Mean		0.2983184	0.3141567	0.1763513	39.47	22.719509	0.052073
Median		0.1897160	0.1833169	0.0008551	29.00	23.016586	0.044650
Mode		0.50000	0.00000	0.00000	21	20.0602	0.0134
Std. Deviation		0.25405564	0.30772161	0.28818903	27.750	1.9938003	0.0951594
Minimum		0.00283	0.00000	0.00000	5	14.6399	-0.2157
Maximum		0.86603	1.00000	0.92687	124	25.9542	0.6642

In general, South African public companies exhibited an average openness ratio of 29.8%, with a mean for inbound OI of 31.4% and 17.6% for outbound OI. The OI ratios were quite spread out, as evidenced by the standard deviations. Further descriptive statistics are set out in Annexure 1.

Outliers were noted in the original model and after removing five of them iteratively, the analysis was run without all the identified outliers, and the result for the model did not change significantly. All the results presented thereafter are without outliers for all the regression runs for the three hypotheses and relate to 100 remaining firms

5.3. Hypothesis 1 – Openness

H1 assumes a linear relationship between Openness and firm financial performance (ROA).

5.3.1. Robustness

5.3.1.1. Model fit and test for independence

The model summary table below outlines the effect of the independent variables on the dependent variable. The *R*-Square, or coefficient of determination, gauges the model's fit to the data. It signifies the proportion of variance in the dependent variable that is explained by the independent variables. The correlation statistic (R) of 16.7%, indicates the degree of correlation between the estimated performance values and the corresponding actual values.

Based on the model summary below, the model was not a good fit. The predictor variables only explained 2.8% of the change in ROA.

Table 4: Model summary

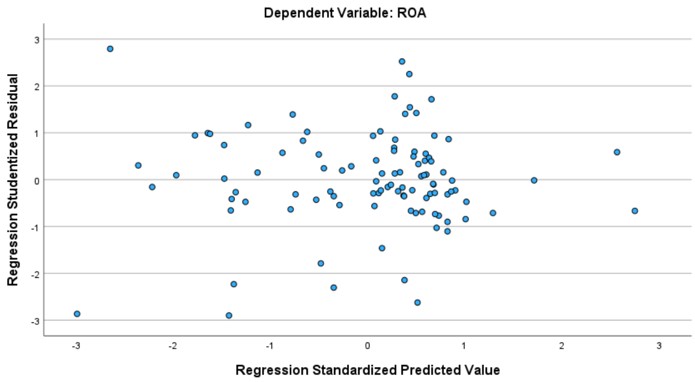
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.167	0.028	-0.023	0.0611059	1.924

Residuals were independent, as assessed by a Durbin-Watson statistic of Durbin-Watson statistic of 1.924, which was within the optimal range of 1.50-2.50. This indicates that there is no significant trend in the model's output. Therefore, we can assume that the predictors are independent of the performance metric.

5.3.1.2. Test for Outliers and Homoscedasticity

Figure 7 shows the scatterplot between the studentised residuals and the predicted values to test for the linear relationship between the dependent and independent variables. The scatter plot can also be used to check for homoscedasticity. The conditions for homoscedasticity are met when the scatter plot of the studentised residual and the unstandardised predicted value do not take a particular shape. The variables appear to be randomly distributed around zero. Through a visual inspection exercise, the relationship between the dependent and independent variables is likely linear for ROA. Furthermore, there is no particular shape to the spread of residuals, supporting the position that there is no heteroskedasticity. This is consistent with the findings based on the Durbin-Watson statistics observed in **Table 4**. This confirmed that there was no significant correlation in the model.

Figure 7: Scatterplots



5.3.1.3. Partial regression plots on the dependent variable

One of the critical requirements for a linear regression model is that of linearity, i.e., there should be a linear relationship between the independent variables and the dependent variable. The partial scatter plots can also be used to test for heteroskedasticity, as set out in Chapter 4.

The model (**Figure *8***), shows that Openness and ROA have a low negative partial correlation As shown in the graph, this indicates a weak linear relationship between these two variables. Therefore, openness does go some way to explaining performance when it is ROA.

Figure 8: Openness partial regression plot

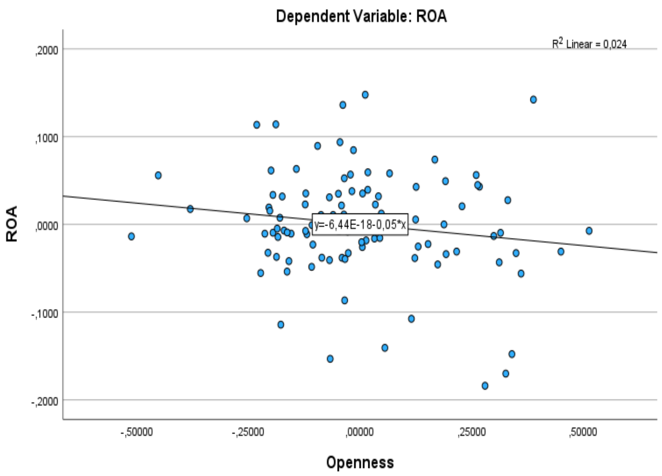
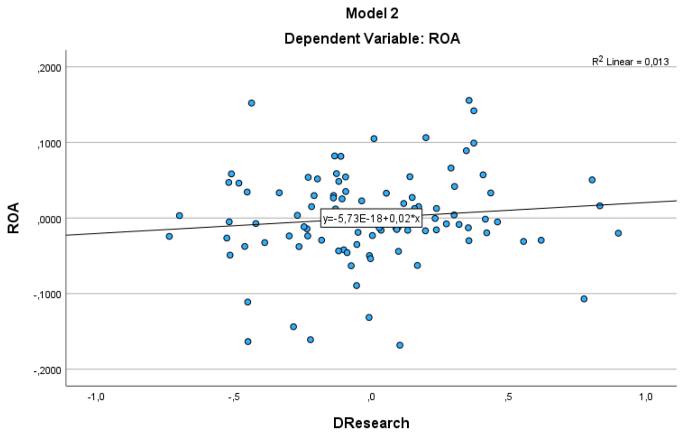


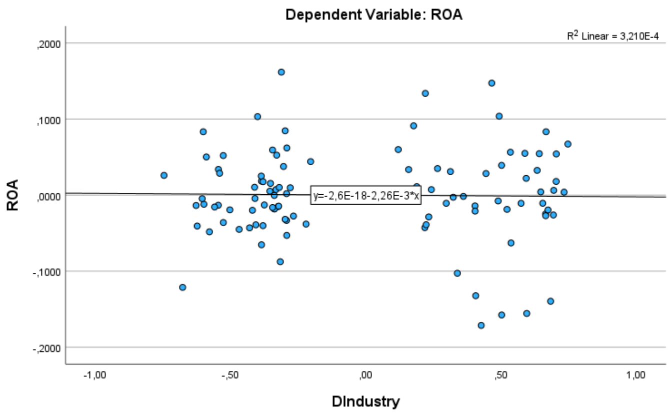
Figure 9 below shows the interaction of performance with DResearch. The fitted line shows a low positive partial correlation between the predictor and ROA. Therefore, this predictor contributed marginally to the predicted variable.

Figure 9: Research partial regression plot



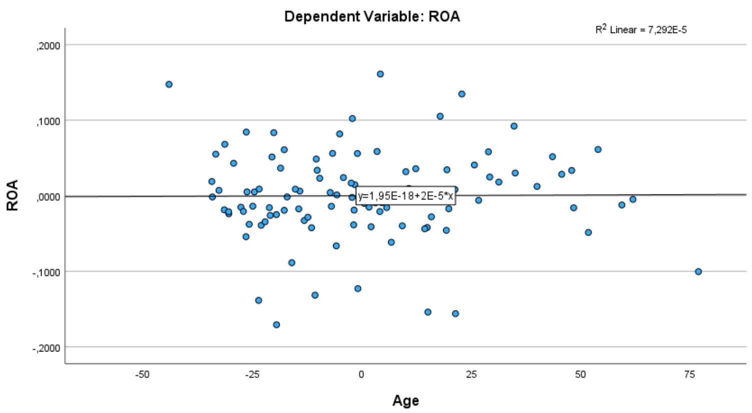
Based on **Figure *10*** below, shows a very low negative partial correlation between the Industry dummy variable and ROA. Therefore, whether or not a firm is DIndustrial is of no value in understanding the performance of the firm.

Figure 10: Industry partial regression plot



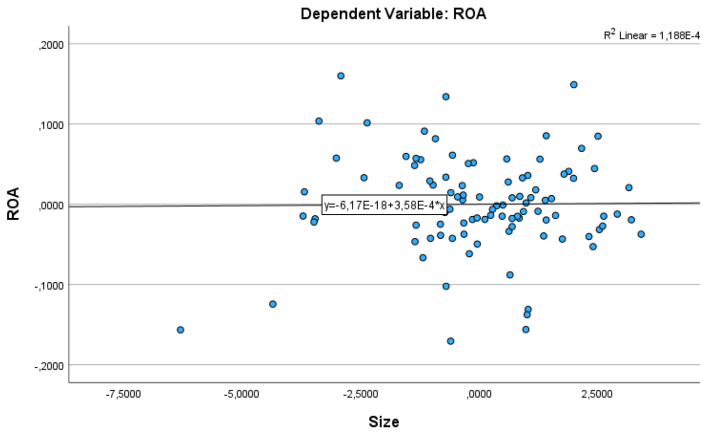
Age has an extremely lor positive partial positive relationship with ROA (**Figure *11***). The regression line displays a low partial positive relationship between the two variables, an indication that age was of little value in explaining performance.

Figure 11: Age partial regression plot



The firm's size exhibited a very low partial correlation with ROA. The relationship was a positive linear one, as evidenced by the regression line. Firm size could be used to elucidate the independent variable to a very limited degree.

Figure 12: Size partial regression plot



5.3.1.4. Multicollinearity test

The Pearson’s correlation absolute values in the second column below indicate comparatively weak correlations between the dependent variable (ROA) and each of the independent variables. All the absolute values are below 0.610.

The predictor variable Openness variable (-0.113) having the highest correlation coefficient with the dependent variable. Openness and DResearch had the strongest relationship with a correlation coefficient of 0.609. As the absolute values of the correlation coefficients of the predictor variables are generally low, this indicates low to no collinearity.

***Table 5*: Pearson correlations**

Model 2	ROA	Openness	DResearch	DIndustry	Age	Size
ROA	1.000					
Openness	-0.113	1.000				
DResearch	0.028	0.609	1.000			
DIndustry	0.003	0.106	0.265	1.000		
Age	0.024	0.066	0.185	0.220	1.000	
Size	0.058	-0.098	0.154	0.041	0.339	1.000

Additionally, all the VIF values in **Error! Reference source not found.** were below 2.000, well below the accepted maximum of 10. This supports the position that multicollinearity would not be an issue.

5.3.1.5. Checking for non-linearity with dependent variable

To check if a non-linear relationship could lead to a stronger association between openness and firm performance, a regression was run with the squared term. The table below outlines the results:

Table 6: Model summary with squared term

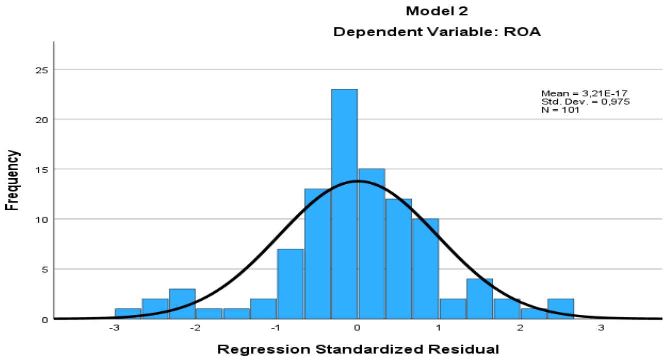
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Sig. F Change	Durbin-Watson
1	0.250	0.062	0.002	0.0603353	0.034	0.067	1.890

Based on the result above, the *R*-square change was 3.4% lending support to the idea that openness might have a curvilinear relationship with performance. The model fit also improved.

5.3.1.6. Checking for Normality

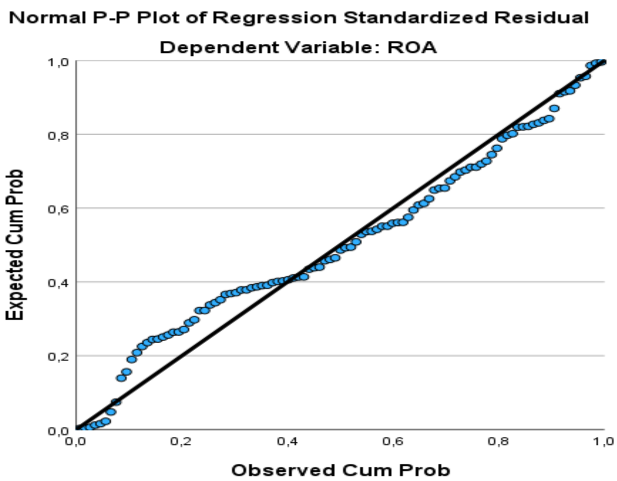
One of the assumptions underlying linear regression is the normal distribution of residuals. Based on **Figure *13***, the standardised residuals appear to be approximately normally distributed. The mean and standard deviation are approximately zero and one, respectively. As noted in the methodology chapter, the assumption of normality is not critical, therefore, an approximation of normality is acceptable. The distribution appears to have an almost normal distribution.

Figure 13: Histogram standardised residuals



The P-P plot was also produced as it can be used to confirm the normality of the residuals. The closer the observations align to the diagonal line, the stronger the normality assumption. The graph, **Figure *14***, shows that the residuals are approximately distributed along the regression line. Therefore, it supports the position that the distribution of residuals is approximately normal.

Figure 14: P-P plot standardised residuals



5.3.2. Coefficients

The unstandardised coefficients (B column in **Table 7**) list all the regression parameter estimates (αi). They depict the anticipated shift in the dependent variable with each incremental change in an independent or control variable, keeping all other variables in check. The null hypothesis (H_0: αi = 0) and the alternative hypothesis (H_1: αi ≠ 0) apply to all the independent variables.

The standardised coefficients (Beta column in **Table 7**) indicate how a predictor variable contributes to the regression model. The results show that the openness variable (-20.3%) contributed the most to the model, followed by the Research dummy variable (15.3%).

Table 7: Coefficients

	Unstandardised Coefficients		Standardised Coefficients			Collinearity Statistics	Collinearity Statistics
Model 1	B	Std. Error	Beta	t	Sig. Tolerance	Tolerance	VIF
(Constant)	0.049	0.076		0.646	0.52		
Openness	-0.048	0.031	-0.203	-1.538	0.127	0.588	1.701
DResearch	0.020	0.018	0.153	1.114	0.268	0.546	1.833
DIndustry	-0.002	0.013	-0.019	-0.175	0.862	0.89	1.123
Age	2.00E-05	0	0.009	0.083	0.934	0.835	1.198
Size	0.000	0.003	0.012	0.106	0.916	0.821	1.218

Inserting the coefficients into the regression model results in the following equations:

Unstandardised equation

ROA = 0.049 – 0.048*Openness* + *0.020DResearch* – 0.002*DIndustry* + 2.000^{-05}*Age* + 0.000*Size*

Standardised equation

ROA = -0.203*Openness* + 0.153*DResearch* –0.019*DIndustry* + 0.009*Age* + 0.012*Size*

Based on the confidence intervals in Annexure 2, all the coefficients (B in **Table 7**) fall within their respective confidence intervals. Therefore, all the slope coefficients are not statistically significant, and this implies that H_0 cannot be rejected.

5.3.3. ANOVA results

ANOVA assesses the statistical significance of the R-square metric, indicating the researchers' confidence in generalising study results to the population from which the sample came (Bell et al., 2019). In business research, a 5% threshold is commonly accepted as the level of statistical significance (Bell et al., 2019). The null hypothesis states that the population *R*-square is zero, meaning none of the model variation in the model can be explained by the predictors. The ANOVA results presented below show that the model lacks statistical significance. Therefore, the null hypothesis cannot be rejected.

The multiple *R*-value of 0.167 (**Table 4**) was associated with an *F*-value of 0.546. The *p*-value of 0.741 is higher than 0.05. With 5 and 95 degrees of freedom, the *F*-value was not statistically significant, $p > 0.05$.

Table 8:ANOVA results

	Sum of Squares	df	Mean Square	F	Sig.
Regression	0.010	5	0.002	0.546	0.741
Residual	0.355	95	0.004		
Total	0.365	100			

5.3.4. Section conclusion

Multiple regression was run to test the relationship between the dependent variable, ROA, with the independent variables (Openness ratio, DResearch, DIndustry, age and size). Both partial regression plots and a plot of studentised residuals against the predicted values assessed linearity. Residuals were independent, as assessed by a Durbin-Watson statistic of 1.924. Homoscedasticity was confirmed by visually inspecting the plot of studentised residuals plotted against the studentised predicted values. The absence of multicollinearity was verified with VIF values consistently below 10. Outliers were removed, however they did not affect the significance of the results. The normality assumption was satisfied, as indicated by the *P-P* plots.

The regression model was not statistically significant with predicted ROA, $F(5, 95)=0.546$, $p > 0.05$, adj R^2=-0.023. Thus, the model could only explain 2% of the variance of the model based on the adjusted R^2.

5.4. Hypothesis 2 testing – Inbound Open innovation

Hypothesis 2 posits that Inbound OI has a quadratic relationship with firm performance ROA. Therefore, to test the hypothesis, a non-linear regression was run on the Inbound OI variable.

The first run had the inbound OI variable and all the control variables identified in Chapter 4, the second run introduced the quadratic term.

5.4.1. Robustness

5.4.1.1. Model fit and test for independence

The independent variables in the model account for 7.4% of the variance in ROA. The residuals were independent, as assessed by a Durbin-Watson statistic (**Table 9**) of 1.921. Therefore, this indicates that there is no significant trend in the model's output.

Table 9: Model summary

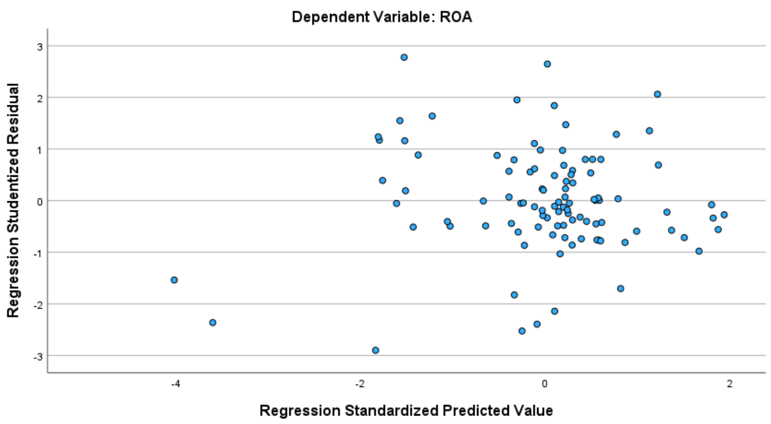
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
2	0.272	0.074	0.015	0.0599633	0.031	3.108	1	94	0.081	1.921

The introduction of the squared inbound OI term had some effect on Model 2, with an *R*-square change of 3.1%.

5.4.1.2. Test for Outliers and Homoscedasticity

A visual check of the scatterplot shows that no residuals fall outside of ±3 units of the graph. Therefore, based on **Figure 15**, there are no major outliers. Furthermore, there is no particular shape to the spread of residual, supporting the position that there is no heteroskedasticity. This is consistent with the results based on the Durbin-Watson statistic above. This further confirmed that there was no significant correlation in the model.

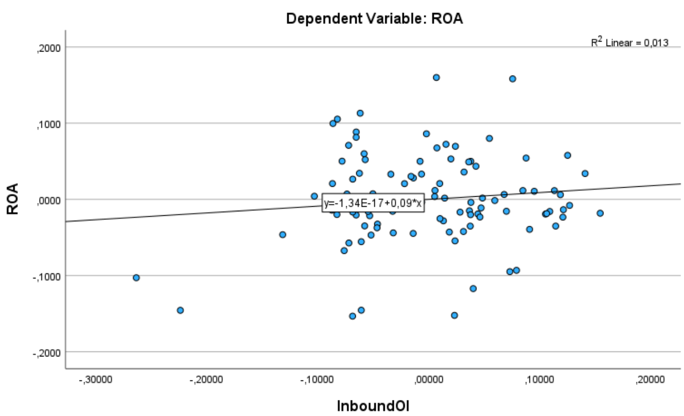
Figure 15: Scatterplot*s*



5.4.1.3. Partial regression plots on the dependent variable

According to the graph below, Inbound OI and ROA exhibit a a low positive partial correlation between the predictor and firm performance. Therefore, Inbound OI contributes somewhat to performance.

Figure 16: Inbound OI partial regression plot



According to **Figure *17***, Model 2 shows that the square of Inbound OI had a low negative partial correlation with firm performance. Thus, the variable could marginally explain firm performance.

Figure 17: Squared Inbound OI partial regression plot

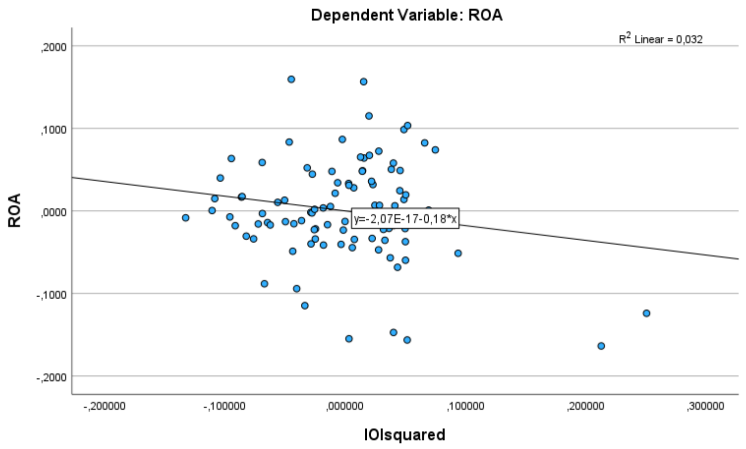


Figure 18 below shows the interaction of performance, with the dummy variable DResearch. The fitted line shows a low positive partial correlation between the variables. The predictor variable can be used to marginally explain ROA.

Figure 18: DResearch partial regression plot

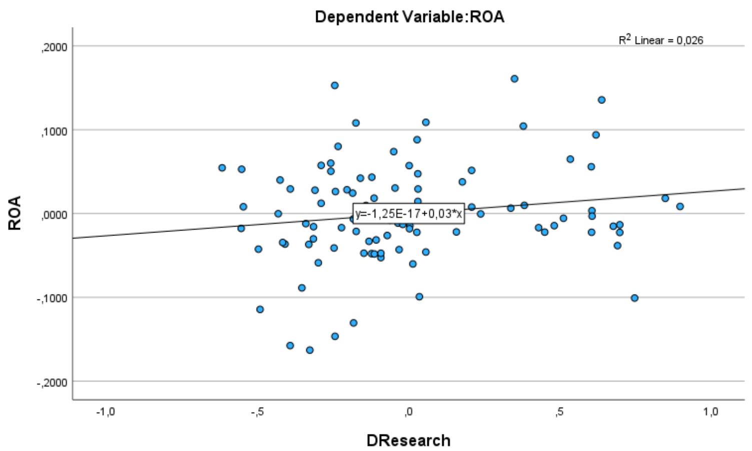
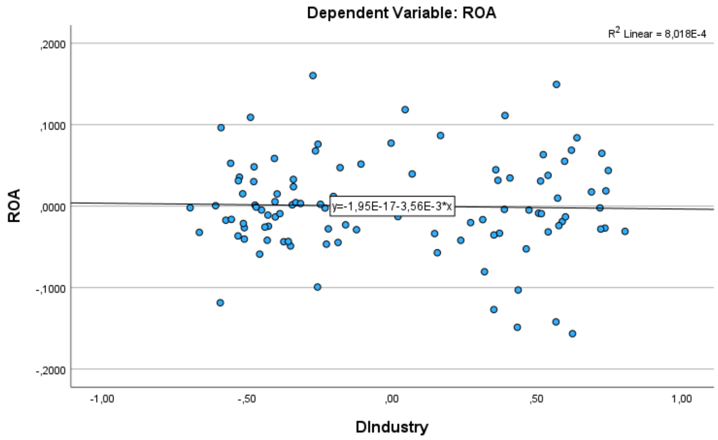


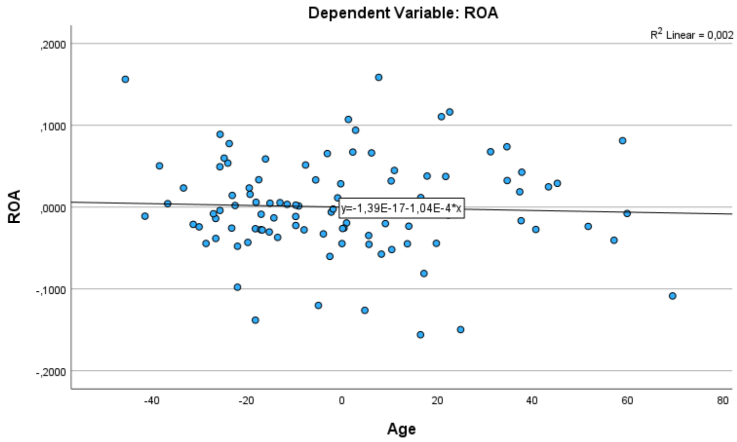
Figure 19 below shows the interaction of performance with the dummy variable, DIndustry. The fitted line shows a very low negative partial correlation between the DIndustry and ROA. This indicates that DIndustry contributes very little to explain the predicted variable.

Figure 19: DIndustry partial regression plot



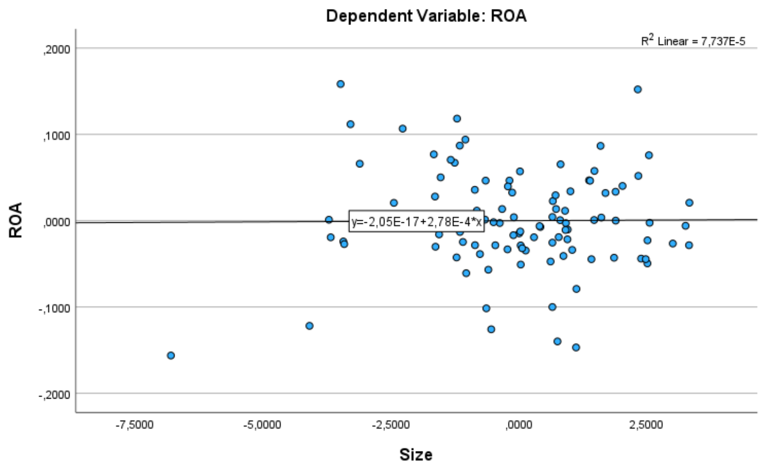
Age (**Figure *20***) has a low negative partial relationship with ROA. Therefore, firm age can be marginally used to explain the performance.

Figure 20: Age partial regression plot



Firm size had a very low positive partial correlation with ROA as seen below. The predictor variable cannot substantially explain the predicted variable to any significant extent.

Figure 21: Size partial regression plot



5.4.1.4. Multicollinearity test

The absolute values in the second column of the table below reveal generally weak correlations between the dependent variables and each predictor variable, except for the relationship between inbound OI and squared Inbound OI. However, this was expected as one is the square of the other and can be ignored in this model. Multicollinearity arising between independent variables should be addressed, however, where predictor product terms are involved (x^2, xy, etc), multicollinearity between the product terms is not considered a problem (Disatnik & Sivan, 2016).

The predictor variable Inbound OI^2 (IOI_squared) exhibited the highest correlation coefficient of -0.200 with the dependent variable. Size had the lowest correlation coefficients to ROA. As the absolute values of the correlation coefficients of the predictor variables are generally low (below 0.500), aside from Inbound OI and squared Inbound OI, this indicates low to no multicollinearity.

Table 10: Pearson correlations

Model 2	ROA	InboundOI	DResearch	DIndustry	Age	Size	IOI_squared
ROA	1,000						
InboundOI	-0,171	1,000					
DResearch	0,028	0,417	1,000				

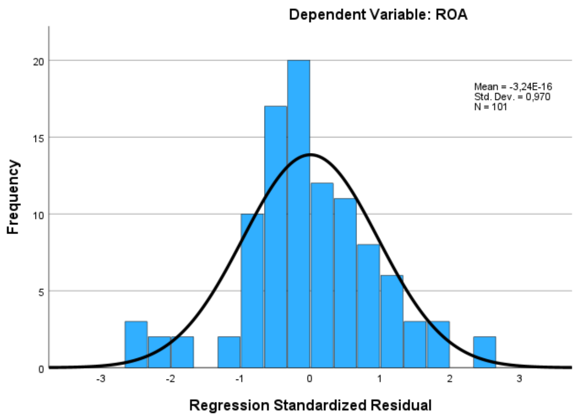
DIndustry	0,003	-0,065	0,265	1,000			
Age	0,024	-0,025	0,185	0,220	1,000		
Size	0,058	-0,112	0,154	0,041	0,339	1,000	
IOI_squared	-0,200	**0,966**	0,469	-0,026	-0,068	-0,118	1,000

A look at the VIF values for the model (**Table 11**) aligns with the correlation results above. Except for Inbound OI and squared Inbound OI variables, all the predictor VIF values were below 1.900. This further supports the position that the model does not exhibit multicollinearity.

5.4.1.5. Checking for Normality

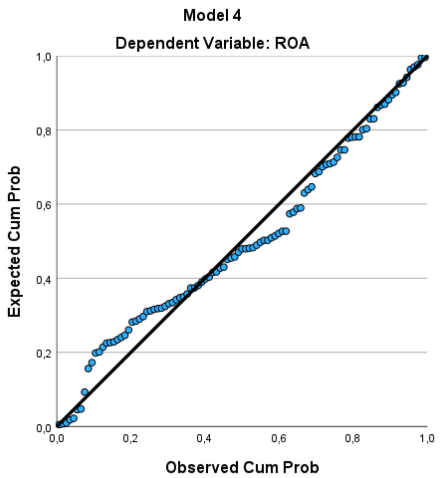
Figure *22* shows that the standardised residuals appear to be approximately normally distributed. The mean and standard deviation are approximately zero and one, respectively.

Figure 22: Histogram standardised residuals



To further confirm normality, the *P-P* plot was also produced in **Figure *23***. The plot shows that the residuals are approximately distributed along the regression line. Therefore, it supports the position that the distribution of residuals is approximately normal for both models.

Figure 23: P-P plot standardised residuals



5.4.2. Coefficients

The standardised coefficients (Beta column in ***Table 11***) show that Inbound OI (24.6%) had the strongest relationship. The R&D variable had the weakest (-5.3%).

Table 11*:* Coefficients

	Unstandardised Coefficients		Standardised Coefficients		Sig.	Collinearity Statistics	
Model 2	**B**	**Std. Error**	**Beta**	**t**	**Tolerance**	**Tolerance**	**VIF**
(Constant)	0.047	0.074		0.635	0.527		
InboundOI	0.089	0.079	0.450	1.123	0.264	0.061	16.322
DResearch	0.027	0.017	0.198	1.591	0.115	0.637	1.569
DIndustry	-0.004	0.013	-0.030	-0.275	0.784	0.853	1.172
Age	0.000	0.000	-0.048	-0.428	0.670	0.787	1.270
Size	0.000	0.003	0.009	0.085	0.932	0.843	1.186
IOI_squared	-0.178	0.101	-0.730	-1.763	0.081	0.057	17.414

Inserting the coefficients into the linear regression model yields the following equations:

Unstandardised equation

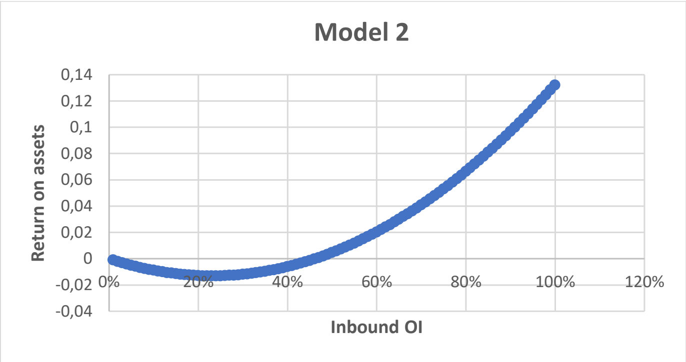
ROA = 0.047 + 0.089 *InboundOI* + 0.027*DResearch* – 0.004*DIndustry* - 0.000*Age* + 0.000*Size* - 178*InboundOI*^{2}`

Standardised equation

ROA = 0.450*InboundOI* + 0.198*DResearch* – 0.030*DIndustry* - 0.048*Age* + 0.009*Size* - 0.730*InboundOI*^{2}

Based on the standardised equations and ignoring the impact of control variables produces the graph below:

Figure 24: Curve plots inbound innovation



Model 2 presented with an inverted U-Shaped curve with a turning point at approximately 37%.

5.4.3. ANOVA Results

The ANOVA results below show that the model is not statistically significant. Therefore, the null hypothesis is accepted. R^2 value of 0.074 was not statistically significant, $F(6,94) = 1.248$, $p > 0.05$.

Table 12: ANOVA results

	Sum of Squares	df	Mean Square	F	Sig.
Regression	0.027	6	0.004	1.248	0.289
Residual	0.338	94	0.004		
Total	0.365	100			

5.4.4. Section Conclusion

Multiple regression was run to test the relationship between the dependent variables, ROA, with the independent variables (Inbound OI, Squared Inbound OI, DResearch, DIndustry, age and size). Linearity was evaluated using partial regression plots and a plot of studentised residuals against predicted values. Residual independence was confirmed with a Durbin-

Watson statistic of 1.921. Homoscedasticity was observed through visual examination of a plot depicting studentised residuals against standardised predicted values. Multicollinearity was not evident, as indicated by VIF values consistently below 10, with the exception of the correlation between Inbound OI and squared Inbound OI. The assumption of normality was met, as assessed by a *P-P* Plot.

The quadratic term coefficients were negative, thus, the model confirmed an Inverted-U quadratic shape between inbound OI and ROA. The correlation coefficients were not significant. Therefore, H2 is not supported.

5.5. H_3 testing – Outbound Open innovation

Hypothesis 3 posits that Outbound OI has a quadratic relationship with firm performance. Therefore, to test the hypothesis, a non-linear regression was run on the Outbound OI variable.

5.5.1. Robustness

5.5.1.1. Test for independence

1.0% of the variability in ROA is attributable to the independent variables as seen in the *R*-square statistic in the model summary below.

Table 13: Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
3	0.098	0.010	-0.054	0.0620052	0.001	0.129	1	94	0.721	1.897

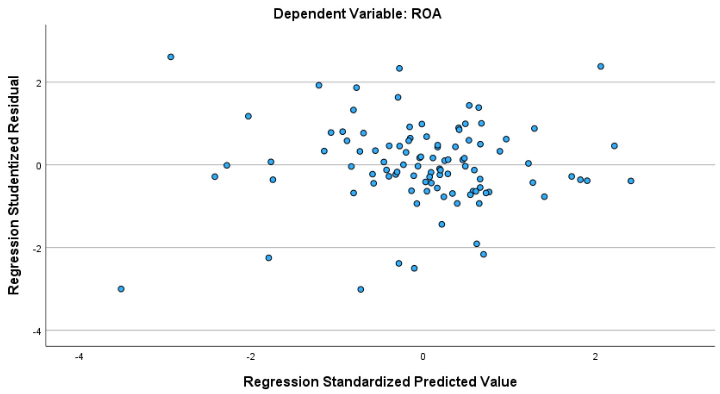
Residuals were independent, as assessed by a Durbin-Watson statistic (**Table 13**) of 1.897. Therefore, this indicates that there is no significant trend in the model's output. The introduction of the squared outbound OI term had little to no effect on the models, with an R-square change of 0.1% in the model. Therefore, the squared terms were not statistically significant in the model.

5.5.1.2. Test for Outliers and Homoscedasticity

A visual check of the scatterplot shows that no residuals fall outside of ±3 units of the graph. Therefore, based on **Figure 25**, an outlier would not be an issue in either model.

Furthermore, there is no particular shape to the spread of residual, supporting the position that there is no heteroskedasticity. This aligns with the conclusion drawn from the Durbin-Watson statistic, confirming the absence of significant autocorrelation in the model.

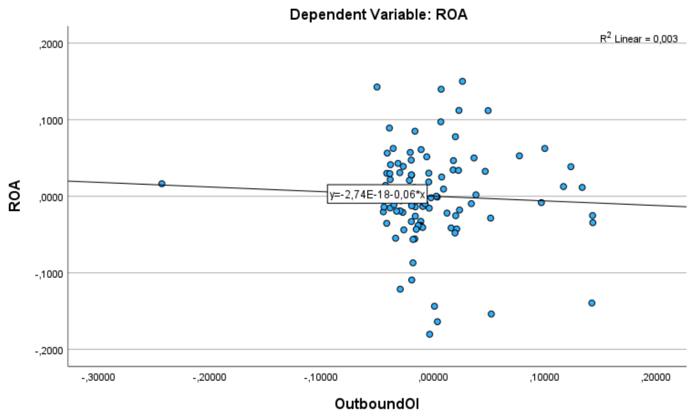
Figure 25: Scatterplots



5.5.1.3. Partial regression plots on the dependent variable

According to **Figure 26** Outbound OI and ROA exhibit a low negative partial correlation. The graph illustrates a linear relationship between the two variables. Therefore, Outbound OI does not contribute significantly to explaining the financial performance of the firm.

Figure 26: Outbound OI partial regression plot



According to **Figure 27**, the square of Outbound OI had a low positive partial correlation with firm performance. The variable could marginally explain firm performance.

Figure 27: Squared Outbound OI partial regression plot

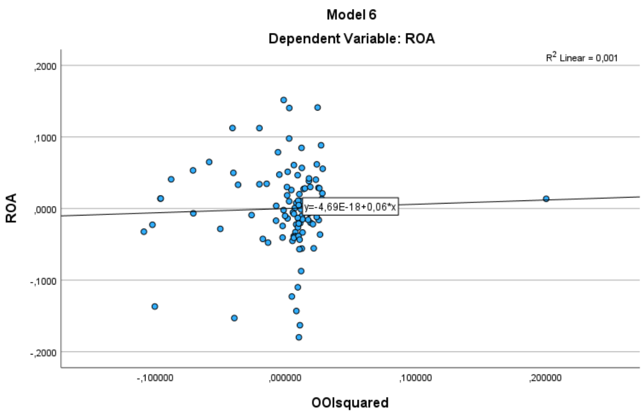


Figure 28 below shows the interaction of performance with the dummy variable DResearch. The fitted line shows a slightly positive partial correlation between the variables. The predictor variable is of very limited value to explain performance.

Figure 28: DResearch partial regression plot

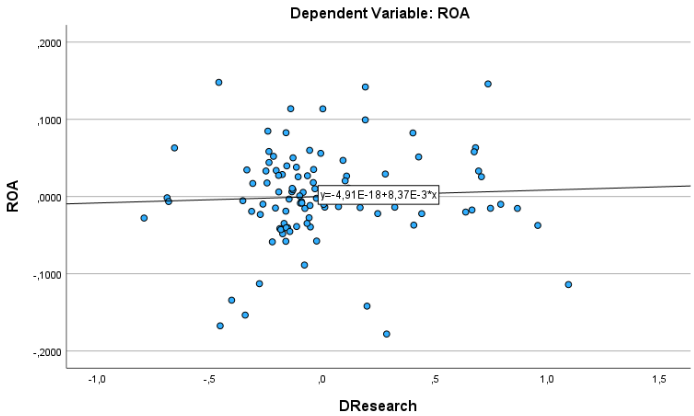
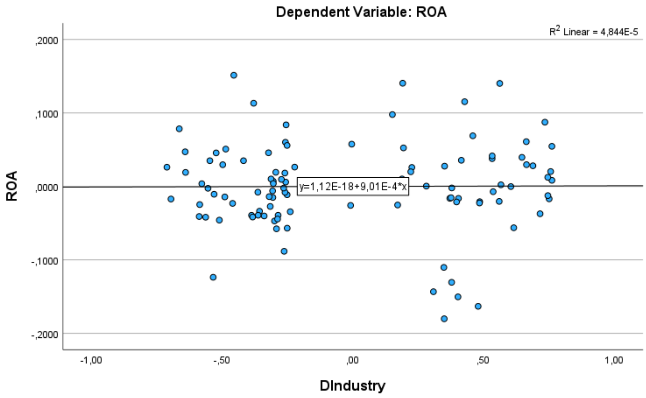


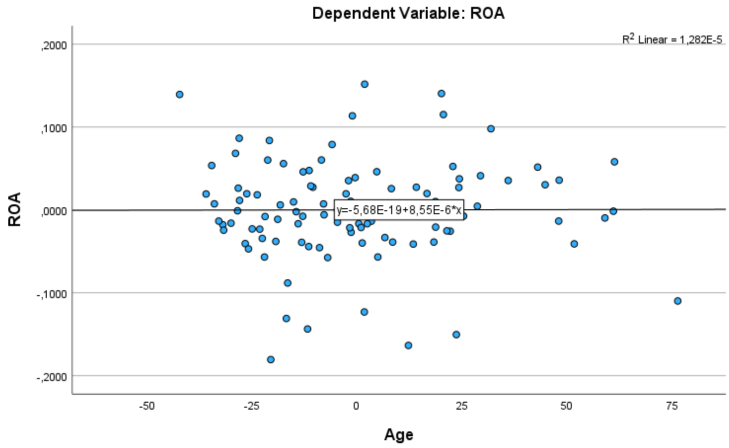
Figure 29 below shows the interaction of performance with the dummy variable, DIndustry. The fitted line exhibits extremely low positive partial correlation. This indicates that the DIndustry was of no value in predicting ROA.

Figure 29: DIndustry partial regression plot



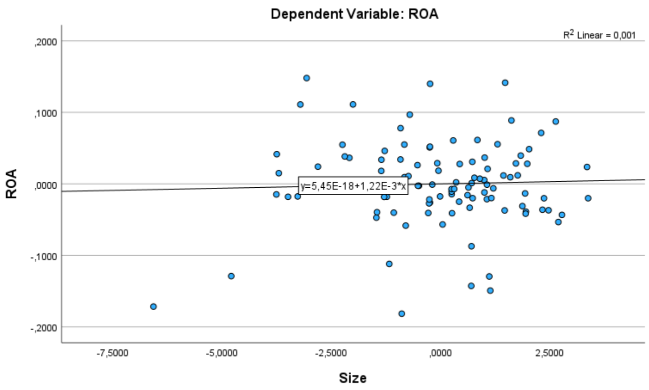
The table below shows that age had a very low positive partial relationship with ROA. Therefore, the predictor is of little to no value in explaining performance.

Figure 30: Age partial regression plot



Firm size had a very low positive partial correlation with ROA, as seen in the graph below Size cannot be used to explain ROA to any significant extent.

Figure 31: Size partial regression plot



5.5.1.4. Multicollinearity test

The absolute values in the second column indicates moderately low correlations between the dependent variable and the independent variables, except for the relationship between Outbound OI and squared Outbound OI. The predictor variable size (0.058) had the highest correlation coefficient with ROA, with Outbound OI^2 having the second highest correlation coefficient with the dependent variable of -0.049. As the absolute values of the correlation coefficients of the predictor variables are all below 0.600, aside from Outbound OI and squared Outbound OI, this indicates low to no multicollinearity.

Table 14: Pearson correlations

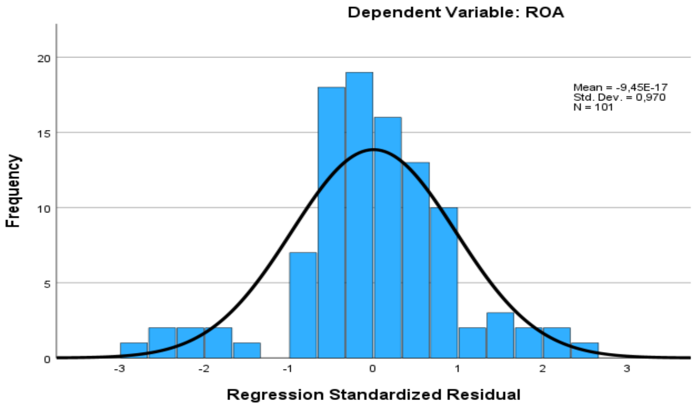
	ROA	OutboundOI	DResearch	DIndustry	Age	Size	OOI_squared
ROA	1.000						
OutboundOI	-0.049	1.000					
DResearch	0.028	0.540	1.000				
DIndustry	0.003	0.215	0.265	1.000			
Age	0.024	0.120	0.185	0.220	1.000		
Size	0.058	-0.068	0.154	0.041	0.339	1.000	
OOI_squared	-0.041	**0.984**	0.535	0.183	0.133	-0.064	1.000

A look at the VIF values aligns with the correlation results above. Except for Outbound OI and squared Outbound OI variables, all the predictor VIF values were below 2.00. This further supports the position that the model does not exhibit multicollinearity.

5.5.1.5. Checking for Normality

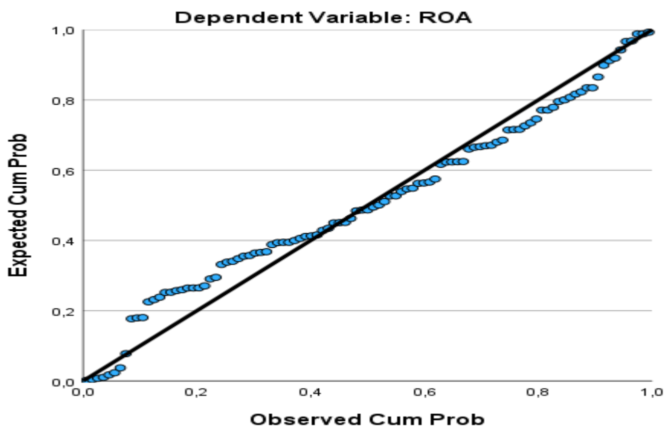
Figure *22* shows that the standardised residuals appear to be approximately normally distributed. The mean and standard deviation are approximately zero and one, respectively. While the histogram shows that the residuals do not have a standard normal distribution for both models, the graph shape still fits the normal curve.

Figure 32: Histogram standardised residuals



To further confirm normality, the *P-P* plots were also produced in **Figure 33**. the plot shows that the residuals are approximately distributed along the regression line. Therefore, it supports the position that the distribution of residuals is approximately normal.

Figure 33: P-P plot standardised residuals



5.5.2. Coefficients

Based on the results in **Table 15**, the most significant predictor is the Outbound OI variable. The standardised coefficients (Beta column in **Table 15**) show that the Outbound OI (-28.7%) had the most impact, and firm age had the least impact (0.40%).

Table 15*:* Coefficients

	Unstandardised Coefficients		Standardised Coefficients		Sig.	Collinearity Statistics	
	B	**Std. Error**	**Beta**	**t**	**Tolerance**	**Tolerance**	**VIF**
(Constant)	0.022	0.075		0.291	0.772		
OutboundOI	-0.060	0.123	-0.287	-0.491	0.625	0.031	32.417
DResearch	0.008	0.017	0.062	0.490	0.626	0.649	1.540
DIndustry	0.001	0.013	0.007	0.067	0.946	0.858	1.165
Age	8.553E-06	0.000	0.004	0.035	0.972	0.820	1.219
Size	0.001	0.003	0.040	0.361	0.719	0.839	1.192
OOI_squared	0.060	0.166	0.208	0.359	0.721	0.031	32.013

The regression model equations can be written as follows:

Unstandardised equation

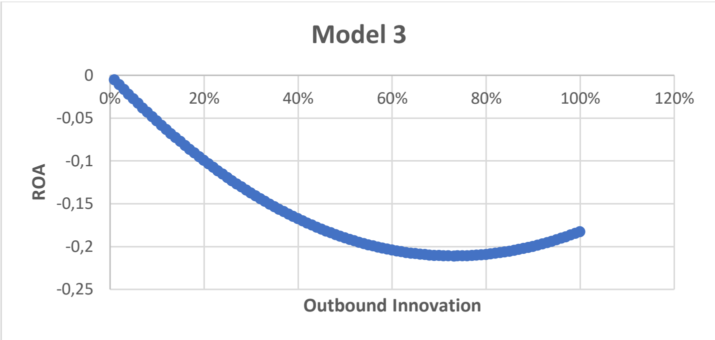
ROA = 0.022 – 0.060*OutboundOI* + 0.008*DResearch* + 0.001*DIndustry* + 0.855^{-06}*Age* + 0.001*Size* + 0.060*OutboundOI*^{2}

Standardised equation

ROA = -0.287*OutboundOI* + 0.062*DResearch* – 0.007*DIndustry* + 0.004*Age* + 0.040*Size* + 0.208*OutboundOI*^{2}

The model presented with a U-shaped curve, however and had a turning point within the data at approximately 69.2%.

Figure 34: Curve plots outbound innovation



5.5.3. Analysis of variance (ANOVA)

The ANOVA results below show that the model is not statistically significant. Therefore, the null hypothesis cannot be rejected. R^2 value of 0.010 was not statistically significant, $F(6,94) = 0.152$, $p>0.05$.

Table 16: ANOVA results

	Sum of Squares	df	Mean Square	F	Sig.
Regression	0.004	6	0.001	0.152	0.988
Residual	0.361	94	0.004		
Total	0.365	100			

5.6. Robustness

To validate the reliability of the findings, additional analysis was performed using a second performance variable, return on equity (ROE). The results of the regression run are set out in Annexure 3, and once again, they showed that all the hypotheses were not supported. The results were not significant for any of the OI variables being investigated.

5.7. Summary

All three hypotheses were not significant at the 5% percent level. None of the predictor variables showed any statistical significance ROA in all 3 models.

Results for Hypothesis 1 indicated that openness did not have a positive association with firm performance. To ensure that there was no curvilinear association between openness and the performance variables, the square of the predictor was added to the model. The model fit improved, with an R-square change of 3.4%. Therefore, there was support for the position that openness had a quadratic relationship with firm performance.

Hypothesis 2 tested for a curvilinear relationship between inbound OI and firm performance. The standardised beta coefficients for the squared terms show the presence of a curvilinear relationship (β = -0.730, p > 0.05). The model inferred an inverted U-shaped relationship between inbound OI and ROA, however, it was not statistically significant and Hypothesis 2 was rejected.

Finally, Hypothesis 3 also tested for a quadratic relationship between outbound OI and firm performance. The standardised beta coefficients, for the squared term show the presence of a curvilinear relationship (β = 0.208, p > 0.05). The model was also not statistically significant. Consequently, it can be inferred that outbound OI does not emerge as a statistically significant predictor of firm performance and Hypothesis 3 is unsupported.

6. Discussion

The results presented in Chapter 5, alongside the existing literature, will be discussed in this chapter. As the literature showed that other studies had observed a relationship between OI practises and performance in other contexts, this research utilised South African public companies to determine if similar relationships could be confirmed. The hypothesis will be discussed in the order it was set out in the previous chapter. The results of the regression modelling were as follows:

1. **Hypothesis 1:** The results indicated that openness did not have a positive association with performance. This result did not align with the hypothesis, which was not significant at the 5% level.
2. **Hypothesis 2:** The model yielded non-significant results regarding the relationship between inbound innovation and firm performance at the 5% level**.** The results showed that the relationship between inbound OI and performance could not be explained using an inverse U-shaped curve. The hypothesis was not supported by the data gathered in this study.
3. **Hypothesis 3:** The results did not show support for a U-shaped relationship between outbound OI and firm performance. The introduction of the squared term led to a non-significant R-square change, this does lead to the question of whether a non-linear relationship was appropriate, as the introduction of the squared term was not significant.

Furthermore, all the control variables did not show a significant relationship with performance in any of the regression models and were of no to little value in explaining performance**.** The results were not in line with the hypotheses, and several factors may have contributed to the non-significance of the results, including the data itself, the methodology utilised, and context-specific circumstances unique to South Africa.

The next sections provide a comprehensive analysis of the results of the research question and its hypotheses. This will provide an understanding of the findings within the study context and in terms of the underlying theory.

6.1. Background to study

Open innovation (OI) has become a requirement for modern businesses to succeed, providing a more competitive edge (Dahlander et al., 2021; Gao et al., 2020). The modern business environment requires firms to respond quicker to market changes in a very complex environment characterised by rapid improvements in technology and shorter product development cycles (Chaudhary et al., 2022). A large number of empirical studies have been carried out in developed countries (Audretsch & Belitski, 2023; Caputo et al., 2016; Laursen &

Salter, 2006; Lu & Chesbrough, 2022; Schäper et al., 2023) and some developing countries such as China (Fu et al., 2019; Wang et al., 2020; Wang & Jiang, 2020; Zhou et al., 2019) and Brazil (Bogers, Burcharth, et al., 2019; de Oliveira et al., 2018; Scaliza et al., 2022). A review of the available literature shows that there are very few studies based on the African context (Dilrukshi et al., 2022), in particular in South Africa. It has been acknowledged that there is a need for more studies in developing countries to add to the body of knowledge on the subject. Therefore, there is a need for more studies that are relevant to Africa.

A considerable volume of literature emphasises the advantages of OI, pointing out that it improves business competitiveness and assists with survival in the long term (Brunswicker & Chesbrough, 2018; Hutton et al., 2021; Scaliza et al., 2022; Teece, 2020). OI has been proven to not only improve innovation performance but firm performance as well. Ogink et al. (2023) highlighted that OI practises influence performance and value through their impact on firm capabilities. By being more open, a firm develops strategies to deal with the information flows that will increasingly cross its boundaries. Its capabilities adapt and improve to utilise the knowledge that is being gathered or shared externally. Therefore, its very structure should become more geared to being innovative. In light of the continued digitalisation of the world and globalisation, there is an increased connection with external parties to find solutions for problems (Bogers, Chesbrough et al., 2019).

However, not all studies have concluded that OI practises are beneficial (Chaudhary et al., 2022; Dahlander et al., 2021; Ovuakporie et al., 2021; Teece, 2020; Zhu et al., 2019). There are costs associated with OI, and investment in OI does not guarantee returns given that there may be a lag between investment and actually achieving returns on that investment. As a firm becomes more open, it may expose valuable internal knowledge or resources to its competitors, thereby empowering them and making itself less competitive (Ovuakporie et al., 2021). Loss of IP not only affects the future earning potential of a firm but also makes it weaker. Therefore, there are risks with being open and they would need to be mitigated in order to fully enjoy OI benefits. Mitigating risks comes with additional costs and these have to be measured against the benefits derived from OI. Studies have also shown that over-search is a potential issue where the information gathered is so much that the resources, skills and time required to sift through all the noise to identify valuable insights and resources would negatively impact OI. An organisation itself may have to adapt to become one that can effectively use OI. This may require changes in management styles and decision-making processes. Change management becomes a key process to ensure alignment throughout the organisation and combat issues such as Not Invented Here (NIH) (Bogers, Burcharth & Chesbrough, 2019). Thus, the benefits of OI can be very firm specific, with differing results between industries and firms. Furthermore, they may not work in low-technology situations and may not be appropriate (Bogers, Chesbrough et al., 2019).

There is a substantial body of literature that has explored the relationship between openness and performance as measured by various metrics (Chesbrough & Bogers, 2014; Greco et al., 2019; Hameed et al., 2021; Laursen & Salter, 2006; Michelino et al., 2015; Scaliza et al., 2022; Singh et al., 2021). OI could be split into inbound, outbound and coupled factors that measure the amount of external knowledge that is internalised and how much internal knowledge is shared in the market (Chesbrough & Bogers, 2014). Furthermore, multiple OI practices have been utilised to determine openness measured against multiple measures of innovation and financial performance.

From these studies, various degrees of OI practises have been found to be beneficial or detrimental to the financial performance of the firm. Therefore, the results strongly suggest that they may be context specific. Studies that have looked at the relationship between OI and performance have reached various conclusions, with some studies finding a positive relationship (Bogers, Burcharth & Chesbrough, 2019; Singh et al., 2021), a negative association (Lu & Chesbrough, 2022), others a non-linear relationship (Caputo et al., 2016; Lu & Chesbrough, 2022; Schäper et al., 2023; Zhou et al., 2019) and no relationship at all (Mazzola et al., 2016). The differences in findings can be attributed to the firm's ability to utilise and convert OI practises into actual value. Some do it better than others. Very few studies have focused on coupled innovation (Ovuakporie et al., 2021; Teece, 2020). This study was limited to looking at openness as well as inbound and outbound innovation, with coupled innovation not a focus of this study as well.

Despite the amount of focus on OI, there have been mixed findings, and as a result, there is a lack of clarity in understanding OI's impact on financial performance. Therefore, it is clear that there are research gaps relating to developing countries and how open innovation activities impact performance.

6.2. Hypotheses

6.2.1. Hypothesis 1

Contrary to the generally established position that OI has a positive association with firm performance (Fu et al., 2019; Moretti & Biancardi, 2020; Zhang et al., 2018), openness did not show a direct relationship with firm performance for South African firms based on the results of this research. This was an unexpected result as the general consensus had been that openness had a positive relationship with performance. This was contrary to previous studies that showed that openness had a positive impact on both innovation and financial performance

(Moretti & Biancardi, 2020) or an inverted relationship (Laursen & Salter, 2006; Noh, 2015; Zhang et al., 2018).

This study showed that openness had a non-significant relationship with financial performance. However, the results were supported by some studies that determined that openness did not have a significant impact on firm performance (Caputo et al., 2016). This outcome can be potentially attributed to several factors, with a primary one being that the expenses associated with embracing openness may not be recouped in the short term. This is particularly relevant considering that a significant portion of innovation spending is directed towards machinery and technology in South Africa (CeSTII, 2020). The period required to recover these costs is likely to extend beyond three years, which was the research time period for this study, indicating that the positive outcomes of such efforts will only manifest in the more distant future. Hence, the observed result is not unrealistic, as the underlying rationale appears to be logical.

Zhang et al. (2018) identified an inverse U-shaped relationship between OI and profitability (measured by Return on Equity). Their results were consistent with findings from other scholars (Fu et al., 2019). The difference in findings between this study and previous scholars may be attributed to differences in contexts and variables. The aforementioned studies were based in China and looked at a singular industry. Their sample population was more homogeneous than the sample for this study, which looked at 10 industries. Furthermore, China is a very different economic market compared to South Africa. The sheer volume of firms in the Chinese context may mean a more competitive environment that requires more innovation compared to the South African market. Studies have shown that firms are more likely to be open and gain benefits from such openness in highly competitive environments (Bigliardi et al., 2020).

Lu and Chesbrough's (2022) study determined an overall positive association of open innovation practises with performance. However, their results also highlighted that not all open innovation practises exhibited the same relationship performance. Contracting and IP-related activities had a weak positive association with performance, in contrast, partnerships and joint-venture activities had a significantly negative association with performance (Lu & Chesbrough, 2022). It must be noted that this study utilised financial figures relating mainly to contracting, intellectual property and joint venture activity. Based on this, there should have been a more significant relationship, and, interestingly, it was not. This merits further research. Therefore, the particular makeup of the openness variable might have a direct bearing on the relationship with performance.

It must be noted that the absence of a relationship between openness and firm performance is also supported in the plan literature, with some studies finding that there was no significant relationship between openness and financial performance (de Oliveira et al., 2018). Based on their study, de Oliveira et al. (2018) ascertained that while openness had a positive relationship with innovation performance, the reverse was true when it came to financial performance. This was attributed to innovation not translating into value creation and, hence, not translating into financial performance.

However, based on the findings of similar studies, a more plausible explanation may be the lower degree of overall openness of South African firms, with most innovating through the purchase of equipment (CeSTII, 2020). Thus, the type of innovation activities carried out could have a bearing on the impact of OI.

6.2.2. Hypothesis 2

The data suggested that there was no direct relation between inbound OI and firm performance, rejecting the hypothesis that there was an inverted U-shaped relationship. This was unexpected as the hypothesis was based on the supposition that as a firm increases inbound innovation, there should be a point beyond which the costs incurred outweigh the benefits. This position would align with general economic theory, the law of diminishing returns. The benefits gained from increasing levels of inbound OI should become proportionally smaller as more money is invested in such practices. However, the results of the study failed to show support for this relationship for the public companies in South Africa. This was contrary to a study carried out by Fu et al. (2019), who established support for a U-shaped relationship. Lu and Chesbrough (2022) also supported this finding using different research methods. However, their research also observed that inbound innovation activities do not uniformly influence performance. Some innovation practices may have a negative impact, others a positive impact, and some may have no discernible effect at all (Lu & Chesbrough, 2022; Mazzola et al., 2016). Consequently, there is a need to better understand better how different inbound innovation practices affect financial performance.

Therefore, the lack of support for the hypothesis is not without merit. The research did not investigate the relationship of the individual components of inbound innovation with performance, instead using a high level measure that incorporated the identified practises into a single measure. Some studies have even shown that some inbound OI activities may have a discordant impact on financial performance, i.e., one practice may positively impact innovation performance, but another would negatively impact financial performance (Mazzola et al., 2016). Lu and Chesbrough (2022) revealed that contracting and IP-related activities actually had a weak positive association with performance, while joint-venture related activities had a negative effect and practise involving collaboration had no impact. Furthermore, their study determined that partnerships and joint-venture activities had a significantly negative association with performance. They also found that certain OI activities could have complementary or substitution effects with each other. However, other studies concluded that the purchase and selling of certain IPs, as well as involvement in joint ventures, had no impact on financial performance (Mazzola et al., 2016). Consequently, the effects of the individual inbound practices may have been muted due to a potential cancelling out effect. As set out in Chapter 4, the calculation of the inbound innovation metric was heavily weighted towards the purchase of intangible assets, including patents, trademarks, and software development costs, which Lu & Chesbrough (2022) observed to have a weak association with performance.

It must be noted that extant literature has been inconclusive when it comes to the association between inbound innovation and financial performance. The correlation between inbound open innovation (OI) and financial performance could be contingent on the specific performance metric employed, along with the chosen open innovation measurement. Different measures of financial performance may give different results for the same innovation measures in different studies.

6.2.3. Hypothesis 3

The study did not find a significant relationship between outbound OI and financial performance therefore, the hypothesis was rejected. Unlike inbound innovation, the study was looking for a U-shaped relationship with performance, which could not be proven. However, this is contrary to empirical studies that have shown that there is a quadratic or U-shaped relationship between outbound OI and performance. Fu et al. (2019) uncovered a U-shaped relationship between outbound OI and performance in the longer term, however, the results were reversed in the short term. Their study highlighted that outbound OI was expected to have a negative correlation with performance in the short term, however, over time and at higher levels of OI, this trend was reversed and performance improved. This was in line with the findings from Caputo et al. (2016), who also identified a U-shaped relationship, however, their study highlighted that only the decreasing portion of the curve was evident in the data range. Those results support the view that benefits from outbound OI benefits are experienced at high levels of activity. Oltra et al. (2018) highlighted that even though outbound innovation practices had a positive association with performance, not many firms actually participated in such practices. This was in line with the findings from this research as not all firms had an outbound innovation measure, supporting the view that outbound OI activities were not as prevalent in South Africa and the levels at which they were practised were low. Additionally, this study found that South African public companies had a very low average outbound innovation ratio of 17.6%, with half the firms from the sample not having an outbound innovation metric of zero. Based on the literature, those levels are too low to start enjoying the benefits of outbound OI. Therefore, the hypothesis that there is a relationship between outbound OI and performance may have been unsubstantiated due to levels of innovation activity being very low. The low levels of outbound activity could be ascribed to the weak institutional context of South Africa. Outbound OI flourishes in an arena with strong IP rights. This is covered further in the chapter.

Furthermore, it has been acknowledged that it can take a long time to develop outbound innovation through such activities as patents and IP (Fu et al., 2019). Costs would be incurred upfront and it would take some time to develop, register and finally sell such innovations. Furthermore, there are costs incurred in safeguarding the output from outbound OI. Therefore, the actual realisation of value from outbound activities would only occur much further in the future. Therefore, it is important to understand how the time horizon has an impact on understanding the relationship between outbound OI and performance. The lead time for intangible assets can be quite long. This research was based on the period between 2016 and 2018 for public firms in South Africa, which would be a very short period when one considers how the time it would take from ideation to development and finally sale of IP. Therefore, although the hypothesis was disproved, this could be related to this being a cross-sectional study. A longer time frame might have yielded different results. Therefore, future studies could

Studies have shown that knowledge sharing with external partners increases a firm's capabilities to identify valuable innovation opportunities and increase innovation performance (Bigliardi et al., 2020; Oltra et al., 2018).

6.2.4. Control variables

Of note was that none of the control variables had a significant contribution to the explanation of the variance of the dependent variable. This was unexpected as studies have shown that the control variables such as firm size, firm age and R&D usage have been useful in explaining firm performance.

A surprising finding was how few firms actually disclosed R&D expenditure, with only a quarter of the sample having a separate line item for R&D in their financial accounts. The data available was not sufficient to differentiate between internal and external R&D. Therefore, the analysis could not be broken down further, and hence, the model variable only indicated whether or not a firm had R&D expenditure. The data would suggest that investment in R&D was still very limited in South Africa in 2016 (the base year). Additionally, other researchers noticed that R&D expenditure in developing economies was not always a formal process, and as a result, it might not be reported separately in the financial accounts (Krammer & Kafouros, 2022). This had a major impact on the calculation of the openness and inbound OI measures, likely understating the overall values and impacting the reliability of the model. Firms that utilise R&D are expected to be more competitive in the market and, hence, perform better (Coluccia et al., 2020). This is in line with a number of scholars who determined that R&D expenditure had a positive impact on performance.

Firm size was controlled for as it might affect the flexibility of the firm and its willingness to innovate. The larger the firm becomes, the slower it is expected to innovate and it is also associated with lower growth prospects (Schäper et al., 2023; Zhou et al., 2019). However, other scholars were of the position that as a firm grows, it will have more access to resources and invest in innovative activities (Bagherzadeh et al., 2020). Therefore, as a firm grows, its innovation performance, and ultimately financial performance, should also grow. Different studies have used different measures of determining firm size, e.g., the number of employees (Bagherzadeh et al., 2020; Lu & Chesbrough, 2022) and average annual income (Fu et al., 2019). However, Caputo et al. (2016) observed conflicting results on the relationship of firm size when sales growth was the dependent variable, firm size and firm age were not significant in their model. This was contrary to the results when Asset turnover and closed EBIT per employee were used, and firm age and size had a positive linear relationship with performance (Caputo et al., 2016). Therefore, it could be implied that the selection of the dependent variable has a bearing on the relationship with age and size.

6.3. Key considerations

As the results of the research were not significant and the hypotheses were not supported, there may be alternative explanations as to why this happened. This section outlines plausible reasons that may explain the findings in Chapter 5.

6.3.1. Open innovation practices

There is an accepted definition of OI practice as set out by Chesbrough and Bogers (2014). However, there have been an increasing number of concepts around how OI can be measured. A commonly acknowledged constraint is that measuring innovation is a challenging task. The body of literature has grown around the factors to be considered when researching OI practices. Lu and Chesbrough (2022) used content analysis to identify six OI topics, concluding that some OI practices had an inverted U-shaped relationship with performance. Schäper et al. (2023) carried out a similar study to calculate an innovation score based on nine very different topics from those identified by Lu and Chesbrough (2022), arriving at an S-shaped relationship between OI and performance. Even though their data dictionaries were very different, they were both attempting to find a way of measuring OI using text-based methods. Other studies have based OI practises on R&D expenditure, IP development including patent activities, and collaboration with external partners. Based on the presence of ambiguity in defining OI practises has a notable effect on research examining the correlation between OI and financial performance. With most studies, the focus has been on a particular aspect of OI rather than consistently using the same measures or factors. The sheer diversity of the measures of OI may have led to the multitude of inconsistencies that cast doubt over the reliability of the study outcomes. Therefore, further studies are required to bring more clarity to this paradigm.

6.3.2. Data differences

Even when studies have utilised the same methodology, there have been differences in the calculation of the OI variables due to contextual limitations. Caputo et al. (2016) utilised financial statements based measured to determine OI indicators for global bio-pharmaceuticals, mainly from Europe and the United States of America (USA). Fu et al. (2019) utilised a similar methodology, however, due to differences between Chinese accounting standards and IFRS/US GAAP, modifications had to be made to make it relevant to the Chinese context. The USA also utilises a 10-K form, which provides a much more detailed breakdown of financial transactions which would not be available in China. Similar modifications had to be done for the South African financials, given the level of detail that was available. While the calculation of openness was similar to the methodology utilised by Fu et al. (2019), there were differences in the underlying factors due to data limitations. As the financials of the South African companies were not as standardised as expected, the level of detail available differed from firm to firm. As a result, a number of assumptions had to be made during the research process. Where joint-venture activity was grouped with transactions from associated companies, the figures were taken as if they fully applied to joint-ventures only. This likely over-inflated the costs and income from joint ventures. Furthermore, all contracting and consulting costs were assumed to qualify as open innovation activities. Identifying revenues from OI activities was challenged by the inconsistent way in which such figures relating to royalty or IP-related income were disclosed and would likely have impacted the calculation of outbound innovation. Not all innovation-related expenditures or income were easily identifiable from the income statement, and a review of the notes in the accounts was not always helpful in clarifying the value of the transactions. This would have reduced the reliability of the predictor. The differences in the calculation of openness may explain the difference in the significance of the independent variables.

The selection of different performance measures in this study could potentially lead to different results. It would be important to understand why such a paradox exists. The use of different financial indicators has been proven to lead to different results in determining the relationship between openness and financial performance. For example, Caputo et al. (2016) established that different performance measures had different associations with openness, e.g., the asset turnover ratio tended to decrease as openness increased, while sales growth had a quadratic relationship with openness. If a singular study utilising different dependent variables can arrive at different results, this implies that the selection of the performance measure might have an impact on the final results. The perplexing connection between measures of innovation and different performance measures underscores the significance of choosing a suitable metric for assessing firm performance. Therefore, it is worth considering that the selection of the dependent variables in this study has led to the results. The selection of different dependent variables could have led to a result more consistent with the general literature. Future studies should investigate why different performance measures may lead to different results regarding the relationship with OI.

6.3.3. Research horizon

Different cross-sectional studies have used different time frames for their studies, arriving at different results. OI may not have an immediate impact on performance as the activities may take time to filter through the organisation and reach the market. Therefore, it makes sense that there should be a lag between the OI activities before a firm begins to experience the benefits and profits from the outcomes of such activities. Fu et al. (2019) determined that inbound innovation had a negative linear relationship with performance in the short-term (within one year), while an inverted U-shaped relationship was found in the longer term (three years). The exact time it would take is ambiguous as it can be very firm and market specific. Other studies have shown that innovation had long-term benefits to forms at the expense of short-term interests (Feng et al., 2021). Therefore, it is not unreasonable to infer that the time lag utilised in this research may have had an impact on the results. South Africa's innovative results often come through quality improvements and not radical innovations. Incremental improvements are unlikely to have a marked impact on performance and may not even be identifiable due to other activities. More longitudinal studies should be carried out in future.

6.3.4. South African context

It has been observed that contextual factors such as across countries and cultures, can influence research methods and hence results (Singhal et al., 2022). These factors were not considered in this research, however, their influence could potentially explain the non-significant result obtained in this thesis. Most of the studies on OI have been carried out in countries or regions which are ranked higher than South Africa (61st) on the Global Innovation Index, including the United Kingdom (4th), Europe (5 nations in the top 10), the USA (2nd) or developing nations such as China (11th) (WIPO, 2022). The report also recognised a lack of consistent improvement over time in South Africa's innovation performance.

Furthermore, different countries would be at different economic levels, and this could affect the implementation of OI (Feng et al., 2021). The South African economy only grew by 0.8% in 2018 after being hit by a recession in the first half of the year (Statistics South Africa, 2019). In 2016, the GDP grew by 0.4% and 1.4% in 2017, with very low growth rates (Statistics South Africa, 2019). Therefore, it is likely that the performance measures might have been depressed by the economic activity at the time. Developed regions would have more mature markets as well and were more likely to be working on radical innovation. In contrast, developing markets focus on cost reduction, improving product quality and frugal innovations (Krammer & Kafouros, 2022). As a result, there is some merit to the argument that expecting similar results based on a South African context might not materialise given the differences in actual innovation and economic activity.

As highlighted before, innovation surveys in South Africa established that the majority of innovative activity came through the purchase of technology and machinery. Such activity is often capital intensive, requiring several years to write off the cost, not accounting for the costs of training and implementation. Granted the up-front cost of such innovation, it might take several years before the benefits of this investment outweigh the costs incurred. Therefore, it is likely that such activity will only be recognised as beneficial several years later. The timeframe utilised in this research was only three years. A longitudinal research design might be better suited to investigate the impacts of OI, given the reality of the innovation landscape in South Africa.

Furthermore, South Africa has several weaknesses which might have impacted the innovation results. It has been noted as having a weak institutional environment, ranking low in entrepreneurship in the economy and business policies (WIPO, 2022). The differences in institutional environments of different countries have been seen to have an impact on firm performance (Feng et al., 2021; Krammer & Kafouros, 2022). Therefore, firms' innovation activity is strongly influenced by the institutional environment it exists in. Alam et al. (2019) ascertained that favourable institutional environments enable access to diverse innovation intermediaries and that such environments attract foreign investments, providing local firms with access to external finance. Given the long-term nature of investments, firms require an environment that protects their intellectual property to encourage them to invest.

Previous research has indicated substantial differences in the institutional environment between developing economies and developed nations, which influenced innovation performance (Bogers, Burcharth & Chesbrough, 2019). Krammer and Kafouros (2022) argued that there were substantial differences in the institutional environments between developing economies and developed nations, which influenced innovation performance. Furthermore, issues such as corruption increase the transaction costs of innovation requiring higher levels of R&D for lower output. On the other side, firms may be reluctant to invest in R&D and would rather invest in protecting their IP (Audretsch & Belitski, 2023). Krammer and Kafouros (2022) discerned that non-market strategies, such as the use of bribes and political connections, may need to be employed to guarantee the success of new offerings. Consequently, corruption can lead to a reduction in R&D or lead to a situation where allocated R&D is not used efficiently, negatively impacting innovation activities. Political instability has been found to have a negative effect on innovation levels (Krammer & Kafouros, 2022). The politically turbulent period covered by this research was characterised by investor unfriendly policies, a technical recession, capital flight and a downgrading of the sovereign credit rating of South Africa (Rapanye & Mgoepe, 2020). An environment that would not be conducive to innovation.

National innovation systems, shaped by institutional factors like the financial system, education, and public policy, are intricately linked to the overall innovation landscape (Alam et al., 2019). South Africa suffers from high corruption levels and has a struggling education system with a mostly unskilled labour force. Such challenges are likely to increase the transactional cost of innovation, requiring firms to invest in training to upskill their workforce. Furthermore, competition for skilled workers drives up the cost of their skills. One of the issues that was noted as negatively affecting innovation performance was the lack of innovation funding both from internal and external sources (CeSTII, 2020). South Africa lags on innovation spending. Having adequate funding is imperative for a firm to be innovative, and lack thereof might mean delays in implementing required innovation resources.

To effectively utilise OI, a firm does require sufficient resources, whether human or financial, to properly assimilate external knowledge and add value to its processes. (Ozturk-Kose et al., 2023). A major challenge highlighted in the 2014-2016 innovation survey was the lack of funding and the skills to truly be innovative (CeSTII, 2020). An argument could be made that South African firms may not yet be in a position to fully utilise the knowledge they gain from open innovation. Therefore, the benefits of OI may not be fully assimilated into the firm and not reflected in the performance metrics. Future studies should investigate if the South African context has a moderating impact on the relationship between OI and firm performance.

6.4. Summary

This study observed that the inverted U-shaped relationship between in/outbound OI and financial performance was not significant in the South African context. Furthermore, the relationship between openness and firm performance was not supported. While this study's initial hypothesis was not confirmed, it is plausible that the alternative explanations set out above could explain why this occurred. This was attributed partly to the unique South African context that experiences generally low levels of innovation and other differences from the contexts set out in the previous studies. The relationship between OI and financial performance is influenced by various factors including firm type, environment and industry, varying risk and cultural attitude, different economic contexts, different innovation types as well and different performance measures (Feng et al., 2021). Further investigations are warranted to explore these possibilities.

In the upcoming Chapter 7, the primary findings of the study will be discussed before delving into the research contributions. Following this, recommendations for management will be presented. The paper will then conclude with the limitations of the study and suggestions for future research.

7. Conclusion

This section sets out a summary of the whole research process as well as the findings from testing the hypotheses. Open innovation (OI) and its relationship with performance is one of the most researched topics in innovation studies, however, the empirical results are still inconclusive (Lu & Chesbrough, 2022; Schäper et al., 2023; Wang & Jiang, 2020; Zhang et al., 2018). Against this backdrop, there has been a call for further studies to try and address this paradox. Most studies have been carried out in developed nations, and it is important to test if those findings also apply in less developed contexts (Bogers, Burcharth & Chesbrough, 2019).

The main research question for this investigation was, "What is the relationship between open innovation practises and a firm's financial performance?". It sought to establish the relationship between different OI forms and financial performance in public companies in South Africa. Three hypotheses were derived from the question: Hypothesis 1 – Openness has a positive relationship with financial performance, Hypothesis 2 – Inbound OI has an inverted U-shaped relationship with financial performance, and Hypothesis 3 – Outbound OI has a U-shaped relationship with financial performance. The final analysis covered 105 public companies across 10 different industries from 2016 and 2018. The results of the analysis are set out in Chapter 5 and summarised below.

7.1. Main findings

This study utilised multilinear regression to examine the relationship between openness and the financial performance of South African public companies, assessed through Return on assets (ROA) for South African public companies. Both inbound and outbound forms of open innovation were also taken into account to increase the understanding of the association between open innovation practices and performance. Based on the results of the analysis, none of the open innovation practices were found to be statistically significant. None of the hypotheses were supported. This was contrary to the prevalent view in the field, which supports that openness has a positive relationship with performance (Dahlander et al., 2021; Ovuakporie et al., 2021; Singh et al., 2021). Interestingly, this research did not find support for this relationship in the South African context. As shown in the previous chapter, this could be due to several factors, including low innovation levels and contextual differences. Other scholars uncovered a non-linear relationship (Laursen & Salter, 2006; Caputo et al., 2016; Schäper et al.,2023) and even a negative relationship (Caputo et al., 2016; Fu et al., 2019).

While South African firms exhibit some levels of openness, it appears the benefits of such activity are not reflected in their performance measures, or they might have an indirect relationship. Different performance measures were used to determine the relationship and the results were all not statistically significant. A look at the open innovation statistics highlighted that the majority of the South African firms had low levels of openness, with an average of 26.5%. A closer look showed that most firms utilised inbound OI at different levels, with an average value of 31.7%. However, very few firms utilised outbound innovation, with an average ratio of 9.4%. The lack of a relationship between openness and performance could be attributed to the South African firms' low OI. This is supported by the business innovation survey, which established that closed innovation, where internal sources are utilised for innovation, was still viewed highly by most businesses in South Africa (CeSTII, 2020). Furthermore, it has been acknowledged that most firms practise incremental innovation, concentrating on improving operations and the quality of their products. This low level of innovation was reflected in the Global Innovation Index, which ranked South Africa 61st overall (WIPO, 2022). Such levels of activity are unlikely to have a marked effect on performance. Caputo et al. (2016) observed conflicting results based on a study of mainly European and American companies, with sales growth exhibiting a positive trend with openness, while operating profit and turnover decreased with OI adoption. The inconclusive nature of the relationship was attributed to low levels of inbound OI leading to cost reduction; however, this would be counteracted by outbound innovation practices, which actually increased costs. This lends some credence to the findings of this research.

Further to that, there could have been a failure to leverage the knowledge and innovation resources from openness due to challenges brought about by weak institutions. Feng et al. (2021) revealed that the institutional environment of a country has an impact on innovation. Weaker institutions lead to both lower innovation levels and benefits of innovation. The costs of corruption have been highlighted as reducing R&D levels in an economy (Alam et al., 2019). As a result, the benefits of OI may not be fully appreciated in light of the South African setting.

This investigation showed that there was no support for a direct relationship between OI practices with firm performance. Openness, inbound and outbound innovation all had non-significant results and their hypotheses were rejected. Therefore, open innovation was not found to have an association with financial performance. Previous research had postulated that OI practises were expected to have a positive impact on performance. However, there have also been contradictory results. Costs related to OI implementation and processes can affect a firm's capability to achieve positive performance returns and, in certain scenarios, may result in unfavourable consequences leading to negative performance (Ozturk-Kose et al., 2023). Therefore, the nature of the relationship could also be viewed as inconclusive, given how the empirical studies results depend on the specific metrics used.

7.2. Research Contribution

There have been multiple calls for more open innovation studies to be carried out in developing regions as the majority of empirical studies have been in developed nations such as Europe, the USA, United Kingdom and for developing nations, concentrated on China and India (Bogers, Burcharth & Chesbrough, 2019; Scaliza et al., 2022). This research sought to contribute to the request for studies of OI and firm performance in different contextual settings. Furthermore, this research extended the work of Caputo et al. (2016) and Fu et al. (2019), whose research utilised public financial statements to determine the relationship between open innovation forms and financial performance. This research looked at South African public companies across 10 different industries.

Although this study did not find support for the previously hypothesised OI relationship in the South African context, it does serve to highlight the potential impact of different contextual settings on perceived relationships. Furthermore, they help build on the understanding of how open innovation practices work in South Africa and serve to point out future research directions. They contribute to the understanding of open innovation in Africa, as studies in Africa are very limited. Thus, it helps build on the body of literature on the continent and may have implications for future research.

7.3. Recommendations for management

The research results showed that firm performance was not affected by some OI practices (Lu & Chesbrough, 2022; Mazzola et al., 2016). Different OI practices have different effects on innovation and firm performance. Applying OI activities indiscriminately without understanding the firm context can be a costly activity, with no results to show if not implemented correctly. Given the range of OI practices, it is very important to pick ones that are complementary to the existing firm resources. Thus, when managers consider the implementation of OI practises in their organisation, they need to be aware of their firm capabilities and resource constraints. Changes may be required in internal processes as well as training to ensure alignment with OI practises. Furthermore, OI is not a panacea for improving firm performance through innovation, rather it is a tool. It has its risks and the costs of mitigating such risks should be considered and accounted for in determining innovation investment requirements. It is important for management to carefully manage the use and levels of innovation within the firm and find the level of openness that best suits them (Zhang et al., 2018).

Furthermore, as the literature suggests that the benefits of OI accrue over time, it should be considered that some activities only show results in the long term and must be accepted that there would be limited to no benefits in the short term. It may be more suited as a long-term strategy. This knowledge may help managers determine which projects and initiatives to get involved in and also more accurately measure the impact of OI activities.

7.4. Study limitations and recommendations for future research

This study was based on a sample of only 113 public companies as it was difficult to find a large sample of public companies who adopted open innovation practises and disclosed these activities in their accounts. Therefore, future studies could look at the impact of increasing the data points. Secondly, the target population was widely defined and included a heterogenous mix of firms with the sample comprising firms from 10 different industrial sectors. This would likely limit the generalisation of results in the future. It would be interesting to see how different the results would be if future research looked at a particular sector only, i.e., a more homogenous population in a sector known for employing innovation.

As the financials of the companies were not as standardised as expected, the level of detail available differed from firm to firm. As a result, a number of assumptions had to be made during the research process. Where joint-venture activity was grouped with transactions from associated companies, the figures were taken as if they fully applied to joint-ventures only. This likely over-inflated the costs and income from joint-ventures. Furthermore, all contracting and consulting costs were assumed to qualify as open innovation activities. Identifying revenues from OI activities was challenged by the inconsistent way in which such figures were disclosed and would likely have impacted the calculation of outbound innovation. This would have reduced the reliability of the predictor.

Not all open innovation practices are accounted for in the financials, i.e., engagement with industry bodies, etc. Therefore, the use of financial accounting figures may not truly reflect the level or impact of such activities (Caputo et al., 2016; Fu et al., 2019). As highlighted in Chapter 5, only a quarter of the firms had R&D expenditure in their accounts, and this had an impact on the calculation of inbound OI. As firms focus more on innovation, the expectation is that such disclosures will become more commonplace and more detailed, allowing for the breakdown of R&D expenditure into its component parts (Fu et al., 2019). This would ultimately improve the reliability of the metrics used in the model. Furthermore, this study did not look at coupled innovation. It has been noted that there is growing interest in this OI practice as most firms utilise both inbound and outbound OI to some extent.

The open innovation statistics were calculated based on the figures in the 2016 financials. 2016 was chosen as the base year as that was the last year of the previous Business innovation survey. Choosing different starting points might lead to different conclusions. Economies go through cycles, with businesses generally doing well when the economy is expanding and less profitable when the economy contracts. Of course, the impact would be different depending on which sector a firm belongs to. Furthermore, there have been major changes since then, and it would be interesting to see how this has changed in the post-COVID world, where firms are being more deliberate about innovation. Another aspect to consider would be the political stability and leanings during the period of research. Changes in political leadership might mean a change to policies that might positively or negatively affect business innovation.

Also, the level and detail of disclosure in the published accounts would be expected to be much improved in light of the increasing focus on innovation in developing countries. Furthermore, as this was a cross-sectional study, scholars have highlighted that it does take time for inbound OI activities to filter through the organisational mechanism and create value (Yuan & Li, 2019). Consequently, further research should be carried out to investigate the impact of OI practices over longer periods of time, i.e., longitudinal studies should be carried out.

Finally, while the NIH syndrome has been considered a blocker to innovation in South Africa, it has been found to be pervasive in developed countries (Bogers, Burcharth & Chesbrough, 2019). It would be interesting for future research to investigate the impact of this phenomenon as well as culture in South Africa and its impact on attitudes to knowledge and assimilation of open innovation practises.

7.5. Summary

Open innovation has been a popular study topic in the past few years, with multiple studies carried out on different constructs. Of importance is the ability to measure the impact of open innovation and its relationship with firm financial performance so as to ascertain the value gained from applying OI practices. This study focused on understanding the relationship of open innovation forms (openness, inbound open innovation and outbound innovation) with the financial performance of South African public companies. A quantitative approach was used based on publicly available financial accounts, and the model results did not find support for the hypotheses, which had implications for further studies.

8. References

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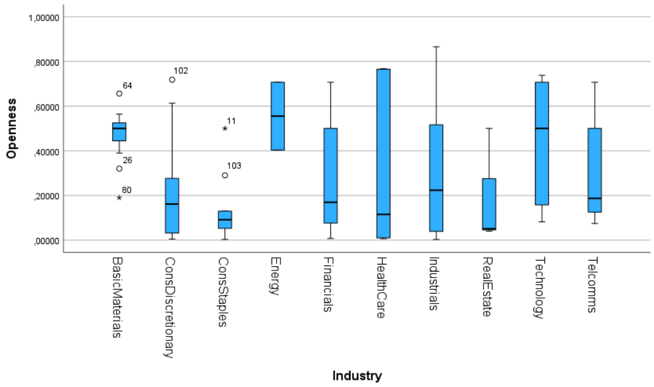
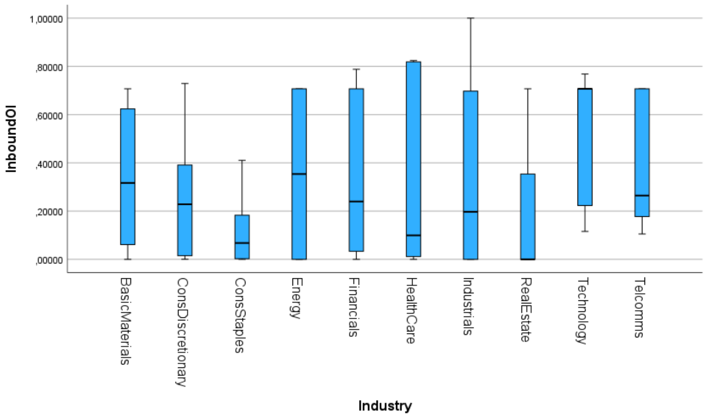
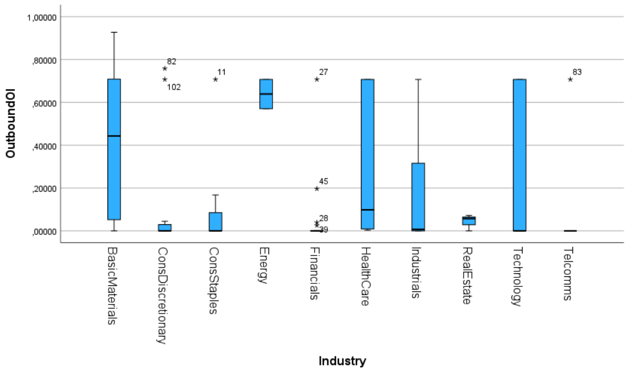
Annexure 1 – Descriptive statistics

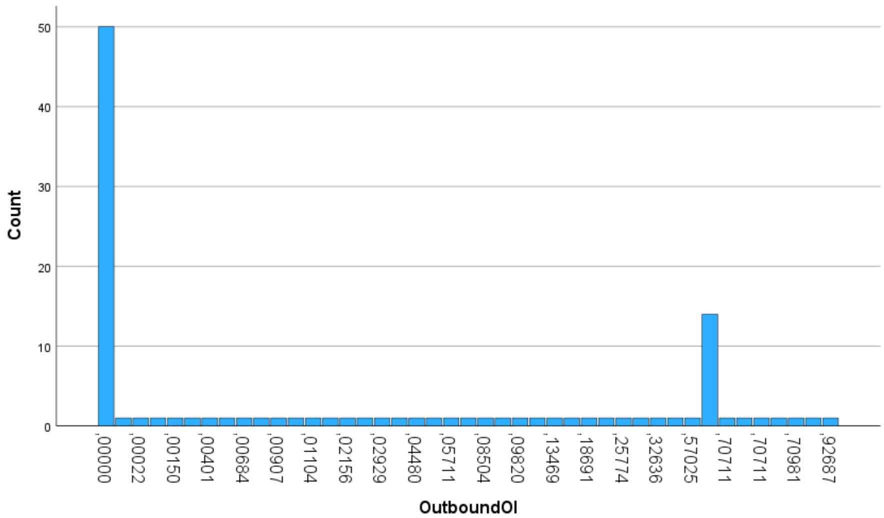
1. Box plots innovation practices







2. Outbound innovation frequencies



Annexure 2 - Confidence intervals and collinearity statistics

1. Model 1

	95,0% Confidence Interval for B		Correlations		
Model 1	**Lower Bound**	**Upper Bound**	**Zero-order**	**Partial**	**Part**
(Constant)	-0.102	0.201			
Openness	-0.111	0.014	-0.113	-0.156	-0.156
DResearch	-0.016	0.057	0.028	0.114	0.113
DIndustry	-0.028	0.023	0.003	-0.018	-0.018
Age	0	0	0.024	0.009	0.008
Size	-0.006	0.007	0.058	0.011	0.011

2. **Model 2**

	95,0% Confidence Interval for B		Correlations		
Model 2	**Lower Bound**	**Upper Bound**	**Zero-order**	**Partial**	**Part**
(Constant)	-0.099	0.193			
Openness	-0.068	0.246	-0.171	0.115	0.111
DResearch	-0.007	0.060	0.028	0.162	0.158
DIndustry	-0.029	0.022	0.003	-0.028	-0.027
Age	-0.001	0.000	0.024	-0.044	-0.042
Size	-0.006	0.007	0.058	0.009	0.008

3. Model 3

	95,0% Confidence Interval for B		Correlations		
	Lower Bound	**Upper Bound**	**Zero-order**	**Partial**	**Part**
(Constant)	-0.127	0.171			
InboundOI	-0.304	0.183	-0.049	-0.051	-0.050
DResearch	-0.026	0.042	0.028	0.050	0.050
DIndustry	-0.026	0.027	0.003	0.007	0.007
Age	0.000	0.000	0.024	0.004	0.004
Size	-0.005	0.008	0.058	0.037	0.037
IOI_squared	-0.270	0.389	-0.041	0.037	0.037

Annexure 3 – Robustness test: ROE regression run results

1. **Openness Regression results**

Correlations

		ROE	Openness	DResearch	DIndustry	Age	Size
Pearson Correlation	ROE	1,000					
	Openness	-,104	1,000				
	DResearch	-,148	,615	1,000			
	DIndustry	-,101	,077	,236	1,000		
	Age	,013	,041	,163	,209	1,000	
	Size	,053	-,129	,125	,062	,348	1,000

Model Summary[b]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,181[a]	,033	-,016	,2446156	,033	,673	5	99	,645	1,858

a. Predictors: (Constant), Size, DIndustry, Openness, Age, DResearch

b. Dependent Variable: ROE

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,201	5	,040	,673	,645[b]
	Residual	5,924	99	,060		
	Total	6,125	104			

a. Dependent Variable: ROE

b. Predictors: (Constant), Size, DIndustry, Openness, Age, DResearch

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound	Correlations Zero-order	Partial	Part	Collinearity Statistics Tolerance	VIF
1	(Constant)	-,027	,301		-,090	,928	-,624	,570					
	Openness	-,006	,125	-,006	-,045	,964	-,253	,242	-,104	-,004	-,004	,575	1,740
	DResearch	-,074	,071	-,139	-1,038	,302	-,216	,068	-,148	-,104	-,103	,548	1,825
	DIndustry	-,038	,050	-,079	-,757	,451	-,138	,062	-,101	-,076	-,075	,907	1,103
	Age	,000	,001	,030	,278	,782	-,002	,002	,013	,028	,027	,837	1,195
	Size	,008	,013	,064	,587	,559	-,019	,034	,053	,059	,058	,816	1,225

a. Dependent Variable: ROE

2. Inbound Open innovation regression results

Correlations

		ROE	InboundOI	IOIsquared	DResearch	DIndustry	Age	Size
Pearson Correlation	ROE	1,000						
	InboundOI	-,050	1,000					
	IOIsquared	-,100	,967	1,000				
	DResearch	-,148	,429	,480	1,000			
	DIndustry	-,101	-,096	-,055	,236	1,000		
	Age	,013	-,041	-,088	,163	,209	1,000	
	Size	,053	-,146	-,152	,125	,062	,348	1,000

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,242[a]	,059	,001	,2425685	,059	1,017	6	98	,419	1,890

a. Predictors: (Constant), Size, DIndustry, IOIsquared, Age, DResearch, InboundOI

b. Dependent Variable: ROE

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,359	6	,060	1,017	,419[b]
	Residual	5,766	98	,059		
	Total	6,125	104			

a. Dependent Variable: ROE

b. Predictors: (Constant), Size, DIndustry, IOIsquared, Age, DResearch, InboundOI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-,063	,294		-,216	,829	-,646	,519					
	InboundOI	,515	,319	,653	1,611	,110	-,119	1,149	-,050	,161	,158	,059	17,084
	IOIsquared	-,662	,407	-,681	-1,627	,107	-1,470	,145	-,100	-,162	-,160	,055	18,221
	DResearch	-,050	,065	-,094	-,765	,446	-,180	,080	-,148	-,077	-,075	,641	1,560
	DIndustry	-,027	,051	-,055	-,523	,602	-,129	,075	-,101	-,053	-,051	,860	1,162
	Age	,000	,001	-,016	-,141	,888	-,002	,002	,013	-,014	-,014	,783	1,277
	Size	,008	,013	,066	,613	,541	-,018	,034	,053	,062	,060	,837	1,195

a. Dependent Variable: ROE

3. Outbound Open innovation regression results

Correlations

	ROE	OutboundOI	OOIsquared	DResearch	DIndustry	Age	Size

Pearson Correlation	ROE	1,000	-,175	-,137	-,148	-,101	,013	,053
	OutboundOI	-,175	1,000	,984	,541	,206	,094	-,077
	OOIsquared	-,137	,984	1,000	,535	,174	,107	-,074
	DResearch	-,148	,541	,535	1,000	,236	,163	,125
	DIndustry	-,101	,206	,174	,236	1,000	,209	,062
	Age	,013	,094	,107	,163	,209	1,000	,348
	Size	,053	-,077	-,074	,125	,062	,348	1,000

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,281[a]	,079	,023	,2399091	,079	1,403	6	98	,221	2,020

a. Predictors: (Constant), Size, DIndustry, OOIsquared, Age, DResearch, OutboundOI

b. Dependent Variable: ROE

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,485	6	,081	1,403	,221[b]
	Residual	5,641	98	,058		
	Total	6,125	104			

a. Dependent Variable: ROE

b. Predictors: (Constant), Size, DIndustry, OOIsquared, Age, DResearch, OutboundOI

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,031	,283		,110	,912	-,531	,594					
	OutboundOI	-1,018	,474	-1,208	-2,146	,034	-1,959	-,076	-,175	-,212	-,208	,030	33,761
	OOIsquared	1,270	,642	1,107	1,980	,051	-,003	2,543	-,137	,196	,192	,030	33,255
	DResearch	-,046	,064	-,087	-,730	,467	-,173	,080	-,148	-,073	-,071	,664	1,506
	DIndustry	-,014	,050	-,030	-,284	,777	-,114	,086	-,101	-,029	-,028	,873	1,146
	Age	9,668E-5	,001	,011	,104	,918	-,002	,002	,013	,010	,010	,824	1,214
	Size	,006	,013	,051	,482	,631	-,019	,032	,053	,049	,047	,843	1,186

a. Dependent Variable: ROE