The effects of Outbound Open Innovation: the Moderating Role of Environmental Factors

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Abstract

This study explores the role of outbound open innovation (OI) in a firm's financial and innovation performance among New Zealand (NZ) firms undertaking collaboration. While innovation is fundamental for firms' survival and growth, today's dynamic business environment makes it difficult for companies to succeed in both the R&D and commercialisation stages. The OI approach enables firms to disperse the risks of failure by sharing and pooling their capital, resources, knowledge, and networks so that they can continue with innovation projects even in adverse business conditions. However, the influence of OI on the performance of NZ businesses is largely unknown. The uniqueness of NZ businesses, characterised by smaller market size, lower resource availability, and less physical proximity to other leading markets, can be potential barriers to OI performance. Thus, it is essential to investigate how OI contributes to NZ businesses.

Further, this thesis identifies the lack of research relating to the outbound dimension of OI strategies (i.e., Selling OI and Revealing OI), as opposed to the more common focus on inbound OI (Sourcing OI and Acquiring OI). This thesis explores the research question: *what are the effects of outbound OI and the moderating role of environmental factors on a firm's performance?* Using survey data from 103 NZ firms and undertaking an ordinary least squares (OLS) regression, results show that Selling OI has a direct impact on financial performance, while it does not relate to innovation performance. Conversely, Revealing OI influences a firm's innovation performance but not its financial performance. However, mediation analysis uncovered that Revealing OI has a strong and positive *indirect effect* on financial performance through innovation performance. Lastly, moderation analysis indicated that outbound OI is more effective for firms operating in a technologically fast-moving industry, compared to a low technologically turbulent industry. Because of complex business dynamics and uncertainty, many firms, specifically those who are resource constrained, struggle to develop the relevant resources and skills for the successful commercialisation of their R&D projects. Thus, outbound OI and drawing on external partners' commercialisation resources might be key. The implications for research and business practice are discussed.

Keywords: outbound open innovation; environmental dynamics; Selling OI; Revealing OI; pecuniary and non-pecuniary OI; mediations

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Glossary and Acronyms

Term	Definition
OI	Open Innovation
R&D	Research and Development
VUCA	Volatile, Uncertain, Complex and Ambiguous
SME	Small and Medium-Sized Enterprise
IP	Intellectual Property
NDA	Non-Disclosure Agreement
CMV	Common Method Variance
CMB	Common Method Bias
RSCPS	Royal Society Code of Professional Standards
AUT	Auckland University of Technology
AUTEC	AUT Ethics Committee
Kaupapa Māori	Māori Research Culture
CR	Critical Ratio
AVE	Average Variance Extracted
CFA	Confirmatory Factor Analysis
PLS	Partial Least Square
OLS	Ordinary Least Square
SEM	Structural Equation Modelling
CB-SEM	Covariance Based Structural Equation Modelling
PLS-SEM	PLS Based Structural Equation Modelling
GFI	Goodness of Fit Index
AGFI	Adjusted Goodness of Fit Index
CFI	Comparative Fit Index
SRMR	Standardised Root Mean Square Residual
RMSEA	Root Mean Square Error of Approximation
IV	Independent Variables

Term	**Definition**
DV	Dependent Variables
DF	Degree of Freedom
CMIN	Chi-Square Statistics
ML	Maximum Likelihood
BLUE	Best Linear Unbiased Estimator
LL	Lower Limit of Confidence Interval
UL	Upper Limit of Confidence Interval
SE	Standard Error
MGA	Multigroup Analysis
MICOM	Measurement Invariance of Composite Models
WLS	Weighted Least Square

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signature: ______________________ **Date: 16th February 2022**

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Further, this thesis conducted data collection from NZ firms, and therefore obtained ethics approval from AUT Ethics Committee (AUTEC); the ethics application was approved on 12th August 2021 (reference number: Ethics Application 21/273).

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Chapter 1 Introduction

1.1 Overview

This thesis explores the effects of open innovation (OI) among New Zealand (NZ) firms undertaking OI activities. In particular, the overarching objective is to investigate the impact of outbound OI on firms' financial and innovation performance and to examine the moderating effect of environmental factors, that is, market and technological turbulence. This chapter first explains the present study's background and motivation, followed by a research statement. Lastly, the structure of the entire thesis is described.

1.2 Study Background

Despite the risks, innovation activities are essential for a firm’s growth and survival, and firms need to keep updating their portfolios even in adverse conditions (Tidd & Bessant, 2020). Chesbrough (2003, p. xvii) stated “most innovation fails, but companies that don’t innovate die”. Nonetheless, many firms see innovation as challenging because it is capital- and knowledge-intensive in nature. Furthermore, the difficulties of innovation, or innovation barriers, become exacerbated, especially in a dynamic business environment or during an economic downturn. On the one hand, the turbulent business environment makes a market and technological trajectory less predictable, leading to a higher rate of unsuccessful innovation projects. On the other hand, an economic downturn makes firms less viable in terms of capital availability, forcing firms to take a defensive stance: securing certain current assets through divestment or abandoning innovation projects (Chesbrough, 2020). Therefore, regardless of the importance of innovation, some firms cannot afford to invest in innovation projects.

In this vein, business environments have been increasingly becoming dynamic, and more and more firms are facing challenges. For example, the COVID-19 pandemic has hit many businesses hard worldwide in terms of their business growth and survival through innovation (Chesbrough, 2020). According to Stats NZ’s statistical report (Stats NZ, 2021), NZ’s Gross Domestic Production (GDP) showed negative growth for three consecutive quarters in 2021, indicating that NZ has officially entered a recession for the first time since the global financial crisis in 2008. Moreover, scholars described today’s business environment as volatile, uncertain, complex, and ambiguous (VUCA) (Enderwick, 2019); for example, geopolitical concerns, hiked oil prices, or inflation concerns have contributed to greater business uncertainties in recent years (Organisation for Economic Co-operation and Development [OECD], 2022). Therefore, firms’ strategic responses to the challenging business environment need more attention.

While overcoming innovation barriers in the VUCA world is not easy, previous empirical data found that firms with innovation activities showed a higher survival rate than those that did not continuously innovate during the global financial crisis, suggesting the importance of continuous innovation projects even in adverse business conditions (Wenzel et al., 2020). Furthermore, continuous innovation generally strengthens a firm’s competitiveness, which, in turn, can drive recovery from an economic recession (Wenzel et al., 2020). Nonetheless, it is a difficult strategic response during turbulent business environments, as many firms cannot afford risky innovation projects (Chesbrough, 2020). Therefore, the key question is how can firms keep innovating even in a challenging environment? As such, the primary interest of this thesis is to explore effective innovation strategies in an uncertain environment. The ability of NZ firms to innovate is of significance to assist recovery and survival from the economic downturn and the financial impacts of the COVID-19 pandemic.

1.3 Open Innovation

Drawing on Chesbrough's concept of OI, this thesis focuses on collaborative innovation to explore an effective strategic response to the dynamic business environment (Chesbrough, 2020). The term OI was coined by Chesbrough in 2003 (Chesbrough et al., 2014), and the concept has gained considerable attention from not only academics but also policymakers as an important driver of firms’ performance (Dahlander et al., 2021; Saeed et al., 2015). In a basic sense, OI refers to collaborative innovation activities among partners (i.e., firms, research agencies, or universities) during the research and development (R&D) and commercialisation stages of a typical innovation project (Bogers et al., 2018). Although OI has some drawbacks, the benefits are considerable. The focal firm can reduce risks and costs associated with innovation by pooling knowledge, technology, and resources among collaborating partners (Dahlander & Gann, 2010). The dispersion of the risks and development costs helps firms ease heightened innovation barriers, encouraging more firms to engage in innovation. Thus, the OI strategy seems to be an important strategic response to cope with the VUCA business environment (Chesbrough, 2020).

Indeed, inter-firm collaborations surged in the 2000s as a firm’s strategic response to overcome unpredictability and uncertainty in a dynamic business environment, which was driven by the forces of globalisation, rapid technological developments, and social change (Chesbrough, 2003). These external factors caused increased business competition and shortened product and innovation lifecycles. Firms, therefore, increased the use of OI to adapt to the fast-moving business world despite some negative consequences of collaboration, such as fewer appropriations, the risk of imitations, and knowledge spillovers (Chesbrough et al., 2014). For these reasons, it is worthwhile to explore how the OI strategy can enhance NZ firms’ financial and innovation performance in today’s VUCA business environment.

In terms of the impacts, there has been extensive research on the OI strategies and their effects (e.g., Aliasghar & Haar, 2021; Lu & Chesbrough, 2021). From the theoretical point of view, OI research has been the subject of recent focus by academics, particularly European and Asian researchers, and their overall implication is that OI has had a positive impact on firms' performance (Dahlander et al., 2021; Gao et al., 2020). Indeed, the OECD's business survey (2017) reported that more than 70% of large innovative firms in many advanced countries collaborated in seeking higher financial and innovation performance. Because of these manifested benefits, many countries, such as Australia and small advanced economies (e.g., Ireland and Switzerland), have been promoting a collaborative innovation environment through incentives and focused R&D funding (Crawford, 2021; George & Tarr, 2021).

1.4 New Zealand's Innovation Environment

As suggested by international evidence, OI strategies can be effective in mitigating the risks and costs of innovations (Dahlander et al., 2021). However, the effectiveness of OI may be different depending on the business environment (Aliasghar & Haar, 2021; Roberts, 2018; Pells & Howard, 2019). In fact, much previous OI research indicated the contingent nature of OI performance (Cassiman & Valentini, 2016; Lu & Chesbrough, 2021; Tsai, 2009). Thus, the unique NZ business ecosystem may hinder OI performance, which, in turn, poses the question of whether or not the collaborative innovations are applicable to NZ firms.

As an illustration of NZ's unique business environment compared to other leading OECD nations, small market size, lack of resource availability, and less physical proximity to other markets can be potential barriers to OI performance (Pells & Howard, 2019). Similarly, the recent study by Aliasghar and Haar (2021) has shown that a considerable number of innovative NZ firms undertake international collaborative innovations, suggesting that a lack of firms' skills in international business can be a unique negative variable to the OI performance of NZ firms. Thus, more OI research focusing on the NZ context is necessary to understand the effects of OI on the performance of NZ businesses.

In theory, however, collaborations should minimise the above-mentioned country-specific disadvantages, as the essence of OI, resource complementarity, fills resource gaps and accelerates the focal firm's innovation process (Chesbrough, 2020; Chesbrough et al., 2014; Ministry of Business, Innovation & Employment [MBIE], 2019). As an illustration, a report on NZ firms by MBIE (Pells & Howard, 2019) revealed that most NZ firms claimed financial, knowledge, and skill-related constraints as their main innovation barriers, which should be mitigated through OI (Chesbrough, 2020; Saeed et al., 2015).

Furthermore, the government has been promoting a collaborative innovation culture in NZ (New Zealand Productivity Commission, 2021). With its ambitious slogan, "by 2027, New Zealand will be a global innovation hub" (MBIE, 2019, p,6), the NZ Government has initiated several projects and policies to encourage firms to collaborate. One example is the Science for

Technological Innovation (SfTI) project, which recently received $106 million in funding to promote innovation and collaboration across NZ firms, industries, and universities (SfTI, 2020). Therefore, several government-led initiatives have been in place to drive NZ's collaborative innovation culture, enabling NZ firms to overcome economic adversity and reach top-class global innovators through collaboration (Pells & Howard, 2019).

1.5 Research Statement

Despite these government initiatives and international evidence, it is yet unclear whether the recent government's promotions for collaboration are applicable to NZ firms due to the lack of evidence of OI performance in the NZ context (Aliasghar & Haar, 2021; Pells & Howard, 2019). OI research among NZ firms is scarce; therefore, it is essential to explore the effects of OI to understand how the strategy helps NZ firms (New Zealand Productivity Commission, 2021). For all these reasons, this thesis investigates the following **research statement**:

The OI strategy is beneficial for NZ firms' financial and innovation performance.

To explore this research statement, this thesis conducts a study relating to innovation strategy among NZ firms, and the rest of the thesis is organised as follows: the next chapter reviews innovation and OI literature to critically analyse the prior innovation scholars' arguments to understand what has been known about OI and what needs to be done to advance the theory. Through the extensive literature review, research gaps and research questions are explained.

Chapter 3 argues for a number of hypotheses aligned with the theory in order to examine the research questions derived in the previous chapter. Accordingly, a summary of the literature review, diagrams, and conceptual models presented in this chapter can be used as a reference for the arguments for the rest of the chapters.

Chapter 4 presents the research design, research philosophy, and research strategies used in this study, followed by a sampling strategy, a data collection method, and ethical considerations. The rationales and justifications for the approaches – a quantitative study, cross-sectional survey, and non-random sampling methods – are explained.

Chapter 5 reports the analysis results and provides justifications for the statistical methods used in this study. Firstly, the earlier sections of the chapter primarily focus on measurements to demonstrate the construct validity and reliability. Then, the regression analysis, mediation, and moderation analysis results are discussed in the later sections. Lastly, the chapter explores several robustness tests to provide evidence of statistical conclusion validity and the assumptions of the main estimator (ordinary least square assumptions).

Finally, Chapter 6 provides a discussion relating to the research questions. The arguments include both theoretical contributions and implications for practice. Further, as with other studies, this thesis elaborates on the limitations of the present study’s approaches and findings, coupled with recommendations for future studies. The thesis ends with a call for further research on the outbound OI dimension and underscores the usefulness of Revealing OI to enhance firms’ performance.

Chapter 2 **Literature Review**

2.1 Introduction

The previous chapter demonstrated the background and rationale for the research statement:

The OI strategy is beneficial for NZ firms' financial and innovation performance.

As such, this chapter aims to investigate how the research statement can be studied and to generate research questions by identifying research gaps through an extensive literature review relating to innovation and OI literature. Section 2.2 briefly looks into the concept of innovation and innovation strategies to highlight the key factors leading to performance through innovation activities. Next, Section 2.3 discusses the OI theory in more detail, including its definition, practices, benefits, and drawbacks. Section 2.4 explores and identifies the research gaps regarding the relationships between OI strategy and its performance from the viewpoint of three key concepts in OI innovation studies: absorptive capacity, search strategy, and appropriability management. Lastly, Section 2.5 sets out the research questions based on the research gaps identified in the prior sections.

2.2 Innovation

It is widely accepted that innovation is vital to a firm's competitiveness and growth (Hanson et al., 2016). A firm aims to achieve a competitive advantage through product innovation, process innovation, and organisational innovation. Above all, product innovation, if successful, can enhance its market position and share, leading to higher performance (Tidd & Bessant, 2020). Indeed, past empirical research has provided evidence to support a causal link between product innovation and a firm's financial performance (Hall, 2002; Huang & Hou, 2019). As such, innovation is recognised as a firm's fundamental strategic activity for success and survival (Keizer et al., 2005).

Accordingly, the importance of innovation is frequently cited by many; however, its concept is often misused and misunderstood (Pells & Howard, 2019). As for product innovation (hereafter innovation), OECD defines innovation as "the implementation of a new or significantly improved product (goods or service)" (OECD, 2005, p.51). In this regard, innovation is a firm's activity to introduce a new product, service, technology, or knowledge into a market. Rothwell (1994) explained that a typical innovation process begins with the idea generation phase and ends with the final stage of product launch in the marketplace. In other words, an innovation process entails two phases: invention and commercialisation (Tranekjer & Knudsen, 2012).

While the R&D stage is arguably imperative to innovation success, some innovation scholars have emphasised the importance of the commercialisation stage (Belderbos et al., 2014; Fiedler & Welpe, 2010). For example, the Resource-Based view (Barney, 1991) argued that a firm enjoys a temporal competitive advantage with resources, ideas or products that are valuable, rare, and hard to imitate, which typically can be created in the R&D stage; however, at the same time, such a competitive advantage needs to be organisationally exploitable to benefit from innovation, and exploitation generally requires success in the commercialisation stage (Tidd & Bessant, 2018). Similarly, Teece (1986) noted that an appropriation strategy is crucial to capture value from innovation and argued that firms should closely monitor an external environment to enhance commercialisation performance in a turbulent business environment. Teece also underscored the role of complementary assets for a commercialisation stage success, which refers to resources needed for commercialisation: distribution network, production capability, or sales and marketing departments (Miotti & Sachwald, 2003). In other words, commercialisation plays as critical a role as an invention in innovation success.

Despite innovation's vital role, the equal importance of the R&D and commercialisation stages makes it difficult for firms to continuously conduct innovation projects (Bogers et al., 2019; Pisano & Teece, 2007). This is mainly because developing and acquiring necessary skills, capabilities, resources, and knowledge in all innovation processes, from idea-generation to product launch, are costly and time-consuming (Chesbrough, 2020). Chesbrough noted that "companies that don't innovate die " (2003, p. xvii), but at the same time, he claimed that "most innovations fail" (2003, p. xvii). In reality, few firms can simultaneously develop these essential skills and resources, as financial and human resources are not infinite. Thus, a firm's manager needs to develop an appropriate innovation strategy considering how the firm can develop necessary skills and resources in each innovation stage, given the limited resource availability.

2.2.1 Innovation Strategy

Innovation research has burgeoned over the past few decades (Dahlander et al., 2021). In particular, many scholars have examined the impacts of an innovation strategy on firms' performance, such as financial and innovation performance (Gao et al., 2020; Greco et al., 2015). Because there is no universal innovation strategy that fits all companies, selecting an appropriate innovation strategy is crucial for profiting from innovation (Teece, 2018; Tidd & Bessant, 2020). Typically, a manager considers their strategic orientations, such as what kinds of innovation the firm desires or how they can achieve an innovation goal. In this sense, academics typically classify innovation types as incremental or radical innovations based on the extent of improvement from the current product features (Van Beers & Zand, 2014). Accordingly, innovation scholars in the past have sought to find a link between innovation types and their performance (Chaney et al., 1991; Geroski et al., 1993).

Furthermore, other innovation scholars contended that a source of invention ideas is an important determinant of innovation success. This research line, often referred to as *search strategy* (Laursen & Salter, 2006), concerns how effectively a firm can find relevant technology, ideas, or capabilities from the external environment for their innovation success. Such research interests often have been ranging from a strategic alliance (Hu et al., 2015) to supply chain network (Cox et al., 2003), ecosystem innovation (Xie & Wang, 2020), and industry-university collaboration (Perkmann & Walsh, 2007). In any case, recent innovation research interests have shifted from the *traditional* innovation approach to the *collaborative* innovation model (Dahlander et al., 2021). Thus, the contemporary research exploring the effects of an innovation strategy has also revolved around a collaborative innovation strategy in the recent decade.

2.2.2 Closed Innovation and Collaborative Innovation Strategies

Traditionally, a firm’s innovation activities were limited to within a firm's boundary. Accordingly, in-house development of R&D capabilities and complementary assets were essential for innovation success (Chesbrough et al., 2014). This internally-oriented organisational practice was reflected in traditional strategy literature, particularly in the second half of the 20th century, such as vertical integration strategy or transaction cost theory (Tidd & Bessant, 2020; Williamson, 1979). In innovation research, academics referred to this internal innovation activity as closed innovation or traditional innovation strategy (Chesbrough, 2003). From this perspective, firms can enjoy a competitive advantage for a long time because all important assets and core knowledge are kept and exploited internally; the exclusivity makes it difficult for competitors to imitate the proprietary knowledge. Besides, a within- or intra-firm innovation project was preferred because it reduced the risks and financial losses from a market failure and high transaction costs associated with the technology market (Arora & Fosfuri, 2003). In short, the closed innovation strategies were the essence of sustained competitive advantages for many firms in the past.

By contrast, closed innovation entails some drawbacks, and one obvious shortcoming is resource and capital intensiveness (Chesbrough, 2003; Dahlander et al., 2021; Teece, 1986). Accordingly, an innovation project based on a closed innovation strategy was mainly limited to large firms with slack resources and appropriate complementary assets (Spithoven et al., 2013). For example, Chesbrough (2003) noted that, based on the United States’ (US) economic report in 1995, large firms in the US accounted for 95% of domestic R&D activities, attributing resource scarcity and the liability of smallness to SMEs’ less involvement in innovation projects in the past. Thus, the traditional innovation studies tended to focus on relatively large firms and the R&D stage as research interests (Chesbrough et al., 2014). Eventually, this convention led to one reason for research gaps in SMEs and commercialisation research within innovation studies (Spithoven et al., 2013; Tranekjer & Knudsen, 2012).

2.2.3 Business Environment: Market and Technological Turbulence

However, as with other business theories, such as the internationalisation strategy, the closed innovation strategy has evolved along with a business environmental change (Scott-Kennel & Enderwick, 2004; Tidd & Bessant, 2020). The speed of changes in the market and technological conditions have increased dramatically due to rapid globalisation, the advent of digital technologies, and societal change over the past few decades (Stiglitz, 2018). As a result, the business environment has become increasingly dynamic. Generally, accelerated business cycles are challenging for the closed innovation model since large initial investments into the development of R&D capabilities, and complementary assets may not generate sufficient returns in a dynamic business environment (Tidd & Bessant, 2020). The degree of dynamicity of the environment in which a firm operates is typically determined by the level of unpredictability, uncertainty, and speed of the market and technological changes, referred to as *market turbulence* and *technological turbulence* (Calantone et al., 2003). These factors contribute to faster innovation cycles and shorter product lifecycles, resulting in a shorter period of competitive advantage (Chesbrough, 2003). As such, some firms forewent the traditional innovation approach to adapt to rapid environmental changes, shifting from the in-house innovation model to the external innovation model to share the risks and costs associated with innovation (Lichtenthaler, 2009). In turn, the importance of external players has risen, and the collaborative innovation strategy has emerged as a strategic response to ever-increasing business uncertainties (Bogers et al., 2018).

2.3 Open Innovation Strategies

The collaborative innovation approach, termed OI (Chesbrough, 2003), was placed in opposition to closed innovation. By definition, the notion of OI was not a new idea, and some scholars had been studying similar concepts for decades before the emergence of the OI concept: R&D partnerships, inter-firm knowledge sharing, or cross-licensing (Trott & Hartmann, 2009). However, these notions were rather fragmented. Consequently, Chesbrough gathered all relevant concepts regarding collaborative innovations and developed this umbrella term with more precise definitions as follows:

OI is defined as "the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and to expand the markets for external use of innovation" (Chesbrough, 2003, p. xxiv).

Accordingly, innovation scholars underscored the role of OI as a key element in achieving a firm’s innovation goal in today’s fast-moving business world (Laursen & Salter, 2014; Van de Vrande et al., 2009). Instead of developing internally, OI strategies emphasise external partners to draw on their capabilities and resources to accelerate innovation projects. Although there are some positive and negative aspects of OI, speeding up an innovation project is critical to cope with the ever-changing market and technological environment (Bogers et al., 2019; Chesbrough et al, 2018). Consequently, both practically and academically, and from both qualitative and quantitative studies, people agreed with the vital role of OI in a firms' financial and innovation performance (Dahlander & Gann, 2021).

2.3.1 The Benefits and Costs of Open Innovation

There are clear benefits to OI but also potential challenges to consider (Greco et al., 2019). As such, the OI strategy is not a versatile strategy that everyone can adopt (Van de Vrande et al., 2009). Rather, a firm's manager is required to evaluate its benefits and costs to ensure its positive effects outweigh the drawbacks (Kobarg et al., 2019). On the positive side, the focal firm can save costs and time in developing required resources and capabilities by drawing on external partners throughout an innovation process. For instance, working with research firms or universities can complement internal R&D activities (Popa et al., 2017), while collaborating with competitors or supply-chain partners allows the focal firm to draw on their complementary assets to commercialise their new invention quickly (Cox et al., 2003; Nieto & Santamaría, 2007). As a result of the increased use of OI among firms, innovation activities spanned out to firms that did not previously have the resources needed for both R&D and commercialisation stages. Consequently, Theyel (2013) reported that more than half of SMEs in the US have engaged in collaborative innovation activities recently, compared to 5% in 1995 (Chesbrough, 2003). Thus, it is clear that many firms, regardless of size, can benefit from OI strategies to enhance their performance.

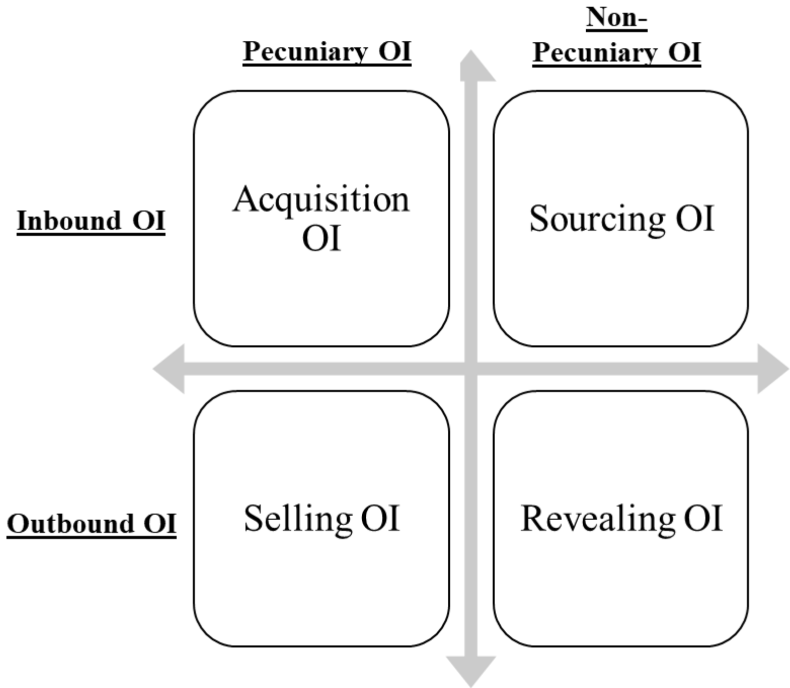
In contrast, some scholars have pointed out the contingent nature of OI performance, suggesting that the drawbacks of OI might be greater than the benefits in some situations (Chaudhary et al., 2022; Greco et al., 2019). Also, some OI studies have been prone to overemphasise the benefits. Chaudhary et al. (2022, p.1010) argued that "eulogising only the positive aspects of open innovation is insufficient to help firms and motivate future research". Thus, it is important to understand the drawbacks of OI. In this respect, some studies reported the slowdown effect of OI due to increased project complexity, management costs, and search costs (Van Beers & Zand, 2014). Guzzin and Iacobucci (2017) agreed with this claim based on their research on university-industry collaborations, arguing that private firms and university researchers often conflict due to differences in innovation motives. These prior studies emphasised the importance of similarities among partners, such as resources, size, orientation, and industry; dissimilarity may reduce collaborative innovation performance (Chung et al., 2000). Thus, finding the right collaboration partners may be vital in managing OI.

Further, another key downside of OI is an increased risk of knowledge leakage and opportunistic behaviours among partners (Veer et al., 2016), and these risks increase as the number of collaborating partners grows (Laursen & Salter, 2006). Further to this, the full potential of value appropriability decreases as the size of collaboration partners grows. Indeed, Fosfuri (2006) claimed that out-licensing might strengthen the licensee's competitiveness, weakening the value of the focal firm's competitive technology. Similarly, Veer et al. (2016) showed that knowledge leakage is an inevitable side effect of the OI strategy. As a result, many scholars argued the importance of an appropriate OI strategy selection to enjoy the advantages of OI (Freel & Robson, 2017; Henttonen et al., 2016; Foege et al., 2019; Ritala et al., 2015).

2.3.2 The Type of Open Innovation Strategy

Figure 1

The Type of Open Innovation



As highlighted in the prior section, the OI strategy needs effective management to ensure the benefits outweigh the costs (Popa et al., 2017). Accordingly, many innovation scholars underscored the necessity of aligning OI strategy with the firm's weaknesses and strengths (Gao et al., 2020). In this regard, Chesbrough (2003) developed the two dimensions of OI: inbound OI and outbound OI. Furthermore, Dahlander and Gann (2010) extended the concept and defined four modes of OI: inbound OI (Sourcing OI and Acquiring OI) and outbound OI (Selling OI and Revealing OI). As **Figure *1*** above shows, this classification is based on knowledge flow direction and knowledge exchange mode. The former describes the direction of knowledge flows: inward (inbound OI) or outward (outbound OI) knowledge flows across the focal firm's boundary. The latter explains whether or not the knowledge flows involve monetary transactions: pecuniary or non-pecuniary (Dahlander & Gann, 2010). As each type of OI strategy has pros and cons, a firm's manager needs a careful OI strategy selection.

2.3.3 Inbound Open Innovation

Inbound OI is defined as “the use of purposive inflows of knowledge” (Chesbrough et al., 2003, p. xxiv), and Brunswicker and Vanhaverbeke (2015) described it as “new ideas flow into an organisation (the focal firm)” (p.1241). Such inflows are necessary during the R&D stage to create new knowledge, resources, or capabilities (Veer et al., 2016). Thus, inbound OI typically occurs during the early phase of an innovation process rather than the commercialisation stage (Van Beers & Zand, 2013). By definition, inbound OI includes sourcing and acquiring practices, and the difference is whether knowledge inflows entail monetary transactions during a collaboration (Dahlander & Gann, 2010). One good illustration of Sourcing OI is information exchange or co-development among supply-chain partners, while Acquisition OI includes transaction-based practices, such as in-licensing or R&D outsourcing (Dahlander & Gann, 2010). Either way, knowledge inflows complement the focal firm’s internal innovation project by filling its resource gaps (West et al., 2014). In doing so, the firm can speed up and save the initial R&D investments in idea generation, building capabilities, and required resources for innovation success.

2.3.4 Outbound Open Innovation

Another dimension of OI strategy, outbound OI, is defined as follows:

“organisation’s deliberate commercialising (exploitation) of knowledge assets to another independent organisation involving a contractual obligation for compensation in monetary or non-monetary terms” (Lichtenthaler 2005, p.233).

Under this concept, outbound OI firms transfer their internal knowledge to external partners for value exploitation; the modes of outbound OI are described as Selling OI and Revealing OI (Dahlander & Gann, 2010). On the one hand, Selling OI includes outward knowledge flows with a monetary transaction, such as R&D contracts, out-licensing, joint ventures, spin-offs, or selling intellectual property (IP) assets (Chemmanur et al., 2014; Helm et al., 2019). On the other hand, Revealing OI entails outward knowledge flows without monetary return (free-reveal) or perhaps discounted return (selective-reveal); Revealing OI practices include IP asset sharing, knowledge transfer, or disclosures of proprietary knowledge (Verreynne et al., 2020). Regardless of the modes, the main characteristic of outbound OI is knowledge exploitation through external partners (Lichtenthaler, 2009); hence, outbound OI is likely to occur during the commercialisation stage as a firm must possess some exploitable assets before undertaking outbound OI (Lichtenthaler, 2005). Thus, successful outbound OI is likely to link to the firm’s performance directly (Lichtenthaler, 2009; Singh et al., 2021).

2.4 Open Innovation and a Firm's Performance

Based on these four modes of the OI strategy, researchers integrated several theories and concepts to explore how to best maximise the benefits of OI while minimising the drawbacks (Dahlander et al., 2021; Gao et al., 2020; Le et al., 2019; Tang et al., 2021). For example, with their extensive literature review and bibliographic analysis on papers published between 2003 and 2013, Randhawa et al. (2016) found five major topics relating to OI strategy:

- Absorptive capacity (Spithoven et al., 2010; Zobel, 2017),
- Search strategy (Aliasghar et al., 2019; Terjesen & Patel, 2017),
- Resource-Based View and dynamic capability (Bogers et al., 2019),
- Management of collaboration networks and alliances (Laursen & Salter, 2014), and
- User-innovations (Bradonjic et al., 2019).

With these theoretical foundations, the following three sections provide essential existing knowledge on the OI strategies and then clarify what has been known and what needs to be done to advance the OI theory. In doing so, this thesis discusses research gaps and research questions that address the research statement of the present thesis. **Table *1*** below summarises the previous findings from the relevant concepts and their research gaps within the OI theory.

2.4.1 Open Innovation Performance from A Capability-Based View

According to several systematic literature reviews on OI papers (Apriliyanti & Alon, 2017; Randhawa et al., 2016), absorptive capacity, referred to as a firm's ability to internalise external knowledge and resources, was identified as one of the most integrated concepts in OI research. Through the extension of the pioneering work by Cohen and Leventhal (1990), Zahara and George (2002) proposed two dimensions of absorptive capacity: potential absorptive capacity and realised absorptive capacity. In simple terms, the former capability describes a firm's searching ability to scan the external environment, knowledge, and technology (Asakawa et al., 2010), while the latter describes a firm's exploitative ability to transform externally available knowledge and technology into internally usable assets (Aliasghar et al., 2019). In the OI domain, both dimensions of absorptive capacity are the critical drivers for OI performance. A lack of either dimension may result in a sub-optimal OI performance because finding the right collaboration partner is a challenging task without a potential absorptive capacity (Bogers et al., 2019; Zobel, 2017). Furthermore, in the absence of realised absorptive capacity, a firm may not be able to assimilate external knowledge and incorporate it into an internal innovation project effectively (Spithoven et al., 2010). Thus, most studies related to this research line supported the importance of absorptive capacity to maximise the benefits of OI, particularly during the inbound OI activities (Aliasghar et al., 2019; Bogers et al., 2019; Zahra & Hayton, 2008; Zobel, 2017).

Table 1

Summary of Literature Review Relating to OI Performance

Category of OI Research	**What Has Been Known**	**Research Gaps**
Capability-Based View	The concept of absorptive capacity has been well studied in OI research because it is regarded as a critical factor for scanning the external environment and internalising external knowledge into an exploitable resource (Zahara & George, 2002) Past research has shown that absorptive capacity is one of the most vital factors to benefit from inbound OI and enhance OI performance (Bogers et al., 2019).	Some scholars criticised that the past research often focused too much on the capabilities of *the focal firm* and the inbound OI dimension (Roldán Bravo et al., 2020). The disproportionate focus has caused research gaps in the outward dimension of OI: how the *knowledge sender's capability* (desorptive capability) and *outbound OI* work for OI performance (Aliasghar & Haar, 2021).
Search Strategy	Search strategy considers how the focal firm can find the best partners to make the most of collaborations. The discussion rests mainly on partner types and the number of partners during OI (Laursen & Salter, 2006). Most researchers agreed that OI improves performance (Laursen & Salter, 2014). However, others cautioned about the paradox of openness. The paradox stems from	There have been no conclusive arguments regarding the extent to which the focal firms should embrace openness (Lennerts et al., 2020). Some studies found an inverted U-shaped relationship between openness and OI performance, arguing that high openness may increase the risks of collaborations, such as complex project management or knowledge leakage (Laursen & Salter, 2006). However, there has been no evidence to date showing the negative effects of outward knowledge flows

	the fact that increased inward knowledge flows from external partners may raise the risks of outward knowledge flows from the focal firm (Wadhwa et al., 2017; Tether, 2002).	stemming from increased openness. This suggests the scarcity of OI research from the outbound OI dimension (Marullo et al., 2021).
Appropriability Management	Appropriability management plays a crucial role in encouraging OI strategies and collaborations (Laursen & Salter, 2014). Most researchers agreed with the important role of IP protections. However, some scholars argued that too much emphasis on IP protections during collaborations might decrease the quality of OI (Grimaldi et al., 2021; Kutvonen, 2011).	The past research indicated a positive relationship between IP protection and the adaptation of OI. However, the effects of such protections on OI performance remain inconclusive to date (Grimaldi et al., 2021; Holgersson & Granstrand, 2017). The arguments on the impacts of IP protections on OI performance remain inconclusive because of the lack of research from the outbound OI dimension (Verreynne et al., 2020). More research into the impact of outbound OI on a firm's OI performance is required (Alexy et al., 2013, 2016).

In contrast, despite the abundant evidence supporting the absorptive capacity's role (Teirlinck & Spithoven, 2013; Tsai, 2009), the growing number of researchers call for more research into the outward knowledge flows and their performance. For example, Roldán Bravo et al. (2020) pointed out the limitation of absorptive capacity-related research as a uni-directional concept and argued that past research often neglected the importance of the bi-directional nature of knowledge flows and exchange during a collaboration. They argued that, on top of the knowledge receiver's absorptive capacity, a knowledge sender's *desorptive capacity* might affect the quality of knowledge the focal firm acquires through inbound OI. As opposed to absorptive capacity, desorptive capacity refers to a firm's capability to scan the external environment and find the right partner for external knowledge exploitation and to transfer internal knowledge effectively to external partners (Lichtenthaler & Lichtenthaler, 2009).

Further, in the context of supply-chain network-based OI, Roldán Bravo et al. (2016) found that OI performance was greater when the focal firm had a higher absorptive capacity, coupled with a certain desorptive capacity among their supply-chain partners. Similarly, Aliasghar and Haar (2021) have recently investigated the role of desorptive capacity across 541 NZ firms and found a crucial role of desorptive capacity in enhancing a firm's performance, arguing that absorptive capacity and desorptive capacity are complementary. However, their finding contradicted Cassiman and Valentini's research (2016), which found no evidence of such complementary effects between inflows and outflows on OI performance. They claimed that increased simultaneous knowledge flows could enhance sales revenue through collaborations, but it could also increase the management costs proportionately, thereby decreasing the overall OI performance. Nonetheless, the role of outward knowledge flows and the related capabilities remains unclear and under-researched, leading to a huge research gap within Capability-Based OI research. Accordingly, several researchers have called for future research to explore the outward knowledge flows (Bogers et al., 2019; Roldán Bravo et al., 2021).

2.4.2 Open Innovation Performance through the Search Strategy

In addition, some innovation scholars argued that scanning an external environment to find the best collaboration partners plays a critical role in enhancing OI performance (Sofka & Grimpe, 2010). This research stream, termed "search strategy", contends how effectively firms can search for ideas, technologies, knowledge, and resources in the external environment to accelerate an internal innovation project (Keupp & Gassmann, 2009; Marullo et al., 2021; Wang et al., 2021). Innovation scholars frequently use the construct 'openness' to explore relationships between the search strategy and OI performance; openness describes how firms are open to external search and collaboration, measured by the number of collaboration partners (breadth) and intensity of collaboration (depth) (Laursen & Salter, 2006; Markovic & Bagherzadeh, 2018). Both factors play a vital role: the larger number of collaboration networks might contribute to greater access to explicit knowledge available among the partners, while a depth collaboration might be necessary to transfer the tacit knowledge (Bengtsson et al., 2015; Yacoub et al., 2020). In any case, previous research concerning search strategy indicated that an appropriate degree of openness is essential for a higher OI performance (Marullo et al., 2021).

In contrast, some scholars faced difficulties determining to what extent the focal firm should embrace openness, and Laursen and Salter (2014) referred to this conundrum as "*the paradox of openness*." (p.868). Consistent with the finding by Laursen and Salter (2006), Caputo et al. (2016) showed an inverted U-shaped relationship between openness and OI performance, concluding that too much openness could be detrimental due to increased outward knowledge flows, transaction costs, search costs, coordination costs, the risk of imitations, and opportunistic behaviours by external partners. Consequently, while openness seems to be a key to OI performance, scholars call for more research to address the paradox of openness (Lennerts et al., 2020). Specifically, despite the "reciprocal nature of OI" (Tranekjer & Knudsen, 2012, p.433), past strategy research has only focused on the inbound OI dimension. As such, little has been known about the role of outward knowledge, and it is unclear whether outward knowledge flows are indeed detrimental (Marullo et al., 2020).

2.4.3 Open Innovation Performance with Appropriability Management

In addition to these negative aspects of openness, Laursen and Salter (2014) claimed that, due to the basis of mutual relationship in collaboration, the degree of knowledge inflows may indicate a similar amount of knowledge outflow across a firms' boundary. Thus, the firms' inbound OI may unintentionally increase the outward knowledge flows, leading to knowledge leakage and loss (Arora et al., 2016). Similarly, Veer et al. (2016) found that OI might induce imitations, particularly in the idea generation stage, and therefore collaboration could be risky if no protection is in place. Thus, several scholars have argued the importance of appropriability protection through informal or formal appropriability protection mechanisms (Marullo et al., 2020).

In this regard, the recent systematic literature review documented the increased number of appropriability management studies within the OI field (Gao et al., 2020; Le et al., 2019). Typical appropriability management entails informal legal practices (e.g., speed-to-market or secrecy) and formal legal practices (patents, trademarks, or non-disclosure agreements) (Grimaldi et al., 2021; Zobel et al., 2017); the high degree of appropriability management ensures the protection of the focal firm's core and proprietary knowledge from being misappropriated by partners. Accordingly, most empirical research showed the critical role of appropriability regime protection in firms' OI engagement (Holgersson & Granstrand, 2017).

Interestingly, as opposed to the claims relating to legal protections' role, recent OI research pointed out the increased use of firms' deliberate knowledge sharing in seeking higher firm performance (Alexy et al., 2013; Baima et al., 2020; Verreynne et al., 2020). Simply put, this research line argues that knowledge should be actively used and exploited externally to generate new value rather than protected and kept internally (Harhoff et al., 2003; Kutvonen, 2011). For example, Grimaldi et al. (2021) showed that a strong appropriability regime induces a firm's engagement in an out-licensing activity. However, the firms with a strong emphasis on legal protections did not achieve the highest return through collaboration. Instead, the firms with active knowledge sharing in both inflows and outflows were found to benefit the most from OI.

Moreover, some qualitative-based studies indicated an important strategic role of outward knowledge flows in OI performance, such as enticing partners to join a collaboration, co-development of the ecosystem, setting an industry standard, or conducting a cross-licensing (Baima et al., 2020; Masucci et al., 2020). Through the Exploitation of shared knowledge, external partners can add more value and new insights to the focal firm's proprietary knowledge. In other words, outward knowledge flows are useful for both capturing value and creating new value (Chesbrough et al., 2018; Verreynne et al., 2020). Nonetheless, past OI researchers have tended to emphasise minimising outward knowledge flows, while maximising inward knowledge flows (Bogers, 2011; Laursen & Salter, 2014). As a result, the outbound OI dimension has received little attention to date (Torres de Oliveira et al., 2021). The lack of research on outbound OI contributes to the substantial research gaps in OI and performance relationships.

2.5 Research Framework

2.5.1 The Importance of Outward Knowledge Flows

The discussion above with three OI-related concepts indicated the considerable research gaps between the inward knowledge flows and the outward knowledge flows (Bogers et al., 2018). In recent years, many OI scholars have pointed out the disproportionate focus on inbound OI and called for more research on the outward dimension of the OI strategy (Aliasghar & Haar, 2021; Masucci et al., 2020; Verreynne et al., 2020). For example, West and Bogers' literature review (2014) showed that, of 291 academic papers concerning OI studies between 2003 and 2013, only 17% of OI research explored the concept of outward knowledge flows. Furthermore, the primary focus of most outbound OI research in the past has been out-licensing in a particular industry: biotech, pharmaceutical, or chemical industries (Hu et al., 2015; Wikhamn, 2019). Thus, there needs to be more research on outbound OI to obtain a rich understanding of outbound OI. Overall, although OI research has been fruitful over the past 20 years since the emergence of the concept, the lack of the outbound OI dimension may be one factor contributing to the inconclusive findings of OI performance in past research (Verreynne et al., 2020). Importantly, the fact that the number of firms conducting inbound OI equally means the number of firms undertaking outbound OI underpins the importance of both dimensions

(Kutvonen, 2011; Torres de Oliveira et al., 2021). For all these reasons, this thesis aims to examine the role of outward knowledge flows in OI performance and to advance the OI theory from the outbound OI dimension.

2.5.2 Contingency Nature of OI Performance: Environmental Dynamics

Another key discussion regarding OI and performance underlies the business environment in which a firm operates (Lichtenthaler, 2009). As OI strategies were developed as a strategic response to cope with the increased dynamic environment, the degree of business dynamics (i.e., market turbulence and technological turbulence) might impact the effectiveness of OI (Hung & Chou, 2013). For example, Teece (1986) argued for the importance of alignment of the innovation strategy with the business environment in which a firm operates. To speed up innovation, firms operating in a fast-moving and growing industry may require a collaborative approach more than firms in a slow-moving and mature industry (Pisano & Teece, 2007). In other words, some firms operating in a dynamic business environment need to look for external partners to overcome the increased business and innovation cycles and to benefit more from innovation. In contrast, other firms in a slow-moving industry can profit from a rather closed innovation approach. Thus, outbound OI can be detrimental to financial and innovation performance (Lichtenthaler, 2009).

As such, a number of inbound OI studies examined the role of environmental dynamics as a moderator and showed the positive influence of environmental turbulence on the relationships between inbound OI and performance (Hung & Chou, 2013; Kutoeven et al., 2011). However, as noted in the above section, there is little research on outbound OI and on the moderating role of environmental dynamics on the relationship between outbound OI and performance. Therefore, more studies are required to understand in what circumstances outbound OI is beneficial to firms.

2.5.3 Research Question

Based on the previous arguments, whether NZ firms can benefit from OI strategies seems to depend on what firms need from collaboration to fill their resource gaps (Chesbrough et al., 2014). In particular, a "*closed or open" innovation* choice depends on whether the internal development of specific knowledge, resource, or capability, is too costly and time-consuming (Lichtenthaler, 2009). In this regard, there are two unique characteristics among NZ firms to be considered: (1) there is a relatively high proportion of high-tech, small but specialised, and globally competitive firms in NZ (OECD, 2017) and (2) the commercialisation stage can be challenging for NZ firms. For example, according to the Global Innovation Index report (Dutta et al., 2019), NZ businesses are globally competitive in some sectors, such as agriculture or biotech. In addition to this, the recent report focusing on NZ businesses indicated globally competitive R&D capabilities and absorptive capacity (Pells & Howard, 2019; Roberts, 2018).

In contrast, the secondary report (MBIE, 2019) showed that NZ firms typically struggle in the commercialisation stage, which could be one reason for fewer global NZ-born firms. In their report, the weakness of the commercialisation stage, a small economy of scale, and a lack of expertise in global market knowledge are attributed to the difficulties in the successful commercialisation of innovation projects (Pells & Howard, 2019). For these reasons, it is more logical to argue that NZ firms can benefit from the outbound OI strategy, which could assist NZ firms' commercialisation phase and complement the abovementioned NZ firms' weaknesses. As such, the following research questions have been developed:

Main research questions

1. What are the effects of outbound OI on NZ firms' financial and innovation performance?

Sub-research questions

2. Do Selling OI and Revealing OI differently influence financial and innovation firms' performance? If so, how?
3. Does business environmental turbulence impact the relationship between outbound OI and firms' financial and innovation performance?

2.6 Summary

This chapter extensively explored literature relating to innovation and OI domains to address the research statement in the present thesis. As such, the thorough literature review has identified the substantial research gaps in the OI field, for example, the lack of research relating to outbound OI. While the majority of the past studies showed the positive effects of OI on firms' performance, some scholars argued for the contingency natures of OI performance, making it difficult to determine whether or not the OI approach is beneficial to NZ firms.

Further to this, despite the fact that OI is about two-way interactions and bilateral knowledge exchange among collaboration partners, past OI studies tended to focus on the inbound OI dimension. Given the fact that outbound OI may have a meaningful effect on a firm's OI performance, extending the OI theory from the outbound OI dimension is critical. For all these reasons, this thesis has set three research questions to explore the relationships between outbound OI and firms' performance, coupled with the effects of environmental dynamics on the relationships.

Chapter 3 Hypothesis Development

3.1 Introduction

Following the research questions raised in the previous sections, this chapter outlines rationales for hypothesis development and the conceptual framework adopted in this study. Particularly, hypothesis testing is applied to explore the research questions, and 13 hypotheses were developed based on a review of the existing literature that had explored and examined the outbound OI dimension (logics and justifications of chosen research strategies are provided in more detail in the next chapter). Accordingly, Sections 3.2 and 3.3 demonstrate five hypotheses relating to the relationships between outbound OI and a firm's financial and innovation performance, followed by eight hypotheses regarding the moderating roles of environmental factors in the relationship between outbound OI and performance in Section 3.4. Lastly, the chapter presents the diagrams of the conceptual model and a summary of the literature review (see **Table *2*** on page 27).

3.2 Selling OI and Financial and Innovation Performance

The research on the relationship between Selling OI and financial performance is relatively advanced compared to Revealing OI (Foege et al., 2019). Particularly, the relationships between Selling OI and financial performance have been explored with a theoretical lens of several research fields: out-licensing (Agrawal, 2006), spin-offs (Chemmanur et al., 2014; Wikhamn & Styhre, 2019), or divestments (Masucci et al., 2020). In this respect, OI researchers agreed on the positive impacts of Selling OI on firms' financial performance (Lichtenthaler, 2009; Singh et al., 2021). One illustration of Selling OI's benefits is an immediate financial return through external commercialisation of the focal firm's core and useable knowledge; out-licensing or provision of the internal IP assets directly contributes to revenue generation (Kollmer & Dowling, 2004). In addition to this, external exploitation of internally non-core and unusable knowledge can enhance the innovation success rate and firms' overall revenue. Generally, internally unusable knowledge created through R&D becomes sunk costs and innovation failures unless firms possess necessary complementary assets to capture its value, which is often costly and time-consuming to develop. Given the high failure rate of firms' innovation activities, external exploitation of internal assets by Selling OI plays a critical role in overcoming the increased speed of product and technology lifecycles (Helm et al., 2019; Lichtenthaler, 2009).

In contrast, some OI scholars disagree with the positive impact of Selling OI due to the required capabilities and resources to manage effective external knowledge transfer (Cheng & Shiu, 2015). For example, Selling OI typically entails legal negotiations and practices. Thus, legal capabilities are necessary to fully benefit from outward knowledge flows (Liao et al., 2020). Further to this, outbound OI scholars have highlighted the importance of experience and desorptive capacity for a profitable Selling OI strategy (Aliasghar & Haar, 2021; Lichtenthaler & Lichtenthaler, 2009). For instance, Fu et al.'s (2019) longitudinal study reported a time-lagged effect, claiming that outbound OI may negatively influence the firm's performance in the short run and then develop into a positive impact in the second and third years. Their finding underpins the critical role of experience and the capabilities to benefit from Selling OI; firms with less experience (first year) may suffer from a negative impact, and then, Selling OI becomes profitable as firms gain more experience and desorptive capacity (Lichtenthaler & Lichtenthaler, 2009). Therefore, it is reasonable to argue that past research claiming the negative outcome of selling OI did not capture the effects of Selling OI *accurately* because inbound OI focused studies rarely include experienced outbound OI firms in their sample (Hung & Chou, 2013). In short, the contradictory result of Selling OI performance may be due to the differences in sampling frame and the sample's experience and capabilities.

Furthermore, although several qualitative-based studies showed the strategic role of selling OI, little research has quantitatively examined the relationships between Selling OI and innovation performance (Masucci et al., 2020). Thus, the generalisability of findings is not clear to date. For example, Cheng and Shiu (2015) found that Selling OI increases financial performance but may reduce product innovativeness. Similarly, Filiou (2021) claimed that Selling OI does not substantially improve the innovation performance of the established bio-pharmaceutical firms. Contrastingly, some scholars argued that strategic Selling OI could improve the innovation performance of large firms (Helm et al., 2019; Kollmer & Dowling, 2004). Large firms often conduct strategic Selling OI to achieve market and industry growth, industry setting, or complementary product enhancement, which can directly improve their innovation performance (Kutvonen, 2011). Similarly, other scholars reported SMEs' increased use of strategic Selling OI to develop the firm's innovativeness; outward knowledge flows can stimulate other players to collaborate, thus increasing the quality and amount of inward knowledge flows for higher innovation performance (Helm et al., 2019). In short, despite a paucity of quantitative studies, it is plausible to argue that selling OI plays a critical role in strengthening a firm's innovativeness (Ovuakporie et al., 2021; Singh et al., 2021). Based on these premises, the following hypotheses were developed:

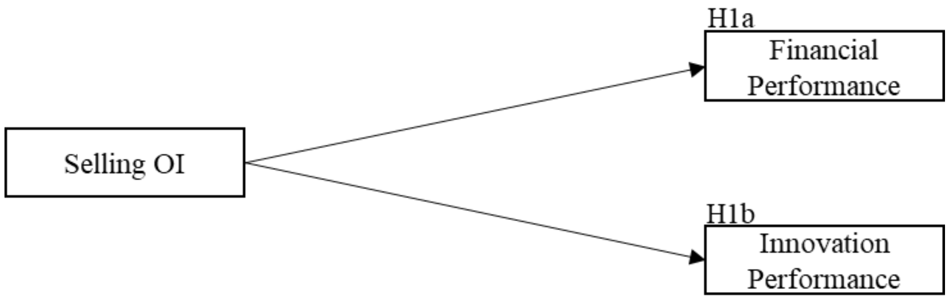
<u>H1a and H1b</u>

A firm's selling OI activities increase the firm's financial (H1a) and innovation (H1b) performance.

The hypothesised relationship is shown in **Figure 2**.

Figure 2

The Conceptual Model for Selling OI and a Firm's Performance



3.3 Revealing OI and Financial and Innovation Performance

In contrast to a pecuniary mode of outbound OI, Revealing OI's influence on firms' performance remains unclear because of the research gap in the OI theory (Henkel et al., 2014; Ritala et al., 2018; Verreynne et al., 2020). Conventionally, many business scholars emphasise the importance of proprietary knowledge protection from competitors to enjoy a sustained competitive advantage (Barney, 1991; Teece, 1986). However, Revealing OI has recently gained increased attention among OI researchers, and the growing amount of evidence indicates the advantages of non-pecuniary outward knowledge flows (Foege et al., 2019; Kutvonen, 2011). In this vein, Baima et al.'s (2020) case study explained several underlying incentives for Revealing OI:

- Expediting industry growth,
- Improving inbound knowledge flows by sharing proprietary knowledge,
- Strengthening the firm's network and market position by increasing reputation, and
- Increasing complementary products.

With their explorative-based study, Foege et al. (2019) reported similar motives in their sample, arguing that Revealing OI could be beneficial across multiple levels of OI players (individual, firm, and industry levels). While the above-mentioned objectives of Revealing OI do not substantially differ from those of strategic Selling OI, the fact that Revealing OI does not incur financial costs to access shared knowledge can reduce hurdles for other players to engage in knowledge exploitation (Baima et al., 2020). This is a crucial aspect of Revealing OI because it can entice a myriad of players who can potentially add extra value to the shared knowledge; collaboration with other industries helps the focal firm gain new valuable market and industry knowledge (Foege et al., 2019; Greco et al., 2019). Further, with their mixed research, Henkel et al. (2014) noted that Revealing OI is a common practice in the software development industry and plays a major role in the focal firm's competitiveness and innovation performance. Particularly, they observed positive loops between the focal firm and knowledge receivers (e.g., consumers and competitors). Instead of losing competitiveness, the collaboration partners help the focal firm create new value by exploiting free knowledge. In turn, the focal firm can keep innovating and updating its portfolios. In short, the benefits of Revealing OI in innovation performance are relatively evident (Ritala et al., 2015; Torres de Oliveira et al., 2021).

In contrast, the impacts of Revealing OI on financial performance are under-researched (Verreynne et al., 2020). Generally, free or selective knowledge sharing inevitably reduces value appropriability and leads to potential loss of control of the proprietary knowledge; therefore, some firms may be financially disadvantaged by Revealing OI (Ritala et al., 2018). The downside of Revealing OI, thus, needs to be compensated by the benefits of Revealing OI, such as increased innovation performance and value creation activities (Torres de Oliveira et al., 2021). In this regard, the expected positive effects of Revealing OI, such as industry standard setting, building the ecosystem, or enhanced complementary products, are believed to contribute to future financial performance. However, as opposed to expectations, two pioneering works related to Revealing OI and financial performance did not find a significant relationship (Torres de Oliveira et al., 2021; Verreynne et al., 2020). They call for future research with a different measurement to explore and build further evidence relating to the Revealing OI and financial performance relationship. Particularly, because Tobin's Q-based econometric scale was adopted in the previous papers, investors' perceptions and a market-based movement may have caused an unwanted influence on the true relationship (Torres de Oliveira et al., 2021). Based on these arguments and empirical evidence from both quantitative and qualitative studies (Baima et al., 2020; Foege et al., 2019; Henkel et al., 2014; Ritala et al., 2015; Verreynne et al., 2020), this thesis hypothesised as follows:

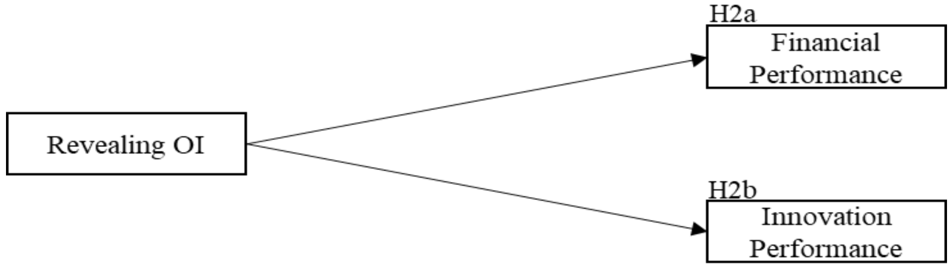
<u>H2a and H2b</u>

A firm's Revealing OI activities increase the firm's financial (H2a) and innovation (H2b) performance.

The proposed relationship is shown in **Figure 3**.

Figure 3

The Conceptual Model for Revealing OI and a Firm's Performance



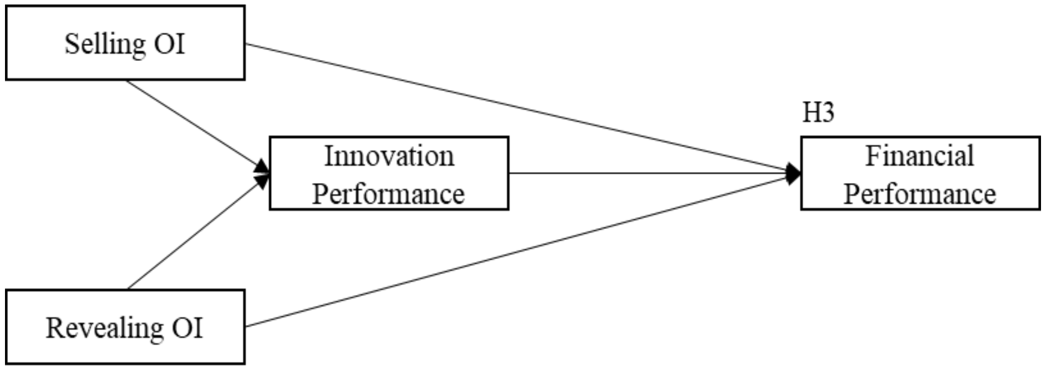
<u>**H3**</u>

A firm's combined outbound OI activities (Selling OI, Revealing OI and innovation performance) increase the firm's financial performance.

The hypothesised relationship is shown in **Figure 4**.

Figure 4

The Overall Conceptual Model



3.4 The Moderating Effects of Environmental Dynamics

Furthermore, the present study investigates the moderating effect of environmental dynamics: market and technological turbulence in which the focal firm operates. As Chesbrough (2003) and other innovation scholars described (Lichtenthaler, 2009), environmental dynamics play an important role as antecedents and moderators in innovation strategies (Henkel et al., 2014). Firms operating in a high market and technological turbulence need to overcome high business uncertainty, competition, and ever-changing customer demands because the firm's competitive knowledge becomes obsolete quickly (Bogers et al., 2018). In this sense, Henkel et al. (2014) documented how Revealing OI has emerged as a common practice in the software development industry despite the strict appropriability protections that had been a convention for a long time. The rapid technological change led the industry firms to shift from a closed innovation model so that firms could cope with the environmental dynamics (Henkel, 2006). Conversely, firms operating in a slow-moving industry (e.g., oil industry) are less incentivised for free-sharing but for more Selling OI because of a long-lasting competitive advantage (Masucci et al., 2020). In short, environmental factors may change the influence of outward knowledge on firms' performance (Henkel et al., 2014). As such, the following hypotheses are developed:

<u>**H4a + H4b**</u>

The degree of market turbulence positively moderates the relationship between Selling OI (H4a), Revealing OI (H4b) and a firm's <u>financial</u> performance.

<u>H4c + H4d</u>

The degree of market turbulence positively moderates the relationship between Selling OI (H4c), Revealing OI (H4d) and a firm's <u>innovation</u> performance.

<u>H5a + H5b</u>

The degree of technological turbulence positively moderates the relationship between Selling OI (H5a), Revealing OI (H5b) and a firm's <u>financial</u> performance.

<u>H5c + H5d</u>

The degree of technological turbulence positively moderates the relationship between Selling OI (H5c), Revealing OI (H5d) and a firm's <u>innovation</u> performance.

The hypothesised relationships are shown in **Figure 5**.

Figure 5

The Conceptual Model with Moderators

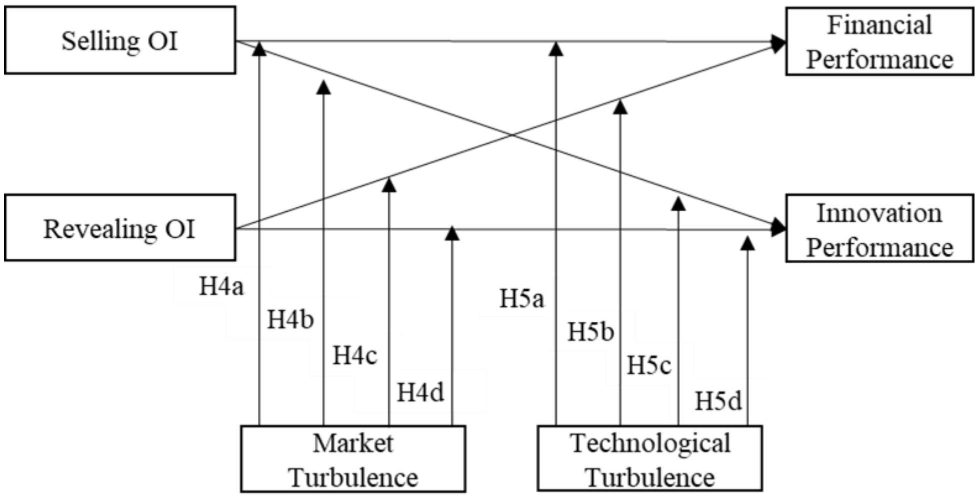


Table 2

Literature Summary for Outbound OI and Firms' Performance

Authors	**Category**	**Journal**	**Key Variables (construct)**	**Methodology**	**Findings**
Hung & Chou, 2013	Selling OI & Financial performance	Technovation (A)	Inbound OI (Strategy) Outbound OI (Strategy) Financial performance (Tobin's Q)	Quantitative research based on ordinary least squares (OLS) regression analysis among 176 Taiwanese high tech manufacturing firms	Inbound OI enhances financial performance while outbound OI does not.
Oltra et al., 2018	Selling OI & Financial performance	Business Process Management Journal (B)	Inbound OI (Practice) Outbound OI (Practice) Financial performance (Self-report, four items)	244 low and medium-tech firms in Spain (more than 50 employees), moderated hierarchical multiple linear regression analysis	Both Selling OI and Revealing OI practices are related to financial performance.
Filiou, 2021	Selling OI & Innovation performance	R&D Management (A)	Inbound OI (Practice) Outbound OI (Practice) Innovation performance (No. of a patent)	A longitudinal data for 66 UK-based bio-pharmaceuticals firms	For established firms, outbound OI is negatively associated with patent performance. For newly established firms, there was no evidence to support a positive influence of outbound OI on patent performance.

Authors	Category	Journal	Key Variables (construct)	Methodology	Findings
Liao et al., 2020	Selling OI & Financial performance	Journal of Business & Industrial Marketing (A)	Inbound OI (Strategy) Outbound OI (Strategy) (adapted from Hung and Chou (2013) Financial performance (self-report, seven items)	Randomised sampling, 238 Chinese high-tech enterprises. Structural equation modelling and linear regression were used	Both inbound OI and outbound OI increase a firm's performance. Technological capability does not moderate outbound OI and performance relationships. It needs the market capability to make outbound OI more effective.
Lichtenthaler, 2009	Selling OI & Financial performance	R&D Management (A)	Outbound OI (Strategy) Financial performance (Tobin's Q)	136 industrial firms based on OLS regression and hierarchical moderation analysis	Environmental turbulence moderates the relationships between outbound OI and OI performance. Outbound OI has a positive effect on firms' financial performance.
Fu et al., 2019	Selling OI & Financial performance	Technology Analysis & Strategic Management (B)	Inbound OI (Transaction) Outbound OI (Transaction) Financial performance (Tobin's Q)	172 biopharmaceutical firms in China for three consecutive years	The effects of outbound OI can be negative in the short-term (1st year) but then becomes positive in the long run (three years).
Cheng & Shiu, 2015	Selling OI & Innovation performance	Management Decision (B)	Inbound OI (Strategy) Outbound OI (Strategy) Innovation performance (radical or incremental)	304 Taiwanese firms based on a three-stage least square analysis	Outbound OI increases incremental innovation and capabilities, namely administrative learning and exploitative capabilities, but reduces technical learning capabilities.

Authors	Category	Journal	Key Variables (construct)	Methodology	Findings
Agrawal, 2006	Selling OI	Strategic Management Journal (A*)	Earlier engagement Commercialisation success	Regression analyses based on 124 license projects	Earlier engagement of knowledge licensee increases the likelihood of success and outbound OI performance.
Frishammar et al., 2012	Selling OI	Journal of Product Innovation Management (A*)	(External exploitation strategy External commercialisation Performance (3 items)	193 manufacturing firms with over 100 employees in Sweden	An outward-looking strategy increases the firm's external exploitation capabilities and then improves external commercial performance.
Aliasghar & Haar, 2021	Selling OI	International Business Review (A)	Desorptive capacity (Strategy) Financial performance (self-report)	541 NZ firms conducting out-licensing using an online panel and non-probability sampling	Desorptive capacity is essential for outbound OI firms to benefit from collaboration. Complementarity between inbound and outbound OI is crucial to enhancing innovation performance.
Cheng & Huizingh, 2014	Selling OI & Innovation performance	Journal of Product Innovation Management (A*)	Inbound OI (practice) Outbound OI (practice) Innovation performance (4 dimensions)	A survey among 232 service firms in Asia	Outbound OI activities are significantly and positively related to all four dimensions of innovation performance: new product/service innovativeness, new product/service success, customer performance, and financial performance.

Authors	Category	Journal	Key Variables (construct)	Methodology	Findings
Caputo et al., 2016	Selling OI & Financial performance	Management Decision (B)	Inbound OI (Transaction value) Outbound OI (Transaction value) Financial performance (Tobin's q)	The top 110 global firms in the bio-pharmaceutical industry between 2008 to 2012 (cross-sectional survey)	An inverted U-shape relationship between outbound and financial performance is found. The use of outbound OI among the sample firms is essential for their financial performance. They argued no synergistic effect between inbound OI and outbound OI.
Singh et al., 2021	Selling OI & Financial performance	Journal of Business Research (A)	Inbound OI (Strategy) Outbound OI (adopted from Lichtenthaler (2009) Financial performance (self-report six items)	Structural equation modelling analysis across 404 SMEs in UAE, Two different sources for different questions	In their young and small-sized firm sample, both inbound OI and outbound OI have a positive influence on their financial performance.
Kollmer & Dowling, 2004	Selling OI & Financial performance	Research Policy (A*)	Licensing Financial attractiveness and transaction value	70 firms' biopharmaceuticals industry (longitudinal study)	Firms with certain complementary assets engage in licensing for strategic reasons, while newly established firms with less complementary assets seek monetary benefits through licensing. Age and size do not matter for licensing activities.

Authors	Category	Journal	Key Variables (construct)	Methodology	Findings
Wikhamn & Styhre, 2019	Selling OI	R&D Management (A)	Not applicable	A case study of the global bio-pharmaceutical firm with a qualitative approach	Spinouts are very challenging when organisational barriers exist, such as Not-Invented-Elsewhere Syndrome.
Chemmanur et al., 2014	Selling OI	Journal of Corporate Finance (A*)	Spin-offs Productivity	A longitudinal data of 196 firms from 1980 to 2000 in the manufacturing sector	Spin-offs increase the productivity of spun-out firms and allow cost-saving effects for parent firms.
Tranekjer & Knudsen, 2012	Selling OI	Journal of Product Innovation Management (A*)	Not applicable	Among their sample of young and small innovative firms, descriptive and T-tests are conducted	The descriptive analysis shows that almost all firms in their sample conduct inbound OI, and half of them engage in outbound OI. The Chi-square test shows that the knowledge providers (outbound OI conductors) are more likely to innovate new products than non-provider.
Kutvonen, 2011	Selling OI	European Journal of Innovation (B)	Not applicable	Conceptual study	While the previous study focused on the monetary benefits of outbound OI, their literature review highlighted a strategic outward knowledge flow, such as industry setting, market growth, or complementary product enhancements.

Authors	Category	Journal	Key Variables (construct)	Methodology	Findings
Masucci et al., 2020	Revealing OI	Research Policy (A*)	Not applicable	A qualitative approach based on 5 sample projects in the oil industry	The effective use of outward knowledge flows, both pecuniary and non-pecuniary by the focal firm, can entice collaboration partners to deploy new technology in the ecosystem. Accordingly, the industry, as a whole, can improve its technology and productivity.
Foege et al., 2019	Revealing OI	Research Policy (A*)	Not applicable	The survey among 227 individuals and then an in-depth 43 interviews	The study identified the tensions between outbound OI firms and individuals when managing IP sharing–protection. Knowledge senders use several approaches to protect their IPs while also producing new value by Revealing OI.
Verreynne et al., 2020	Revealing OI & Innovation performance	Scientometrics (A)	Revealing Tobin's Q Innovation performance (Patent data)	A systematic scale development and testing scale among 164 firms in Australia	The scale development was based on a structured four-step process (DeVellis, 2017). The scales were tested and provided statistical evidence to the measurement validity concerning revealing OI.
Ritala et al., 2015	Revealing OI & Innovation performance	Technovation (A)	External knowledge sharing (organisational practices) Innovation performance	A survey among 150 high-tech firms in Finland	External knowledge sharing increased the innovation performance among the sample firms.

Authors	Category	Journal	Key Variables (construct)	Methodology	Findings
Henkel et al., 2014	Revealing OI	Research Policy (A*)	Engagement in Revealing OI Motivational factors (6 items)	Exploratory and mixed methods based on 16 in-depth and semi-structured interviews in the first stage. Then 74 surveys in the second quantitative stage	The finding suggested that a market and industry environment force firms change their strategy from internal-looking to selective-revealing strategy. Revealing OI firms in the software development industry enjoyed marketing- and related technological benefits through outbound OI.
Torres de Oliveira et al., 2021	Revealing OI & Financial and Innovation performance	Journal of Business Research (A)	Revealing OI (Verreynne's scale) Appropriability regime Innovation breath Tobin's Q Innovation performance (Patent data and self-report)	The cross-sectional survey among large 164 Australian firms listed on the Australian Stock Exchange	Revealing OI does not increase financial performance while enhancing innovation performance. Appropriability protection was an important enabler for Revealing OI.
Baima et al., 2020	Revealing OI	Business Process Management Journal (B)	Not applicable	A case study of the firm in the food industry based on semi-structured interviews with the CEO and CMO	The result showed that Revealing OI enhances the firm's competitive position through the market-, technological-, and industry-related benefits.

3.5 Summary

This chapter presented 13 hypotheses addressing research questions raised in the previous chapter. In particular, the effects of outbound OI on a firm's performance will be investigated through hypothesis testing and examination of the relationships between outbound OI (Selling OI and Revealing OI) and OI performance (financial and innovation performance). Moreover, the last section has demonstrated the rationale for testing the influences of environmental dynamics as a moderator. Because the majority of innovation and OI literature suggests the importance of innovation strategies to match a firm's business environment, the examination of environmental factors in outbound OI research is crucial. The next chapter will discuss the research strategy, approach, and methods applied to test the hypotheses.

Chapter 4 Research Design and Methodology

4.1 Introduction

So far, the previous three chapters have explored OI literature to address the research statement specified in Chapter 1. Also, Chapter 2 derived three research questions, and Chapter 3 developed 13 hypotheses to explore the research statement. This chapter discusses research design and methodology and demonstrates how to conduct trustworthy research to address the research questions, coupled with justifications for choosing the research strategies.

This chapter is comprised of six sections: a research design, research philosophy, research strategies, sampling methods, data collection methods, and ethical considerations. Firstly, Section 4.2 discusses the research design development process. In particular, the section concerns the foundation of the present research design, such as research transparency, research philosophy, and research goal. Furthermore, Section 4.3 elaborates on research strategies, including the rationales for selecting a quantitative methodology and cross-sectional survey approach; the discussion includes the advantages and limitations of the chosen methodologies. Then, sampling and data collection strategies, such as sampling frame, population, sampling methods, sample size, and survey administration, are discussed in Section 4.4 and Section 4.5. Finally, Section 4.6 describes ethical considerations and illustrates how this thesis takes steps to adhere to AUT's ethics guidelines.

4.2 Research Design Development

4.2.1 Transparency

Responding to the recent call for improved research replicability, this thesis first discusses the necessity of research transparency associated with research designs, approaches, and strategies (Aguinis et al., 2018; Beugelsdijk et al., 2020). Most academic researchers have agreed on the vital role of transparent research design so that other researchers can reproduce the equivalent result using similar instruments and research settings (Easterby-Smith et al., 2021; Saunders et al., 2019). By definition, research transparency can be improved by disclosing every detail of research design and methodologies: a conceptual model, methodological and philosophical approach, data collection methods, and statistical analysis techniques (DeCelles et al., 2021). Thus, this thesis, although it could be a rather detailed and long argument, follows the guideline from the seminal paper published in the Academy of Management to demonstrate the highest level of research transparency (Aguinis et al., 2018).

4.2.2 Research Design

The first step relating to research transparency is defining the research goal, research strategy, and epistemological viewpoint adopted in a study (Aguinis et al., 2018). Firstly, a research goal stands for a study's purpose, such as a descriptive study, exploratory research, or explanatory research (Saunders et al., 2019; Wright et al., 2005). Secondly, a research strategy is defined as an approach to achieving a research goal: deductive, inductive, or abductive reasoning (Creswell & Creswell, 2017). Lastly, an epistemological view is an investigator's research philosophy, such as ontology and epistemology (Lee & Lings, 2008; Moon & Blackman, 2014). The manifestation of these elements enhances the interpretability of the findings and increases the result's replicability (Aguinis et al., 2018).

4.2.3 Research Goal

The research goal of the present thesis is to explore the role of outbound OI on firms' performance. This entails both aspects of the research goal: exploration (theory-building) and explanation (theory-testing) (Colquitt & Zapata-Phelan, 2007). Firstly, the relationships between outbound OI and firm performance have been empirically tested in past research (Henkel et al., 2014; Torres de Oliveira et al., 2021). Thus, the hypotheses in this study are grounded in the previous papers. According to their classification (Colquitt & Zapata-Phelan, 2007), testing previously proposed relationships is regarded as theory testing, which assumes the highest level of theoretical contribution; theory testing allows the advancement of the theory by providing empirical evidence to either support or reject the proposed theories and relationships (Lee & Lings, 2008).

Moreover, the hypotheses of this thesis cover a relatively unexplored phenomenon: (1) Selling OI and Innovation performance and (2) Revealing OI and Financial performance (Foege et al., 2019; Ritala et al., 2015). The investigation of underdeveloped theoretical relationships contributes to a theory by expanding the current body of knowledge (Saunders et al., 2019). Thus, theory-building plays an essential role in "opening up new avenues for theory-driven research" (Colquitt & Zapata-Phelan, 2007, p.1284). Overall, the degree of theoretical contributions that the present study aims to achieve is regarded as impactful.

4.2.4 Research Approach and Epistemological View

The dominance of deductive reasoning in innovation research has been noted by previous papers (Alvesson & Sandberg, 2013; Faems, 2020). As already demonstrated in previous chapters, this thesis generated the hypotheses from the existing theory, which clearly indicates a deductive reasoning approach (Creswell & Creswell, 2017). Moreover, a research philosophy of authors, such as ontological and epistemological views, often dictates a research strategy, design, and methodology (Easterby-Smith et al., 2021; Saunders et al., 2019). Research philosophy is described as a researcher's views toward knowledge; for example, how a researcher perceives reality (ontology) and how a person acquires knowledge (epistemology) eventually dictates the research paradigm for a study (Collis & Hussey, 2013; Wilson, 2014). In this regard, the present study reflects the author's positivist view, which assumes the notion that knowledge creation should be undertaken objectively (Lee & Lings, 2008; Lussier, 2011). Correspondingly, the quantitative approach is a suitable choice (Easterby-Smith et al., 2021).

4.3 Research Strategies

The research goal, philosophy, and reasoning discussed above can guide an appropriate research strategy: how research should be conducted and how knowledge should be created. Particularly, the fact that theory-testing requires high objectivity and generalisability with large-scale data collection underpins the quantitative, deductive, and survey approach used in this study (Easterby-Smith et al., 2021). Moreover, qualitatively proposed relationships need to be quantitatively examined to advance a theory (Saunders et al., 2019). Accordingly, hypothesis testing through a survey method is the best choice to investigate the research questions comprehensively and objectively(Krosnick, 1999; Scandura & Williams, 2000). The following sections demonstrate the choice of research methodologies and strategies in this study with justifications.

4.3.1 Quantitative Approach

The quantitative approach is better suited to achieve the study's goal from the positivist standpoint. However, no methodologies are perfect, and a quantitative approach has some limitations (Collis & Hussey, 2013). Thus, the benefits and drawbacks of the approach should be acknowledged. To start with a criticism, qualitative and interpretivism researchers often criticise it as having no flexibility in the research findings due to a well-structured research design (Nardi, 2018). Secondly, some researchers argue that constructs and measurements in quantitative studies often lack clarity and accuracy, resulting in untrustable statistical results (Wilson, 2014). Thirdly, while a quantitative approach provides a more generalisable result than a qualitative approach, this benefit should not be taken for granted since achieving high generalisability requires appropriate sampling and data collection (Saunders et al., 2019). Lastly, a quantitative study could be a more costly approach than a qualitative-based study depending on the statistical techniques being used (Lussier, 2011). Ultimately, researchers determine an ideal research approach with considerations regarding the study's goal, resource availability, and sample size requirement for a particular study purpose.

4.3.2 Justification for the Quantitative Approach

A quantitative approach is suited for the theory-testing to investigate the relationships between outbound OI and a firm's OI performance. While several qualitative-based studies are relatively abundant, large-scale studies on this topic are scarce to date (Henkel et al., 2014; Masuccia et al., 2020; Tranekjer & Knudsen, 2012). Thus, the propositions from the previous qualitative research need to be quantitatively tested for theory extension.

Moreover, criticisms against the lack of accuracy and clarity of the construct's measurements are often associated with researchers' malpractices in the way of handling outliers and adopting measurements without proper measurement development procedures (Aguinis et al., 2013; Aguinis et al., 2018; Morgado et al., 2017). In this regard, the measurements in the present thesis were adopted from the existing papers, which have demonstrated the detailed measurement generation process in their papers (Hung & Chou, 2013; Lichtenthaler, 2009; Torres de Oliveira et al., 2021; Verreynne et al., 2020). Further, this thesis took an appropriate step for outlier handling, and a thorough discussion is given in Chapter 5. Thus, this thesis believes that the critiques relating to accuracy and clarity are less problematic in this study.

4.3.3 Cross-Sectional Survey Approach

Despite some drawbacks, the benefits of a cross-sectional study can outperform other modes depending on the goal and research settings (Nardi, 2018). While typical quantitative studies entail experimental, quasi-experimental, longitudinal, or cross-sectional research, this thesis adopted the cross-sectional survey approach for several reasons. Firstly, the cross-sectional approach allows more flexibility to researchers in terms of design and resource constraints than other modes. This is perhaps the most critical dimension, especially for a typical postgraduate student, because of a relatively shorter timeframe and resource availability (Easterby-Smith, 2021).

Another rationale for choosing a cross-sectional survey underlines the purpose of this study; investigation of the relatively underdeveloped field of outbound OI generally requires a certain quantity of empirical studies to solidify the previous findings and advance the theory (Corley & Gioia, 2011). Because budget-friendliness is one superiority of the cross-sectional approach, more research can be accomplished in a given budget (Collis & Hussey, 2013). As such, since the research goal is not intended for making a strong causal claim with a high degree of theory-testing design, which typically requires an experimental or longitudinal approach, the cross-sectional approach is more suitable for the present study's goal (Colquitt & Zapata-Phelan, 2007).

4.3.4 Limitations of Survey and Cross-Sectional Studies

Despite the clear benefits of the cross-sectional approach, it should be used with caution when a study aims to make an inference claim (Aguinis et al., 2019; Antonakis et al., 2010). Because a cross-sectional study is a reflection of the relationships at a single point in time, some argue that it can hardly be used for a cause-and-effect purpose (Rindfleisch et al., 2008). This criticism rests on the four fundamental criteria for a causality claim as follows (Sande & Ghosh, 2018; Saunders et al., 2019; Van der Stede, 2014):

(1) covariance of variables,
(2) theoretical adherence,
(3) alternative explanations, and
(4) time temperance.

Typically, a cross-sectional approach has a limitation in (1) and (4) because of the risks of common method variance (CMV) and the absence of time temporality in a research setting (Antonakis et al., 2010; Rindfleisch et al., 2008). Similarly, unlike random sampling-based experimental designs, (3) can be, at best, theoretically justified (Wright et al., 2005). Thus, while a causal inference is one of the most important objectives for quantitative business researchers, some argue to avoid the cross-sectional approach for cause-and-effect purposes (Van der Stede, 2014). For these reasons, this thesis avoids a strong causal claim and instead provides an appropriate interpretation of analysis results, drawing on some previous cross-sectional research using a cross-sectional survey (Markovic et al., 2020; Zobel, 2017). Nonetheless, the following sections demonstrate some strategies to improve the quality of statistical inference and mitigate the drawbacks of cross-sectional research.

Covariance of Variables

First of all, the most vital factor of a causal claim is the magnitude of covariance among the variables of interest. One cannot argue a causality without statistically significant relationships between the variables (Antonakis et al., 2010). Although the "probabilistic nature of covariation in social science" (Rindfleisch et al., 2008, p.204) or predominant emphasis on P-value-based outcomes are often criticised by many scholars (Antonakis et al., 2014), statistical significance and covariance play a fundamental role in causal inference.

However, such a covariance relationship can be spurious with the presence of CMV, although CMV is unavoidable in a cross-sectional study without certain remedies in place (Antonakis et al., 2014). CMV is defined as systematic shared variance caused by "measurement method rather than to the construct of interest" (Bagozzi et al., 1991, p.421), and such method variances often generate a biased result, known as common method bias (CMB) (Podsakoff et al., 2003). Although some researchers argue that the effect of CMB is negligible (e.g., Spector et al., 2019), a general view is that CMB may inflate measurement errors and the magnitude of the relationships because of shared variance, leading to spurious relationships between the variables of interest (Tehseen et al., 2017). Thus, the covariance of the variables can be suspicious in the absence of a proper CMB remedy in a study (Rindfleisch, 2008: Podsakoff et al., 2003; Van der Stede, 2014). Thus, this thesis applied prior (e.g., survey design) and post (statistical remedies) CMV mitigation approaches.

Theoretical Adherence

Theoretical adherence refers to the extent to which an observed statistical association is consistent with prior theoretical expectations and findings (Van der Stede, 2014). Researchers should provide theoretical justifications for such associations because a statistically significant result found in a study does not automatically suggest a causality linkage between the variables (Easterby-Smith et al., 2021). This way, reviewers and readers can understand that statistical association is theoretically expected rather than a chance.

Alternative Explanations

As with theoretical adherence, alternative explanations should be discussed and addressed through the literature review (Easterby-Smith et al., 2021; Lussier, 2011). In statistical terms, alternative explanations refer to factors influencing both dependent variables and independent variables. Other phenomena, such as omitted variables and confounding variables, can attenuate or inflate the true relationships of interest. This leads to untrustable research findings (Drost, 2011). In this regard, this thesis has provided a thorough literature review in Chapter 2 and demonstrated how variables are expected to link together in Chapter 3. Thus, theoretical adherence is explained and justified. Moreover, this thesis addresses the concerns of alternative explanation by including the following five control variables in the statistical model, drawing on similar innovation studies (Hung & Chou, 2013; Lichtenthaler, 2009; Verreynne et al., 2020):

- firm size,
- firm age,
- R&D intensity,
- market turbulence, and
- technological turbulence.

The first three control variables eliminate firm-specific influences, while the latter two can exclude industry-specific influences (Hung & Chou, 2013). Further, this thesis ensures the robustness of the research findings with an instrumental variable approach (Ullah et al., 2021), described in more detail in Chapter 5. As such, this thesis believes that alternative explanations are not an issue in this study (Antonakis et al., 2014).

Time Temperance

Lastly, time temporality is another fundamental criterion for causality claim because X (independent variable) must *cause* Y (dependent variable), and X must precede Y, not vice versa (Taylor, 2013; Ullah et al., 2021). The time temporality criterion is perhaps the most difficult element to achieve in cross-sectional business studies because the beginning and end of X’s effect on Y are difficult to manage and justify (Van der Stede, 2014); even longitudinal studies cannot often prove this criterion because the concepts, such as strategies, perceptions, or behaviours, can be hardly estimated in terms of the time that the effects of interest start and end (Saunders et al., 2019). Thus, researchers can, at best, present theoretical justification for the time temperance claim.

In this sense, this study's theory-driven approach and deductive reasoning help establish support for the time temporality criterion (Easterby-Smith et al., 2021). Although the time temporality of the effects of outbound OI cannot control in a cross-sectional study design, previous studies have shown that strategies typically precede the expected outcome (Hall, 2002; Huang & Hou, 2019). Thus, time temporality should not be a critical issue to undermine the present study's research findings. Most importantly, causality claim is not a dichotomic choice; rather it is a matter of degree of inference (Taylor, 2013). Thus, this thesis hopes to mitigate the criticisms associated with a cross-sectional study with the arguments above and statistical approaches taken in this study, which will be discussed in the next section.

4.3.5 Research Quality

Overall, this thesis aims to achieve a high quality of research outcomes by providing evidence of reliability and validity, which are two key criteria for valuable quantitative research (Saunders et al., 2019). By definition, reliability refers to the extent to which the measurement used in a study can produce similar results over time (Lee & Lings, 2008), while validity is defined as the extent to which a study addresses a research question precisely and appropriately (Taylor, 2013). In general, with a quantitative approach it is easier to achieve higher reliability than with qualitative studies because a research method, namely measurements, sampling approaches, or analysis tools, is highly structured (Drost, 2011). Thus, the systematic research design can increase reproducibility (Aguinis et al., 2018). In terms of the validity of research findings, internal validity and external validity are used to measure the appropriateness of findings in most research (Wilson, 2014). Therefore, the present thesis provides evidence of statistical conclusion validity and construct validity in more detail in Chapter 5.

4.4 Data Collection Strategy

The following two sections cover the data collection procedures: sampling and data collection strategies. Having an appropriate sampling design is vital to scientific research (Kohler et al., 2019). The purpose of sampling in research is due to the fact that most studies cannot investigate a whole population of interest due to the population size and resource limitations (Saunders et al., 2019). Researchers randomly extract a set of data (sample) from the population of interest and infer the whole population using the findings based on the sample's result (Lussier, 2011). Thus, providing precise information about the sample's size, characteristics, and sampling method are essential factors for research transparency, replicability, and the generalisability of research findings (Aguinis et al., 2018).

4.4.1 Sampling Design, Population, and Sample Frame

The population is defined as "a total group about which the researcher describes and makes inferences" (Lussie, 2011, p.117). To answer the research questions and infer the population of interest, a sample frame in question must adhere to the specification of the research purpose. In this regard, this study's research question, *the investigation of effects of outbound OI among NZ firms*, essentially delineates some specifications of the population of interest as follows:

- Firms that conduct outbound OI. In particular, those who make transaction-based outbound OI, such as out-licensing or selling their IPs.
- Firms that conduct collaborative innovation projects.
- Firms that operate in New Zealand.

4.4.2 Sample Size and Power Analysis

In terms of sample size, this thesis has run the power analysis to derive an appropriate sample size needed for valid statistical analysis. The power analysis allows researchers to estimate a minimum required sample size based on the research goal, the degree of statistical power, and the expected effect sizes of variables of interest (Faul et al., 2009). Following Aguinis et al.'s (2018) recommendation, a clear explanation of the *a Priori* power analysis is provided to improve research transparency.

Below, the thesis has run the analysis using G*power software (Erdfelder et al., 1996), drawing on the effect size from the previous literature with conventional statistical power (5% for *a* and 80% for *b*, *a* denotes significance level, while *b* refers to the statistical power) (Lakens, 2021).

The effect size is estimated based on the following two studies:

- Aliasghar and Haar (2021) examined the role of capabilities in inbound and outbound OI on financial performance using 534 NZ out-licensing firms.
- Lichtenthaler (2009) investigated the effects of outbound OI on a firm's performance among 136 industrial firms undertaking out-licensing.

Accordingly, an average variance (R^2) of 0.15 from two studies was adopted to estimate the expected effect size (f^2) of outbound OI on OI performance (Cohen, 1992). Also, following the convention in business study discipline, *a* and *b* levels were set as 5% and 80%, respectively. Secondly, seven predictors were added to the software to take the influence of the degree of freedom (DF) into consideration. Consequently, an *a Priori* test indicated that the minimum required sample size for this study's design is 89 firms to achieve 80% statistical power. Based on this estimated number and the recommendation by Aguinis et al. (2021), the total sample size was set as above 100 observations; 10% additional observations can be useful to mitigate the potential unexpected sampling fluctuation and sampling errors associated with non-probability sampling and the online panel-based survey administration used in this study.

4.4.3 Limitations of Small Sample Size Studies

Although the scale (*n*=100) of this study is not large, it is still of use to achieve this study's goal and make theoretical contributions (Laken, 2021). Some limitations to a small scale study are sampling fluctuation and sampling errors, which make it difficult to evaluate the results and statistical significance found in a study. Conventionally in many disciplines[1], scholars aim to achieve a 95% confidence level and a 5% margin of error to claim the accuracy and preciseness of the research findings (Cohen, 1992; Hazra, 2017). Similarly, many management journals nowadays require researchers to report confidence intervals (CIs) along with their P-value (Murphy & Aguinis, 2019). However, empirical results with a small-scale sample study face a wider width of CIs, which may lead some reviewers and readers to undervalue the research findings.

Nonetheless, Lakens (2021) provided insights into the usefulness of small sample size studies considering practical aspects such as cost and time constraints. Laken (2021) noted that "(d)espite the omnipresence of resource limitations, the topic often receives little attention" (p. 4) and argued a careful consideration when evaluating a finding based on a small sample size as follows:

- Small-scale sample studies may produce a higher sampling error but still provide useful insights, as opposed to having no information about the topic of interest.
- A future meta-analysis study can include the study's findings, in which case the finding contributes to the accumulation of knowledge in a meaningful way.
- The explorative phase of theory building can be conducted to identify the presence of relationships rather than theory testing, which requires a larger dataset.

For all these reasons, even with a small study design (*n*= approximately 100), the author of the present thesis believes that this research's findings are of importance in knowledge accumulation and theory building.

4.4.4 Non-Random Sampling

This thesis adopted a non-random sampling method to collect data from the sample, which is often controversial because of the representativeness of the sampled data (Aguinis et al., 2021;

[1] This sampling size approach typically requires the estimated total population size to identify the sample size. In this regard, this thesis used Business operation survey report (Stats NZ, 2020) to estimate the total population size; firms engaging in out-licensing accounted for approximately 3,500 firms based in NZ, excluding a micro-sized firm. This leads to the minimum sample size of 347 is required to meet the criteria of confidence level (95%) and margin of error (5%) (Raosoft, 2004).

Porter et al., 2019). Nonetheless, recent studies have shown no evidence of the differences between random sampling and non-random sampling, as opposed to the frequent criticisms against using non-random sampling (Walter et al., 2019). Thus, as with prior studies applying non-random sampling methods in innovation studies (e.g., Aliasghar & Haar, 2021), this thesis believes in the quality of sample representativeness of the population in this study (please see Section 4.5.5 for a more detailed discussion on this topic).

4.5 Survey Administration

This section describes the way in which the present thesis collected data from the targeted sample group. In brief, this thesis used a web-based survey method and collected data from the sample through a data collection company (Cint). The following sections describe the advantages, limitations, and justifications of the choices.

4.5.1 Delivery Mode: Web Survey

The survey administration is described as "the act or process of systematic data gathering from a sample" (Donohoe & Karadakis, 2014, p.6481). Such processes include, for example, participant recruitment and data collection (Saunders et al., 2019). Researchers chose an appropriate survey administration method to complete a data collection based on their resource availability, population characteristics, questionnaire content, costs, and timeframe (Fowler, 2014).

4.5.2 Advantages and Disadvantages of Web-Based Survey

This thesis conducted data collection through a web survey approach because of several advantages over other methods, such as mail, telephone, or face-to-face interview. Firstly, the online survey's unit cost is considerably lower than other modes because reaching out to potential participants through the Internet typically does not incur financial costs other than physical costs (Saunders et al., 2019). Secondly, compared to other modes, online surveys can secure anonymity and confidentiality, which can mitigate potential ethical issues (Lussier, 2011). Also, online surveys are argued to be more convenient than other modes as the participants can complete a survey anywhere and anytime as long as they have access to digital devices (Fowler, 2014). In its era, the COVID-19 pandemic is a crucial aspect as some firms require their employees to work from home. Thus, mail surveys and face-to-face interviews can be difficult during lockdown periods (Adom et al., 2020).

In contrast, some authors pointed out the limitation of online surveys due to the risks of non-response bias, non-coverage bias, low response rate, and poor-quality data (e.g., Collis & Hussey, 2013). These factors might lead to inferior sample representativeness of the population of interest, causing less generalisability power (Saunders et al., 2019). Firstly, for example, the non-coverage bias can occur when some potential participants are not approachable due to no access to digital devices or email addresses (Evans & Mathur, 2018). Secondly, because web surveys are self-administered, respondents may not be able to provide accurate answers if the questions are ambiguous (Fowler, 2014). Thirdly, the non-coverage and non-response biases may hugely depend on the quality of the database (address lists) used for participant recruitment (Fowler, 2014). Eventually, all these factors may result in biased data and poor sample representativeness. Thereby, web surveys may pose a threat to the validity of collected data without a proper measurement (Aguinis et al., 2021; Evans & Mathur, 2018).

Nonetheless, this thesis adopted the web-based survey as a data collection method for the following reasons:

- The lower cost is the biggest advantage for cost-constrained postgraduate students to conduct a study (Lussier, 2011).
- Given the limited time for thesis completion (normally less than 12 months), the speed of data collection through online surveys is superior to mail- or interviewer-based data collection when a target population size is relatively large (Fowler, 2014).
- Obtaining a contact list for survey recruitment and then approaching potential participants are challenging for mail- and interview-based data collection because of the target sampling frame and characteristics used in this study (firms with out-licensing and open innovation are hard to find).
- Non-coverage bias, which is often regarded as one disadvantage of online surveys, is less likely in this study because the target sample frame is high-level employees in management positions, who should have access to the Internet and an email address (Saunders et al., 2019).
- In the era of COVID-19, surveys through the mail, phone, and face-to-face interview may be difficult to conduct due to the lockdown rules set by the Government (Adom et al., 2020).
- The web surveys enable confidentiality and anonymity, which can be difficult with other modes of data collection. Anonymity is necessary to reduce the common method bias and ethical concerns (Saunders et al., 2019).
- Although non-response bias can cause a serious issue of data representativeness, it is rather a problem associated with a survey method, not online surveys per se (Evans & Mathur, 2018). In fact, web surveys can reduce non-response bias through frequent follow-up emails at no cost (Fowler, 2014; Rogelberg & Stanton, 2007).
- The use of a third-party data collection firm enables access to a good quality database matching the survey requirements and reaching out to as many potential respondents as

possible. In turn, non-coverage and non-response bias are less problematic than with other modes (Porter et al., 2019).

4.5.3 Data Collection Companies and Online Panel Data

Further, this thesis resorted to a third-party data collection company (Cint) and their online panel database. The online panel data is described as the pre-registered database based on members willing to participate in future research (Callegaro et al., 2014), and third-party data collection companies undertake some of the data collection processes on behalf of researchers. In this study, the use of Cint facilitated the data collection process, such as recruiting potential participants through their pre-registered database based on the sample's characteristics, sending a survey invitation, following up emails and gathering data from the participants.

In general, several difficulties of participant recruitment in business research underpin the usefulness of survey administration through online panel firms (Schoenherr et al., 2015). For example, researchers may face problems in (1) finding and creating a contact list of firms matching a study's interest; (2) overcoming the decreasing response rates in any survey research; and (3) reaching out to the potential participants considering the current strict rule of corporate governance and email filtering features (Evans & Mathur, 2018; Schoenherr et al., 2015). Consequently, the use of online panel firms and their database has burgeoned rapidly over the past two decades, from merely two papers in 2006 to 214 papers in 2017, showing a rapid penetration of online panel surveys and data collection companies in business studies (Porter et al.,2019).

4.5.4 Limitations of Online Panel Data

Despite its growing popularity, data collection through the online panel data has been frequently criticised by many researchers mainly due to its sampling method being named in many ways: "volunteer" sampling (Evans & Mathur, 2018, p.202), convenience sampling (Landers & Behrend, 2015), or non-probability sampling (Kohler et al., 2019). It is argued that online panel data may not be able to cover a whole population of interest because potential respondents pre-register for the online panel firm's membership voluntarily (Aguinis et al., 2021). In particular, reaching out to those who are not on the online panel firms' database is impossible, thus, causing non-coverage bias, self-selection bias, and inferior sample representativeness. In turn, these factors undermine the external validity of the findings (Mercer et al., 2017; Rogelberg & Stanton, 2007). Consequently, criticism towards online panel data is prevalent in organisational research, specifically for inference-based studies using an online panel collection method (Kohler et al., 2019; Landers & Behrend, 2015).

Another key criticism is attributed to the quality of online panel data, which may severely affect the internal validity of the findings (Kohler et al., 2019). As described by multiple researchers, “insufficient effort responding” (Walter et al., 2019, p.428) or “subpar data quality” (Porter et al., 2019) can pose a threat to internal validity and statistical conclusion. Some factors contributing to the poor-quality online panel data stem from the existence of “professional respondents” (Hillygus et al., 2014, p.219), respondent's inattentiveness, and an inappropriate survey design (Walter et al., 2019). For example, professional respondents are incentivised with monetary rewards for taking surveys. This could result in speed responses and patterned answers without reading questions because of the monetary incentives; the more surveys are completed, the more financial returns they receive (Schoenherr et al., 2015). Also, poor survey design, lengthy surveys, and ambiguous questions can negatively affect survey takers’ attention and attrition rate (Schoenherr et al., 2015). Consequently, these negative factors may cause CMV and unexpectedly deflate or inflate relationships between the variables, resulting in a spurious relationship or invalid statistical conclusion (Aguinis et al., 2021; Porter et al., 2019).

4.5.5 Strategies to Overcome the Limitations of Online Panel Data

To prevent sub-quality data, this thesis considered several screening questions and techniques: reverse coded questions, monitoring survey completion time, and rejecting patterned answers (Potrer et al., 2019; Saunders et al., 2019). The whole survey questions are available in **Appendix A,** and the strategies to address professional respondents are discussed in more detail in **Appendix B.**

Moreover, Walter et al. (2019) argued that external validity with online panel data is not a serious issue when the study’s purpose is theoretical generalisation instead of prediction and estimation of an exact population mean, such as a poll survey or consumer market research (Sackett & Larson Jr, 1990). While the point estimation requires high representativeness of a sample to infer an accurate population mean, theoretical generalisation aims at investigating the relationships between the constructs in different times, research settings, and sample characteristics (Sackett & Larson Jr, 1990). Thus, the fact that theory generation requires a variety of sample representativeness across multiple studies justifies the usefulness of online panel data, even if the sample representativeness could fluctuate due to a non-random sampling method. Based on these premises, the benefits of online panel data outweigh its costs since the present study aims to explore the role of outbound OI from a theoretical generation viewpoint rather than a precise estimation of the outbound OI effects. Accordingly, the criticisms of external validity using an online survey should not be a big issue (Walter et al., 2019).

Most importantly, as opposed to the accusations of inferior internal validity, recent research undertook a comparative meta-analysis of the study’s results between an online panel data and a random sampling approach, and the result showed no evidence of the differences in the effect size of variables and scale’s internal consistency (Walter et al., 2019). Several researchers argue that the quality of collected data and internal validity based on online panel data are not as problematic as some researchers criticise (Porter et al., 2019). Thus, drawing on previous scholars' discussions (e.g., Aliasghar & Haar, 2021), this thesis believes that data and sample are of good quality based on the chosen data collection strategy.

4.6 Ethical Considerations

The last section of this chapter demonstrates the ethical considerations taken in this study. As with other scientific research, this thesis ensured conforming to relevant the codes of conduct set by the Auckland University of Technology (AUT) and the Royal Society Code of Professional Standards (RSCPS). The RSCPS provides a guideline for NZ researchers with 12 criteria[2] of value and principles to achieve "exemplary ethical behaviour and world-class research and scholarly practices" (Royal Society of New Zealand Te Apārangi, 2019, p1). These important criteria include the principles of, for example, justice and integrity, which can guide researchers on how to conduct research ethically in the NZ context. The universally required research ethics concepts, respect for participants, non-maleficence, and no harm to participants, are well incorporated into the RSCPS principles. Above all, the codes emphasise indigenous rights, including Maori research culture (Kaupapa), Maori epistemological views, and the Treaty of Waitangi principle: partnership, protection, and participation (Hudson & Russell, 2009).

The RSCPS is critically important for AUT researchers, as the AUT's codes integrate the above-mentioned research guidelines into the core heart of its ethical principle (AUT, 2019). Consistent with the universal research standards, the AUT's codes require the highest level of tika (integrity) and pono (respect), preventing any breach of the codes or research misconduct (e.g., fabrication of data, deceptive behaviour, or plagiarism). This way, research can contribute "to advance science, technology and the humanities in Aotearoa New Zealand" (AUT, 2019, p3). In this sense, a survey study allows data collection to minimally harm the participants as researchers do not directly involve data collection (Fowler, 2014). Thus, this thesis assumes the low risks of the negative aspects of the data collection procedure that may harm the participants: power imbalance, unmercenary pressures associated with face-to-face interviews, and concerns of confidentiality and anonymity (Saunders et al., 2019).

Further, this thesis held a consultation with the Research Ethics Advisor from the AUT Ethics Committee (AUTEC) on 17th February 2021, and the ethics application was approved by AUTEC on 12th August 2021 (reference number: Ethics Application 21/273. Please see **Appendix C** for the approved letter and **Appendix D** for the participation information sheet).

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[2] They are Tika, Mana, Whakapapa, Manaakitanga, Pūkenga, Kaitiakitanga, Justice, Duty of care
, Beneficence, Non-maleficence, Respect, and Integrity. The precise definition of each criterion is available at https://www.royalsociety.org.nz/assets/Uploads/Code-Overview-A3-web.pdf (RSCPS, 2019).

Consistent with the ethical codes, an information sheet was provided to all potential participants before they answered the questionnaire. The information sheet clearly stated the key important ethical considerations as follows:

- the purpose of the study;
- the reason why this thesis approached the potential participants;
- the voluntary basis of survey participation;
- no burdens when the participant decided to withdraw;
- full protection of anonymity, non-traceability, and confidentiality;
- management of collected data, including storage and deletion procedures;
- estimated completion time (around 15 minutes) to answer the survey as a possible cost; and
- information relating to informed consent

4.7 Summary

The present chapter demonstrated the rationales for the research design, research strategies, data collection, and sampling methods adopted in this study. The reasoning included research philosophy and the research goal of this thesis, that is, a theory-testing, theory-building, and generalisation of the research findings to a wider community. Importantly, the first section of this chapter explicitly emphasised the importance of research transparency, which has been a concerning issue for researchers in the past few decades.

The next sections discussed the logic for choosing a quantitative and cross-sectional survey approach in the present thesis. Acknowledging the limitations of the chosen methods, the sections explained why these approaches were the best to address the research questions of the present thesis.

Further, the data collection and sampling strategies were discussed in Section 4.4. As such, the target sampling frame was selected based on three key criteria:

- Firms undertaking out-licensing or selling their IPs.
- Firms that undertake collaborative innovation projects.
- Firms that operate in NZ.

The section further discussed a sampling strategy and determined the minimum sample size as over 100 participants to achieve enough statistical power. Next, Section 4.5 highlighted how the survey would be administered in this thesis. To overcome the limitations of student-led studies, time and cost limitations, this thesis resorted to a survey collection company (Cint) and their online panel data to recruit potential survey participants effectively.

Moreover, the section extensively discussed both advantages and disadvantages of online panel firms and their data, namely non-random sampling methods, inferior sample representativeness, and low-quality response, and the section demonstrated why the benefits of the online panel data outweigh its cost. Lastly, this chapter concluded by emphasising the importance of ethical considerations. Adhering to research ethics is of importance for any researcher when a study involves participants and communities in NZ. Thus, the chapter explained how this thesis maintains the research ethics set by AUT and RSCPS.

Chapter 5 Data Analysis and Results

5.1 Introduction

This chapter aims to demonstrate the steps, justifications of the selected statistical approaches, statistical analysis processes, and findings through the analyses. Firstly, Section 5.2 reports the data collection procedures and the details of the participants used in this study. The discussion includes the measurements used in this study and descriptive statistics, such as demographics, normality, and outliers. Further, Section 5.3 gives in-depth arguments for the measurement validation procedures: factor analysis, statistical software, and model assessment processes. As such, the results for construct validity, convergent validity, and discriminant validity are presented. Moreover, Section 5.4 shows the results of the regression, mediation, and moderation analyses and then elaborates on the findings relating to the 13 hypotheses. Lastly, the chapter concludes with the section presenting robustness checks conducted for increased statistical conclusion validity.

Importantly, as with the previous chapter, this thesis followed the recommendations by Aguinis et al. (2018) and aimed to provide as much detailed information as possible in terms of justifications for the chosen strategies, statistical packages, and rationale for claiming a statistical conclusion. Thus, the discussions below will be relatively long and in-depth; however, this is essential for higher reproducibility and research transparency.

5.2 Data Collection, Sample, and Measurements

5.2.1 Data Collection and Participants

Based on the argument in Section 4.4.2, this thesis recruited a total of 107 participants through Cint, drawing on their online panel data; the targeted respondents were senior managers or above of the NZ firms, who were familiar with their firm’s innovation strategies. In addition, a sampling frame was NZ firms conducting pecuniary outbound OI, such as out-licensing or selling their IP assets over the past three years. This naturally led to a smaller available sample of managers to be recruited.

The soft launch with a target sample size of 20 was conducted on 16th August 2021 to identify any potential critical failures in the design, questionnaire, or screening questions (Saunders et al., 2019). Then, the preliminary result was used to estimate the unit cost of the whole survey collection process for this study. Accordingly, the target sample size was set as above 100, as originally planned based on the Power analysis.

Before moving to the full launch, the data collection was held off due to a nationwide lockdown from 18 August 2021 for five weeks. This was a precaution to avoid the possibility of non-coverage bias because some businesses were not allowed to operate during the lockdown period. Accordingly, the survey collection resumed on 22 September 2021 when Auckland moved down the alert level to three, and the collection of the 107 surveys was completed. Thus, one limitation of this timing was that a COVID-19 lockdown did interfere with the data collection. But this was beyond the control of the student.

5.2.2 Measurement Design

The operationalisation of measurements plays a critical role in terms of statistical conclusion validity and construct validity. Generally, hypothesised concepts and constructs in a business study are “latent rather than manifest” (DeVellis, 2017, p.24), and a phenomenon is typically not directly observable in many social studies (Lussier, 2011). Thus, researchers use observed variables, defined as “characteristics of a phenomenon that can be directly observed”, to construct the latent variable and investigate relationships of interest (Collis & Hussey, 2013, p.201).

In terms of the measurements, this thesis adopted the existing constructs from the previous papers for two reasons: the development of its own scales takes time and lacks reasonable justifications why the existing scales are not suitable for the study (DeVellis, 2017). As a result that the present study builds on the previous papers and their conceptual models, it is more reasonable to rely on the existing measurements. Further to this, using previously validated measurements can give confidence in construct-related validity, such as content validity and face validity (Taylor, 2013). Moreover, all measurements used in this study were multi-item and reflective constructs based on previous studies (Hung & Chou, 2013; Torres de Oliveira et al., 2021). The participants were asked to evaluate their firms’ business environment, the outbound OI strategies, and recent firm financial and innovation performance, with a Likert-scale format ranging from one (strongly disagree) to seven (strongly agree). The following sections describe the variables and constructs with their reliability and validity indicators, such as Cronbach’s *alpha* (*a*), composite reliability score (CR), and average variance extracted (AVE) (Saunders et al., 2019).

Dependent Variables

This thesis adopted two constructs from previous innovation literature for dependent variables: ***Financial Performance*** measurements were adopted by the study by Wiklund and Shepherd (2005) and originally measured with five items; one item was deleted due to poor loading. Overall, the construct ***FinnPF*** showed satisfactory reliability (*a* = 0.75, CR = 0.84, AVE = 0.57).

Innovation Performance was measured through a six-item construct developed by Cheng and Huizingh (2014). The two items were dropped due to high-cross loading, and the four items were used to form ***InnoPF***. The construct also showed good reliability (*a* = 0.74, CR = 0.84, AVE = 0.56).

Independent Variables

Selling OI was initially measured by five items developed by Hung and Chou (2013). Two items were deleted due to poor factor loading and to improve theoretical differentiation between pecuniary and non-pecuniary outbound OI. Since the remaining three questions explicitly asked the business practices related to a monetary-based outbound OI (e.g., IP sells or license-out), all three items are believed to reflect the pecuniary side of outbound OI. Overall, the three items were used to form ***SelOI***, and it showed sufficient reliability (*a* = 0.71, CR = 0.84, AVE = 0.63).

Revealing OI was adopted by Torres de Oliveira et al. (2021), who used a higher-order construct model with 12 items and three sub-dimensions. However, because this higher-order model led to increased complexity, the observed items were parcelled based on the homogeneous item parcelling approach to mitigate the impact of negative effects associated with the model complexity in small-scale research like the present study (please see Section 5.3.4 for a more detailed discussion on the parcelling strategy) (Cole et al., 2016). Overall, the construct, ***RevOI***, was measured with three items, and it showed excellent reliability (*a* = 0.87, CR = 0.92, AVE = 0.79).

Moderation Variables

This study followed the conceptual model of Hung and Chou (2013) and Lichtenthaler's work (2009), which used **market and technological turbulence** as moderators. Specifically, their moderation measurement was adopted from the influential research conducted by Jaworski and Kohli (1993), who developed the constructs of environmental dynamics. As such, three items measuring the construct ***Mar*** (market turbulence), and ***Tech*** (technological turbulence) were constructed by three items after deleting one item due to poor loading. Overall. Both constructs showed acceptable reliability, *Mar* (*a* = 0.78, CR = 0.87, AVE = 0.69) and *Tech* (*a* = 0.93, CR = 0.94, AVE = 0.85).

Control Variables

Lastly, the thesis used several control variables to exclude alternative explanations in the regression model. Previous business papers have provided evidence of the impacts on financial and innovation performance by the degree of firms' innovativeness, firm size and age, and industry-specific environment in which a firm operates (e.g., see Aliasghar & Harr, 2021). In particular, knowledge-intensive firms in the high-tech industry tend to spend more on R&D, which leads to higher financial and innovation performance (Laursen & Salter, 2006, 2014;

Tsai, 2009). Thus, R&D expenditure is the most widely used control variable in innovation research (Filiou, 2021; Liao et al., 2020). Similarly, firm age and size (measured by the number of employees) are frequently adopted as control variables in business studies (Hu et al., 2015). The fact that older and larger firms have more resources and capabilities to undertake innovation projects than those who suffer from the liability of smallness often leads to their higher innovation performance (Hung & Chou, 2013). However, within the research of outbound OI, the effect of firm age and size is controversial because small firms with less complimentary assets could generate higher performance through active out-licensing or IP assets transfer (Arora & Ceccagnoli, 2006; Fiedler & Welpe, 2010; Fosfuri, 2006; Li et al., 2017). Nonetheless, these discussions are inconclusive; thus, this study followed the conventional approach and used all key control variables to avoid the risks of confounding and omitted variables.

Other Variables

This thesis also included the questions of an instrumental variable and a marker variable for robustness analyses. The former deals with endogeneity issues (Antonakis et al., 2014; Ullah et al., 2021), while the latter is increasingly recognised as a statistical remedy for CMB (Podsakoff et al., 2003, 2012). Although the effectiveness of these two variables is often controversial (Rönkkö & Ylitalo, 2011), this study adopted these techniques and asked two questions: the percentage of a firm's institutional investors' ownership (instrumental variable) and a respondent's age (marker variable) (Tehseen et al., 2017).

Accordingly, a robustness check using the instrumental variable was conducted, and the results are provided in Section 5.5. On this note, this thesis decided not to use the marker variable after it showed, although it should not have, a positive relationship with Revealing OI unexpectedly. One reason for this surprising association could be that the younger generations are more required to be open because they are small and newer firms; thus, potentially leading to higher Revealing OI activities than those who are larger and older firms (Henkel et al., 2014; Torres de Oliveira et al., 2021). Nonetheless, this assertion needs to be more explored; thus, this thesis did not use the marker variable. Instead, Harman's single-factor test was used to deal with CMB (Podsakoff et al., 2003).

5.2.3 Descriptive Statistics

Next, this thesis conducted descriptive analyses to examine the characteristics and quality of collected data. This is especially important for a study using online panel data because of the possibility of poor quality and invalid responses (Hillygus et al., 2014; Porter et al., 2019). The initial data screening process identified errors and eventually removed three bot-made responses and one duplicate response from the collected data, leaving the total sample size *n*=103.

The demographic information as well as the distribution frequency of firm age, firm size, industry type and the variables are summarised in **Table 3**, **Table 4**, and **Table 5**. Interestingly, the distribution of the variables (mean and standard deviation), firm age and size are similar to the previous NZ-focused study (*n*=543) (Aliasghar & Haar, 2021). For example, compared with the study above, the firm age distribution between 20 and 29 years is exactly the same at 14.6%, while the firm size, less than 50, is also close to each other at 11.7% (8.5% for the abovementioned study). Despite the relatively small sample size used in this study (*n*=103), these similarities in the demographic statistics suggest a good representation of sample characteristics in this study.

Table 3

Study Demographics

Firm age	**No. of firms**	**Percentage**
5 years or less	2	1.9%
6-9 years	28	27.2%
10-19 years	41	39.8%
20-29 years	15	14.6%
30 years or more	17	16.5%
Firm size		
small-size (less than 50)	12	11.7%
mid-size (50 to 149)	56	54.4%
large size (over 150)	35	33.9%

Note: *n*=103

Table 4

Type of Industry

Industry	**No. of firms**	**Percentage**
Construction	3	2.9%
Electricity, Gas, Water and Waste Services	2	1.9%
Financial and Insurance Services	46	44.7%
Information media and Communication	17	16.5%
Manufacturing	6	5.8%
Professional, Scientific and Technical Services	10	9.7%
Wholesale and Retail Trade	6	5.8%
Others	13	12.6%

Note: *n*=103

Table 5

Distribution Frequencies of the Variables

	FinPF	InnoPF	SelOI	RevOI	Mar	Tech	R&D_INT
Mean (M)	5.98	5.72	5.88	5.87	5.77	4.97	3.25
Standard Deviation (SD)	0.78	0.82	0.77	0.73	0.93	1.68	0.76

Note: *n*=103

All variables were measured with a seven-point Likert Scale.

FinFP (financial performance), InnoPF(innovation performance), SelOI(Selling OI), RevOI(Revealing OI), Mar (Market Turbulence), Tech (Tech Turbulence), R&D_INT (R&D Intensity).

5.2.4 Normality

Further, the normality test was conducted as many statistical analyses rely on the assumption of data normality (Hair et al., 2014). Accordingly, this thesis conducted Kolmogorov-Smirnov and Shapiro-Wilk tests to investigate data normality. The two tests showed a significantly different result (<.001) from a normal distribution, suggesting the possibility of the nonparametric nature of the collected data (Wooldridge, 2015). However, these two tests are often subject to the sample size and, therefore, may not offer a conclusive result, particularly in the case of a small sample size. Instead, Kim (2013) suggested using the value of skewness and kurtosis to evaluate the distribution curve. In this sense, Hair et al. (2014) and West et al. (1995) argued a threshold line as +- 2 for skewness and +- 7 for kurtosis for data to be considered normally distributed. Based on their thresholds, all values of dependent and independent variables fall within the acceptable threshold line, providing evidence of the normality assumption.

5.2.5 Outliers

This thesis followed the framework proposed by Aguinis et al. (2013) to handle and report outliers. Researchers (e.g., Cortina, 2002) called for careful consideration when dealing with outliers, given the fact that many studies tended to delete outliers without giving a sufficient justification. Aguinis et al. (2013) explained three types of outliers: error outliers, interesting outliers, and influential outliers and argued that each type needs a different approach to treat outliers. As described in their framework (Aguinis et al., 2013), this thesis first conducted visual inspections through a scatter plot and then statistically analysed the observed data based on three techniques to detect outliers (Mahalanobis distance, Cook's D, and Leverage values) (Cohen et al., 2014; Tabachnick et al., 2019). Employing three approaches simultaneously is important to increase accuracy because depending on one technique can often be too sensitive to sampling errors and unique characteristics of outliers (Osborne & Overbay, 2004). Accordingly, the outlier analysis showed the possibility of seven outliers in this study.

The treatment of outliers, whether to delete them, has been controversial among researchers (Aguinis et al., 2013). However, this thesis decided not to remove them from the data, as it is difficult to argue if they are error-specific or meaningful outliers. Thus, this thesis avoided outlier deletion for the purpose of increased research transparency despite acknowledging the consequences of having outliers in the sample data, such as heteroscedastic data or larger standard deviation (Cortina, 2002). Instead, following the recommendation by Aguinis et al. (2013), this thesis conducted a comparative test based on the dataset with and without outliers. The test showed no substantial difference in the regression results by having outliers in the data, providing evidence of statistical conclusion validity (Aguinis et al., 2013). The details of the analysis are provided in **Appendix E.**

5.3 Measurement Model and Construct Validation

After the data cleaning, testing the reliability and validity of measurements is another important process for a valid statistical conclusion, as unreliable measurements generate an inaccurate and biased conclusion (Yong & Pearce, 2013). In this thesis, the measurement's reliability was checked with Cronbach's *a*, which is one of the most widely used indicators to examine internal consistency, that is whether a set of items are measuring the same concept (Cronbach, 1951).

Also, taking the recent call regarding the use of Cronbach's *a* into consideration, this thesis presents a CR score to demonstrate the measurement reliability (Cho & Kim, 2015). While Cronbach's *a* imposes two assumptions, uni-dimensionality and tau-equivalency (i.e., equal factor loading and variance in measurement error), the tau-equivalency [3]assumption is difficult to meet in social science research. Thus, an increased number of experts suggest using CR instead of Cronbach's *a* (Cho & Kim, 2015; Goodboy & Martin, 2020).

5.3.1 The Overview of Factor Analysis Procedures

Byrne (2013) suggested Confirmatory Factor Analysis (CFA) for evaluating the measurement quality when the constructs have already been tested in previous studies. Thus, this thesis undertook CFA through AMOS 26 and Smart PLS 3.0 to test the measurement reliability and validity. All variables were examined on AMOS as per the model and theoretical relationships identified in the previous studies (Hung & Chou, 2013; Torres de Oliveira et al., 2021).

CFA provides researchers with fit indices, which can be used to evaluate to what extent the researcher's conceptual model matches the collected data (Niemand & Mai, 2018). In CFA, researchers impose the structure of relationships between observed variables and its representing latent construct, including relationships across latent constructs. Then, CFA gives

[3] Goodboy and Martin (2020) argued that the tau-equivalency assumption in social science is rarely met because each measurement item tends to have a different impact on its underlying concept, which falls into the assumptions of congeneric model. Thus, when using a factor score model, Cronbach's alpha may underestimate the reliability score. Hence, the current experts call for the use of an appropriate reliability indicator, such as a CR indicator (Cho & Kim, 2015).

fit indices, parameter estimations, and factor loadings through the evaluation of whether the observed data fit the specified model (Lussier, 2011). In other words, the fit index is an indicator of how well the observed variables represent a targeted latent construct in an expected way; a good fitness means that the specified model is approximately correct. Hence, it can be said that constructs are unidimensional and reliable (Brahma, 2009; Doll & Xia, 1994).

Initially, the present study applied CFA on AMOS and explored the best fit model drawing on the fit indices of each measurement model (Hair et al., 2019). As such, several alternative models were tested (detailed discussion follows in the next sections). Eventually, this thesis undertook homogenous item parcelling strategies on the construct of Revealing OI; the item parcelling strategies were necessary due to the small sample size used in this study, as opposed to the complexity and the number of observed variables (Cole et al., 2016; Little et al., 2013).

Additionally, following the recommendations by several business scholars (Hair et al., 2019; Snell & Dean, 1992; Dai et al., 2018), some observed variables were deleted due to poor and high-cross loading. Further, although the final measurement model showed an acceptable range of fit indices, the presence of negative variance on AMOS made it difficult to use the parameters and estimations derived on AMOS (Chen et al., 2001). Accordingly, this thesis decided to proceed with further measurement analysis through a variance-based approach using SmartPLS.

5.3.2 Statistical Package for Analyses

Acknowledging the differences between covariance- and variance-based measurement models (Evermann, & Rönkkö, 2021; Hair et al., 2017), this thesis used the partial least square structural equation modelling (PLS-SEM) approach to test the measurement reliability and validity for the final model derived from CFA on AMOS. This hybrid approach is not uncommon and has been increasingly adopted in recent studies published in top business journals (e.g., Karami & Tang, 2019; Kloutsiniotis & Mihail, 2020). Although there has been an academic debate among researchers on the legitimacy of PLS-SEM (e.g., Evermann & Rönkkö, 2021), this thesis believes that the main criticisms (i.e., the misconception among researchers and measurement errors) associated with the PLS approach are not a big issue in this study (supporting arguments follow in the next sections). In contrast, the exploratory nature of the research goal in this study underpins the usefulness of the PLS-SEM approach (Hair et al., 2019). Thus, the benefits of Smart PLS outweigh its costs.

CB-SEM

The covariance-based structural equation modelling (CB-SEM) approach has been a dominant measurement validation technique in social science research (Hair et al., 2019). Some primary reasons for this popularity stem from the ease of statistical analysis for the complex model involving multiple latent constructs; it allows the assessment of structural relationships and measurement quality simultaneously by providing relevant fit indices, parameters, and estimations (Byrne, 2013). Further, unlike the multi regression-based approach that assumes no or minimal measurement error, CB-SEM accounts for a measurement error in the observed variables, which enables more rigorous results (Rönkkö et al., 2016). For these reasons, a covariance-based approach is frequently used in theory testing and explanatory type research (Niemand & Mai, 2018). Accordingly, many journals nowadays ask researchers to provide fit indices through CFA for measurement validity claims.

PLS-SEM

Despite its popularity, one clear limitation of CB-SEM is that it requires a large-scale and multivariate normal dataset for a stable and valid result (Hair et al., 2011). To overcome such drawbacks, researchers often apply a PLS-SEM approach when a study includes a complex structural model, but an explorative phase of theory generation with a small scale sample (Dash & Paul, 2021). PLS-SEM involves a set of OLS regression across specified model paths and calculates parameters, such as factor loadings and path estimates (Rönkkö et al., 2016). Hair et al. (2011) described PLS-SEM as “a silver bullet” (p. 333) because, unlike strict assumptions on sample size and multivariate data normality of CB-SEM and the Maximum likelihood (ML) estimator, PLS-SEM is typically said to be robust to these conditions (Hair et al., 2019). For this reason, researchers employ a PLS-based approach to overcome the downsides of sample limitations when using an SEM approach (Hair et al., 2017: Hair et al., 2019; Sarstedt et al., 2016).

Misconceptions of PLS-SEM

However, there are mainly two criticisms against the use of PLS-SEM: (1) misconceptions about PLS-SEM among researchers and (2) measurement errors associated with the method (Evermann & Rönkkö, 2021). Firstly, the opponents disagree with the benefits of the PLS approach due to the OLS estimator being used in PLS-SEM (Rönkkö et al., 2016). Although the proponents frequently argue the usefulness of the PLS-SEM approach based on the robustness of the small sample size and data non-normality, the OLS assumptions play a critical role here; the OLS assumptions, although more tolerable than CB-SEM, may also be susceptible to sample size and data characteristics (Hair et al., 2019). In other words, small sample size and data nonnormality may not be as severe issues as CB-SEM; however, this does not necessarily mean that the PLS results are unbiased and consistent under these conditions (Evermann & Rönkkö, 2021). Indeed, the developers of SmartPLS software cautioned the current researchers’ misconceptions about the small sample size and data characteristics benefits when using the PLS approach as follows:

> “PLS-SEM provides solutions when methods such as CB-SEM develop inadmissible results… small sample sizes, regardless of whether the data originates…. PLS-SEM can certainly be used with smaller samples, but the

> population's nature determines the situations in which small sample sizes are acceptable" (Hair et al., 2019, p.5).

This quote highlights the importance of data representativeness through valid sampling strategy and data collection mode when using the PLS approach in a small sample size study. In this sense, the top section of this chapter showed the good quality of the collected data. Also, this thesis considers the OLS assumptions and measurement errors deeply, and the later section in this chapter provides a thorough robustness check for the OLS assumptions. Thus, typical criticisms associated with PLS-SEM are justified and not an issue in the present study (Hair et al., 2019).

Measurement error of PLS-SEM

Further, the way in which PLS-SEM treats and forms latent constructs, namely regression-based weighting composite score to form a latent variable, has been debatable (Benitez et al., 2020; Rönkkö et al., 2016). Whereas CB-SEM assumes a latent variable with classical test theory (i.e., separation of a true score, measurement error, and specific error within an observed item), PLS-SEM relies on a variance-based approach (i.e., maximising the variance of a latent variable) (Hair, 2020). Thereby, the latter approach inevitably contains a measurement error to 'some' extent (Evermann & Rönkkö, 2021). Consequently, the measurement error could potentially attenuate a true score or inflate relationships (Benitez et al., 2020). In contrast, the proponents argue that a regression-based weighting score is a robust approach to reduce the measurement error, as weighting will be larger on items that explain more variance of the latent construct (Hair et al., 2020; Sarstedt et al., 2016). Statistically speaking, as the number of observed variables per latent variable and the focal construct's reliability indicator increase, the contamination of measurement errors in composite variables is minimised (Roldán Bravo et al., 2021; Cheah et al., 2018; Gefen et al., 2011). In other words, the weighting composite variable approach can be as good as the covariance-based measurement model when having a sufficient level of measurement reliability (Sarstedt et al., 2020). Taken together, this thesis believes that the criticisms associated with the measurement errors using the PLS approach are not an issue.

5.3.3 Measurement Model Assessment Criteria

This thesis relied on a common practice of the measurement model assessment procedures in business studies and evaluated the quality of the measurements using fit indices (Byrne, 2013). Some of the well-used fit indices in business studies are exact fit, absolute fit, comparative fit, and parsimony measures; these include the traditional chi-square test, the goodness of fit index (GFI), adjusted goodness of fit index (AGFI), comparative fit index (CFI), standardised root mean square residual (SRMR), and root mean square error of approximation (RMSEA) (Barrett, 2007; Niemand & Mai, 2018). In any case, researchers report the relevant indices to claim a good fitness of the sample data.

Limitation of Fit Indices

As summarised in **Table 6** below, many researchers use a conventional cutoff value to argue whether the measurement shows good fitness (e.g., Hair et al., 2019). However, these threshold lines are often controversial as the fit indices are susceptible to sample characteristics, such as the number of observed variables, the complexity of the conceptual model, sample size, and data normality (Niemand & Mai, 2018). For example, McNeish and Wolf (2021) cautioned that “fixed cutoffs are inherently at risk of overgeneralisation because there is no single global definition of good fit index values”. They questioned the conventional fixed cutoffs with an example of a sample size calculation using Power analysis. While researchers using Power analysis are flexible on deriving an “ideal” sample size based on the research context, research setting, research goal, and desired statistical power, the current practice of model fit assessment heavily relies on fixed cutoff values, which was proposed in the single research setting by Hu and Bentler (1998). Thus, the generalisation of these conventional fit indices can often be questionable (Niemand & Mai, 2018; McNeish & Wolf, 2021).

Table 6

Fit Indices Summary

Measure	Impact to measures		Conventional cutoffs		Flexible cutoffs	Fit indices	Model fitness evaluation	
	Kurtosis	Sample size	Terrible	Excellent	Excellent	(Final model)	Conventional	Flexible
$\chi 2$	----	----	----	----	----	326.724	----	----
CMIN/DF	High	----	>5	>1	----	2.1	Acceptable	----
CFI	High	Less	<0.85	>0.95	**<0.78**	**0.848**	Terrible	Excellent
SRMR	High	Less	>0.10	<0.08	**<0.08**	**0.08**	Excellent	Excellent
TLI	High	Less	<0.90	>0.95	**<0.72**	**0.814**	Terrible	Excellent
RMSEA	High	High	>0.08	<0.06	<0.06	0.10	Terrible	Terrible
Pclose	High	High	<0.01	>0.05	----	0.00	Terrible	Terrible
GFI	High	High	<0.85	>0.95	<0.75	0.85	Acceptable	Excellent
AGFI	High	High	<0.85	>0.95	<0.53	0.67	Terrible	Excellent

Note. Final model development process is described in the following sections.

Impacts to measures describes to what extent the corresponding measurements are influenced by the level of kurtosis and sample size conditions.

Model fitness evaluation describes how the present study’s fit indices fall into the existing evaluation criteria.

The conventional cutoffs are based on the work by Hu and Bentler (1998) and Lowry and Gaskin (2014).

The flexible cutoff values are calculated based on the software developed by Niemand and Mai (2018) and available on their website at https://flexiblecutoffs.org/.

Another illustration of the problem associated with fit indices is the fact that many fit indices substantially depend on $\chi 2$ values, which is the exact fit value derived from the chi-squared significance test (Barrett, 2007). The $\chi 2$ values are generally susceptible to data characteristics, sample size, model complexity, and the number of indicators used in a study. Similarly, the $\chi 2$ value tends to be inflated when the observed data violates the multivariate data normality assumptions of the estimator being used, such as the ML estimator (Niemand & Mai, 2018). Thus, the inflated $\chi 2$ values due to these data characteristics can inevitably decrease the relevant fit indices even when the model is approximately a correct and acceptable fit (McNeish & Wolf, 2021).

The definition of Acceptable Fit indices

The previous statistical methodology studies suggested that multivariate data non-normality affects most fit indices. Similarly, the measures, such as RMSEA and GFI, are susceptible to sample size (Fan et al., 1999). Accordingly, several researchers used their own cutoff line to argue the good model fit. For example, while the conventional cutoff of the CFI value is 0.95 (Hair et al., 2019), some papers argued that CFI = 0.80 is a good model fit (e.g., Doll et al., 1995). Similarly, Bollen (1989) perceived that CFI = 0.85 is an acceptable level. Further, in recent years, there has been a call for a more flexible approach in terms of an acceptable model fit by taking data characteristics into more consideration (McNeish & Wolf, 2021). In their Monte Carlo simulations, Niemand and Mai (2018) showed that the correctly specified model gives a lower fit index value due to the following factors: limited sample size, multivariate data non-normality, and model complexity. With their simulation, the model in the condition of the present thesis should be regarded as a good model fit when the fit indices exceed the following fit index values: CFI=0.78, SRMR = 0.08 or TLI = 0.72. In short, drawing on the statisticians' and experts' arguments, this thesis used a flexible fit indices threshold considering the fact that the observed data in this study is a small scale and mildly multivariate non-normal.

5.3.4 Assessment Procedure

Item Parcelling

This thesis underwent several steps to verify the most suitable measurement model. Firstly, as seen in **Table 7Error! Reference source not found.** below, the CFA on AMOS showed a poor fit for the original conceptual model (***the original model***, refer to **Appendix F** for diagram), indicating a miss-specification within the original model (Hu & Bentler, 1998; McNeish & Wolf, 2021). As such, this thesis continued with a model assessment to identify the source of this miss-specification and improve the model fitness with alternative models.

Secondly, this study explored whether higher-order constructs in the original model were the source of poor fit because it inevitably increases the model complexity due to the high number of items being used against the sample size (Niemand & Mai, 2018). In this regard, Bandalos (2002) recommended an item parcelling approach to simplify the model when a sample size is small[4] (e.g., *n* >250) with non-normal data. Accordingly, based on expert suggestions, this study employed *the homogenous item-parcelling strategy*, which is especially useful for a higher-order structural model because it is argued to maintain the meaning of each sub-dimension after item parcelling (Cole et al., 2016; Little et al., 2013; Marsh et al., 2013). Homogenous item parcelling combines all observed variables in each dimension of lower-order constructs into one aggregated variable, and then the parcelled variables represent a higher-order construct. In this study, 12 variables across three sub-dimensions were combined into three variables. As a result of item parcelling, the fit indices of alternative model 3 showed a dramatic improvement, decreasing the $\chi 2$ value by 467.701 from the original model. Nonetheless, because the improved fit indices were still below the conventional cutoffs, this thesis further explored the potential source of miss-specification at item levels, such as modification indices, cross-loadings, and factor loadings (Brahma, 2009).

Table 7

Measurement Model Development Process

Results of Confirmatory Factor Analysis.

	Model fit indices				Model differences			
	$\chi 2$	df	CFI	SRMR	$\chi 2$	Δdf	p	Details
Final model	**326.774**	**155.000**	**.848**	**.085**	39.497	9	<.001	Alternative Model 1 and Final model
Alternative Model 1	366.271	164.000	.821	.088	284.678	120	<.001	Alternative Model 2 and Alternative Model 1
Alternative Model 2	650.949	284.000	.776	.101	467.701	248	<.001	Alternative Model 3 and Alternative Model 2
Alternative Model 3	1118.650	532.000	.730	.096	65.452	10	<.001	Original model and Alternative model 3
Original model	1184.102	542.000	.705	.101	857.328	387	<.001	Final model and original model

Note. Final model= Item deleted, and item parcelled four factors model (2 IVs, 2 DVs, 2 Moderators)
Alternative Model 1 = Item deleted and two factors model (1 IV, 1 DV, 2 Moderators).
Alternative Model 2 = All items and items parcelled (2 IVs, 2 DVs, 2 Moderators).
Alternative Model 3 = All items and no higher-order (2 IVs, 2 DVs, 2 Moderators).
Original model = All items and original model (2 IVs, 2 DVs, 2 Moderators).
The result of $\chi 2$ difference is significant at $p < .05$.

[4] Other scholars, such as Matsunaga (2008), argued that the item parcelling strategy should be considered when the sample size is less than 400, and the data is multivariate non-normal (Matsunaga, 2008).

Item Deletions

Following the common practice among scholars, the items were regarded as problematic when meeting two criteria: poor loading (factor loading less than 0.5) and high cross-loading (the difference of factor loading less than 0.1 across multiple latent constructs) (Dai et al., 2018; Snell & Dean, 1992). As such, the item-level investigation identified six items as the potential source of miss-specifications. Specifically, two items were deleted from Selling OI and two items from innovation performance due to high-cross loadings. Similarly, one item was deleted from financial performance and one item from Tech due to poor loading (Anderson & Gerbing, 1988; Hair et al., 2019). As a result of item deletion, all fit indices improved dramatically, with some measures being in the acceptable range based on the *flexible cutoff* criteria mentioned above (***Final model*, SRMR = 0.85, CFI = .848).** Thus, this study concludes that the final model is the best model[5] (Niemand & Mai, 2018; McNeish & Wolf, 2021). Overall, CFA confirmed that the measurements in this study were uni-dimensional and reliable (Hair et al., 2019; Ziegler & Hagemann, 2015).

5.3.5 Negative Variance

Lastly, although the final model was believed to show an acceptable model fit, the CB-SEM approach could not be used for further analyses due to the presence of negative variances across parameters and estimates (Gerbing & Anderson, 1987). These are often called a Heywood case or improper solutions, which could be caused by sampling fluctuation due to small sample size, miss-specification of the model; violation of multivariate assumptions of estimators, or influences of outliers (Chen et al., 2001; Kolenikov & Bollen, 2012). Nonetheless, the previous statistical methodology papers showed that fit indices were not affected by the presence of negative variance, while factor loading, correlation parameters and estimations could be biased (Chen et al., 2001; Gerbing & Anderson, 1987). For this reason, this thesis proceeded with further measurement analysis through PLS-SEM for the final measurement model derived from the CFA process on AMOS.

5.3.6 Construct Validity

Table 8 below summarises the key information for the measurement construct validity: factor loading, Cronbach's *a*, CR and AVE. As the table shows, all measures demonstrated a

[5] Following the common approach of model assessment (e.g., Aliasghar & Haar, 2021), this thesis further explored the better model by comparing the final model with the alternative models. In particular, because Revealing OI and Selling OI (independent variables) and innovation performance and financial performance (dependent variables) used in this study can be regarded as a similar concept, one could argue the superiority of the one-factor model, instead of the two-factor model used for the final model. Thus, as a comparison, these factors were combined into one factor and tested. Consequently, the comparison result showed that the two-factor model (the final model) had a better fit in terms of model fit (as shown in **Table 7Error! Reference source not found.** above) and is significantly different at p < .0 level, suggesting the superiority of the final model.

satisfactory level of factor loading into one factor, suggesting the unidimensionality of the constructs (Brahma, 2009; Ziegler & Hagemann, 2015). Moreover, both CR and AVE exceeded the conventional threshold of 0.7 (CR) and 0.5 (AVE) across all measures. Thus, this thesis believes that the measurements used in this study have a good level of convergent validity (Cheah et al., 2018; Hair et al., 2019).

In terms of discriminant validity, the Fornell-Larcker approach was adopted to examine the relationships between the constructs (Benitez et al., 2020; Rönkkö & Cho, 2020). The Fornell-Larcker criterion argues that discriminant validity is achieved when the focal construct's squared AVE is greater than any of the correlation values for all other constructs (Fornell & Larcker, 1981). As shown in ***Table*** **9Error! Reference source not found.** below, the measurements show a good level of discriminant validity. Taken together, the constructs in this study are argued to have a sufficient level of construct validity.

Table 8

Measurement Model Table

	Factor Loading						Cronbach's a	Composite reliability	AVE
	FinPF	InnoPF	SelOI	RevOI	Mar	Tech			
FP_2	0.73								
FP_3	0.75								
FP_4	0.78								
FP_5	0.77						0.75	0.84	0.57
IP_1		0.77							
IP_2		0.74							
IP_3		0.75							
IP_6		0.74					0.74	0.84	0.56
Sell_2			0.78						
Sell_3			0.78						
Sell_4			0.82				0.71	0.84	0.63
Rev1				0.84					
Rev2				0.89					
Rev3				0.93			0.87	0.92	0.79
Mar_1					0.84				
Mar_2					0.89				
Mar_3					0.77		0.78	0.87	0.69
Tech_2						0.94			
Tech_3						0.87			
Tech_4						0.94	0.93	0.94	0.85

Note. FP_1, Sel_5 and ech_1are deleted due to poor loading. Also, IP_4, IP_5 and Sel_1 are deleted due to high cross-loading (Hair et al., 2019).

Rev_1, Rev_2 and Rev_3 are item parcelled (Matsunaga, 2008).

n=103

Table 9

Correlation Table and Fornell-Larcker Criterion

	FinPF	InnoPF	SelOI	RevOI	Mar	Tech	R&D INT	Firm age	Firm size
FinPF	**.76**								
InnoPF	.67**	**.75**							
SelOI	.52**	.58**	**.79**						
RevOI	.50**	.74**	.74**	**.89**					
Mar	.51**	.43**	.45**	.60**	**.83**				
Tech	-.01	-.08	.07	.01	.06	**.92**			
R&D_INT	.20*	.39**	.38**	.35**	.11	-.33**	-		
Firm age	.14	.25*	.10	.11	.06	-.17	.09	-	
Firm size	.12	.40**	.39**	.39**	-.08	-.17	.29**	.33**	-
Instrumental	.13	.33**	.46**	.45**	.37**	-.13	.41**	.17	.24*

Note. *n*=103. *p<.05, **p<.01. SD = Standard deviation. *Instrumental* is an instrumental variable used in this study. Numbers in bold are squared AVE of the latent construct.

5.4 Analyses and Results

5.4.1 **Multilinear Regression Analysis**

Following the practices used in the previous papers (Vlačić et al., 2019; Shafiee, 2021; Zhang et al., 2020), this study conducted a set of regression analyses on SPSS Statistics 27 using the composite scores derived from the final model through the SmartPLS model assessment. Further, the mediation and moderation analyses were undertaken through Haye's PROCESS macro (Aliasghar & Haar, 2021; Haar et al., 2021; Hayes, 2018). Also, since this thesis applied the OLS regression approach, some underlying assumptions were tested in the prior and post-hoc stages. Consequently, the robustness check confirmed that the OLS assumptions in the study were sufficiently met. Hence, the OLS estimator is argued to be the best linear unbiased estimator (BLUE)(Hair, 2014).

Table 10 below shows the result of hierarchical regression analyses for financial performance (models 1, 2, and 3) and innovation performance (models 4 and 5). First of all, the regression analysis indicated the difference in firms' performance development between Selling OI and Revealing OI. More specifically, Selling OI was significantly related to financial performance, while Revealing OI was significantly associated with innovation performance, supporting the hypothesis 1a (β = .33 (SE = .12), p = .002, LL = .08, UL = .58) and 2b (β = .60 (SE =.12), p < .000, LL = .41, UL = .92). Moreover, as opposed to the theoretical expectations (Torres de

Oliveira et al., 2021), there were no statistical association between Revealing OI and financial performance, as well as Selling OI and innovation performance, rejecting hypothesis 1b (β = .02 (SE =.11), p = .843, LL = -.19, UL = .23) and 2a (β = .08 (SE =.15), p = .563, LL = -.21, UL = .39). As a whole, two predictors accounted for 7% (p< .001, **model 2**) of variance for financial performance and 16% (p< .001, **model 5**) of variance for innovation performance over the control variables (**model 1**, R^2 Change = .30 for financial performance and **model 4**, R^2 Change = .44 for innovation performance).

Table 10

Regression Analysis Result Table

	Financial Performance						***Innovation Performance***			
	model 1		**model 2**		**model 3**		**model 4**		**model 5**	
	B	**SE**	**B**	**SE**	**B**	**SE**	**B**	**SE**	**B**	**SE**
Step 1: Controls										
INT	.13	.10	.02	.10	-.08	.09	.13	.10	.15	.08
FIRM AGE	.09	.07	.06	.07	.00(1)	.06	.09	.07	.16	.05
FIRM SIZE	.09	.06	.07	.06	-.11	.06	.09	.06	.06	.06
Mar	**.50*****	.07	**.31*****	.09	**.28****	.08	**.50*****	.07	.03	.08
Tech	.02	.04	-.05	.04	-.06	.04	.02	.04	.00(3)	.04
Step 2: Predictors										
SelOI			**.33*****	.12	**.32****	.15			.02	.11
RevOI			.08	.15	**-.32****	.11			**.60*****	.13
INNOPF					**.66*****	.10				
R^2 change	.30***		.07**		.25***		.44***		.16**	
Total R^2	.30		.38		.55		.44		.59	
Adjusted R^2	.27		.34		.52		41		.56	
F statistic	8.631***		8.401***		14.779***		8.631***		19.802***	

Note: significant effects are bolded. β = unstandardized regression coefficients, SE= standard error. Confidence Intervals are not shown in the table. Please refer to the report in the main text. All significance tests were two-tailed.

5.4.2 Mediation Analysis

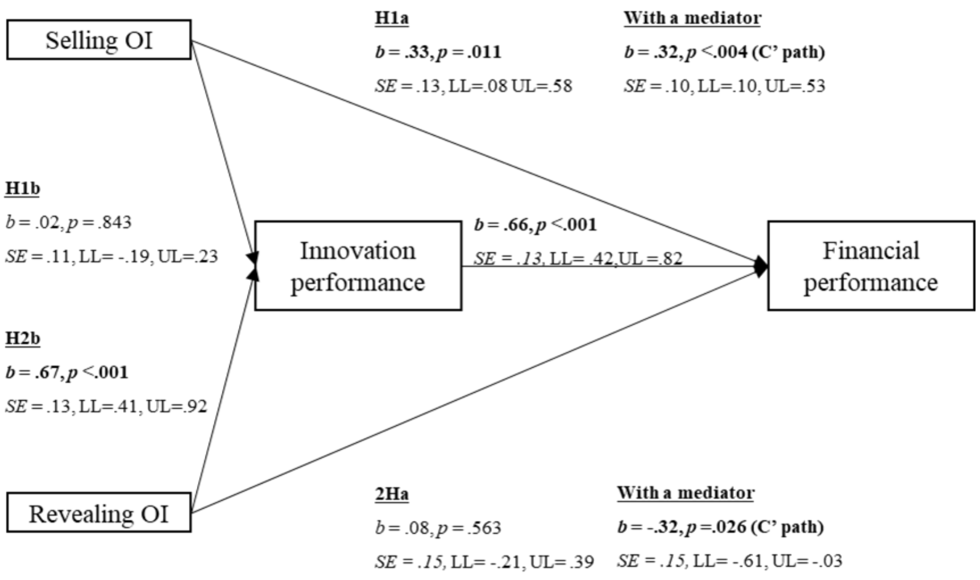
Further, as shown in **model 3**, innovation performance was added as a predictor to investigate the combined effect of outbound OI on financial performance. Surprisingly, the result of model 3 demonstrated an unexpected downward change in the effect size of Revealing OI on financial performance (β = -.32 (SE = .15), p =.026, LL= -.61, UL= -.03), while the impacts of innovation performance (β =.66 (SE =.13), p <.001, LL= .42, UL =.82) and Selling OI (β = .32 (SE =.10), p <.004, LL=.10, UL=.53) were consistent with the prior expectations (Verreynne et al., 2020). However, H3 was rejected due to the unexpected result of Revealing OI. At this point, because the previous mediation literature suggested the possibility of mediation effect when meeting three criteria as follows, this thesis further undertook mediation analysis (Hair, 2014):

(1) A significant relationship between Revealing OI and innovation performance (a path),
(2) A significant relationship between financial and innovation performance (m path), and
(3) Huge suppression of coefficient of Revealing OI on financial performance by including innovation performance (a possible mediator) (Baron & Kenny, 1986; Hayes, 2009).

Accordingly, this thesis conducted the mediation analysis using the PROCESS Macro's model 4 approach (Hayes, 2018), and **Figure 6** below shows the results of the overall structural path. The analysis found a strong indirect effect of Revealing OI (b = .40, (SE = .14), LL= .11 UL= .67), through the mediation of innovation performance, on financial performance. In contrast, Selling OI did not show such indirect effects through innovation performance (b = -.01, (SE = .10), LL= -.13 UL= .27).

Figure 6

The Result of the Overall Structural Path



Note. β = unstandardised regression coefficients, SE= standard error. Confidence Intervals are 95% and LL=Lower Limit, UL=Upper Limit. All significance tests were two-tailed.

In summary, the mediation analysis indicated an important implication for firms undertaking outbound OI practices. While outbound OI, as a whole, has a positive influence on financial performance, innovation performance is by far the strongest effect. Therefore, although focusing on Selling OI might contribute to financial performance for a short time, the strategies to increase innovation performance, such as Revealing OI, seem to play an important role in benefiting from outbound OI in the long run.

5.4.3 Moderation Analysis

Further, the following section shows the result of the moderation analysis. This thesis applied Hayes' process macro (model 1) to examine the moderation effects of market and technological turbulence on the relationships between outbound OI and OI performance (Hayes, 2018; Hung & Chou, 2013). Following the previous research, this thesis undertook a hierarchical regression method by entering a mean-centred interaction term into each model separately (Hung & Chou, 2013). Models 6 to 9 display interactions between market turbulence and outbound OI (Selling OI and Revealing), and models 10 to 13 present the result of moderation effects of technological turbulence. As for the result, market turbulence, shown in **Table 11** below, seems to have no impact as a moderator on the relationships. Thus, hypotheses h4a, 4b, 4c, and 4d were rejected.

Table 11

Moderation Result for Market Turbulence

	Financial performance				Innovation performance			
Market Turbulence	model 6		model 7		model 8		model 9	
	B	SE	B	SE	B	SE	B	SE
INT	.01	.11	.04	.11	.13	.08	.14	.09
FIRM AGE	.07	.07	.08	.07	.12	.06	.14	.06
FIRM SIZE	-.05	.06	-.04	.07	.06	.06	.07	.06
Mar	**.26****	.07	**.24****	.11	.08	.08	.05	.08
Tech	-.02	.04	-.04	.04	-.07	.04	-.04	.04
Step 2: Predictors								
SelOI	**.36****	.14	**.32****	.13	.05	.11	.05	.11
RevOI	.09	.15	.08	.15	**.65*****	.15	**.64*****	.13
Step 3: Moderators								
Mar*SelOI	.03	.08			.13	.06		
Mar*RevOI			.03	.10			.06	.07
R^2 change	.00(1)		.00(1)		.01		.00(2)	
Total R^2	.38		.38		.60		.60	
Adjusted R^2	.34		.34		.57		.56	
F statistic	7.303***		7.297***		17.786***		17.257***	

Note: significant effects are bolded. β = unstandardized regression coefficients, SE= standard error. Confidence Intervals are not shown in the table. All significance tests were two-tailed.

Further, as seen in **Table *12*** below, the technological environment has a major impact as a moderator on the relationship between outbound OI and OI performance. Specifically, as illustrated in **Figure 7**, **Figure 8**, and **Figure *9***, under the low technological turbulent environment, a firm with a lower degree of outbound OI strategy was associated with better OI performance compared to the firms with a higher degree of outbound OI strategy. Contrastingly, under the high technological turbulent environment, a firm undertaking a higher degree of outbound OI strategy showed better OI performance.

Table 12

Moderation Result for Technological Turbulence

	Financial performance				Innovation performance			
Technological Turbulence	**model 10**		**model 11**		**model 12**		**model 13**	
	B	**SE**	**B**	**SE**	**B**	**SE**	**B**	**SE**
INT	-.01	.09	-.02	.10	.13	.08	.14	.09
FIRM AGE	.05	.06	.06	.06	.12	.06	.14	.06
FIRM SIZE	-.07	.07	-.07	.06	.06	.06	.07	.06
Mar	**.37****	.09	**.33****	.09	.08	.08	.05	.08
Tech	-.15	.05	-.17	.05	-.07	.04	-.04	.04
Step 2: Predictors								
SelOI	**.37****	.13	**.40****	.12	.05	.11	.05	.11
RevOI	.15	.15	.17	.15	**.65*****	.15	**.64*****	.13
Step 3: Moderators								
Tech*SelOI	**.14***	.06			**.18***	.05		
Tech*RevOI			**.16***	.06			.10	.05
R^2 change	**.04****		**.04***		**.02**		.01	
Total R^2	.42		.42		.61		.60	
Adjusted R^2	.37		.37		.58		.57	
F statistic	8.566**		8.525**		18.652***		17.528***	

Note: significant effects are bolded. β = unstandardized regression coefficients, SE= standard error. Confidence Intervals are not shown in the table. All significance tests were two-tailed.

In more detail, the interaction term **model 10** (Tech*SelOI, β =.14 (SE =.06), p =.013, LL= .03, UL =.26) and **model 11** (Tech*RevOI, β =.16 (SE =.06), p =.015, LL= .03, UL =.26) both account for the additional R^2 by 4% of the financial performance from the base model. Similarly, **model 12** (Tech*SelOI, β =.11 (SE =.05), p =.029, LL= .01, UL =.21) showed a small R^2 change by 2% of innovation performance from the base model. In short, on the one hand, a firm tends to benefit more by exploiting the core technology internally when the technological market is less dynamic. On the other hand, a firm tends to benefit more by externalising the core technology when there is high technological turbulence. Overall, this moderation analysis provided evidence to support the hypotheses H5a, H5b, and H5c but reject H5d.

Figure 7

The Result of Moderation Effects (Selling OI and Financial Performance)

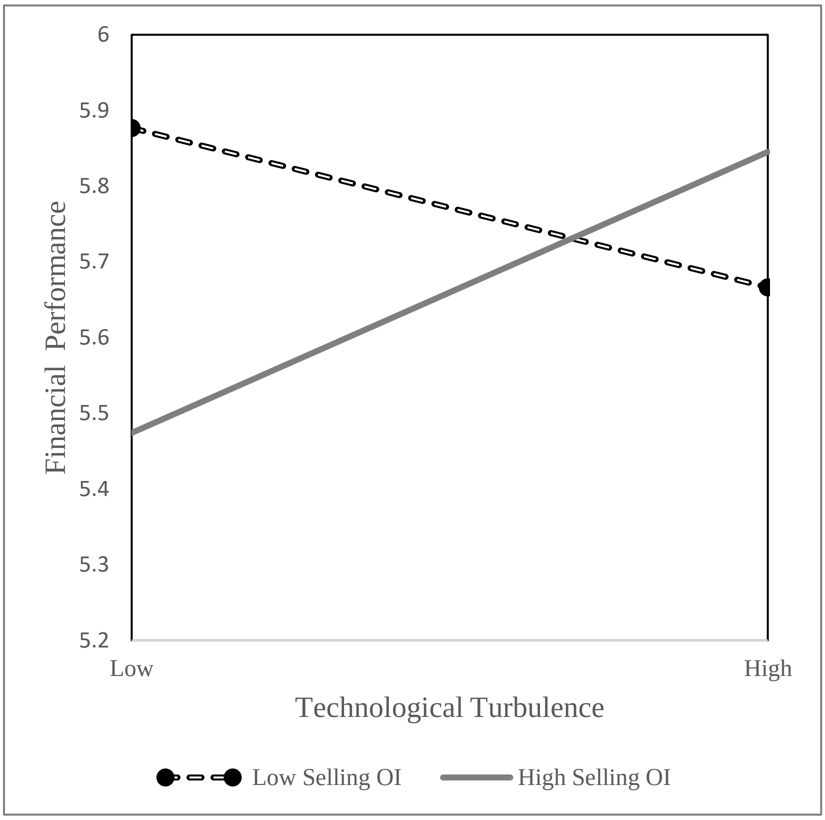


Figure 8

The result of moderation effects (Revealing OI and Financial Performance)

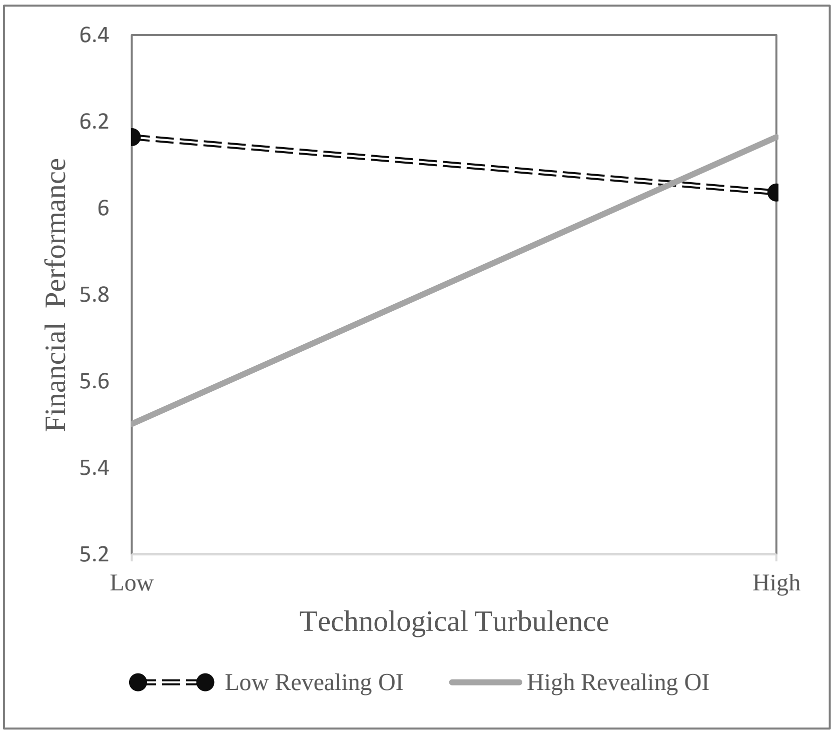
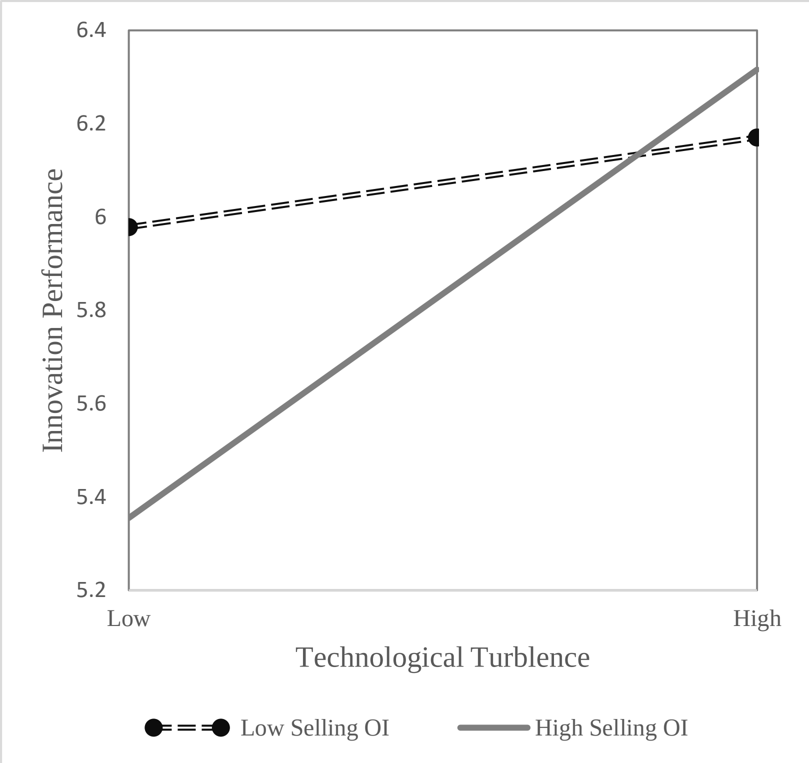


Figure 9

The Result of Moderation Effects (Selling OI and Innovation Performance)



5.5 Robustness Check

To validate the findings in this study, multiple robustness analyses were conducted. Firstly, this thesis undertook a sensitivity test to see if the results were sensitive to the design of this study rather than reflecting a true phenomenon. Secondly, as previous papers called for careful attention to the heterogeneous effect of the effect size of innovation strategies (e.g., Sarstedt et al., 2020), this thesis ran multigroup analysis (cluster analysis) by splitting some variables in half (above the median and below the median) to see whether or not the effects were heterogeneous (Miroshnychenko et al., 2020; Liao et al., 2020). Thirdly, since this study employed the OLS approach, the OLS assumptions were thoroughly checked to claim OLS as the best linear unbiased estimator (BLUE) (Hair, 2014). Briefly, the present study checked the assumptions: linearity, homoscedasticity, multicollinearity, and endogeneity (Torres de Oliveira et al., 2021; Hung & Chou, 2013).

5.5.1 Sensitivity Test

Following the procedures of the sensitivity test by Torres de Oliveira et al. (2021) and Verreynne et al. (2020), this study substituted the innovation performance construct with Innovation Breadth; the measure, a well-used indicator in innovation studies, was developed by

Laursen and Salter (2006). In brief, the sensitivity analysis examines if the results are sensitive to a particular research setting, survey questions, and sample characteristics used in a study. The substitution should not dramatically change the relationships found in a study because the related concepts, such as innovation breadth and innovation performance, are theoretically expected to have a similar effect (Verreynne et al., 2020). Failing the sensitivity test may indicate less power of the statistical claim.

As for the analysis result, this thesis found no evidence of substantial differences in the relationships across the conceptual model after the substitution, and this result aligns with the two studies discussed above (Torres de Oliveira et al., 2021; Verreynne et al., 2020). Although the substitution changed the magnitude, the overall relationships were similar to the main result, suggesting that sensitivity was not an issue in this study. The supplementary information and table are provided in **Appendix G.**

5.5.2 Heterogeneous Effects Testing

As some previous papers reported a heterogeneous effect (differences in the effect size or direction of the effects due to sample characteristics) of the OI strategy on firms' performance, this thesis explored the possibility of the heterogeneous effect across subgroups with different sample characteristics (Freel & Robson, 2017; Jugend et al., 2018; Spithoven et al., 2013; Usman & Vanhaverbeke, 2017). The six subgroups were created based on the variables firm age (younger and older), firm size (smaller and larger), and the degree of R&D intensity (low spenders and high spenders).

Following the procedures of recently published papers (Jugend et al., 2018; Hair et al., 2019), this thesis conducted a multigroup analysis (MGA) using the PLS-MGA on SmartPLS. The three abovementioned variables were divided into two groups based on the median score, a lower-than-the-median group and a higher-than-the-median group. Then, the PLS-MGA compared the groups to see if any parameters and estimates were significantly different from each other (Sarstedt et al., 2016). Importantly, because the MGA assumes measurement invariance across subgroups, this thesis applied the measurement invariance of composite models (MICOM) and the permutation testing approaches on SmartPLS (Klesel et al., 2019; Schlägel & Sarstedt, 2016). Accordingly, the tests showed measurement invariance across the subgroups. Thus, the MGA analysis was regarded as meaningful (Sarstedt et al., 2020).

In terms of the result, the MGA test found no evidence of a heterogeneous effect of outbound OI strategy on a firm's performance across several subgroups. Thus, it can be concluded that the role of outbound OI on performance is rather more homogeneous than heterogeneous in the present study research setting (Sarstedt et al., 2020). One caution is, however, that while this research confirmed no heterogeneity in the collected data, the relatively non-normal nature of the dataset has a limitation to making an inference about the entire population. Also, it is important to note that P-value significance is subject to the effect size and sample size (Lussier, 2011). Refer to **Appendix H** for more details.

5.5.3 Ordinary Least Squares Assumptions

The OLS approach assumes certain criteria[6] for its results to be more robust. The OLS assumption holds when meeting the criteria of linear relationships between variables, no multicollinearity, no endogeneity, and constant variance in residuals (Hair et al., 2019; Sarstedt et al., 2020), and not fulfilling these criteria may result in biased and inconsistent outcomes when using the OLS estimator (Ronkko et al., 2016). Accordingly, the following tests were adopted to provide evidence of the OLS assumptions in this study (the supplementary information and a table are provided in **Appendix I** and **Appendix J**.

First of all, the linearity assumption was checked visually based on a scatter plot and then tested statistically by adding the quadratic term of independent variables in each model (Sarstedt et al., 2020; Zhang et al., 2020). As such, the non-significant regression results of the quadratic term were confirmed, suggesting the linearity of the relationships between the variables; therefore, the linearity assumption was met (Bagherzadeh et al., 2019; Sarstedt et al., 2020). Second, the present study found no evidence of multicollinearity in this study based on the results of the variance inflated factor (VIF >3.5) (Hair et al., 2017). Third, CMB was checked with Harman's one-factor approach (Podsakoff et al., 2002). The test on SPSS showed that the shared variance across 35 items (before item deletion) was 31%, which is well below the threshold line of 50% (Aliasghar & Haar, 2021). Thus, this thesis concludes that CMB is not a problem in this study (Podsakoff et al., 2012). Fourth, the homoscedasticity assumption was visually and statistically examined, and this thesis believes that, although the mild presence of heteroscedasticity in the data was detected, the homoscedasticity assumption was met based on the result of the comparison analysis between the OLS estimator and heteroscedasticity-consistent standard error estimator; thus, the OLS estimator is argued to be the best approach. Lastly, the endogeneity assumption was checked through the Durbin-Wu-Hausman test on STATA17 using the instrumental variable, and this thesis found no evidence of endogeneity in the independent variables. Taken together, the OLS assumptions were thoroughly examined, and all evidence suggests the robustness of the findings in this study.

[6] Some researchers contend that data normality should be included in the OLS assumption, while others have a more flexible view, arguing that normality assumption does not play a major role in the OLS assumptions (Rönkkö et al., 2016). This thesis took the latter viewpoint.

5.6 Summary

This chapter provided the results of hypothesis testing using SPSS27, AMOS26, SmartPLS3, and STATA17. Firstly, the thesis examined the data quality, and descriptive statistics were provided. The result of participants' demographics showed the similarity of the study's sample characteristics between the previous large-scale NZ innovation study and the present study, suggesting a good representation of the collected data in this study (Aliasghar & Haar, 2021).

Next, typical data cleaning processes were conducted, and some outliers and data non-normality were noted. As for the outliers, this thesis decided not to delete any outliers despite detecting seven influential outliers through the investigation (Aguinis et al., 2013). Instead, following recommendations (Aguinis et al., 2018), this thesis undertook a comparative analysis based on the dataset with and without outliers. As such, the regression result without outliers did not significantly differ from the main result. Thus, this thesis concludes that outliers are not influential in terms of the statistical claim in this study.

Regarding the data normality, this thesis followed the definition of Hair et al. (2014) and West et al. (1995), who argued that data with a threshold line of +/-2 for skewness and +/-7 for kurtosis is considered a normal distribution. Based on their arguments, the data normality of the variables is not an issue in this study, and the OLS regression approach is applicable.

As for the measurement model, despite this thesis initially using CB-SEM and AMOS to explore the best measurement model, the construct parameters and estimations on AMOS were not reliable because of the presence of negative variance, attributed to the high multivariate data non-normality, outliers, and small sample size (Chen et al., 2001). Instead, this thesis adopted PLS-SEM to validate the measurement model. Although some may argue the legitimacy of PLS-SEM (Evermann & Rönkkö, 2021), this thesis believes in its usefulness. A thorough discussion associated with drawbacks and advantages was present, providing the logic for using PLS-SEM for measurement development in this study (Hair et al., 2017).

Further, the latent constructs were analysed on PLS-SEM, and it provided evidence of the construct validity (Hair et al., 2019). Specifically, all relevant indicators, Cronbach's *a*, CR, and AVE, showed an acceptable level, indicating a good level of convergent validity. In addition to this, divergent validity was achieved through the Fornell Larcker criterion.

Section 5.4 presented the results of a set of regression tests on SPSS, mediation analysis and moderation analysis through Hayes' PROCESS macro approach (Hair, 2010; Hayes, 2018). As summarised in **Table 13** below, all hypotheses were tested; the regression analysis provided evidence of a positive role of outbound OI on firms' performance. Particularly, Selling OI has an influence on firms' financial performance, while Revealing OI contributes to firms' innovation performance. Moreover, the mediation analysis showed a strong indirect effect of Revealing OI on firms' financial performance through the mediation of innovation performance. Lastly, the moderation analysis showed that technological turbulence plays a moderating role in the relationships between outbound OI and firms' performance, while market turbulence has limited influence.

Table 13

Hypothesis Testing Results

H1a	Selling OI improves financial performance	**Supported**
H1b	Selling OI improves Innovation performance	Rejected
H2a	Revealing OI improves financial performance	Rejected
H2b	Revealing OI improves Innovation performance	**Supported**
H3	Selling OI, Revealing OI, and Innovation PF ***all directly*** improve financial performance**. (The mediation analysis confirmed the significant indirect effect of Revealing OI).**	Rejected
H4a	Moderating effect on Selling OI and Financial PF (market)	Rejected
H4b	Moderating effect on Revealing OI and Financial PF (market)	Rejected
H4c	Moderating effect on Selling OI and Innovation PF (market)	Rejected
H4d	Moderating effect on Revealing OI and Innovation PF (market)	Rejected
H5a	Moderating effect on Selling OI and Financial PF (Technological)	**Supported**
H5b	Moderating effect on Revealing OI and Financial PF (Technological)	**Supported**
H5c	Moderating effect on Selling OI and Innovation PF (Technological)	**Supported**
H5d	Moderating effect on Revealing OI and Innovation PF (Technological)	Rejected

In the last section of this chapter, several robustness checks were carried out to improve the statistical validity. Following the techniques by Torres de Oliveira et al. (2021) and Verreynne (2020), this thesis undertook a multigroup analysis (PLS-MGA) and sensitivity check; the results found no evidence of heterogeneous effects and sensitivity. Thus, this thesis concludes that the statistical results in this study were robust and applicable across other research settings (Sarstedt et al., 2020). Further to this, the OLS assumptions were tested. The assumption testing, namely linearity, multicollinearity, homoscedasticity, and endogeneity, all showed a good result, concluding that the statistical results in this study based on the OLS estimator are robust.

Chapter 6 Discussion and Conclusion

6.1 Introduction

The last chapter of the thesis aims to provide an in-depth discussion relating the hypotheses, research statements, and research questions. This chapter consists of five sections: discussion, implications and contributions, the limitations of the present study, recommendations for future studies, and conclusion. The first section provides a discussion and interpretation of the results from the last chapter. The following section gives an in-depth discussion regarding theoretical and practical contributions. The present thesis argues for adding several contributions to the open innovation (OI) theory and business practices. Further, as with other studies, the limitations of this study, such as the cross-sectional study and the presence of outliers, as well as the recommendations for future research, will be discussed. Lastly, this chapter concludes with a summary of the findings and a discussion of the entire thesis.

6.2 Discussion

This study investigated the role of outbound OI in firms' financial and innovation performance among 103 NZ firms that fit the criteria of firms conducting outbound OI activities over the past three years. The purpose of the study was to fill a research gap in two ways: (1) the scarcity of outbound OI research, compared to inbound OI, and (2) the lack of OI research focused on NZ's business environment (Aliasghar & Haar, 2021; Lichtenthaler, 2009). Filling these research gaps was crucial to investigate the research statement of whether the OI strategy is beneficial to NZ firms and to address the research question: *What are the effects of outbound OI on NZ firms' financial and innovation performance and the moderating roles of environmental factors?*

Through the literature review, the thesis demonstrated the usefulness of the outbound OI strategy to overcome increased business uncertainties or a turbulent business environment like the current COVID-19 world (Chesbrough, 2020). By pooling knowledge and resources across partners, firms can mitigate financial pressures associated with innovation projects so the firms can continue with their innovation projects even in a financially difficult situation. As past research showed that firms with continuous innovation had a higher survival and growth rate after the global financial crisis than those who did not keep their innovation activities (Wenzel et al., 2020), this thesis examined whether NZ firms could benefit from outbound OI and fill their resource gaps, such as a lack of complementary assets and commercialisation capabilities (Pells & Howard, 2019; Teece, 1986); the ability of NZ firms to keep innovation is of significance to assist their survival and growth.

Research Question One: Effects of Outbound OI on a Firm's Performance

The present study applied the ordinary least square (OLS) regression analysis to examine the relationships between two independent variables, transaction-based outbound OI (Selling OI) and non-transaction-based outbound OI (Revealing OI), and two outcome variables, financial and innovation performance, coupled with environmental dynamics as two moderators (market turbulence and technological turbulence). Importantly, the findings uncovered the different mechanisms of each mode of outbound OI in developing firms' financial and innovation performance. More specifically, the results showed that while Selling OI directly improves financial performance, Revealing OI per se does not directly, but indirectly through mediation, contribute to financial performance. Conversely, Revealing OI plays a crucial role in innovation performance, while Selling OI has no relationship with innovation performance. Further, the mediation analysis provided evidence of mediation effects of innovation performance on Revealing OI; therefore, Revealing OI indirectly improves financial performance. Lastly, the moderation analysis showed the importance of the technological turbulence when conducting outbound OI, while the market environment seems to have limited effects.

Research Question Two: Different Mechanisms of Outbound OI Strategies

The present study has discovered the different roles of each outbound strategy (Selling OI and Revealing OI) on firms' performance. Firstly, the analysis result relating to relationships between Selling OI on financial performance is in line with the past research. For example, Lichtenthaler (2009) showed a significant relationship between Selling OI and a firm's financial performance. Although this positive relationship contradicted the finding by Hung and Chou (2013), this discrepancy may be attributed to a sample characteristic used in their study because Lichtenthaler's research and the present study used the sampling frame as firms conducting out-licensing activities, while the latter study did not have such a focus. Assuming that firms that actively conduct out-licensing have more experience and specific resources for externalisation activities than those that do not usually undertake Selling OI, this contradicting result may indicate the differences in a firm's *outward* capabilities, such as desorptive capabilities (Aliasghar & Haar, 2021; Lichtenthaler, 2015), legal capabilities (Veer et al., 2016), or market capabilities (Liao et al., 2020). As noted by some scholars (Fosfuri, 2006; Ritala & Stefan, 2021), the Selling OI strategy needs caution because externalisation may strengthen a licensee's product portfolios in the absence of certain capabilities to generate a sufficient return. In turn, Selling OI may intensify the competitiveness within the industry in which the focal firm operates, therefore decreasing a firm's overall revenue.

As such, while Selling OI is positively related to a firm's financial performance within this study's research setting, caution is required. For example, although not significant, the PLS-MGA analysis indicated the differences in the effect size of Selling OI on financial performance between small and large firms. Specifically, larger firms seem to have lower benefits from

Selling OI, while smaller firms gain more benefits from Selling OI. In this regard, consistent with the prior arguments (Spithoven et al., 2013), SMEs seem to conduct out-licensing *only* when they expect a direct financial return, while larger firms do so for more strategic-oriented reasons. For this reason, although the firm size differences were not statistically significant in this study, the MGA result may be due to low statistical power because the MGA analysis split an already small-scale sample (*n*=103) into half. Thus, a future study may see a different result of Selling OI effects depending on the research setting (i.e., larger sample size).

Secondly, several qualitative researchers have pointed out the strategic use of the Selling OI strategy to improve their innovation performance (Kutvonen, 2011; Masucci et al., 2020). However, this study found no evidence to support this claim within the dataset used. One reason for this contradiction could be that NZ average firm sizes may differ from other larger OECD countries; the liability of smallness makes it difficult to conduct a strategic use of Selling OI. Because the strategic use, such as cross-licensing or setting industry standards, typically requires high internal resources to fully benefit from strategic outbound OI, smaller firms may not be actively involving strategic Selling OI. Thus, NZ firms, at least the firms in this study's setting, may not be able to capture the benefits of the strategic use of Selling OI. In fact, Kollmer and Dowling (2004) and Spithoven et al. (2013) argued that large firms with more slack resources tend to engage in strategic Selling OI. Therefore, this thesis argues that Selling OI may be susceptible to firm size and capabilities, which opens interesting research questions for future studies. Given the context of New Zealand, where 98% of firms are small-sized (20 employees or less), Selling OI might be an extremely limited option for most firms.

Thirdly, the result of the present thesis pertaining to the roles of Revealing OI is consistent with the previous literature. Particularly, this study strongly supports the findings of Torres de Oliveira et al. (2021) and Verreynne et al. (2020), who showed the positive relationship between Revealing OI and innovation performance. While the past research on the OI theory tended to focus on the inbound dimension of OI and argued that inbound OI is an important determinant for a firm's innovation performance, this thesis documented a critical role of Revealing OI in enhancing innovation performance.

Fourthly, the study found a significant and strong indirect effect of Revealing OI on a firm's performance through innovation performance. Initially, as with the study by Torres de Oliveira et al. (2021), who did not find evidence to support a positive relationship between revealing OI and financial performance, this research contended that Revealing OI's effect on financial performance was negligible. However, further mediation analysis uncovered a strong indirect effect of Revealing OI, which is indeed a stronger effect than the direct effect of Selling OI on financial performance. Thus, this thesis emphasises Revealing OI's importance in both a firm's financial and innovation performance.

Taken together, although protection or revealing is a difficult decision for firms undertaking collaboration, known as the *paradox of openness* (Ritala & Stefan, 2021), this study showed the positive role of Revealing OI on both financial and innovation performance. Some innovation scholars in the past perceived that a firm's core knowledge and technology should be protected and knowledge leakage should be minimised during collaboration (Laursen & Salter, 2014; Ritala et al., 2015); however, the question remains: to what extent can the firms protect them through the legal methods (e.g., patents) and for how long can the firms enjoy exclusive rents in today's fast-moving business environment (Chesbrough et al., 2018)? In contrast, the outbound OI activities seem to play a crucial role in not only exploiting the proprietary knowledge but also creating new values, opportunities, markets, and industries if embraced strategically (Grimaldi et al., 2021), thereby potentially leading to higher performance (Torres de Oliveira et al., 2021).

Research Question Three: Environmental Dynamics and Outbound OI

Lastly, the present thesis examined the role of environmental factors, market turbulence and technological turbulence, on the relationships between outbound OI and firm performance. The moderation analysis result found that the market environment seems to have limited influence, while technological turbulence showed meaningful moderating effects on the relationships. Especially for firms operating in a low technological turbulent environment, firms undertaking less outbound OI activities show higher OI performance, while firms in a technologically fast-moving turbulent environment tend to perform better by the frequent use of outbound OI strategy. These results support the previous findings of Lichtenthaler (2009) and Hung and Chou (2013), who showed the positive moderating effects of technological turbulence on the relationship between outbound OI and financial performance. Considering Teece's argument (1986), the finding supports the notion of his appropriation strategy. Teece argued that firms should exploit internally when a firm operates in a slow-moving business environment because they have a certain time to develop complementary assets to make the most of their technology's appropriability. Hence, keeping it *internal* is the best appropriation strategy. In contrast, when a firm operates in a turbulent technological environment, an internal exploitation strategy entails some risks because of increased business uncertainty. By the time a firm develops complementary assets to exploit from the competitive knowledge, there may be a new technological cycle. Thus, firms in high technological turbulence may benefit more by *externalising* their competitive technology, although this reduces the maximum potential profits from innovation (Pisano & Teece, 2007).

6.3 Implications

6.3.1 Theoretical Contribution

This thesis contributes to the OI literature in two ways. Firstly, while previous research was inclined to the inbound dimension, this thesis extended the OI theory by investigating the role of outbound OI, both pecuniary (e.g., out-licensing or selling IPs) and non-pecuniary (e.g., knowledge sharing) modes. The lack of outbound OI research is unfortunate given the fact that the number of firms conducting inbound OI equally means the number of firms conducting outbound OI (Henkel et al., 2014; Verreynne et al., 2020). Thus, this study's contribution is important to the OI theory.

Secondly, within outbound OI research, the non-pecuniary mode of outbound OI research has been rarely explored. Some exceptions are a study by Torres de Oliveira et al. (2021) and Verreynne et al. (2021), who explored the Revealing OI strategy in the Australian market. The present research's findings are consistent with theirs and support their arguments on Revealing OI's role. More importantly, the findings of this thesis add a novel insight into the OI theory by providing evidence of the significant indirect effect of Revealing OI on financial performance. While Torres de Oliveira et al.'s study (2021) did not find such a relationship, this study extends the body of knowledge regarding Revealing OI by presenting the mediation mechanism.

6.3.2 Contributions to Practice

Policymakers in NZ

There are several practical contributions, and the present study's findings are especially important for firms' OI activities. First, the vital role of the commercialisation stage during a typical innovation process is emphasised, as opposed to the prevailed misconception about innovation held by business managers and policymakers. As documented in MBIE's survey (MBIE, 2019), some entrepreneurs and managers in NZ are prone to think that R&D and inventions are the most important determinant of successful innovation. However, as many innovation researchers argued, an effective commercialisation strategy is required to profit from innovation (Chesbrough et al., 2018). In this regard, this thesis showed that outbound OI, which typically occurs in the commercialisation phase and supplements a firm's commercialisation activities, is positively and significantly associated with higher financial and innovation performance. Thus, this thesis calls NZ policymakers for more attention to the development of the commercialisation strategy and ability among NZ firms, perhaps through outbound OI to benefit from innovation.

Business Practitioners in NZ

In a similar vein, despite the growing popularity of the OI strategy, many firms are prone to favour inbound OI over outbound OI (Liao et al., 2020; Tranekjer & Knudsen, 2012). One of the reasons is the fear of losing competitiveness and misappropriation through the increased outward knowledge flows. Practically speaking, *the paradox of openness*, the risk of knowledge leakage due to the increased outward and inward knowledge flows, is a considerable concern because such leakages may negatively influence the focal firm's performance (Laursen & Salter, 2014). However, this thesis perceives that fear of the loss stems from a firm's perception towards outward knowledge flows: whether firms are willing to protect their proprietary knowledge internally for sustained competitiveness or to exploit it externally to capture and create value. External knowledge sharing and exploitation can be beneficial if conducted strategically but can be detrimental when it occurs unintentionally. Nevertheless, knowledge leakage could occur regardless of the focal firm's effort in today's digitally-driven business world (Veer et al., 2016).

Overall Implications

Limiting outward knowledge flows may be able to avoid unintentional knowledge leakage and protect competitive knowledge for a longer time. However, it is questionable to what extent and for how long the firms can sustain their competitiveness in today's VUCA business environment, characterised by the ever-changing digital technology advancement, supply-chain disruptions due to the COVID-19 pandemic, or the risks of geopolitical issues. Too much focus on internal exploitation and knowledge protection can be a riskier innovation strategy because of the costs and time required to develop the complementary assets needed for commercialisation: distribution network, production capability, or sales and marketing departments (Miotti & Sachwald, 2003). Thus, this thesis argues that, although there is a possibility of fewer appropriations, outbound OI is an effective innovation strategy for firms' survival and growth in a dynamic business environment. Therefore, this thesis concludes that OI is beneficial to NZ firms if adopted strategically.

Moreover, firms should be aware of the difference between each outbound OI mode. While it is obvious that Selling OI, such as out-licensing, can deliver an immediate financial return, the present thesis showed susceptibility of the Selling OI's effects. Although the positive and significant association is confirmed, the pecuniary mode of outbound OI may be subjected to the sample's characteristics (Hung & Chou, 2013; Liao et al., 2020), and the result may vary depending on the firms' resource availability and the relevant capabilities. Thus, firms may not have sufficient returns until more experience and capabilities are developed (Fu et al., 2019).

Further, although the managers' negative perceptions towards Revealing OI could be understandable, Revealing OI seems to play an essential role in enhancing firms' financial and innovation performance. For example, the free or selective disclosure of valuable knowledge can entice other players to integrate shared knowledge into their products such that knowledge receivers can add new or extra value by creating new opportunities, complementary products, new ideas, or new markets; thus, Revealing OI multiplies the value of proprietary knowledge and technology. Moreover, unlike the Selling OI, the strong positive relationships found in this study seem not to be bounded by sample characteristics (Aguinis et al., 2018). Thus, this thesis believes in the good generalisability of the findings and therefore recommends firms consider the Revealing OI strategy to capture and create value by active knowledge sharing (Chesbrough et al., 2018; Torres de Oliveira et al., 2021).

6.4 Limitations and Recommendations

6.4.1 Causal Claim and Endogeneity

As with other studies, this study has several limitations. Firstly, as highlighted in Section 4.3.4, cross-sectional studies have a limitation on a causal claim (Fowler, 2014: Saunders et al., 2019). Although multiple approaches and practices were in place, this study does not strongly claim a causal inference. Similarly, one can question the credibility of the inference about the population due to the relatively non-normal nature of collected data, the presence of outliers, and the variance-based measurement model. Especially, the relationship between Selling OI and financial performance was just above the p-value threshold line; thus, future studies could find a different result (Aguinis et al., 2013). Nevertheless, this study provided sufficient evidence of the robustness of the statistical conclusion and therefore implies a potential causal link between outbound OI and firms' performance.

Similarly, although another disadvantage of cross-sectional studies, common method bias (CMB), was clearly explained and demonstrated throughout the chapters, this thesis cannot eliminate the potential source of CMB. Also, although this thesis followed the role model paper's approach and used the instrumental variable to mitigate the endogeneity issue (Torres de Oliveira et al., 2021), the effectiveness of institutional investors as an instrumental variable and the higher-order model for the Revealing construct still needs further exploration (Torres de Oliveira et al., 2021). For these reasons, future research could look into other research designs, such as collecting the data from two different sources (e.g., primary data for independent variables and secondary data for dependent variables) and time separation (collecting a financial report from a different point of time to eliminate a simultaneity and endogeneity concern) (Antonakis et al., 2014; Saunders et al., 2019).

6.4.2 Statistical Conclusion

Further, because of the presence of mild heteroscedasticity, outliers and the non-normal nature of collected data, it is important to acknowledge that these properties can bias the result when using OLS estimation (Hair et al., 2019). Specifically, outliers can influence the coefficient line substantially, and the fact that this thesis decided not to delete those outliers may lead to a different result in a future research setting (Aguinis et al., 2013). In this sense, the outliers typically showed the opposite direction to this research's findings (i.e., outbound OI decrease the firm's performance), and these outliers may imply other confounding variables, such as capability factors (Aliasghar & Haar, 2021). Although this thesis used the level of R&D intensity to capture these capabilities (Lausen & Salter, 2006), a future study could look into a more nuanced interaction between a firm's capability (e.g., desorptive capacity) and strategic choices.

6.4.3 Generalisability

Another major limitation of this study is the generalisability of the study's result due to the use of a non-random sampling method and the possibility of heterogeneous effects (Antonakis et al., 2014). As acknowledged in the earlier sections in this chapter, OI's motives and expected outcomes can substantially differ between SMEs and large firms. Thus, the fact that this study's sample pooled the different firm sizes (small, medium and large firms) may have an unexpected impact on the result and may undermine the validity of the findings. To overcome this limitation, this study conducted the MGA test and provided evidence of no heterogeneous effects of outbound OI across sub-groups, such as firm size, firm age or the degree of R&D intensity. However, it is also important to note that the results of the multiple group analysis may be subject to a lower statistical power because it split the already small sample size in half (Jugend et al., 2018; Sarstedt et al., 2020). Thus, a large-scale future study could extend and support the findings of this study.

6.4.4 Context and Research Particularity

Lastly, in this research setting, this thesis particularly screened out firms not conducting out-licensing. Thus, the research findings cannot be expanded to a wider population, such as firms conducting OI strategy, but only inbound OI. Also, survival bias and unobserved heterogeneity should be investigated in a future study because the role of outbound OI cannot be truly reflected without the investigation of those who do not conduct the outbound OI and comparing the two groups (Sarstedt et al., 2020; Sande & Ghosh, 2018). As such, while there is a lack of generalisability towards NZ firms in general, there is much more attributed focus to those NZ firms engaging in out-licensing.

6.5 Conclusion

The present study investigated the effects of outbound OI across 103 NZ firms undertaking outbound OI on firms' performance and demonstrated the positive role of outward knowledge flows. As with the past studies, this study found positive relationships between transaction-based outbound OI (i.e., out-licensing) and firms' financial performance. Moreover, this thesis explored the untapped dimension of OI strategy, Revealing OI (i.e., free knowledge sharing), and provided strong evidence of the positive effect on their OI performance. Especially, the positive relationships between Revealing OI and innovation performance and the indirect effects of Revealing OI on financial performance through innovation performance were confirmed. As such, this thesis added a novel insight into the different mechanics of outbound OI's effects on firms' performance and discovered how Revealing OI works in terms of firms' OI performance. Lastly, the moderation analysis showed that technological turbulence moderates the relationship between outbound OI and a firm's performance.

By exploring the relatively unexplored field of OI, this thesis has demonstrated the importance of outbound OI in firms' OI performance. Understanding the outbound OI dimension is of significance to extending the OI theory because the past OI research focused extensively on the knowledge receiver's dimensions (inbound OI) despite the fact that collaboration entails two directions of knowledge flows (i.e., knowledge receiver and knowledge sender). Accordingly, this disproportionate focus may be a contributing factor to the inconclusive results of the past OI performance research. The number of OI studies has burgeoned over the past two decades, but the unequal research focus should be corrected in order to expand the OI theory. The thesis ends with a call for more research on the outbound OI dimension and exploring the usefulness of Revealing OI to enhance firms' performance.

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Appendices

Appendix A

Survey Form

Survey Form

Screeners

Please select your role from the following choices.

- ◯ R&D Manager
- ◯ Sales Manager
- ◯ Warehouse Manager
- ◯ Quality Control Manager
- ◯ Senior Top Manager
- ◯ IT Manager
- ◯ Product Design Manager
- ◯ CEO (Chief Executive Officer) Technology
- ◯ Human Resources Manager
- ◯ CFO (Chief Financial Officer)
- ◯ Accounting Manager
- ◯ Marketing Manager
- ◯ Customer Service Manager
- ◯ CTO (Chief Technology Officer)
- ◯ Technical Support Manager
- ◯ CIO (Chief Information Officer)
- ◯ Manager
- ◯ Others

Screen 2

Over the past three years, has your firm conducted any of following business practices? (Multiple choices allowed)

- ☐ **Licensed-in technologies or IP assets from other companies.**
- ☐ **Sold your intellectual property assets to other firms.**
- ☐ **Hired PhD students.**
- ☐ **Participated to trade show(s) as an exhibitor.**
- ☐ **Applied for IP registration, such as trademarks, industrial designs or patents.**
- ☐ **Worked with Universities to innovate.**
- ☐ **Applied for COVID-19 Wage Subsidy.**
- ☐ **Out-licensed your technologies or IP assets to other companies.**
- ☐ **Applied for Callaghan Innovation R&D funding.**
- ☐ **Worked with NZTE (New Zealand Trade and Enterprise) to export.**
- ☐ **Collaborated with foreign firms to innovate.**

Have you had filled any questionnaires concerning innovation strategies before?

- ○ **No**
- ○ **Yes**

screen 3

Over the past three years, has your firm had any collaborations during the research and development (R&D) and commercialisation stage with external companies, such as customers(clients), competitors, research institutes, consultants, suppliers, government, agencies or Universities?

Additional information
*Commercialisation stage refers to the process of getting your new product/service derived from R&D activities into a market. Successful commercialisation often requires developing or establishing a new supply chain network, manufacturing capability, and sales and marketing functions to launch new products/service into the market.

*Collaborations with external partners are, for example, consultations, co-developments or sourcing external technology to facilitate internal R&D and commercialisation process.

Yes No

Technological uncertainty

Please indicate your agreement with each of the following statements with respect to **your firm's technological environment** over the past three years on a scale from 1 to 7.

e.g.,
1 = strongly disagree.
7 = strongly agree.

	Strongly disagree 1	2	3	Neutral 4	5	6	Strongly agree 7
It was very difficult to forecast technology developments in our industry.	◯	◯	◯	◯	◯	◯	◯
Technology environment was highly uncertain.	◯	◯	◯	◯	◯	◯	◯
Technological developments were highly unpredictable.	◯	◯	◯	◯	◯	◯	◯
Technologically, our industry was a very complex environment.	◯	◯	◯	◯	◯	◯	◯

Performance innovation

Please assess **your firm's innovation performance** compared with competitors in the past three years on a scale from 1 to 7.

e.g.,
1 = much worse than competitors.
7 = much better than competitors.

	Much worse 1	2	3	Neutral 4	5	6	Much Better 7
New products/service introduction rate relative to the largest competitor.	○	○	○	○	○	○	○
First to market with new applications	○	○	○	○	○	○	○
Degree of products/service differentiation.	○	○	○	○	○	○	○
New products/service cycle time (e.g., inception to rollout) relative to the largest competitor.	○	○	○	○	○	○	○
Acquiring the reputation of an innovative supplier relative to the largest competitor.	○	○	○	○	○	○	○
New products/service success rate relative to the largest competitor.	○	○	○	○	○	○	○

performances (financial)

Please assess **your firm's financial performance** over the past three years compared with competitors on a scale from 1 to 7.

e.g.,
1 = much worse than competitors.
7 = much better than competitors.

	Much worse 1	2	3	Neutral 4	5	6	Much better 7
Profit growth.	○	○	○	○	○	○	○

	Much worse 1	2	3	Neutral 4	5	6	Much better 7
Return on assets.	○	○	○	○	○	○	○
Sales growth.	○	○	○	○	○	○	○
Market share growth.	○	○	○	○	○	○	○
Cash flow.	○	○	○	○	○	○	○

Market uncertainty

Please indicate your agreement with each of the following statements with respect to **your firm's market environment** on a scale from 1 to 7.

e.g.,
1 = strongly disagree.
7 = strongly agree.

	Strongly disagree 1	2	3	Neutral 4	5	6	Strongly agree 7
Customer needs and product preferences changed quite rapidly.	○	○	○	○	○	○	○
Customer product demands and preferences were highly uncertain.	○	○	○	○	○	○	○
It was difficult to predict changes in customer needs and preferences.	○	○	○	○	○	○	○

Complementary assets

Please think about your company's ownership of the following resources and assets, then assess them **in terms of competitiveness over your competitors** on a scale from 1 to 7.

e.g.,
1 = much less than competitors.
7 = much more than competitors.

	Much less 1	2	3	Neutral 4	5	6	Much More 7
Capital or financial resources.	○	○	○	○	○	○	○
R&D department	○	○	○	○	○	○	○
Know-how (the firm's core competitive knowledge).	○	○	○	○	○	○	○
Manufacturing equipment or facility.	○	○	○	○	○	○	○
Marketing or sales team.	○	○	○	○	○	○	○
After-sales service team.	○	○	○	○	○	○	○
Reputation/brand name.	○	○	○	○	○	○	○
Experience with regulation and legal practices.	○	○	○	○	○	○	○

Selling

Please indicate the extent to which you agree with the following statements on a scale from 1 to 7.

e.g.,
1 = strongly disagree.
7 = strongly agree.

	Strongly disagree 1	2	3	Neutral 4	5	6	Strongly agree 7
We are proactive in managing outward knowledge flow.	○	○	○	○	○	○	○

	Strongly disagree 1	2	3	Neutral 4	5	6	Strongly agree 7
We make it a formal practice to sell technological knowledge and intellectual property in the market.	○	○	○	○	○	○	○
We have a dedicated unit (i.e., gatekeepers, promoters) to commercialise knowledge assets (e.g., selling, cross-licensing patents, or spin-off).	○	○	○	○	○	○	○
We welcome others to purchase and use our technological knowledge or intellectual property.	○	○	○	○	○	○	○
We co-exploit technology with external organisations.	○	○	○	○	○	○	○

Appropriability regime

On a scale, how important are the following **legal** methods to protect the intellectual property assets of your firm?

e.g.,
1 = not important at all to protect IP assets.
7 = very important to protect IP assets.

	Not important 1	2	3	Neutral 4	5	6	Very important 7
patents	○	○	○	○	○	○	○
trademarks	○	○	○	○	○	○	○
confidentiality agreements	○	○	○	○	○	○	○
copyrights	○	○	○	○	○	○	○
design (e.g. registration of designs)	○	○	○	○	○	○	○

On a scale from 1 to 7, how important are the following **non-legal** methods to protect the intellectual property assets of your firm?

e.g.,
1 = not important at all.
7 = very important.

Secrecy refers to keeping IP assets internally and hide them from your competitors to protect your assets.
Complexity of design refers to making your IP asset design complex so that competitors can not copy your IP assets.
Employment contracts ensure that current and former employees do not leak any confidential information to other companies.
Lead-time advantages mean that your R&D cycle is faster so that your competitors can not exploit your technology.

	Not important 1	2	3	Neutral 4	5	6	Very important 7
secrecy	○	○	○	○	○	○	○
complexity of product/process/design	○	○	○	○	○	○	○
employment contracts	○	○	○	○	○	○	○
lead-time advantages (speed to market)	○	○	○	○	○	○	○

Revealing complementary

Please indicate the extent to which you agree with the following statements.

e.g.,
1 = strongly disagree.
7 = strongly agree.

	Strongly disagree 1	2	3	Neutral 4	5	6	Strongly agree 7
We disclose details of innovation-related challenges to seek input from other parties.	○	○	○	○	○	○	○
Our firm reveals selected problems to third parties to find new ideas.	○	○	○	○	○	○	○

	Strongly disagree 1	2	3	Neutral 4	5	6	Strongly agree 7
Our firm communicates technological or similar aspirations to external parties to seek solutions.	○	○	○	○	○	○	○
We make targeted knowledge disclosures that can attract outside contributors who are useful for our innovation activities.	○	○	○	○	○	○	○
Our firm exposes innovation knowledge to convince high-value collaborators to join our product or service development efforts.	○	○	○	○	○	○	○
Other parties who are knowledgeable of our innovation activities wish to collaborate with us.	○	○	○	○	○	○	○

Revealing co-creation

Thank you for your time and efforts.
There will be a few more pages to complete!

Please indicate the extent to which you agree with the following statements.

e.g.,
1 = strongly disagree.
7 = strongly agree.

	Strongly disagree 1	2	3	Neutral 4	5	6	Strongly agree 7
Our firm engages in joint R&D projects.	○	○	○	○	○	○	○
We develop products or services in collaborative arrangements.	○	○	○	○	○	○	○

	Strongly disagree 1	2	3	Neutral 4	5	6	Strongly agree 7
Our firm attracts others from the market so we can fill a gap of resource, knowledge or technological capabilities needed to innovate.	○	○	○	○	○	○	○

Revealing enhancement

Please indicate the extent to which you agree with the following statement.

e.g.,
1 = strongly disagree.
7 = strongly agree.

	Strongly disagree 1	2	3	Neutral 4	5	6	Strongly agree 7
Our firm encourages other firms to develop complementary products or services that support us.	○	○	○	○	○	○	○
Improvements by other firms enhance the reliability of our company's existing products or services.	○	○	○	○	○	○	○
We have the view that it is important that we help solve common technological problems in our industry.	○	○	○	○	○	○	○

Inbound OI

Please indicate the extent to which you agree with the following statement.

e.g.,
1 = strongly disagree.
7 = strongly agree.

	Strongly disagree 1	2	3	Neutral 4	5	6	Strongly agree 7
We often acquire technological knowledge from outside for our use.	○	○	○	○	○	○	○
We regularly search for external ideas that may create value for us.	○	○	○	○	○	○	○
We have a sound system to search for and acquire external technology and intellectual property.	○	○	○	○	○	○	○
We proactively reach out to external parties for better technological knowledge or products.	○	○	○	○	○	○	○
We tend to build greater ties with external parties and rely on their innovation.	○	○	○	○	○	○	○

Partner

Please think about the sources of information you have used for innovation activities. Then, **assess the level of importance** of each of the following sources on a scale from 1 to 7.

e.g.,
1 = not important at all.
7 = very important.

	Not important 1	2	3	Neutral 4	5	6	Very important 7
Suppliers	○	○	○	○	○	○	○
Clients / customers	○	○	○	○	○	○	○
Competitors	○	○	○	○	○	○	○
Consultants and private R&D institutes	○	○	○	○	○	○	○
Universities	○	○	○	○	○	○	○
Public research institutes	○	○	○	○	○	○	○

	Not important 1	2	3	Neutral 4	5	6	Very important 7
Foreign companies	◯	◯	◯	◯	◯	◯	◯
Companies from different industries	◯	◯	◯	◯	◯	◯	◯

Control variables 1

Please indicate your company's approximate percentage of the number of R&D employees to the number of total employees.

- ◯ **Fewer than 2%**
- ◯ **2% to fewer than 4%**
- ◯ **4% to fewer than 15%**
- ◯ **16% to fewer than 30%**
- ◯ **30% or more**

What is the age of your firm?

- ◯ **under 5 years**
- ◯ **under10 years**
- ◯ **under 20 years**
- ◯ **under 30 years**
- ◯ **over 31 years**

How many years of experience do you have in your field?

- **under 5 years**
- **under10 years**
- **under 20 years**
- **under 30 years**
- **over 31 years**

How many years of experience do you have in out-licensing?

- **under 3 years**
- **under 5 years**
- **under 10 years**
- **under 20 years**
- **over 21 years**

How many employees are working at your company?

- **Less than 10**
- **11 - 19**
- **20 - 49**
- **50 - 99**
- **100 - 150**
- **more than 151**

Control variables 2

Approximately, what was your firm's **revenue from technology licensing** in 2019? (NZ$)

*Technology licensing:
Agreement whereby an owner of a technological intellectual property (the licensor) allows another party (the licensee) to use, modify, and/or resell that property (such as patents, copyrights, trademarks, and trade secrets) in exchange for a compensation(e.g. a royalty payment).

- $ 0-500k
- $ 500k-1 million
- $ 1-3 million
- $ 3-5 million
- $ 5-10 million
- $ 10-30 million
- $ 30-100 million
- Over $100 million

Approximately, what was **your firm's total revenue in 2019**? (NZ$)

- $ 0-500k
- $ 500k-1 million
- $ 1-3 million
- $ 3-5 million
- $ 5-10 million
- $ 10-30 million
- $ 30-100 million
- Over $100 million

Have the intellectual property assets of your firm been negatively affected by co-operating, out-licensing or selling in the past three years?

e.g. your IP assets have been imitated or stolen by other companies.

Yes No

Control variables 3

Thank you for your time and efforts.
It is almost there to complete and there will be a few more questions!

Please indicate the percentage of ownership that **institutional investors** have in your firm.

e.g.
Institutional investors are companies or organisations that make a large-scale investment on behalf of other investors, such as Investment funds, Insurance companies, Pension funds, Venture capitals or Hedge funds.

- ◯ **under 5%**
- ◯ **under 10%**
- ◯ **under 15%**
- ◯ **under 20%**
- ◯ **under 25%**
- ◯ **Under 30%**
- ◯ **Over 31%**

How old are you? (your age)

- ◯ **under 25**
- ◯ **between 26 - 35**
- ◯ **between 36 - 45**
- ◯ **between 46 - 55**
- ◯ **between 56 - 65**
- ◯ **over 66**

Control variables 4

In which sector does your firm primarily operate?

- ◯ **Agriculture, Forestry and Fishing**
- ◯ **Construction**
- ◯ **Electricity, Gas, Water and Waste Services**
- ◯ **Financial and Insurance Services**
- ◯ **Information media and Communication**
- ◯ **Mining**
- ◯ **Manufacturing**
- ◯ **Professional, Scientific and Technical Services**
- ◯ **Rental, Hiring and Real Estate Services**
- ◯ **Wholesale and Retail Trade**
- ◯ [ ] **Other (please specify)**

Please indicate your agreement with each of the following statements with respect to **your firm's market environment** on a scale from 1 to 7.

e.g.,
1 = strongly disagree.
7 = strongly agree.

	Strongly disagree			Neutral			strongly agree
	1	2	3	4	5	6	7
Competition in our market is cut-throat.	◯	◯	◯	◯	◯	◯	◯
There are many "promotion wars" in our market.	◯	◯	◯	◯	◯	◯	◯
Anything that one competitor can offer in our market, others can match readily	◯	◯	◯	◯	◯	◯	◯
Price competition is a hallmark of our market.	◯	◯	◯	◯	◯	◯	◯

	Strongly disagree 1	2	3	Neutral 4	5	6	strongly agree 7
One hears of a new competitive move in our market frequently.	○	○	○	○	○	○	○

Please describe your firm's type/characteristic by answering the following questions.

	Answer	
	Yes	No
Is your firm part of an enterprise group?	○	○
Is your firm a family business?	○	○
Is your firm listed as a public company?	○	○
Is your firm owned by a privately held company?	○	○
Is your firm owned by the government, education, or nonprofit organisation?	○	○

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Appendix B

Strategies to Overcome Poor Data

Screening Questions

Screening out those who are not relevant to the study’s purpose is essential for better sample representation when using online panel data (Aguinis et al., 2021). Although most irrelevant responders can be ruled out with a simple screening-out question, it is often difficult to get rid of professional responders as their aim is to get qualified for as many surveys as possible so they can receive higher financial rewards (Walter et al., 2019). In other words, failing to have effective screen-out questions leads to poor quality data when using online panel surveys (Schoenherr et al., 2015).

Originally, this thesis planned to use a “YES” or “NO” screening question. Furthermore, the cover letter was prepared with detailed information about the study’s purpose, as per AUT’s ethics requirements. However, following the discussion with Cint and practice recommendations by Schoenherr et al. (2015), this thesis used multiple-choice screening questions, which increased the difficulties for respondents to guess the survey’s purpose and to get qualified. Similarly, the present study’s information in the cover letter was reduced to the minimum level of the ethical requirements to avoid professional survey-takers getting qualified for the survey.

Data Completion Time

Potrer et al. (2019) argued for a careful attention to the collected data when using online panel data. Because some participants aim to take as many surveys as possible for a higher financial return, they tend to complete the survey in a much shorter time than usual survey takers. Therefore, a researcher should carefully monitor patterned answers (straightliners) and speed responders (Schoenherr et al., 2015). For example, this thesis originally sought to include reverse coded questions in a survey, which are useful to detect patterned and speed responses; since they typically do not read questions, they respond to the reverse question in an expected way (Saunders et al., 2019). Nonetheless, considering its effect on common method bias, reverse coded questions were not used in this study.

Appendix C

Ethical Approval

Auckland University of Technology Ethics Committee (AUTEC)

Auckland University of Technology
D-88, Private Bag 92006, Auckland 1142, NZ
T: +64 9 921 9999 ext. 8316
E: ethics@aut.ac.nz
www.aut.ac.nz/researchethics

12 August 2021

Simon Mowatt
Faculty of Business Economics and Law

Dear Simon

Re Ethics Application: **21/273 The effects of outbound open innovation on firm's performances**

Thank you for providing evidence as requested, which satisfies the points raised by the Auckland University of Technology Ethics Committee (AUTEC).

Your ethics application has been approved for three years until 12 August 2024.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC in this application.
2. A progress report is due annually on the anniversary of the approval date, using the EA2 form.
3. A final report is due at the expiration of the approval period, or, upon completion of project, using the EA3 form.
4. Any amendments to the project must be approved by AUTEC prior to being implemented. Amendments can be requested using the EA2 form.
5. Any serious or unexpected adverse events must be reported to AUTEC Secretariat as a matter of priority.
6. Any unforeseen events that might affect continued ethical acceptability of the project should also be reported to the AUTEC Secretariat as a matter of priority.
7. It is your responsibility to ensure that the spelling and grammar of documents being provided to participants or external organisations is of a high standard and that all the dates on the documents are updated.
8. AUTEC grants ethical approval only. You are responsible for obtaining management approval for access for your research from any institution or organisation at which your research is being conducted and you need to meet all ethical, legal, public health, and locality obligations or requirements for the jurisdictions in which the research is being undertaken.

Please quote the application number and title on all future correspondence related to this project.

For any enquiries please contact ethics@aut.ac.nz. The forms mentioned above are available online through http://www.aut.ac.nz/research/researchethics

(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat
Auckland University of Technology Ethics Committee

Cc: tkd0570@aut.ac.nz

Appendix D

Information Sheet

Information sheet

Participant Information Sheet

An Invitation
My name is Tetsuya Totsuka. I am a postgraduate student at Auckland University of Technology (AUT) and undertaking business research as partial fulfilment of the requirements for the Master of Business degree. This study is entitled 'T***he Effects Of Innovation Strategy On Firms' Performances Among NZ Firms***, and the purpose of the study is to deepen our understanding of innovation practices to overcome a fast-moving and turbulent world, such as the post-Covid-19 environment.

I would like to invite you to participate in this study by completing an anonymous online questionnaire. Neither your name nor your company will be identifiable. Following strict procedures for research involving human subjects at AUT, this study has been assessed and approved by AUT Ethics Committee.

The potential participants of this study are identified and contacted via CINT based on their panel data and those who previously signed up to the panels to complete surveys, and invitations will be invited to participate based on profiling match.

The questionnaire can be completed on the website and should take no more than 15 minutes of your time. I would be most grateful if you could complete the survey by **the end of August, 2021**.

Please note that a survey participation is totally voluntary and you can withdraw from the survey at any point. However, once you complete and submit the survey, it indicates your consent to participate in this study, and the collected data is no longer retrievable due to the non-identifiability of the data.

Thank you very much for your time and help in making this study possible.

For additional information about this study, see below **(for mobile devices with a small screen, please zoom or turn your device horizontally)**.
Please do not hesitate to contact Associate Professor Simon Mowatt and me, should you have any questions.

What is the purpose of this research?

The present thesis aims to explore the role of innovation strategies to improve a firm's performance

How do I agree to participate in this research?

Your participation in this research is voluntary (it is your choice). As the collected data will be non-identifiable, whether or not you choose to participate will neither advantage nor disadvantage you. If you agree to proceed with the web-based survey, you can simply start it by clicking "NEXT", displayed below.

You are able to withdraw from the study at any time. If you choose to withdraw from the study, you can simply do so by closing the webpage before the completion of the survey. The participation of this research will be completed when you have answered all questionnaires in the web-based survey.

Please note that once the findings have been produced, the removal of your data may not be possible.

What will happen in this research?

When you agree to participate and click the link, the survey will begin. The questionnaires ask innovation-related organisational practices-related questions. Your personal data and response will be non-identifiable in this survey, and the completion of the questionnaires should take no more than 15 minutes.

A summary of the findings of this research will be provided after the completion of the research.

What are the discomforts and risks?

This research is designed to involve no discomforts and risks when filling the survey. Although the survey will take 10 to 15 minutes to complete, any other risks, such as confidential and sensitive information, are non-traceable. Besides, the participant decision is totally voluntary. Should you feel any discomforts and risks, you may opt-out anytime during the survey and/or before the completion of the survey.

What are the benefits?

The benefits associated with this research are threefold:

- I (the researcher) will increase my expertise in the field of innovation strategy and acquire the qualification at AUT.
- Upon a request, you will be provided with a summary of the research outcome by CINT. Then you (participants) may be able to learn how other companies in NZ do to improve their innovation and financial performances.
- In a broad term, the findings can be used as evidence by policymakers to promote the collaborative innovation environment at an industry- and national level.

What compensation is available for injury or negligence?

There will be no compensation available. Since this is web-based survey research, no injury and negligence are expected.

Will my privacy be protected?

Privacy is protected with the following steps:

- The data are non-identifiable and non-traceable.
- The collected data will be stored in a secure place at AUT and accessible only by the researchers only.
- The collected data will be deleted by supervisors at AUT six years later from the data collection date

What are the costs of participating in this research?

The only cost in this research is time to compete with the survey, which should take no longer than 15 minutes.

What opportunity do I have to consider this invitation?

The potential participants will have two weeks' period to consider if they wish to join.

Will I receive feedback on the results of this research?

You will be provided with an URL, where you can see a one- or two-page summary of the findings after the completion of the research.

What do I do if I have concerns about this research?

Any concerns regarding the nature of this project should be notified in the first instance to the Project Supervisor.

Associate Professor Simon Mowatt

International Business, Strategy & Entrepreneurship Department

Auckland University of Technology

09 921 9999 ext 5424, Email: simon.mowatt@aut.ac.nz

Concerns regarding the conduct of the research should be notified to the Executive Secretary of AUTEC, ethics@aut.ac.nz (+649) 921 9999 ext 6038.

Whom do I contact for further information about this research?

Please keep this Information Sheet and a copy of the Consent Form for your future reference. You are also able to contact the research team as follows:

Researcher Contact Details:

Tetsuya Totsuka (the primary researcher)

Contact: tkd0570@aut.ac.nz

Approved by the Auckland University of Technology Ethics Committee on type the date final ethics approval was granted, AUTEC Reference number 21/27.

Appendix E

Handling Outliers

The detection of outliers used in this study was based on three approaches, Mahalanobis distance, Cook's D, and Leverage values (Cohen et al., 2014; Tabachnick et al., 2019). Adapting three methods can increase the stability of outlier detection, compared to using one method or relying on the scatter plot, because it gives the overall distance from the average score (Tabachnick et al., 2019). As for the Mahalanobis distance, the cutoff value was set at 21.67 for financial performance and 20.1 for innovation performance based on the degree of freedom in an equation model and desired P-value (p= <.001). Similarly, the cutoffs for Cook’s D were calculated based on the equation , 4/(N (sample size) – K (the number of predictors) – 1), and the leverage values were derived based on the equation, (2K +2)/ N. Accordingly, the cutoffs were set as 0.903 (financial performance), 0.913 (Innovation performance) for Cook’s D , and 0.194 (financial performance) 0.174 (Innovation performance) for leverage values. Overall, the test found seven possible outliers from the dataset (Osborne & Overbay, 2004).

Further, to understand the impact of the detected outliers on the main regression result, this thesis ran a comparative analysis between the complete dataset and the dataset without outliers (*n*= 96). As can be seen in **Table 14** below, no substantial differences were found in the comparison, indicating that the presence of outliers in the complete data set is mild or negligible (Cohen et al., 2014). Thus, this thesis concludes that no outliers are problematic to the main result (Aguinis et al., 2013).

Table 14

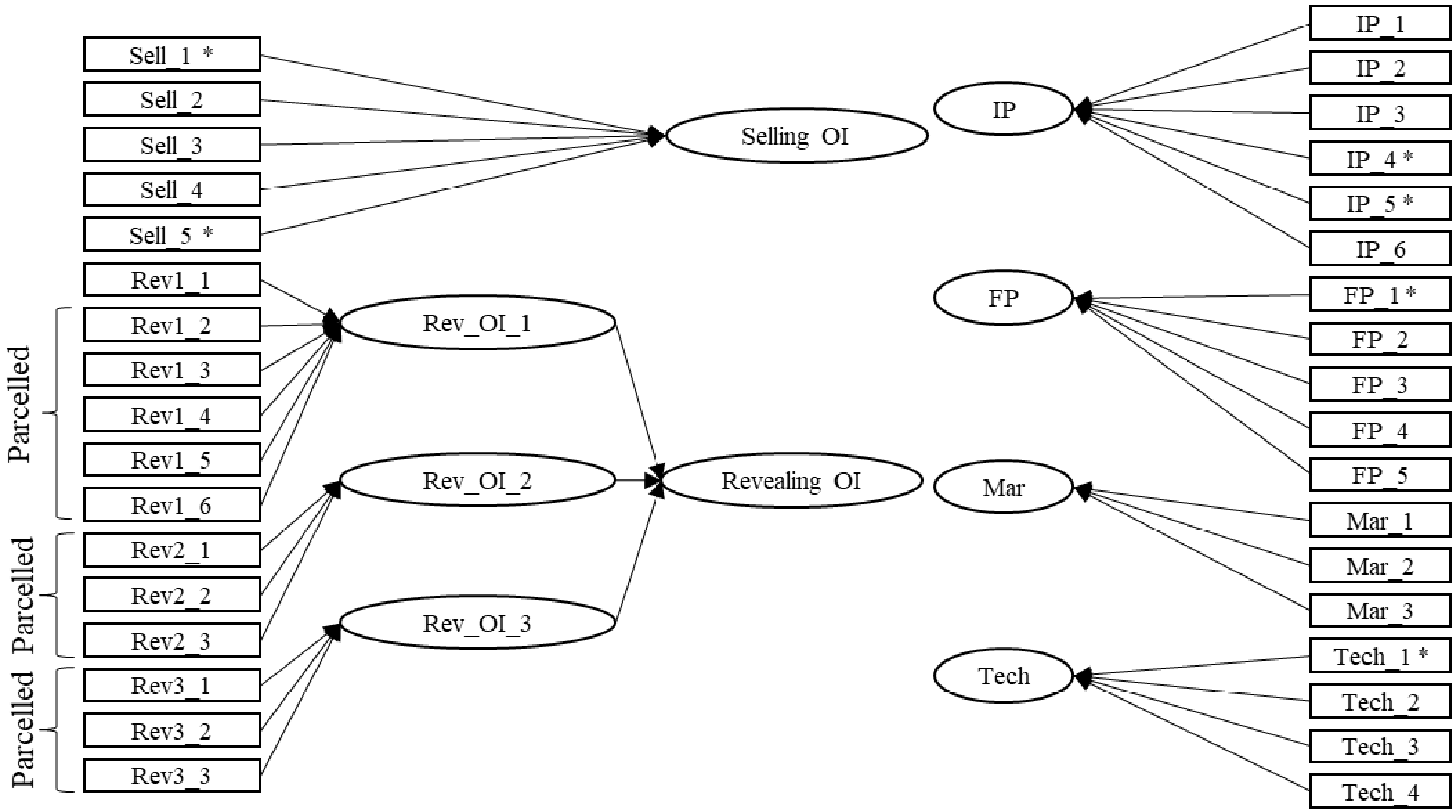
The Comparison of the Regression Coefficients for Financial Performance

	model 3		**No outliers**	
	B	**SE**	**B**	**SE**
Step 1: Controls				
INT	-.08	.09	-.07	.08
FIRM AGE	.00(1)	.06	-.02	.05
FIRM SIZE	-.11	.06	-.04	.06
Mar	**.28****	.08	.09	.09
Tech	-.06	.04	.10	.03
Step 2: Predictors				
SelOI	**.32****	.15	**.26****	.12
RevOI	**-.32****	.11	.10	.16
INNOPF	**.66*****	.10	**.58*****	.10
R^2 change	.25***		.34***	
Total R^2	.55		.69	
Adjusted R^2	.52		.67	
F statistic	14.779***		24.520***	

Note: significant effects are bolded. β = unstandardized regression coefficients, SE= standard error. Confidence Intervals are not shown in the table. Please refer to the report in the main text. All significance tests were two-tailed.

Appendix F

Diagrams for the Original Conceptual Model and Observed Items



Appendix G

Sensitivity Analysis

The sensitivity analysis explores if the relationships found in this study depend on the research setting used in this study or the reflection of the true associations (Torres de Oliveira et al., 2021). Theoretically, substituting innovation performance with innovation breadth should have no substantial changes in the structural relationships identified in this study because innovation breadth is highly correlated to innovation performance. In this regard, as **Table 15** shows, there was no considerable difference between the substitution model and the original model, indicating that sensitivity is not an issue in this study.

Table 15

Sensitivity Analysis

	Regression Coefficients for Financial Performance			
	Substitution		**model 3**	
	B	**SE**	**B**	**SE**
Step 1: Controls				
INT	.03	.10	-.08	.09
FIRM AGE	.10	.06	.00(1)	.06
FIRM SIZE	-.07	.07	-.11	.06
Mar	**.27****	.09	**.28****	.08
Tech	-.05	.04	-.06	.04
Step 2: Predictors				
SelOI	**.31*****	.12	**.32****	.15
RevOI	-.07	.15	**-.32****	.11
INNOPF			**.66*****	.10
Inno Breadth	**.23*****	.02		

Note: significant effects are bolded. β = unstandardized regression coefficients, SE= standard error. Confidence Intervals are not shown in the table. Please refer to the report in the main text. All significance tests were two-tailed.

Appendix H

Heterogeneous Effects

The table below shows the result of the MGA analysis. As can be seen in **Table 16**, the results were not statistically different between the higher median and smaller median groups across the several groups: R&D intensity, Firm Age, and Firm size. This result indicates no heterogeneous effects in the dataset used in this study.

Table 16

The Result of Multigroup Analysis

	Path coefficient	Path coefficient	differences p-Value
R&D Intensity	Higher median group	smaller median group	
Innopf -> finfp	.67	.68	.989
revOI -> Innopf	.08	.62	.110
revOI -> finfp	-.03	-.26	.570
sell_OI -> Innopf	.16	.04	.632
sell_OI -> finfp	.05	.44	.217
Age			
Innopf -> finfp	.68	.58	.787
revOI -> Innopf	.53	.61	.842
revOI -> finfp	.22	-.37	.232
sell_OI -> Innopf	.11	-.08	.524
sell_OI -> finfp	.00	.37	.261
Size			
Innopf -> finfp	.68	.68	.989
revOI -> Innopf	.06	.63	.100
revOI -> finfp	-.37	-.27	.824
sell_OI -> Innopf	.21	.01	.516
sell_OI -> finfp	.09	.48	.272

Note: significant effects are bolded. Only regression coefficients are shown.

Appendix I

Homoscedasticity Assumption

Previous papers suggest several approaches for handling heteroscedasticity; for example, employing weighted least square (WLS) estimation or a robust standard error estimator instead of the OLS (Hayes & Cai, 2007). The former approach is problematic when researchers have difficulties the cause and identify a particular pattern of heteroscedasticity because researchers using this approach need to specify a weighting value based on these two factors (Long & Ervin, 2000). In contrast, the latter approach does not need to specify the form of heteroscedasticity (Cai and Hayes, 2008).

However, Hayes and Cai (2007) cautioned researchers because these approaches could also bias an outcome under certain conditions, such as a small sample size study and a mild degree of heteroscedasticity. Thus, the OLS approach is a better choice under these conditions. Indeed, Hayes and Cai (2007) argued that heteroscedasticity is a matter of degree and not a problem of presence or absence. They stated that "relatively mild heteroskedasticity is not going to produce profound problems and is unlikely to swing" and "OLS is unbiased and strongly consistent under heteroscedasticity". For this reason, although the Breusch-Pagan test indicated the presence of heteroscedasticity, the OLS approach may still be the best estimator in this study because of the mildness of heteroscedasticity (Hayes and Cai, 2007).

To explore the potential influence of mild heteroscedasticity on the OLS estimator’s result , this thesis compared the regression result between the OLS estimator and the heteroscedasticity-consistent standard error estimator (Cai & Hayes, 2008). The downside of using the OLS estimators under a heteroscedastic condition is the underestimation of the standard errors; the standard error is used for T-test, F-test and confidence interval, and therefore increases the risk of type 1 error (Hayes and Cai, 2007). In this regard, as **Table 17** shows, the comparison of the result for standard error did not substantially differ from each other. Thus, this thesis concludes that heteroscedasticity in terms of the statistical conclusion is not an issue in this study (Bagherzadeh et al., 2019).

Table 17

The Comparison between OLS and Robust Estimators

	OLS estimator (model 2)				**HC2 estimator (model 2)**			
	B	**SE**	**T**	**P**	**B**	**SE**	**T**	**P**
Step 1: Controls								
INT	.13	.10	-1.02	0.310	.13	.09	-0.94	0.349
FIRM AGE	.09	.07	-0.04	0.968	.09	.06	-0.03	0.973
FIRM SIZE	.09	.06	-1.29	0.200	.09	.07	-1.13	0.261
Mar	**.50*** **	.07	2.87	0.005	.50	.13	1.79	0.076
Tech	.02	.04	-0.48	0.636	.02	.03	-0.48	0.632
Step 2: Predictors								
SelOI	**.32****	.15	3.05	0.019	**.32***	.16	2.02	0.047
RevOI	**-.32****	.11	-2.39	0.003	-.32	.25	-1.35	0.180
INNOPF	**.66*** **	.10	6.43	0.000	**.66****	.21	3.15	0.002

Note: significant effects are bolded. β = unstandardized regression coefficients, SE= standard error. Confidence Intervals are not shown in the table. Please refer to the report in the main text. All significance tests were two-tailed

Appendix J

Endogeneity Tests

Simultaneity and reverse causation are of importance in cross-sectional studies because a study cannot control the time temporality and the occurrence and the endpoint of the effect (Antonakis et al., 2014). In this sense, Ullah et al. (2021) demonstrated several statistical techniques using instrumental variables and argued for the use of instrumental variables to address Simultaneity and endogeneity issues. The key criteria when using an instrumental variable approach underlies the fact that the instrumental variable must be exogenous to the dependent variable while correlating to independent variables (IVs) (Ullah et al., 2021). Theoretically, the instrumental variable can partial out the effect of endogeneity by regressing IVs on the instrumental variable to create a predicted IV's score, which can then be used to predict dependent variables (DVs). Moreover, the predicted IVs' score should not be related to DV's error term because the instrumental variable is exogenous. Thus, it is useful to identify and remedy the effect of endogeneity (Antonakis et al., 2014). In the case of endogeneity, the model using the predicated IV's score and the original IVs in the main model becomes significantly different from each other because the original IVs are endogenous.

Based on these premises, this thesis undertook the Durbin-Wu-Hausman test on STATA17, which is a widely used test to detect the endogeneity of endogenous variables by examining the differences between the model using the predicted IV's and the original IVs (Ullah et al., 2021). The Durbin-Wu-Hausman test result did not reject the null hypothesis, which states that IVs are *endogenous* variables, indicating that the variables in this study are *exogenous*. Thus, this thesis assumes that endogeneity issues are not a critical for the cross-sectional based present study (Torres de Oliveira et al., 2021; Sande & Ghosh, 2018).