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The Impact of Innovation Strategy on Business Performance: Unlocking Higher Returns from Investments in Intangible Assets

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Abstract

In the dynamic realm where business success hinges on innovation, this thesis explores how an innovation strategy influences business performance, specifically aiming to unlock greater returns from investments in intangible assets. Recognizing the pervasive challenge that most innovations face failure, the study delves into the moderating role of an innovation strategy on the relationship between a firm's investments in intangible assets and overall economic performance. Employing a PLS-SEM analysis grounded in data from the European Commission's Innobarometer surveys, the research aims to uncover some of the intricate mechanisms through which an innovation strategy catalyzes enhanced returns from investments in intangible assets. Here, Innovation Strategy is conceptualized as a higher-order construct, and the choice of PLS-SEM serves as a sophisticated method for moderation analysis on the resulting complex relations.

This study provides valuable insights into the moderating role of an innovation strategy on the relationship between investments in intangible assets and business performance. Our study affirms that firms investing in intangible assets experience increased innovation and economic growth. Firms generally introduce more new innovations with increasing investments in intangible assets. We found a strong and significant direct effect of a firm’s innovation strategy: a higher degree of presence of an innovation strategy correlates with more new innovations being introduced. Intriguingly, we found that an innovation strategy is negatively moderating the relationship between a firm’s investments in intangible assets and its introduction of new innovations. As the degree of the firm’s innovation strategy increases, there is less increase in introduction of new innovations per investment in intangible assets, possibly due to the strong direct effect of an innovation strategy. Firms with a high degree of innovation strategy will have a less increasing rate of introduction of new innovations per investment in intangible assets compared to those with low degrees, although at a higher level of introduction of new innovations.

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Nord University, November 2023

Hedda M. Olsvik

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1 Introduction

1.1 Background of the Study

«Most innovations fail. And companies that don't innovate die. » Henry Chesbrough (2003).

As Chesbrough (2003) states; a firm cannot survive without being innovative, and most firms fail at introducing new innovations to the market. Over the past several decades we have seen several small firms grow into extremely large firms in a short amount of time due to their innovation capability and their ability to transform their innovation output into products that in turn lead to substantial economic growth. Innovation is highlighted as one of the most important sources for a firm to increase growth and sustain competitive advantage (Gunar, Ulusoy, Kilic, & Lufihak, 2011; Ahlstrom, 2010), and is mostly, but not exclusively, a result of the research and development activities a firm participates in (Haneda & Ono, 2022). At the same time, the innovation process is about more than just R&D investments, it is also training, design, brand, and reputation among others (Chesbrough, 2003). Firms that have an innovation strategy are both more successful and innovative, and having an innovation strategy will positively affect a firm's innovation performance (Bessant & Tidd, 2007; Oke, Walumbwa, & Myers, 2012; Verhees & Meulenberg, 2004). Hence, we propose that having an innovation strategy will not only make a firm more innovative and perform better in terms of its innovations, but it will generally make the firm more successful.

As suggested by Motohashi (1998), for a firm to survive in the globally competitive business environment it's crucial not only to manage their innovations but also to successfully commercialize these. Indeed, innovation is broadly considered the main source of competitive advantage. In addition, intangible assets (IA) are also considered an essential element of a firm's competitive advantage (Eustace, 2000), and Montresor and Vezzani (2016) describe a positive relationship between investing in IA and the introduction of new innovations. Innovation strategy is considered an essential driver for a firm's economic growth and competitive advantage as it points out the direction for the exploitation of resources to reach the firm's innovation goals, creates value, and creates competitive advantages (Dodgson, Gann, & Salter, 2008). But despite there being a broad consensus on the importance of IA in launching new innovations, and that innovation strategy is a driver for economic growth, there is a gap in our understanding of how an innovation strategy influences the relation between a firm's investments in IA and its economic growth.

By exploring deeper into this subject, we hope to give evidence of how an innovation strategy moderates, or influences, the relationships between investing in IA and economic growth, investing in IA and the introduction of new innovations, and the introduction of new innovations and economic growth. With hypotheses related to this, we aim to explore the possibility for a firm to increase its growth by utilizing an innovation strategy to increase its innovation performance based on the firm's investments in IA. In addition, we hope to contribute to an increased understanding of firm economic growth driven by IA and innovation and to help create a nuanced picture of the mechanisms at hand.

1.2 Purpose and Research question

Most firms have limited resources, and their ability to introduce new innovations will greatly impact the firm's ability to create value and maintain a competitive advantage. With this as a basis, the purpose of this study is to explore how a firm could increase its own growth by implementing innovation strategies to increase their innovation outputs from the firm's investments in IA. Based on this we present the following research question:
"How does an innovation strategy impact the relationship between a firm's investments in intangible assets and the firm's economic growth?"

To give an answer to the research question we conducted a search for prior research and existing literature, and performed a quantitative analysis of the data from the European Commission's Innobarometer surveys, specifically Innobarometer 2009 and 2016 (European Comission, 2023). These surveys focus on innovative trends and ask multiple questions regarding IA, innovation, strategy and economy. The surveys ask several similar questions, although not always with the same measurement scales. Even though these surveys have some differences, they provide solid data sources to answer our research question. The study will go into how having an innovation strategy can contribute to turning investments in intangible assets into higher economic growth by maximizing the innovation output from investments in IA and turn introduction of new innovations to increased economic growth. By this we aim to give evidence as to how an innovation strategy affects a firm's innovation process, from investments in IA to introducing new innovations and gaining economic growth.

1.3 Structure of the Thesis

There are six chapters that address each stage of the research process.

Chapter 1 gives a background for the study and the subject, the importance of doing the research to understand how IA helps gain economic growth, and the role innovation strategy has as a moderator to this relationship. The chapter also gives the motivation for the research and presents a research question for the study.

Chapter 2 provides the theoretical backdrop and establishes the hypotheses of the study. The chapter elaborates on the subjects IA, innovation and economic growth, before going into innovation strategy, and how innovation strategy affects the relationships between IA, innovation, and economic growth.

Chapter 3 gives an overview of the method chosen for the research process, and why we chose it. It also presents our data sources, Innobarometer 2009 (IB09) and Innobarometer 2016 (IB16), and operationalization of variables from these.

Chapter 4 presents the empirical study in the form of PLS-SEM analyses of the data sources. Hypotheses are also explored and tested in this chapter.

Chapter 5 discusses the results of the data analyses, and the findings are critically evaluated in the context of the theory.

Chapter 6 presents the conclusion and findings of the research, revisits the purpose of the study and aims to answer the research question and hypotheses. The chapter also elaborates on the limitations and implications of the study, as well as presenting our recommendations for further research.

2 Theory

In this chapter, we are presenting theory and literature that are considered relevant to this study. We first present theories about IA, innovation, and the relation between IA and the introduction of new innovations. Thereafter we go into the relation between the introduction of new innovations and economic growth. Lastly, we will elucidate the role of innovation strategies on these relationships and go into recent research looking into how innovation strategies affect the relationships between investing in IA, the introduction of new innovations, and economic growth.

2.1 Intangible assets

The interest in IA has steadily increased in the last century (Grimaldi, Corvello, Mauro, & Scarmozzino, 2017). In the end of the last century Nonaka and Tekuchi (1995) presented a highly influential work with "the knowledge creating company" paving the way for research on IA. In the 21st century we have had an array of studies on the concept of non-physical assets which has proven to sustain the competitive advantages of firms (Grimaldi, Corvello, Mauro, & Scarmozzino, 2017). This research has confirmed an even stronger role of IA and has led to an increasing rate of publications in academic journals (Grimaldi, Corvello, Mauro, & Scarmozzino, 2017).

Many definitions can be found for IA in literature. Some researchers refer to specific aspects among IA such as brand, trademark etc. (Ocak & Findik, 2019). Other researchers view these assets in a broader sense, as the influential work of Hall (1993), who view it as assets that have no physical substance. Augier & Teece (2005) argues that IA are non-current assets and different from tangible (physical) assets. They point to these differences as IA are used by one party, their transfer costs are hard to calibrate, their property rights are limited, and the enforcement of property rights is relatively difficult (Ocak & Findik, 2019). In more explanatory terms IA are commonly referred to as trademarks, design, brand, software, trade secrets, capitalized research and development, goodwill, databases, domains, human capital, consumer lists, market share, marketing rights, etc. (Ocak & Findik, 2019)

So why do firms invest in these non-physical assets? IA contribute to a firm's ability to produce goods or deliver services, or are expected to create future economic benefits for the entity or individuals controlling their distribution (Eustace, 2000). IA are essential for firms due to their ability to drive innovation, enhance market positioning, and contribute to long-term growth. They can provide companies with a competitive edge by enabling the protection of unique ideas, processes, and products. Additionally, IA often play a crucial role in attracting investors, forming strategic partnerships, and building a strong brand identity (Hall R. , 1993). IA are essential for firms due to their ability to drive innovation, enhance market positioning, and contribute to long-term growth. They can provide firms with a competitive edge by enabling the protection of unique ideas, processes, and products. With this increased focus on IA, and how they contribute to creating knowledge, innovation, and consequently, economic growth, physical and financial resources are increasingly seen as commodities (Eustace, 2000).

In innovation studies, IA has usually been treated as a simple independent variable along with physical or tangible ones (e.g., equipment and labor) (Montresor & Vezzani, 2016). The role of IA has been studied across European countries in research projects as INNODRIVE, COINVEST, IDICSER and IAREG focusing on different forms of IA and the relationship to economic growth (Montresor & Vezzani, 2016). Where these, according to Montresor & Vezzani (2016), fall short is how they treat IA as one simple variable (normally R&D) and don't include the full spectrum of activities within IA. Since these non-tangible resources should have a broader definition than just one activity, the importance of spectrum, or how various aspects affect each other is still not fully understood.

2.1.1 The relationship between IA and Economic growth

There are a lot of empirical studies supporting the hypothesis that investments in IA have a positive effect on the ability to innovate, which in turn leads to greater productivity (Piyush & Leung, 2021; Eustace, 2000; Montresor & Vezzani, 2016). We have already noted in the introduction (chapter 1.1) that several strategy researchers have pointed out that IA can be considered the most likely source of a company's sustained competitive advantage since they are neither easy to acquire nor to replicate.

Although a lot of the literature point towards a direct link between IA and a firms financial success, other researches such as Piyush & Leung (2021) and Rui, Li, & We (2022) shows that higher R&D intensity can have a negative effect on short-term profitability, but a positive effect on a firm's long term performance. This might highlight that turning investments in IA into innovation and hence economic growth takes time. To measure a firm's investments in IA and the corresponding relationship with economic growth should therefore be separated in time.

The general consensus in theory (Bagna & Enrico, 2021) is that investments in IA have an effect on a firm's economic growth through the introduction of new innovations. Hence investments in IA, without it resulting in innovations, would not lead to any economic growth. One could argue that investing in IA (e.g., new systems, human capital or branding) without any innovation output would be hurting a firm's finances and economic growth if there is no increased productivity or other gains. For instance, the whole objective of investing in R&D is to find new applications and innovations (Hall & Rosenberg, 2010). Normally R&D will increase productivity by increasing the quality of or reducing the average production costs of existing goods (Hall R. , 1993).

Several studies show divergent results when trying to understand the relation between IA and a firm's performance. As an example, Fernando, Jabbour and Wah (2019), showed no link between IA and a firm's business performance. Nor did Weqar et al (2020), when viewing the relation between IA and firm performance in Africa, where the conclusion was that there were no significant relationships between market value, productivity, and profitability. One has still left to confirm the relationship between these three (Miala, et al., 2021). Yet another study from 2015, looking into 141 U.S. firms, found no significant relationship between a firm's investments in basic, exploratory R&D and the firms value on the stock market (O'Connor, 2019). The study concludes that these findings support the already existing research that shows that there is no connection between exploratory R&D and the firm's market performance, or in some cases a negative connection (O'Connor, 2019). This shows that investing in R&D on its own will not cause an increase in a firm's value. On the other hand, in a study from 2014, Crass and Peters (2014) examining data on German firms from 2006 to 2010, found IA to have an important role in promoting firm's productivity, and showed complementary effects between different types of IA. The previously mentioned studies are looking into the effects which IA have on the performance, but none have measured the effect of IA on performance, competitive advantage, and sustainability of firms, collectively in firms.

Over the last fifty years there has been an increasing desire to be able to measure the relationship between spending in IA and the financial return (Hall & Rosenberg, 2010). The majority of research has focused on the economy-wide returns, but economists are mostly interested in how investments in IA would benefit firms and give them return on their investments (Hall & Rosenberg, 2010). Literature has mostly focused on a familiar growth accounting framework where investments in R&D are linked to the total factor productivity

(Hall & Rosenberg, 2010). In these models' researchers try to showcase the residual growth factor in production that is not explained by physical assets such as labor or capital.

Most of the literature that measures the relationship between IA (e.g., R&D, knowledge capital or other inputs) and firm performance use one of two approaches (Hall & Rosenberg, 2010). The first method is the primal approach where one uses the Cobb-Douglas production function augmented with knowledge capital. In these models one estimates the increase in productivity with tangible assets, form specific knowledge capital and external knowledge capital (Hall & Rosenberg, 2010). This method describes a firm's boost in performance, or production output, by advancements in knowledge capital. This increase in knowledge capital, e.g. R&D, is directed to new methods of production (process R&D) and new or improved goods (product R&D) (Hall & Rosenberg, 2010). The other approach does not limit the technical representation, but additionally includes an assumption of optimizing behavior (Hall & Rosenberg, 2010). All firms will have incentives of cost minimization, profit maximation or to maximize a firm's value. The approach differs from the primal approach by not assuming the returns from investments in IA are constant, but will differ with variations in prices, R&D spillovers, output, and quasi-fixed inputs (Hall & Rosenberg, 2010).

In Hall and Rosenberg's (2010) review of research papers mapping the relationship between investments in IA and the expected rate of return, they discovered that by using a product function (the given economic output from inputs), the rate of return in developed economies in the past half century have been strongly positive and may be as high as 75% but more likely an average in the 20-30% range (Hall & Rosenberg, 2010). In the dual approach, which is frequently used on sector-specific ranges more than firm-specific, finds that the return of IA has a two-to-three-time bigger return than investments in tangible assets (Hall & Rosenberg, 2010).

Using the product function researchers have found a strong correlation between investing in IA and a firms' returns (Hall, Foray, & Mairesse, 2007; Rogers, 2009; Griffith, Harrison, & Van Reenen, 2006; Kafouros, 2005; Mairesse, Mohnen, & Kremp, 2005). However, some literature research (Rui, Li, & Wei, 2022) indicates that in the short term, higher investments in IA might hurt the rate of return. In order to investigate whether the literature correlates with our own findings we have derived the first hypothesis to be:

H1: *Firm's investments in intangible assets have a positive relationship with the firm's economic growth.*

2.2 Investing in intangible assets and introduction of new innovations

The role of IA in a firm's innovation output is widely known in academic and political areas (Montresor & Vezzani, 2016). Typically, one would think of IA as research and development, but researchers such as Carlsson et al. (2002) makes the argument that IA and innovation is more than just a linear approach and introduce the term "open-innovation method". They are supported by Chesbrough (2003), who argues the innovation process is about much more than investments in R&D, and points to areas as training, design, brand, and reputation as resources that contribute to innovation.

The relationship between resources and innovation has always been a key focus area for research within innovation and strategic management (Fang, Marshal, & Yugang, 2023). The research on the area is mixed, where some studies show that there is a positive impact of IA and innovation (Chen & Huang, 2009; Khan, Atlas, Ghani, Akhtar, & Khan, 2020; Liu, Kim, & Yoo, 2019; Roberts & Dowling, 2002), and others find a negative relationship (Cox Pahnke, Mcdonald, Wang, & Hallen, 2015; Dahlander, O`mahony, & Gann, 2016). Fang et al. (2023) illustrates that existing literature and research doesn't adequately explain the inconsistency, and showcased a framework to analyze how and why IA can impact firms' innovation. They found that the discrepancy in the literature is because the relationship between IA and innovation performance follows an inverted U-shape. The argument behind this U-shape is that when a company has a low level of IA there will be a negative relationship on innovation because a firm's imitation incentives are more likely to overwhelm innovation invectives. On the other hand, when a firm has a high level of IA there is a positive relation between IA and returns because the profits from innovation exceed the potential risks.

2.2.1 Mediating effects

In chapter 2.1 we presented how IA are essential for companies due to their ability to drive innovation, enhance market positioning and contribute to long-term growth through providing companies with a competitive edge. This relationship between a firm's investments in IA and the firm's growth is thought to be due to the mediating effect of innovations (Piyush & Leung, 2021).

The role of innovations in the link between IA and economic growth is as an explanatory and mediating variable as to why companies with higher investments in IA have higher economic growth. The general consensus in theory (Bagna & Enrico, 2021; Ocak & Findik, 2019) is that investments in IA has an effect on a firm's economic growth through the launches of new innovations. A criterion for discovering a useful mediating effect in statistical analysis is that one needs specific theory why innovation is mediating the relationship between IA and economic growth. Substantial a priori theoretical support as to why innovations (as a result of investments in IA) help economic growth is needed to fully draw conclusions from statistical analysis (Holland, Shore, & Cortina, 2016).

2.2.2 A firm's size and the role of intangible resources and innovation

Knott & Vieregger (2022) claims that there is a prevailing view in the press and modern literature that R&D productivity decreases with size, combined with the fact that R&D investments increase with size. This seems like an irrational move by big firms, as increasing spending gives decreasing returns. This might be due to one of two reasons, (1) we are measuring R&D productivity wrong, or (2) firm size endogenously drives R&D strategy, and the return to R&D strategies depends on scale. Knott & Vieregger (2022) found that in contrast to prior literature, there is evidence that returns from R&D spending actually increases with a firm's size. They allure this to the fact that the more a company can put a strategy behind its spending, the higher return it would have.

2.2.3 Success drivers of innovation

Why do some innovations succeed, and why do some fail? Only one of 7-10 products that launches turns into a commercial success (Cooper, 2018). The top 25 % of firms have 12 times the productivity in new product development, achieving 39 times the return on investment in R&D for new product sales, while the bottom 25 % of firms achieve only three times the return (Cooper, 2023). Products with unique benefits and a compelling value proposition for the customers are far more likely to separate winners from losers than any other single factor. Products with unique selling points have a four to five time more commercial success (Cooper, 2018; Golder & Mitra, 2018). To explain these differences in performance Cooper (2018) have defined three categories of success drivers for successful innovation. These three categories are: individual new-product projects, organization, and strategic factors, and having the right systems and processes.

Within the category of success drivers for individual new-product projects Cooper (2018) names, among other, drivers such as having superior products, having a market-driven focus, and succeeding with the launch of the product as critical areas for success. In the category regarding having the right systems and processes Cooper (2018) focuses on the firm's internal limiting factors for succeeding. These are, among others, having gating systems (idea-to-launch systems), being agile in development, and the quality in execution of key tasks in the innovation process from the beginning to finished product.

Where the two mentioned strategies focus on how to succeed with the process of a single innovation, the organizational and strategic factors are arguably more important. The first step for any firm would be to have a strategy for product innovation and technology.
Having a strategy for new product innovation is strongly linked to a firm's performance (Cooper, 2018). One of the factors that should be included in such a strategy is having defined objectives and goals for innovation (e.g., how many new products do we want to launch?) (Cooper & Edgett, 2015). Cooper (2018) argues that companies are suffering from too many projects and not enough resources to sufficiently follow up each project. This lack of prioritizing hurts all projects and does not sufficiently direct the competencies to the deserving projects. In this scenario the firm is wasting valuable resources on bad projects, and not providing the right projects enough resources.

Furthermore, Cooper (2018) argues that when a firm is not building on its strengths, new products fare poorly on average. Having synergies between a firm's competencies, strengths and product developments are crucial for the firm's success. Different areas where a firm should have good synergies with the innovation is, among other, R&D (technology resources), marketing, branding, manufacturing, technical support, and management capabilities (Cooper, 2018). Many projects or initiatives suffer from a lack of time and/or financial commitment. This can result in much higher failure rates (APQC, 2003). This can be seen as related to the point regarding project selection, where a company needs to have a strategy on which projects to choose, and where to allocate the resources.

Firms should also investigate a market's attractiveness and dimension accordingly. Questioning the potential of the markets, or in other words "how big could it get", and the competitive situation is essential for succeeding with innovation (Cooper, 2018).
Furthermore, Cooper (2018) argues that product innovation is very much a team effort. Integration between specialists so that they have the foundation to create successful innovation, is key to a firm's success (Nakata & Im, 2010). According to Cooper (2018) every project should have a clearly assigned project team, and the project teams should be cross-functional with team members from R&D, sales, marketing, and operations. Another key success factor is that these team members should be on the project from start to end. Lastly,

factors such as climate and culture (having the right positive environment for innovation) and having top management support distinguishing top performing firms (Cooper, 2018).

2.2.4 The relationship between IA and the introduction of new innovations as viewed in the CDM Model

The CDM Model (Crepon, Duguet, & Mairesse, 1998), as illustrated in Figure 1 below, is the most used model for explaining the economics of innovation in a three-stage procedure where investments in IA result in patens and then to productivity improvements. Later we are going to explore the second part of the model (from innovation to growth), but here we are focusing on the first part of the model.

Figure 1 CDM Model by Crepon, Duguet & Mairesse (1998)

The model consists of three different sections: (1) the firm initially decides whether to invest in R&D, and how much to invest, (2) the innovative input leads to innovation output (e.g. a new product, process innovation, technology or organizational change), (3) lastly, the output leads to increased labor productivity (Rybalka, 2015).

Newer research has expanded the first part of the model to include other factors than R&D in the first stage of the model. Rybalka (2015) includes investments in ICT (information and communication technology) and finds that investments in ICT is correlated with innovation output, although not as strongly as R&D is. This CDM model has become a workhorse for empirical literature on innovation and productivity and has for example been applied to micro data for over 40 countries (Loof, Mairesse, & Mohnen, 2017). In addition to Rybalka's (2015) use of the model (introducing ICT), there has been several variations of the original CDM Model using continuous or discrete data, using various variables and various estimation methods (Loof, Mairesse, & Mohnen, 2017).

In this study we want to confirm the relationship presented in the CDM model, but we are broadening the variable R&D to include several IA described in chapter 2.2.1 The CDM framework is mostly used as a methodology, and expanding on the variables is common (Loof, Mairesse, & Mohnen, 2017). We will also be using the Oslo Manual (OECD/Eurostat, 2005) as the interpretation of innovation, that has also been used heavily in the CDM model (Loof, Mairesse, & Mohnen, 2017). The Oslo Manual (OECD/Eurostat, 2005) defines inputs to innovation not only as R&D, but also "non-R&D activities" and defines all activities that firms need to use new technologies as innovation input. Hence, we will have a broader view on innovation input as the sum of all intangible assets, as illustrated in Figure 2.

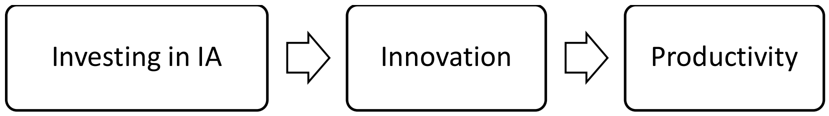

Figure 2The CDM Model with IA as a variable

This has led to the hypothesis:

H2: *Firms investing in intangible assets are introducing more new innovations.*

2.3 Innovation and economic growth

2.3.1 Innovation

As mentioned above, The Oslo Manual has been used in a the CDM model, as Community Innovation Surveys has been based on its guidelines (Loof, Mairesse, & Mohnen, 2017). The Oslo manual (OECD/Eurostat, 2005) uses the term TPP (technological product and process innovations) to define how one can look at the characteristics of innovation.
In a firm's innovation process economists have traditionally considered knowledge diffusion as a key factor for encouraging economic growth (Galindo & Medez, 2014). The reasoning behind this train of thought is that innovation makes products more competitive and allows firms to introduce products into more markets.

Within the modern economy, with increasingly more knowledge-based firms, innovation is seen to play a vital role. However, until recently, the processes around innovation have not been sufficiently known (OECD/Eurostat, 2005). According to OECD (2005) innovative firms have several characteristics that can be grouped into two different categories; strategic skills (i.e., the ability to identify market trends) and organizational skills. It's a common practice to model innovation output as a product function (Freel, 2005). The product function, where the output is some innovation measure, contains the inputs R&D expenditure and internally or externally sourced resources. In other words, innovation is linked to the firm's funding and its investment in skilled labor, either in new employees or by training of experienced staff.

According to Haneda & Ono (2022) innovation plays an important role in a firm's productivity and growth. They argue that innovation is, in large part, a result of the research and development activities the firm undergoes. A large array of studies has shown that investment in R&D are closely related to a firm's economic growth, and studies from Alam et al. (2018) and Coad & Grassano (2019), among other, shows a clear correlation between funding R&D and a firm's success.

Romer (1990) introduces the concept of endogenous growth theory, which represents a significant deviation from the traditional neoclassical growth models. The central idea of this theory is that technological progress and innovation are not exogenous or external factors, but are endogenously determined by economic factors within a firm. Romer points to several different factors that affect a company's innovation. Among these are: the role of ideas, the role of human capital and innovation, increasing returns to scale, market structure, policy implications and empirical relevance.

The article "The future of productivity" from the OECD (2015) summarizes the challenges and opportunities that lie ahead for improving productivity for economic growth. The article showcases recent macro trends within productivity growth and shows the reduction in productivity gains in advanced economies in the last twenty years or so. The article highlights technological progress, innovation, investment in physical and human capital and efficient resource allocation as key inputs in innovation.

The ability to be innovative is one of the fundamental instruments for growth strategies to enter new markets or increase existing market share, and to provide the company with a competitive edge (Gunar, Ulusoy, Kilic, & Lufihak, 2011). Seeing the increasing globalization and competition in global markets, firms have started seeing the importance of innovation. In the last two decades, innovativeness has turned into an attractive area to study for researchers who are trying to understand its economic performance impacts.

Innovation does not solely relate to the output of new products or processes, but it can be related to marketing and organization (Gunar, Ulusoy, Kilic, & Lufihak, 2011). Schumpeter (1934) describes seven different forms of innovation that can happen within a firm:

Firstly, introduction of a new goods or services (product innovation): Schumpeter argued that one of the most common forms of innovation is the introduction of a new product or service into the market. This type of innovation involves creating something that did not exist before or significantly improving upon existing offerings. Product innovation can lead to economic development by creating new industries, generating employment, and satisfying consumer needs more effectively.

Introduction of a new method of production (process innovation). Process innovation refers to the development of new methods, techniques, or processes for producing goods or services. It often involves increasing efficiency, reducing costs, and improving the quality of production. Process innovation can lead to economic development by increasing productivity, reducing waste, and making industries more competitive.

Opening of new markets (market innovation). Schumpeter also highlighted the importance of opening up new markets as a form of innovation. This can involve identifying untapped customer segments or entering new geographical markets. Market innovation can lead to economic development by expanding business opportunities, increasing sales, and driving economic growth.

Discovery of new sources of supply (resource innovation): Resource innovation involves the discovery or development of new sources of raw materials, energy, or other critical inputs for production. This type of innovation can reduce production costs, enhance resource sustainability, and promote economic development by ensuring a stable supply of essential resources.

Creation of new organizational structures (organizational innovation): Schumpeter recognized that innovation can also occur at the organizational level. This includes the development of new business models, management practices, and organizational structures. Organizational innovation can improve the efficiency of firms, enhance their competitiveness, and drive economic development.

Implementation of new financial methods (financial innovation): Financial innovation relates to the creation of new financial instruments, institutions, or methods of financing economic activities. It can include innovations in banking, investment, insurance, and financial markets. Financial innovation can have a profound impact on economic development by facilitating access to capital, reducing financial risks, and promoting investment.

Changes in market structure (market structure innovation): Schumpeter also noted that innovation can lead to changes in the market structure, such as the emergence of monopolies or oligopolies. These structural changes can have both positive and negative effects on economic development, depending on their impact on competition and market efficiency.

2.3.2 The link between innovation and economic growth

Researchers studying forms of innovation output and economic growth have found that investment in innovation has had a positive impact on a firm's economic performance. Hitt et al. (2000) studied the relationship between innovation and firm performance, with a specific focus on Canadian firms. They found empirical evidence supporting the idea that there is a positive relationship, measured as R&D intensity, and a firm's economic performance. The researchers underscore the importance of innovation as a driver of competitiveness and profitability.

Since Schumpeter (1934) described the role of innovation in economic development, innovation is widely regarded to be an important factor in firms' economic performance (Shouyu, 2017). Innovation is a single variable that alone cannot explain the relationship with a firm's performance. Therefore, several researchers have analyzed the relationship between innovation and firm performance looking at the direct influence, but also the mediating and moderating effects (Shouyu, 2017). Mediating effects were described in chapter 2.2.1, and exists when there is an indirect effect on the relationship between two or more variables (Holland, Shore, & Cortina, 2016). Moderating effects occur when innovation influences the strength or direction of some other relationship (Holland, Shore, & Cortina, 2016).

The direct effects innovation has on a firm's performance has been confirmed to be positive by many researchers. As cited in Shouyo (2017) Roberts (1999) found that innovation would have a positive impact on a firms return on investment in a study of the U.S pharmaceutical industry. Furthermore, a study by Cho and Pucik (2005) found that in fortune 1000 firms, innovation was positively related to a firm's profitability and even growth. Other researchers cited in Shouyo (2017) have found similar links between innovation and firm performance in industries such as the personal computer industry, and Greek and Australian service industries. Other relevant studies have found that the more innovative a firm is, the more likely they are to achieve higher performance of their firm (Shouyu, 2017).

Other researchers have found that the relationship between innovation and a firm's performance is not as direct as illustrated above. Haung and Rice (2009), as cited in Shouyu (2017), argues that the relationship between the firm's performance and it's innovation is not as deterministic, and is affected by factors such as capital stock and external factors such as market and environmental factors. To illustrate this argument; in a stable environment, customers don't want to change, and an innovative firm who changes its products would be damaging to their own success. In a dynamic environment, firms launching innovations are the winners, but in a stable environment innovation could be hurting the firms (Shouyu, 2017).

The last effect on the relationship between innovation and a firm's performance is mediating effects. In this field on research on performance and innovation Neely et al. (2001) conceptualized how a firms performance relates to innovation, and how internal and external factors can affect innovation within a company, as illustrated in Figure 3. This concept of mediating effects could illustrate how various kinds of innovation would results different categories of outcomes, that in turn would boost business performance through (1) return on investment, (2) market share, (3) competitive position or (4) value to customers.

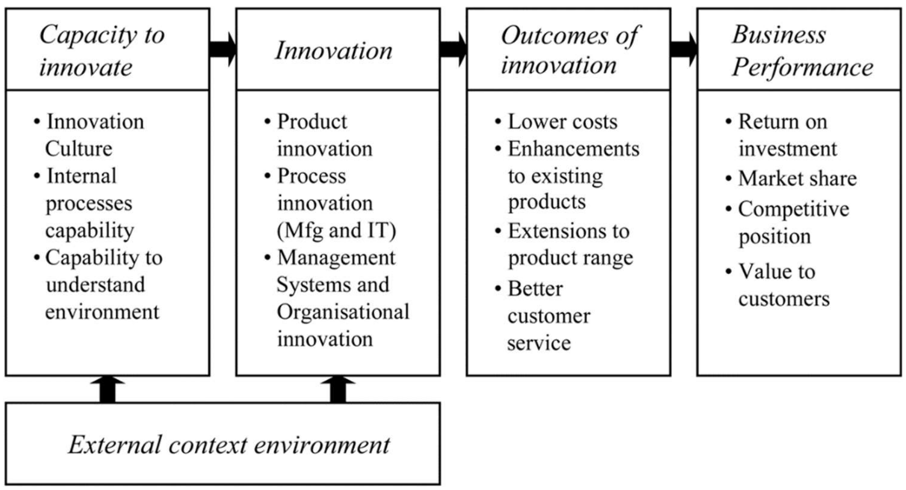

Figure 3 Links between types of innovation and outcomes of innovation (Neely, Filippini, Forza, & Vinelli, 2001))

In conclusion there are three different ways to view how the impact of innovation affects a firm's performance. In the direct method described, one tries to see if innovation has a direct effect on a firm's performance. As documented by, among others, Robert's (1999) and Cho and Puchik (2005) there is a positive relationship between innovation and firm performance. Other researchers argue that there are moderating variables affecting the relationship, and the main argument being that the environment needs to be changing in order for innovation to actually produce profits. The last method included mediating variables such as industry, innovation output, IT investment, market position etc. (Shouyu, 2017). With this theoretical framework we have concluded in the research hypothesis:

H3: *Firms introducing more innovations have greater economic growth.*

The hypotheses H1, H2 and H3, and the constructs which these hypotheses are related to, are illustrated in Figure 4. These constructs and the relationships between them are from now on referred to as the base model.

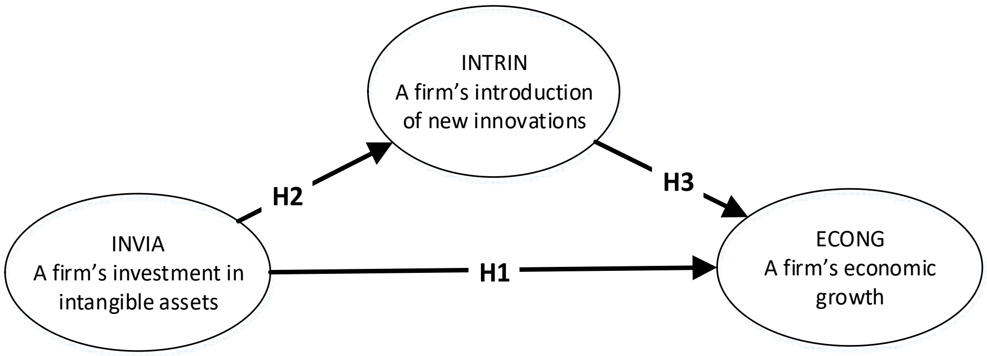

Figure 4 The structural base model

2.4 Innovation strategy

The globalization of the world has changed the way in which commercial activities are conducted (Ameen, et al., 2023; Aziz, et al., 2023; Malik, et al., 2019; Qadeer, et al., 2023).With this, the changing customer needs, increased competitor rivalry and the introduction of new technologies transform the market which firms operate in (Mohamad, Mustapa, & Razak, 2021). It is becoming increasingly difficult for firms to maintain its competitive advantage and growth as the markets which firms operate in are becoming more aggressive (Labas & Courvisanos, 2022). To meet the changing conditions, firms must have a stated path to follow, a strategy that is aligned with the transformations in the market. Strategy is about charting a course for the firm to follow forward (Torvatn, Rolfsen, Heggernes, & Sørheim, 2016). It defines a firm's direction, says where the firm wants to be, and gives an indication of how to get there and achieve the stated goals (Kuratko, Morris, & Covin, 2011). Theory clearly states that firms with a strategy perform better than those without (O'regan, Ghobadian, & Gallear, 2006; Miller & Cardinal, 1994; Greenley, 1994; Handoyo, Suharman, & Soedarsono, 2023).

An innovation strategy describes how a firm ought to increase its own ability to innovate, which methods to use, and what skills and knowledge to develop within the firm (Bason, 2010). Put in other words, an innovation strategy defines goals, and the road map to achieve them. An innovation strategy must state how a firm is to create value for both itself and its customers, identify the innovative products and processes that need to be evolved, and which resources that need to be allocated to achieve this (Pisano, 2015). The innovation strategy, and innovation, must be viewed in coherence with other strategies the firm has.

Pisano (2015) defines a good innovation strategy as one that enhances cooperation between different branches in the firm, defines goals and prioritization, and increases the firm's dedication to achieve the stated goals. The innovation strategy must therefore be based on the overall strategies of the firm and must be understood in the context of the overall business strategy. Together they give clear directions for the firm’s short- and long-term goals (Gaubinger, Rabl, Swan, & Werani, 2015). Tang (1998) formulates three important questions that an innovation strategy should give answer to: (1) What types of innovations will be performed by the firm? (2) How will the firm perform these innovations? and (3) By which methods will the firm introduce its innovations to the market? A firm may also build its innovation strategy on different assets (Tidd & Bessant, 2013), both internal; e.g. its employees and leaders, and external; as technology, requirements of efficiency, customers and other stakeholders (Fuglsang, 2006).

There is a general agreement in theory that firms who have an innovation strategy are more successful and more innovative, and innovation strategy will positively affect a firm's innovation performance (Bessant & Tidd, 2007; Oke, Walumbwa, & Myers, 2012; Verhees & Meulenberg, 2004). A clearly defined innovation strategy will therefore be an important element in a firm's innovation performance and growth (Clark & Fujimoto, 1991; Schilling & Hill, 1998; Björk, Frishammar, & Sundström, 2023). In addition, innovation strategy is considered an essential driver for a firm’s economic growth and competitive advantage as it points out the direction for the exploitation of resources to reach the firm’s innovation goals, creates value, and creates competitive advantages (Dodgson, Gann, & Salter, 2008).

Despite that implementing an innovation strategy has clear advantages, few firms have implemented a clear innovation strategy (Katz, Preez, & Schutte, 2010), and it’s rare for a firm to define its innovation strategies and align these with its business strategies (Pisano, 2015). Defining an innovation strategy for one’s firm is challenging as there is no step list for developing and implementing good innovation strategies (Dodgson, Gann, & Salter, 2008), and it’s not clearly defined what shapes an innovation strategy, its boundaries, or how often it should be adjusted or amended.

The term “open-innovation method” was briefly introduced in chapter 2.2. As a strategy open innovation focuses the firms innovate efforts by exploiting their knowledge and exploring the knowledge of their environment (Chesbrough, 2006). The concept of open innovation focuses on gaining access to the best technologies and competencies, as well as utilizing their solutions experience to enter new markets, in contrast to closed innovations that focuses internally (Gambardella & Panico, 2014). Yun et al. (2020) imply that open innovation has several advantages over closed ones: possibly obtaining a greater number of solutions, faster to finding a solution and lower economic cost. Some firms use a hybrid of these two, and thus gain two possible sources of innovation. They focus on both closed innovations, and thus stimulates their development within the firm, and open innovations, gaining valuable input from the innovation ecosystem (Nambisan, Siegel, & Kenney, 2018).

To succeed with a firm's innovation opportunities sufficient resources, the right people, open innovation, and market orientation have been highlighted as essential elements (Barney, 1991; Sirmon, Hitt, Ireland, & Gilbert, 2010; Carnes, Chirico, Hitt, Huh, & Pisano, 2017). There has though been less attention to innovation strategy (Søndergaard, Knudsen, & Laugesen, 2021). It can be especially challenging for a firm to radical innovate new products for the market (Hill & Rothaermel, 2003; O'Connor & DeMartino, Organizing for Radical Innovation: An Exploratory Study of the Structural Aspects of RI Management Systems in Large Established Firms, 2006; Sainio, Ritala, & Hurmelinna-Laukkanen, 2012). Søndergaard, Knudsen and Laugesen (2021) argues that due to the number of uncertainties associated with radical innovation it's necessary to have an innovation strategy that is based on a leadership mindset that embraces the vast amount of uncertainties. As this in a fundamental difference from the established approached to business strategy (Kuratko, Covin, & Hornsby, 2014), its further argued that existing firm strategy tools impairs a firm's chances for success with its radical innovations.

Strategic innovation leadership consists of analyzing the mechanism of the competition, creating innovative visions, harmonizing business strategies, implementing strategies on every level, reading, and predicting the trends in the market, comprehending current and coming technologies, and understanding the actions of the competition (Sanchez, Lago, Ferras, & Ribera, 2011). Verhees and Meulenberg (2004) have also shown a positive relation between the activities that a firm's top management conducts, in accordance with the firm's own innovation strategy, and the firm's innovation performance.

Research shows that firms who focus on creating value for the long term in their day-to-day business gain both greater and more stable economic performance than their competitors. In addition, firms who have a strategy which focuses on making decisions for the long term tend to be more effective in an economic downturn (Kurznack & Timmer, 2019). Despite this, a survey from 2017 states that 54% of innovation organizations struggle with closing the gap between, and aligning, their overall business strategy and their innovation strategy (PwC's Innovation Benchmark, 2017). This is despite the fact that a McKinsey Global Survey in 2010 showed that 96% of top leaders had defined innovation as a strategic priority or had plans to do so (Capozzi, Gregg, & Howe, 2010). What is clear is that an innovation strategy is a key tool to increase a firm's ability to succeed with its innovations.

2.4.1 Speed of Innovation

Wang and Wang (2012) define the speed of innovation as the time required by a firm from creating a concept and initiating a process to offering a new product to the market. The speed of innovation can be used as an innovation strategy, where the result of the speed of innovation delivers new products that will affect the firm's performance (Hecker & Ganter, 2013). A firm's ability to create and introduce new innovations at a high speed without being preceded by its competitors is the key to the success of firms in highly competitive sectors, such as technology industries. The speed of innovation is therefore a key element in gaining a competitive advantage (Casadesus-Masanell & Zhu, 2012). Intense competition in markets combined with a fast-moving technological revolution requires firms to have a high speed of innovation (Purnamawati, Jie, Hong, & Yuniarta, 2022).

2.4.2 The direct effect of innovation strategy.

The exploitation of resources and the allocation of these are equally important and both must be executed in a long-term perspective in order to ensure consistency in effort and intent in a firm (Hamel & Prahalad, 1993). As previously stated; there is a general consensus in theory that investments in IA have an effect on a firm's economic growth by influencing the introduction of new innovations (Bagna & Enrico, 2021; Ocak & Findik, 2019). Takizawa (2015) states that firms investing in both tangible and intangible assets can achieve a steady growth in productivity. Verhees and Meulenberg (2004) shows that innovation strategy has a positive impact on firms' innovation performance. In addition, a positive correlation has been shown between the activities top leaders conduct within the scope of innovation strategy and firm innovation performance. Literature also show that innovation strategy has a positive effect on both the quality of a firm's innovation and how the firm performs with its innovations (Wu & Lin, 2011). It's also suggested that innovation strategy has a positive impact on firm innovation performance indicators (Bessant & Tidd, 2007; Oke, Walumbwa, & Myers, 2012; Verhees & Meulenberg, 2004).

Innovation management is currently in transformation among manufacturing firms, shifting from a closed focus to being more open. Thus, the firms are increasingly more integrated and smarter about digitalization and opening to a vast number of opportunities for new capabilities, functionality, and utilization (Ramachandran, 2020). As stated in chapter 2.4 Open innovation strategy is a strategy where firms seek to exploit their own knowledge and the knowledge of their environment to innovate (Chesbrough, 2006). Open innovation has been shown to have an important impact on small and medium-sized enterprises innovative activity and has the possibility to be a driver for both national and regional economic growth (Tsai, Cabrilo, Chou, Hu, & Tang, 2022). Open innovation helps firms to a quicker release of new innovations (Albats, Alexander, Mahdad, Miller, & Post, 2020; Alvarez-Meaza, Pikatza-Gorrotxategi, & Rio-Belver, 2020). Hence, open innovation helps firms improve their innovation performance and productivity (Greco, Grimaldi, Locatelli, Serafini, & Mattia, 2021; Lyu, Zhu, Han, He, & Bao, 2020; Liu, et al., 2022). However, for small and medium-sized enterprises to be successful with open innovation their efforts must be on a long-term timeframe (Radziwon & Bogers, 2019). This will in turn increase the small and medium-sized enterprises competitive advantage over their competitors (Yun, Ahn, Lee, Park, & Zhao, 2022; Singh, Gupta, Busso, & Kamboj, 2021).

Pisano (2015) argues that without an innovation strategy that's aligned with the firm's overall business strategy and the firm's core values, most initiatives to boost a firm's capacity to innovate will fail. Terziovski (2010) also show that firms that have an innovation strategy when managing their innovations will likely improve the firm's innovation performance, and that when firms accept that innovation culture is a key element in the innovation process it's likely that the firms performance and ability to manage its innovations will improve. This shows that implementing an innovative culture, supported by rewards and incentives, may foster the launch of new ideas and innovative behavior by firm employees (Khazanchi, Lewis, & Boyer, 2007). Khan and Manopichetwattana (1989) also argues that formal structure within a firm promotes resistance to change throughout the process of implementation. This is something firm leaders should be mindful of; the way an innovation is perceived in the firm depends on the degree of complexity and the nature of change. Both can cause negative consequences in form of resistance within the firm or encourage the development of innovation (Bilichenko, Tolmachev, Polozova, Aniskevych, & Mohammad, 2022). Therefore, adapting a flexible and organic firm structure will enable firm leaders to create an environment that enhances innovation performance. To have a strategy with clearly aligned goals for change or development, enforced by the firm leaders, triggers a sense of urgency within the firm, and the bottom-up creative involvement fosters enthusiasm and positive energy (Si, Loch, & Stelios, 2023).

Studies shows that exploiting a firm's resources in accordance with the firm's strategic intent, and thus ensuring a consistent resource allocation over time, will be key to implementing the strategy in the firm, and to help implement the firm's goals within all levels of the firm (Hamel & Prahalad, 2005). Leading firms have shown that by linking their internal R&D activities more tightly with their business strategy and utilizing external assets to gain complementary knowledge and complete their technology portfolios, they have increased the efficiency of their R&D process, making it more successful (OECD, 2002). It has also been shown to increase the success rate of a project when management ensures that there is a customer demand for the new product or service one wishes to develop, and that introducing it to a market will be profitable, before initiating IA projects (Jaruzelski, 2005).

For a firm to gain economic value from intellectual assets depends significantly on the firm's management capabilities and the implementation of appropriate business strategies. A fair part of a firm's R&D projects will not result in a successful new product or service, but the ones that do will more than compensate for this. For firm leaders it is important to invest in areas of higher expected returns and develop processes that ensure that those returns are realized (OECD, 2006). The OECD states that there is significant empirical work supporting the view that the quality of management will determine the effect the utilization of intellectual assets and technologies have. Bloom et al. (2005) shows in a study that management practices, including management of human capital and technology, setting targets and reporting on performance, vary widely both within and between countries and within industries. From this we can derive that for a firm to gain value from their investments in IA it is paramount that the firm manages their assets in line with the overall strategic intent, and having a clearly stated innovation strategy will assist the firm's management in doing so.

Research done by McKinsey over the past 15 years, studying over 4000 firms, shows evidence that the firms who outperforms their competitors tend to have a constant focus on the following growth imperatives: expanding the core of the firm, introducing new innovations that expands into adjacent markets and igniting breakout growth

(Chariyawattanarut, Cvetanovski, Hazan, Kelly, & Spillecke, 2022) . In addition, it is argued that all success starts with having an ambition and mindset to grow, along with the ability to make decisive actions. In other words, a strategy for innovation is a key element in succeeding with innovations. A firm needs to innovate not only within their core business, but also beyond, to reach their growth goals. Research indicates that firms who expand into adjacent markets or industries are 20% more likely to have a greater growth than their competitors (Chariyawattanarut, Cvetanovski, Hazan, Kelly, & Spillecke, 2022). A recent study further supports these views as it shows how innovation strategies as a positive effect on firm performance, and thus concluded that firms who have a clear innovation strategy were both more innovative and more successful in their innovations (Kalay & Lynn, 2015).

When looking into firm leaders, research shows that they are generally conclusive about innovation being essential to a firm's growth, yet few are satisfied with their own firm's innovation performance. A McKinsey survey from 2008, which has been frequently cited, indicated that 84% of leaders agreed on innovation being essential to a firm's growth. At the same time 6% were satisfied with their own firms' innovation performance (McKinsey&Company, 2023; O'Connor, 2019). Another survey from 2015 strengthens this as 84% of firm leaders asked believed the firm's success in the future to be very or extremely dependent on innovation (Accenture, 2016). Yet some claim that firm leaders fail to adequately take into consideration the types of innovation projects that the firm needs to maintain or strengthen its competitive advantage, and focuses far too much on measuring the projects along the standard metrics of performance as net present value (Si, Loch, & Stelios, 2023). This tends to result in a firm's innovation projects to a minor degree being related to the firm's stated strategic goals, or in the worst case, they work against the firm's strategy.

In a recent article, McKinsey states that even though over 80% of firm leaders claim that innovation is in their top three priorities, yet less than 10% of the surveyed leaders stated that they were satisfied with their own firm's innovation performance (Jong, Furstenthal, & Roth, 2022). In addition, KPMG and Innovation Leader have, in a recent study, found that when firm leaders were asked to rate how advanced their firm's innovation efforts were on a one-to-five-point scale, almost 60% of the surveyed reported that their firms were in the two earliest stages, while only 2% reported innovation activities to be optimized (KPMG LLP, 2019). These studies clearly show that even though innovation is a priority, firms struggle to succeed with their innovation activities.

When looking into the effect an innovation strategy will have on economic growth, research also shows that there is a positive relationship between the development of innovation strategies and the productivity of manufacturing companies (Seclen-Luna, Moya-Fernández, & Pereira, 2021). A study conducted by Booz &Co. in 2011 investigated the effects firms would have of aligning their innovation strategy with their overall business strategy and having a positive innovation culture would have on firm's market growth and found a 30% rise over firms that didn't have both (Groth, 2011).

2.4.3 The moderating effect of innovation strategy on the relationships between intangible assets, the introduction of new innovations and economic growth.

As stated earlier; innovation strategy is an important element in a firm's innovation performance and growth (Clark & Fujimoto, 1991; Schilling & Hill, 1998; Björk, Frishammar, & Sundström, 2023), and that I''s considered an essential driver for a firm's economic growth and competitive advantage (Dodgson, Gann, & Salter, 2008). We therefore expect innovation strategy to have a moderating effect on the relationships in our base model. A moderating effect is when one variable, in this case, innovation strategy, influences the relation between two other variables. In statistics, moderation is when a variable or a construct changes the strength or the direction of a relationship between two other variables (Becker, Ringle, & Sarstedt, 2018), and a moderating model addresses when or for whom a variable explains or causes an outcome variable (Frazier, Tix, & Barron, 2004).

When looking into the moderating effect of innovation strategy, Purnamawati et al. (2022) is highly relevant, stating that increased investment in IA will not increase the firms' innovation as much as its strategic choice to dedicate internal resources and competence to innovation. In line with this, Montresor & Vezzani (2016) suggest that investments in IA on their own don't increase a firm's ability to introduce new innovations, but that it's the strategic decision made to commit internal resources to develop their IA that do. Sáenz et al. (2013) state that aligning the buyer and supplier innovation objectives in a supply chain has been shown to directly influence the outcomes for the supplier (Sáenz, Revilla, & Knoppen, 2013). As Martins and Terblanche (2003) state, the merging of one's prioritized innovation goals will both create and nurture a joint commitment to develop capabilities that in turn will sustain innovation. It's also relevant to note that we could not identify any studies that take on the entire specter of IA, and how investments in these affect a firm's ability to innovate. Most studies focus on how investment in R&D increases the firm's ability to innovate, and thus consider R&D to be primarily what sets the stage for a firm's ability to innovate (Hirsch-Kreinsen, Jacobson, Laestadius, & Smith, 2005). Most studies that go into the drivers for a firm's innovation primarily focus on the drivers for product and process innovation, and a combination of these (Cabagnols & Le Bas, 2002; Du, Love, & Roper, 2007).

A study that researched the small- and medium-sized enterprises in the Sonora Region of Mexico and their innovative business strategies in the face of COVID-19, indicates that open innovation strategies have a positive and significant effect on innovation leadership and the firm's performance and that innovation leadership has a positive and significant effect on the firm's performance (Surya, et al., 2021). Another study indicates that an economic growth strategy linked with a firm's technological innovation increases the firm's productivity (Surya, et al., 2021). In a study by Booz &Co. (Groth, 2011) it was also found that more innovative firms have a generally stronger growth in both revenue, 11%, and in earnings before interests, taxes, depreciation, and amortization (EBITDA), 22 %.

Based on the above we therefor wish to further explore the way innovation strategy moderates the relation between the firm's investments in IA its economic growth, and pose the following hypothesis:

H4: *Innovation strategy has a positive moderating effect on the relation between a firm's investments in intangible assets and its economic growth.*

Terziovski (2010) found that innovation strategy and formal structure in a firm are key drivers for innovation and that by implementing these the firm has the possibility to improve firm performance, and thus supports the findings in these studies. Formal structure includes the entirety of defines hierarchy or chain of command, rules, and code of conduct that exists within a firm and in employees work relationships (Gordon, 2012). In addition, in a study conducted by Purnamawati, Jie, Hong and Yuniarta (2022), it is proposed that the speed of innovation is crucial to increasing one's own economic performance, and Seclen-Luna, Moya-Fernández and Pereira (2021) shows that developing innovation strategies will have a positive effect on a firm's productivity.

In a report from KPMG (KPMG LLP, 2019), based on a survey of 215 respondents compared to a "role model" group consisting of companies at "the more advanced end of the innovation maturity spectrum", KPMG found that 80% of the role model group claimed their innovation team to be completely integrated with or highly collaborative with the firms strategy group versus 56% for the other respondents. In the same study, 60% of the respondents stated that competing priorities were one of their greatest challenges in scaling innovation. This further implies the importance of an innovation strategy combined with a stated risk acceptance, to help focus a firm's innovative measures. To gain a successful output and increase and economic growth from one's innovation, when faced with complex problems to solve and limited resources and funding, having a strategic focus, with clear priorities connected to the firm's overall goals, is essential.

Huang et al. (2011) states that, from a resource-based view, IA can have a big impact on gaining competitive advantage, and as IA are vital for fostering effective innovative processes, aligning these assets to a firm's innovative process has become a priority for firms. Firm leaders should think strategically when choosing which IA to invest in as it will affect how the firm performs with its innovations. By increasing its investments in IA, a firm's ability to innovate will increase. This is especially true for IA with higher technological content as it will stimulate the introduction of new technological innovations (Montresor & Vezzani, 2016). These findings suggest that investments in any IA should be done in accordance with the firm's overall innovation strategy and that different types of innovations should be paired with specific types of IA based on the nature of the innovation. From this, combined with that it's strongly indicated that IA generate and enhances innovative capability (Huang, Mei-Chi, & Lin, 2011), we propose that to get the most out of one's investments a firm should have a clearly stated innovation strategy. This will give direction to the investments in IA and thus gaining an increased innovative capability, and improving the firm's ability to introduce new innovations, and making the firm more productive in their innovative efforts. We therefore find it interesting to further explore the way innovation strategy moderates the relation between the firm's investments in IA and its ability to introduce new innovations, and pose the following hypothesis:

H5: *Innovation strategy has a positive moderating effect on the relation between a firm's investments in intangible assets and its introduction of new innovations.*

Kalay and Lynn (2015) states that the impacts of strategic innovation management practices, where innovation strategy is the leading determinant, on firm innovation performance are controversial within the literature. In literature, those who have the resource-based approach argue that firms with innovation strategy, flexible organizational structure, innovation culture, technological capability, effective customer and supplier relationships, and innovative products achieve higher performance compared to their competitors that do not (Han, Kim, & Srivastava, 1998). This suggests that firms that are more innovative and have significant differences from their competitors, provide value to their customers and will increase their own competitive advantage as a result. On the other side, it has also been claimed that products and services that are less innovative are less uncertain and may possess more synergy, leading them to be more successful (Calantone, Chan, & Cui, 2006). This is supported by Sengupta (2003) who emphasize how complementary products offer increased opportunities for firms, and how developing of products within a firm's core lines of business help reduce risk related to new developments. Sengupta's findings indicate that the competitive advantage in complementary product strategy stems from the innovativeness of the complementary product itself and from the potential increased effect on sales of the primary product (Sengupta, 2003).

When looking further into the relation between IA and economic growth multiple studies claim that managing intangible resources is taking an increasingly bigger part of the foundation of a firms competitive advantage compared to managing tangible ones, which have traditionally been dominant (Lev, 2008; Haskel & Westlake, 2018). Yet management of these assets are easily neglected as they do not always lead to direct benefits for the firm (Haskel & Westlake, 2018). To produce value IA needs to be managed effectively and efficiently, and in accordance with firms' goals (Bavdaž, Caloghirou, Dimitrić, & Protogerou, 2022).

Overall, an innovation strategy gives direction to the exploitation of resources to reach appointed innovation goals, increase value, and create competitive advantages (Dodgson, Gann, & Salter, 2008). We therefore wish to further explore the way innovation strategy moderates the relation between the firm's ability to introduce new innovations and its economic growth, and pose the following hypothesis:

H6: *Innovation strategy has a positive moderating effect on the relation between a firm's introduction of new innovations and its economic growth.*

The structural model in Figure 5 aims to describe the way innovation strategy is hypothesized to influence the relation between investing in IA and economic growth (H4), IA and the introduction of new innovations (H5), and the introduction of new innovations and economic growth (H6). With these hypotheses we aim to explore the possibility for a firm to increase its own growth by utilizing an innovation strategy to increase its own innovation performance based on the firm's investment in IA.

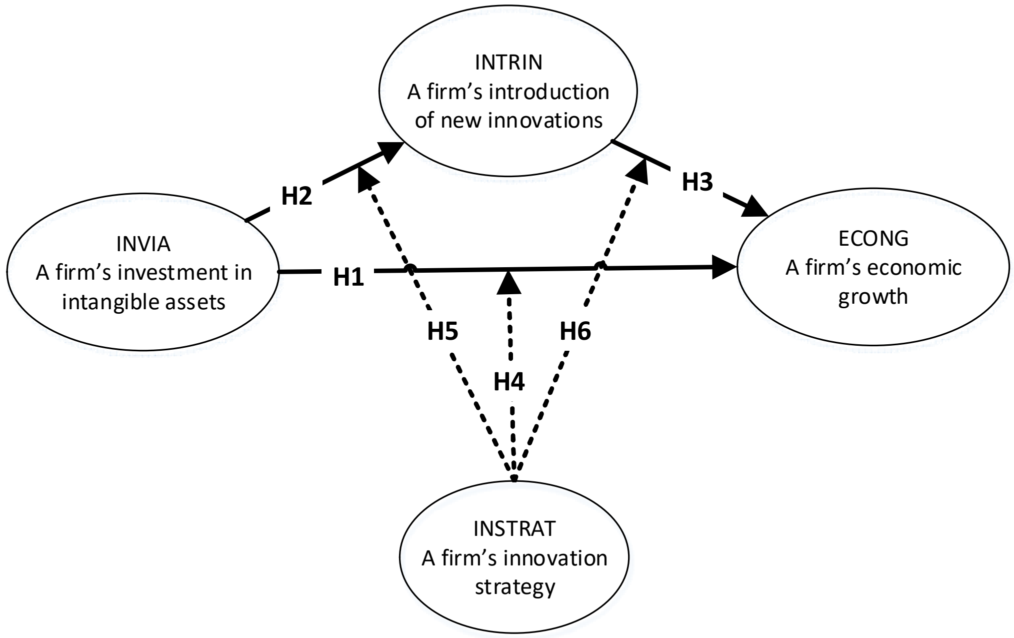

Figure 5 The full structural model illustrating the constructs and the hypothesized relationships between them.

3 Method

3.1 Literature search

In order to identify relevant articles and research reports for our research topic, we have mainly used Google, Google Scholar, and Nord University's library search; Oria. For the literature search, we have for example used keywords such as "innovation strategy", "intangible assets", "innovation performance", "innovation + intangible", "innovation management", "innovation + growth", "innovation + mediating", "innovation + moderating" etc. For the literature search for the method, we have for example used keywords such as "PLS-SEM", "PLS-SEM + moderation", "PLS-SEM + mediation", "PLS-SEM + higher order construct", "PLS-SEM + Innobarometer" etc. We have been searching for both English and Norwegian sources and have obtained numerous results, with a substantial portion being relevant journal articles and research reports which we have referenced in our study.

3.2 Research design

3.2.1 Introduction

Empirical research revolves around the interplay of theory and empirical evidence. Such research can be conducted through two distinct approaches: deductive or inductive (Johannessen, Christoffersen, & Tufte, 2020). This could also be categorized as confirmatory (explanatory) and exploratory (Sarstedt & Mooi, 2019).

In a deductive or confirmatory approach, the research is carried out based on a pre-existing theory that the researcher aims to confirm and strengthen (Johannessen, Christoffersen, & Tufte, 2020). Data is collected to assess whether the empirical evidence supports the theory or not. Deductive research aims to confirm or explain the relationship between observations or variables and is also termed explanatory research or hypothesis testing research.

In an inductive or exploratory approach, on the other hand, the researcher initiates the inquiry without a well-established theoretical framework (Johannessen, Christoffersen, & Tufte, 2020). Data is gathered and analyzed with the intention of drawing generalizable conclusions and developing new theories. In general, exploratory research is conducted when investigating uncharted territory where prior research is limited or even non-existent.

Within these research approaches, two distinct research methodologies can be employed: qualitative and quantitative methods (Johannessen, Christoffersen, & Tufte, 2020). Qualitative research methods include gathering and interpreting non-numerical data, for example from interviews, case studies or observations. Quantitative research methods, in contrast, rely heavily on numerical data and statistical analysis, and data are typically gathered by questionnaires or extracted from company records or various statistical data sources. Quantitative analyses could for example test causal relationships, correlations, collinearities of explained variances among variables in the data.

3.2.2 Choice of research design

As seen in the literature review in chapter 2, there is substantial prior research and pre-existing theory regarding the positive relationship between a firm investing in IA and the firm's economic growth, including the mediating role of a firm's introduction of new innovations. The part of our research which is concerning these relationships, which are illustrated in Figure 4, therefore uses a deductive approach where we aim to confirm established theories by testing hypotheses H1, H2 and H3.

In the other part of our research, we are studying an innovation strategy's moderating effect on the relationships in the base model, as illustrated in Figure 5. There is relatively scarce prior research investigating such effects of an innovation strategy, so this part of our research will therefore use an inductive approach, where we test hypotheses H4, H5 and H6 to explore the role of an innovation strategy on the relationships in the base model.

One of the factors distinguishing qualitative from quantitative studies is the nature of the intended outcome (Johannessen, Christoffersen, & Tufte, 2020). Qualitative researchers seek to learn from details of the testimonies of their informants, and such research is often focused on answering the "why" behind a phenomenon. In contrast, quantitative data are analyzed numerically to develop a statistical picture of a trend or relationship, and such research is often focused on answering the questions of "what" or "how" with regards to a phenomenon. As we are looking to study what kind of relationships there are between various variables (or constructs), we therefore chose to use a quantitative method for our research study.

By employing different research designs for different aspects of the research, our study could contribute to confirm existing theories related to the base model, as well as contributing to the scarce literature concerning the roles of innovation strategies.

3.3 Data Sources

We considered making and conducting our own survey for this research study but concluded that we would probably get much better and more comprehensive data by using publicly available secondary data. Secondary data are data that have already been gathered, often for a different research purpose and some time ago (Sarstedt & Mooi, 2019). Secondary data, such as EU's community innovation surveys (CIS) (Eurostat, 2023), are increasingly available to explore real-world phenomena, and are often used in exploratory research to propose causal relationships in situations that have little clearly defined theory (Hair, Sarstedt, & Ringle, 2019). Other advantages with secondary data are that sample sizes tend to be bigger, research results are easier to compare to other research using the same data, and the data tend to have more authority. Some possible disadvantages with secondary data are that it may not fully fit the problem or that it may not be reported in the desired form (Sarstedt & Mooi, 2019).

Our initial intention was to use CIS, which is the reference survey on innovation in enterprises (Eurostat, 2023), as the source of data for our research. However, it proved tedious and challenging to gain access to this data, so to ensure that we had data available in time for our research, we decided to use the European Commission's Innobarometer surveys instead (European Comission, 2023). The Innobarometer surveys aims at collecting information about the innovation activities and spendings of firms, as well as strategic trends and other topics, and overall, the Innobarometer data are highly suitable and relevant for our research study.

There are several pros and cons of the various Innobarometer surveys. Innobarometer 2013 has for example a very high focus on IA, but very little related to innovation strategy. Innobarometer 2016 (IB16) generally has very relevant questions for our research, but the questions which are related to innovation strategy are concerning the future while the questions related to intangibles and economic results are retrospectively concerning the preceding years. The indicators are thus not “parallel in time”, and some assumptions will have to be made to use them in an analysis. Innobarometer 2009 (IB09) has very relevant questions for our research, but the survey is done right after the 2008 financial crisis, so economic results might be atypical. On the other side, IB09 has a good selection of questions related to innovation strategy which also are concurrent with the other variables of interest.

Due to various pros and cons of the various Innobarometer surveys, and to increase the validity of our findings, we decided to use two Innobarometer surveys for our research; 2009 and 2016. These surveys could be considered complementary as they ask several similar questions, although not always with the same measurement scales. An important advantage of these Innobarometer surveys is that they focus on innovation and its drivers as an overarching main theme, rather than treating innovation as a subordinate part of a larger data collection. Both these Innobarometer surveys ask, among other things, about firms' investments in IA, introduction of new innovations, economic development, and several strategic factors related to innovation, such as for example firms’ use of methods to support innovation, the firm’s main reasons for investing in innovation, international activities in support of innovation, and strategic relationships in support of innovation.

3.3.1 Innobarometer 2009 Data Collection and Methodology

The IB09 survey (European Commission, 2010) was carried out by Gallup Europe and other survey firms in the 27 member states of the European Union, in Switzerland and in Norway between the 1st and 9th of April 2009. There were 5,238 firms interviewed, all with 20 or more employees. The sampling procedure was probability-stratified, which means that the target population was divided into separate and mutually exclusive segments (strata) covering the entire population. Independent random samples were then drawn from each segment. Interviews were conducted with key decision makers of firms via telephone in their native language on behalf of the European Commission.

3.3.2 Innobarometer 2016 Data Collection and Methodology

The IB16 survey (European Commission, 2016) was carried out by TNS Political & Social network in the 28 member states of the European Union, in Switzerland and in the United States between the 1st and 19th of February 2016. There were 14,117 firms interviewed, of which 13,117 were from the 28 EU Member states, and 500 each from Switzerland and the United States. The sample included firms with one or more employees in manufacturing, services, and industry, and they were selected from an international database with additional selections from local sources where necessary. The sampling procedure was the same as for IB09.

3.3.3 Measurement scales and coding of Innobarometer 2009 and 2016

The various questions in IB09 and IB16 represent indicators with various measurement scales (Johannessen, Christoffersen, & Tufte, 2020). Several of the questions have response options with a categorical scale, such as question Q9 in IB16, which asks about what the focus will be for the planned innovation in the next 12 months, and which have several categories available and multiple answers possible. To use categorical variables in regression or similar analyses, they must be recoded to a set of dummy (binary) variables where each dummy variable represents one category of the original categorical variable (Trinchera, Russolillo, & Lauro, 2008; Hair, Hult, Ringle, & Sarstedt, 2022).

Several of the questions have response options with a measurement scale based on intervals, but none of these intervals are on equidistant scales. So these indicators are not measured on an interval scale but rather on an ordinal scale (Johannessen, Christoffersen, & Tufte, 2020). An example of this is question D4 (including D4a and D4b) in IB09, which asks about the change in turnover over the preceding 3 years, and which have the following response options: decrease by more than 25%, decrease by 5-25%, decrease by less than 5%, remain approximately the same within 5%, increase by less than 10%, increase by 10-50%, increase by more than 50%. Several analysis techniques require ordinal scales with equidistant data points, i.e., quasi-metric scales (Sarstedt & Mooi, 2019; Hair, Hult, Ringle, & Sarstedt, 2022), so we have therefore recoded such scales to ratio scales. Since we do not have any additional information about probability distribution etc., to ease the analysis, we have recoded the mentioned D4 example to the following ratio scale: -30%, -15%, -5%, 0%, +10%, +30%, +60%.

Most of the relevant questions in IB09 and IB16 are binary yes or no questions. These, and the recoded categorical variables are therefore dichotomous variables; nominal variables which have only two categories or levels (Johannessen, Christoffersen, & Tufte, 2020) and which we have coded 0 for no (or not present), and 1 for yes (or present).

3.4 Choice of statistical analysis method

Multivariate analysis techniques, such as multiple regression and analysis of variance, are well-established statistical methods that researchers use to empirically test hypotheses about relationships between variables of interest (Johannessen, Christoffersen, & Tufte, 2020). However, what is common to these techniques is that they have three limitations in common: (1) the postulation of a simple model structure, (2) the assumption that all variables can be considered observable, and (3) the conjecture that all variables are measured without error (Haenlein & Kaplan, 2004).

To overcome these limitations, researchers have increasingly turned to structural equation modeling (SEM), which enables them to model and estimate complex relationships between multiple dependent and independent variables simultaneously. When estimating the relationships, SEM takes measurement errors in observed variables into consideration, and as a result, the method provides a more precise measurement of the theoretical concepts of interest (Cole & Preacher, 2014). Two popular methods dominate SEM in practice: covariance-based SEM (CB-SEM) and Partial Least Squares SEM (PLS-SEM). CB-SEM is primarily used for confirmatory research, while PLS has been introduced as an exploratory and "causal-predictive" approach to SEM (Jöreskog & Wold, 1982).

Several quantitative methods could be used in the analysis of the data from IB09 and IB16 for our research study. However, after considering several options, we chose PLS-SEM. Hair et al. (2019) provide several compelling justifications for when PLS-SEM should be selected, including the following which are the most relevant for our research study:

- When the structural model is complex and includes numerous constructs, indicators, and/or model relationships.
- When the model includes one or more formatively measured constructs.
- When the research objective is to better understand increasing complexity by exploring theoretical extensions of established theories (exploratory research for theory development).
- When the research involves financial ratios or similar types of data artifacts.
- When distribution issues are a concern, such as non-normality.
- When the research is based on secondary/archival data, which may lack a comprehensive substantiation on the grounds of measurement theory.

PLS-SEM is widely used in many social science disciplines, including organizational management (Sosik, Kahai, & Piovoso, 2009) and strategic leadership (Hair J. , Sarstedt, Pieper, & Ringle, 2012).

Composite measures, where constructs are created by combining information from multiple individual indicators, are often referred to as latent variables (DeVellis & Thorpe, 2022). PLS-SEM has become a popular approach for estimating models with latent variables and the relationships between them. The method was originally known as PLS-path modeling (Hair, Risher, Sarstedt, & Ringle, 2019), and the method estimates partial model structures by combining principal component analysis with ordinary least squares regressions (Mateos-Aparicio, 2011).

PLS-SEM works well with binary coded indicators, but need special attention, such as careful interpretation in exogenous constructs (Hair J. F., Sarstedt, Ringle, & Mena, 2012; Hair, Hult, Ringle, & Sarstedt, 2022). It might be hard to interpret the results of standardized binary predictors, and such occurrences might require manual un-standardization to make them interpretable. Sarstedt, Hair, et al. (2022) expect the use of discrete variables in PLS path models, such as when estimating data from choice experiments, to gain traction in the future.

PLS-SEM also proves valuable for analyzing secondary data from a measurement theory perspective (Hair, Hult, Ringle, & Sarstedt, 2022). Secondary data, such as financial ratios and other variables, are typically reported in the form of formative indices. A major advantage of PLS-SEM is that it permits the unrestricted use of single-item and formative measures.

In statistics, the coefficient of determination, denoted R^2, is the proportion of the variation in the dependent variable that is predictable from the independent variables (the amount of explained variance). PLS-SEM applies ordinary least squares regression with the objective of minimizing the error terms (i.e., the residual variance) of the endogenous constructs. In short, PLS-SEM estimates path model relationships with the goal of maximizing the R^2 values of the target endogenous constructs (Hair, Hult, Ringle, & Sarstedt, 2022). That is, PLS-SEM maximizes the explanatory power of the model.

PLS-SEM is not only suitable for exploratory research but also for confirmatory research (Hair, Hult, Ringle, & Sarstedt, 2022). Hensler (2018) argues that PLS-SEM can be useful for confirmatory, explanatory, exploratory, descriptive, and predictive research, and the method should thus be a good choice for all parts of our research.

3.5 Operationalization - specification of theoretical model for analysis

A path model in an PLS-SEM analysis is made up of two elements: (1) the structural model, which describes the relationships between the latent variables, and (2) the measurement models, which describes the relationships between the latent variable and their corresponding indicators (Sarstedt, Ringle, & Hair, 2022). Measurement theory specifies how to measure latent variables, and researchers can generally choose between two different types of measurement models, which are categorized as reflective and formative (Sarstedt M. , Hair, Ringle, Thiele, & Gudergan, 2016). Reflective indicators represent the effects (or manifestations) of an underlying construct. One could say that reflective indicators are consequences of the construct (Rossiter, 2002).

In contrast, in a formative measurement model the construct is a linear combination (Fornell & Bookstein, 1982) (or a formative index) of the indicators. Each indicator of a formative construct adds a specific aspect to the construct, and formative constructs are assumed to be error free (Diamantopoulos A. , 2006). The indicators of a formative construct therefore determine the meaning of the construct, which implies that omitting an indicator potentially alters the nature of the construct. Consequently, breadth of coverage of the construct's domain is therefore very important to ensure that the intended content of the construct is adequately captured by the contributing indicators (Diamantopoulos & Winklhofer, 2001).

3.5.1 Specification of the structural model

The structural model for our research study is already illustrated in Figure 5, and this could be used directly in our PLS-SEM model for both IB09 and IB16 based data. Each dataset's model consists of the 4 latent variables (or constructs):

- INVIA: A firm's investment in intangible assets
- ECONG: A firm's economic growth
- INTRIN: A firm's introduction of new innovations
- INSTRAT: A firm's innovation strategy

The arrows and their direction between these latent variables illustrate the research hypotheses and therefore the predictive and explanatory relationships of the model. Constructs that act only as independent variables are generally referred to as exogenous latent variables, and constructs considered dependent in a structural model are called endogenous latent variables (Hair, Hult, Ringle, & Sarstedt, 2022). INVIA and INSTRAT are thus exogenous latent variables while ECONG and INTRIN are endogenous latent variables. INTRIN is hypothesized to be mediating the relationship between INVIA and ECONG, while INSTRAT is hypothesized to be moderating all the relationships in the base model. The theoretical basis for the relationships in the structural model is already described in more depth in chapter 2.

Since we are looking at two different surveys with each of their own datasets and constructs, we are denoting variables belonging to IB09 with the suffix _09 appended to them, and variables belonging to IB16 with the suffix _16 appended to them.

3.5.2 Specification of the measurement models

The 4 constructs and their relations which we are researching in this study, and which are illustrated in Figure 5, are complex phenomena which cannot be examined in their entirety. Complex phenomena can be simplified by selecting indicators which are typical for the phenomena we are researching (Johannessen, Christoffersen, & Tufte, 2020).

To identify suitable measures of a construct, most social science researchers today use established measurement approaches published in prior research studies or in scale handbooks (Hair, Hult, Ringle, & Sarstedt, 2022). Some examples of such scale handbooks are those compiled by Bearden, Netemeyer and Haws (2011), Bruner (2019) and Zarantonella & Pauwels-Delassus (2015). If an existing measurement scale is used, it is usually a signal of good quality if the scale originates from reputed journal publications, something which improves the 'face validity' of the scales and items reported (Becker, Hwa, Ghollamzadeh, Ringle, & Sarstedt, 2023).

However, in some situations the researcher is faced with the lack of an established measurement approach and must therefore develop a new set of measures or modify an existing approach. A description of the general process for developing indicators to measure a construct can be long and detailed, as described by for example DeVellis and Thorpe (2022). PLS-SEM is increasingly being applied for scale development and confirmation (Hair, Howard, & Nitzl, 2020).

3.5.2.1 Measuring INVIA_09: A firm's investment in intangible assets

There are several published scales for measuring investment in intangible assets. One example is the scale used in the report "Measuring Investment in Intangible Assets in the UK: Results from a New Survey" (Awano, Franklin, Haskel, & Kastrinaki, 2010). The Oslo Manual (OECD /Eurostat, 2018) supports the measurement of investment in intangible assets, providing explicit measurement recommendations. OECD, in their report "Measuring Intangible Investment" (Young, 1998), list a relative extensive list of possible components of intangible investments. All the 7 indicators of IB09's question Q1 are covered by these references, so building the construct INVIA_09 from a formative combination of these 7 indicators has solid support in the literature. The 7 indicators of the INVIA_09 construct are listed in Appendix A.

It should be noted that the indicator q1_c is quite broad. In addition to the well-established intangible asset "Software", it also includes the tangible assets machinery and equipment. However, use of new machinery and equipment is often associated with intangibles like training and competency, so it should not be controversial to include this indicator.

The indicators of INVIA_09 are binary, and as we are standardizing all indicators and constructs during the calculations throughout this study, the measurement scale of the latent variable INVIA_09 must be interpreted as how many types of intangible assets the firm has invested in, from few to many, standardized around the average amount.

3.5.2.2 Measuring INVIA_16: A firm's investment in intangible assets

INVIA_16 is constructed from a formative combination of the 7 indicators of question Q4 in IB16. Most of these indicators are the same as used for measuring INVIA_09. But those which are not the same, such as company reputation and branding, have support in the same literature sources which are referenced for INVIA_09 as indicators for intangible assets. However, the indicators of INVIA_16 are not binary, but recoded to a ratio scale in the same way as described for recoding of D4 in chapter 3.3.3. The measurement scale of the latent variable INVIA_16 must be interpreted as what percentage of its total revenue the firm has invested in intangible assets, standardized around the average amount. This is different from INVIA_09, which is a standardized scale of how many types of intangible assets the firm has invested in. The 7 indicators of the INVIA_16 construct, including the recoded ratio scale used for this study, are listed in Appendix B.

3.5.2.3 Measuring ECONG_09: A firm's economic growth

The endogenous latent variable ECONG_09 is measured by the single item D4+D4a+D4b of IB09, which is listed in Appendix A. The construct has been recoded to a ratio indicator measuring how many percent the turnover of the firm changed over the preceding 3 years. The ratio coding of this scale is described in more detail in chapter 3.3.3. A single item scale like this does not require a measurement theory, as it is simply this indicator being measured. It should be noted that it is turnover, the total value of sales, and not profit, which is measured by this indicator, but an increasing turnover and growth are often used interchangeably.

3.5.2.4 Measuring ECONG_16: A firm's economic growth

The endogenous latent variable ECONG_16, is also measured by a single indicator from IB16; D6, as listen in Appendix B. After recoding, D6 is a ratio indicator measuring how many percent the revenue of the firm changed over the preceding 3 years. The recoded alternatives are -30%, -15%, 0%, 15% and 30% respectively. ECONG_16 is measuring change in revenue, while ECONG_09 is measuring change in turnover.

3.5.2.5 Measuring INTRIN_09 and INTRIN_16: A firm's introduction of new innovations

Introduction of new innovations is measured with an almost identical question in IB09 (question Q6) and IB16 (question Q2). While the newer 2018 edition of the Oslo Manual is only differentiating between two main types of innovations: product innovations and business process innovations (OECD /Eurostat, 2018), IB09 and IB16 are differentiating between 5 types of innovation types, in accordance with the 2005 edition of the Oslo manual (2005). These 5 types are listed in Appendix A for IB09 and Appendix B for IB16. We have defined INTRIN_09 and INTRIN_16 as a formative construct of the indicator representing the types of innovations being introduced.

The indicators of INTRIN_09 and INTRIN_16 are binary but have been standardized during the calculations. The measurement scales therefore must be interpreted as how many types of innovations the firm has introduced, from few to many, standardized around the average amount.

3.5.3 Specification of higher order constructs for measurement of innovation strategies

The Oslo Manual (2018) recognizes that the organization of innovation activities within the firm includes the development or modification of an innovation strategy. Researchers have adapted measures from strategic management research to explore the existence, nature, and extent of innovation strategies, and two distinct types of strategic orientation measures can be identified in the literature (Adams, Bessant, & Phelps, 2006). The first types of strategic measures are those that measure whether the firm has an innovation strategy or not. This can be evaluated in several ways, such as by an explicit question (does the firm have an innovation strategy?) (Miller & Friesen, 1982) or measured by identifiable roles for new products and services (Cooper, 2023; Haiyun, Zhixiong, Yüksel, & Dinçer, 2021). The second type of measures regards an innovation strategy as a dynamic instrument that shapes and guides innovation in the firm, and these measures assume that a strategy exists and asks questions about how effective this strategy is in shaping and guiding (Adams, Bessant, &

Phelps, 2006). Examples of such questions are: “are structures and systems aligned?” (Bessant J. R., 2003), “is the role of new product development in achieving business goals clearly articulated?” (Acur, Kandemir, & Boer, 2012) and related questions about strategic fit.

As presented in chapter 2.4, Tang (1998) presents three important questions that must be answered regarding an innovation strategy. In a MSc thesis by Begüm Aydınoğlu (2007), a questionnaire with 15 strategy related questions was developed to measure Innovation strategy. A study by Mile Terziovski (2010) used a nine items scale to measure innovation strategy. The measures used by Terziovski has also been used in several subsequent studies, such as the studies by Kalay and Lynn (2015), Kamasak (2015) and Taghizadeh, et al. (2020).

The Oslo Manual (2018) could be considered the reference guide for measurement of innovation. It has not defined specific measures for innovation strategies, but suggests several qualitative measures of innovation objectives and outcomes. Innovation objectives consist of a firm’s identifiable goals that reflect its motives and underlying strategies with respect to its innovation efforts (OECD /Eurostat, 2018). Several of the measures of innovation objectives and outcomes could therefore be used to measure a firm’s innovation strategy.

However, we could not identify a measurement scale for innovation strategy in widespread use in the literature. One possible reason why there is a lack of such an established scale is that innovation strategy is a complex and multidimensional concept that may vary depending on the context, industry, and type of innovation. Therefore, it may be difficult to develop a universal and standardized scale that can capture all the aspects and nuances of innovation strategies. Even though it is not advisable (Becker, Hwa, Ghollamzadeh, Ringle, & Sarstedt, 2023), and due to the fact that we are using secondary data in this study, we used a bottom-up approach to measure innovation strategy by combining available Innobarometer indicators and constructs that appeared to fit together in terms of their relevance for innovation strategies.

We combined several questions into a higher order construct representing innovation strategy for IB09 and IB16 respectively. Higher order constructs have several advantageous features, such as helping to reduce the number of path model relationships and thereby simplifying the model (Edwards, 2001; Johnson, Rosen, & Chang, 2011; Polites, Roberts, & Thatcher, 2012). By using higher order constructs, researchers can summarize the independent constructs in a higher order construct instead of specifying relationships between multiple independent and dependent constructs in a path model (Sarstedt M. , Hair, Cheah, Becker, & Ringle, 2019).

Another advantage with using higher order constructs, is that they help to overcome the bandwidth-fidelity dilemma (Cronbach & Gleser, 1965), where one will have to make a tradeoff "between variety of information (bandwidth) and thoroughness of testing to obtain more certain information (fidelity)." In addition, higher order constructs could be a method for reducing collinearity among formative indicators by offering an approach to re-arrange the indicators and/or constructs across different sub-constructs of the more abstract higher order construct (Hair J. , Sarstedt, Ringle, & Gudergan, 2018).

3.5.3.1 Measuring INSTRAT_09: A firm's innovation strategy

Based on available questions in IB09 and inspired by suggested measures for innovation strategies in the references in the preceding section, we defined the measurement model for INSTRAT_09 to be the higher order formative construct, as illustrated in Appendix C. INSTRAT_09 is the combination of the variables Q9, Q10, Q11, Q12 and Q13, all with binary indicators, as summarized in Appendix A. All the binary indicators of the variables which are combined into INSTRAT_09 have been standardized during all calculations. The INSTRAT_09 construct therefore must be interpreted as to what degree the firm has an innovation strategy, from low to high, standardized around the average degree of presence of an innovation strategy.

3.5.3.2 Measuring INSTRAT_16: A firm's innovation strategy

In a similar way as for INSTRAT_09, INSTRAT_16 is based on questions available in IB16 which are of relevance for an innovation strategy. The measurement model for INSTRAT_16 is the higher order construct as illustrated in Appendix D. INSTRAT_16 is the combination of the variables Q9, Q10a, Q12 and Q13, all with binary indicators, as summarized in Appendix B. As for INSTRAT_09, all the binary indicators of the variables which are combined into INSTRAT_16 have been standardized during all calculations. The INSTRAT_16 construct therefore also must be interpreted as to what degree the firm has an innovation strategy, from low to high, standardized around the average degree of presence of such.

It should also be noted that all the questions which are contributing to the INSTRAT_16 construct are concerning the future, while the other constructs in the model (INVIA_16, INTRIN_16 and ECONG_16) are concerning the past. We have therefore assumed that a company which has an innovation strategy for the future also had it to the same degree in the past, during the same period as the other questions are considering. Due to slow processes usually being involved in strategy developments, and due to the importance of a long horizon as a key element of competitive strategy (Sołoducho-Pelc, 2015), this should not be an unreasonable assumption.

3.6 Statistical power and minimum sample size

As with any multivariate analysis method, the use of large samples is usually advantageous. Of the 443 studies reviewed by Sarstedt et al (2022), 47% of the studies reported small sample size as a reason for using PLS-SEM. But the more heterogeneous the population, the larger the sample size needed to achieve an acceptable sampling error (Cochran, 1977). If basic sampling theory guidelines are not considered, questionable results are produced (Sarstedt, Bengart, Shaltoni, & Lehmann, 2018). Kock and Hadaya's (2016) inverse square root method is often used for minimum sample size estimation in PLS-SEM. This conservative method considers the probability that the ratio of a path coefficient and its standard error will be greater than the critical value of a test statistic for a specific significance level. To achieve a statistical power of 80% for the path coefficient with minimum magnitude (P_{min}) in the PLS path model, the minimum sample size (n_{min}) for a significance level of 1% and 5% respectively, is with this method given by the following equations (Hair, Hult, Ringle, & Sarstedt, 2022):

Significance level = 1%: $n_{min} > \left(\frac{3.168}{|P_{min}|}\right)^2$ (1)

Significance level = 5%: $n_{min} > \left(\frac{2.486}{|P_{min}|}\right)^2$ (2)

In the confirmatory testing of hypotheses H1, H2 and H3, we are expecting strong and significant relationships. The relationships hypothesized are well founded in prior studies, so it should not be unreasonable to expect a strict significance level of 1% in the test results. But from theory we are not expecting economic growth to be explained in full by investments in intangible assets, only that there is a positive relationship, so the path coefficient is not expected to be very high. To achieve a statistical power of 80% if we are looking for a minimum path coefficient of 0.1 at a significance level of 1%, we will need a minimum sample size of 1004 samples from equation 1 above.

In the exploratory testing of hypotheses H4, H5 and H6 we have less opinions about what to expect. According to Hair, Hult et al. (2022), a significance level of 5% is used in most analyses, but 10% is also commonly used in studies that are exploratory. To achieve a statistical power of 80% if we are looking for a minimum path coefficient of 0.05 at a significance level of 5%, we will need a minimum sample size of 2472 samples from the equation above.

Both IB09 and IB16 have significantly more samples than 2472, but since there are missing values in the datasets and we do not know whether the actual minimum path coefficients are within the minimum path coefficient level suggested above, we might need even more samples to meet the minimum criteria.

3.7 Control variables

A confounding variable is an unmeasured third variable which is not a factor being considered in a study or experiment, but which may be at least partially responsible for the observed outcomes (Earl & Nicholson, 2021). To truly understand the role that confounding variables play in an empirical relationship, it is necessary that researchers address control variables (CV) in their hypotheses, results, and discussion (Atinc, Simmering, & Kroll, 2012). Variables such as firm size, firm age, and whether the firm has international activities have all been empirically demonstrated to have a significant effect on innovation (Duran, Kammerlander, van Essen, & Zellweger, 2015; Molden & Clausen, 2021), and we should thus expect to see significant effects from these CVs in our models.

Becker, et al. (2016) provides 10 essential recommendations about selecting CVs, and we chose to follow their recommendation number 1; When in doubt, leave them out! The main reason we chose to leave CVs out, was that that our study was already quite extensive, and addressing control variables in hypotheses, results, and discussion would require further expansion of the study, potentially without adding much value. We were also uncertain about the associations between potential CVs and innovation strategies, and could not articulate a clear purpose for including them in this study, and therefore chose to leave them out.

3.8 Omitted variables

Omitted variable bias occurs when a statistical model fails to include one or more relevant variables. In other words, it means that an important factor is left out of the analysis. The bias results in the model attributing the effect of the missing variables to those that were included (Johannessen, Christoffersen, & Tufte, 2020). There are several variables in the Innobarometer surveys we could have included to better explain a firm's introduction of new innovations and economic growth. One such example is question Q5 in IB16, which considers the firm's problems with commercialization of innovations. This could be an important factor in explaining both the lower introduction of new innovations as well as lower economic growth. Another example is question Q15 in IB09, which considers various external policy-related factors, such as public financial support etc. These factors could be important in explaining variations in firms' introduction of new innovations as well as their economic growth.

As the main focus of our study is to explore the moderating effect of an innovation strategy, and not to explain economic growth or lack thereof in itself, we intentionally left out several variables which could increase the explanatory power of our model. But we think that we have selected the most reasonable variables to include in our study, without making the model too complex and risking obscuring the intent and findings of the research.

3.9 Ethical considerations

Research ethics is a concept that refers to the values, norms, and institutional rules designed to establish guidelines and regulate scientific activities (NESH, 2016). These rules are rooted in the established moral standards of society. When conducting a scientific study, researchers should not only be responsible for adhering to established norms and values, but also consider the well-being of individuals, groups, and institutions.

As researchers we have set high ethical standards for our conduct. For the purpose of ethical guidance, we found Ringdal (2013) and his three guidelines concerning research ethics for quantitative methods to be useful. Ringdal holds that an ethical conduct must encompass a responsible research process, privacy concerns and a responsible research motivation.

In this study, we have chosen a research process which did not contain any human subjects for the purpose of data collection. Therefore, we do not need to consider human dignity, privacy, and other aspects that could influence individuals extensively. We have instead used publicly available quantitative datasets as our data sources. These data sources, the Innobarometer studies, are fully anonymized at the firm level, so there were no privacy concerns, and the study therefore has no data collection which is subject to careful handling and reporting.

3.10 Reliability and validity of the study

Reliability refers to the consistency of a measure; "the degree to which a set of indicators of a latent construct is internally consistent in their measurements" (Hair, Babin, Anderson, & Black, 2019), and whether the results can be reproduced under the same conditions (Johannessen, Christoffersen, & Tufte, 2020). A distinct advantage with using established secondary data sources, such as Innobarometer, is that it enables replicable research, something which is very much in demand in strategic management research in general (Makadok, Burton, & Barney, 2018). The use of commonly available data provides the opportunity for delivering both narrow replication (e.g., same data on same research design) and quasi replication (e.g., same data for new design) (Bettis, Helfat, & Shaver, 2016). By using a well-defined quantitative method such as PLS-SEM, we consider it to be very easy to reproduce our research, and therefore consider it to have high reliability.

Validity refers to the accuracy of a measure, or "the degree to which a measure accurately represents what it is supposed to" (Hair, Babin, Anderson, & Black, 2019). Using secondary data, such as the Innobarometer data (European Comission, 2023), is advantageous from a quality perspective since it is organized by highly proficient entities (European Commission and Eurostat) and the surveys are conducted by well-established researchers at public statistical agencies. The resources put into making sure the quality of the data is up to the standards required for precise empirical research makes for a good reliability claim. Moreover, the use of these data in previous peer reviewed research (e.g. (Molden & Clausen, 2021; Archibugi & Filippetti, 2010; Grigorescu, Maer-Matei, Mocanu, & Zamfir, 2020)), also imply a considerable face validity of the data.

It is considered to be an established standard that the reliability and validity of both measurement and structural models are confirmed as part of a PLS-SEM analysis (Hair, Babin, Anderson, & Black, 2019). When we are doing the same analyses on two different datasets (IB09 and IB16) we are also increasing the validity of the results. In total, we consider the study to have both high reliability and validity. However, a weakness of our study is the use of two different constructs to measure innovation strategy, both which are constructed by a bottom-up approach, and both which are lacking solid support in the literature, as discussed in chapter 3.5.3.

4 Analysis

Testing a theory by using PLS-SEM follows a two-step process where we first test the measurement theory to confirm the reliability and validity of the measurement models, and then move on to testing the structural theory (Hair, Babin, Anderson, & Black, 2019). The logic is that we must first confirm the measurement theory before testing the structural theory, because structural theory cannot be confirmed if the measures are unreliable or invalid (Hair, Hult, Ringle, & Sarstedt, 2022).

We settled on a dualistic approach for our research design, with a confirmatory approach to the relationships in the base model in Figure 4, and an exploratory approach to analyze the moderating effect of an innovation strategy on these relationships. Becker et al. (2023) recommends that the main-effect relationship should be estimated without the moderator being included if the aim of the study is to test the moderating effect as well as the direct effect being moderated. This is because the interpretation of the main-effect changes when a moderator is included.

A standardized moderator is zero at its mean value. When a moderator is included, the main-effect relationship quantifies the effect of an exogenous variable on the endogenous variable when the moderator value is at its mean value (zero), instead of representing an average effect (Hair, Hult, Ringle, & Sarstedt, 2022). We therefore first analyzed the base model without moderation, and thereafter included the moderator to assess its impact. At the same time, researchers should be aware that a significant moderator provides evidence that the direct effect, as estimated in a model without the moderator, is misleading because the estimate is subject to heterogeneity (Becker, Hwa, Ghollamzadeh, Ringle, & Sarstedt, 2023).

4.1 Data evaluation

As described in chapter 3.3, the Innobarometer studies are based on random samples of firms from a lot of different countries. The firms vary in size, country of residence, type of business, years in existence and several other characteristics. Both IB09 and IB16 datasets include a multitude of various weights which could be applied to the samples in the dataset for various purposes, such as studying subgroups etc. It is generally recommended to apply sampling weights in case of a mismatch between sample and population with regards to key characteristics (Sarstedt, Bengart, Shaltoni, & Lehmann, 2018). But we have not theorized about any specific key characteristics of the firms, we have therefore used equal weights for all the samples in this study.

4.1.1 Missing Value Treatment

As reported in chapter 3.3, the full dataset of IB09 consists of data from 5,238 firms while IB16 consists of data from 14,117 firms. But several of the questions in these surveys are not applicable for all firms, and some firms have not replied to all applicable questions. There are thus missing values in the datasets which need to be dealt with.

We are unable to do model estimations for those cases which have missing data for the target endogenous construct ECONG, so we started by excluding those cases. Hair, Hult et al. (2022) also recommends excluding those cases which exceeds 15% missing values from the dataset. After making these exclusions, we were left with 4,718 firms in the IB09 dataset, and 13,258 firms in the IB16 dataset.

Using the after-exclusions-datasets, the total percentage of missing values are listed in Table 1 for the constructs of the base model. The percentage of missing values for each construct is provided as the percentage of missing values for the total of all the indicators contributing to the construct. The percentage of cases with missing values for at least one of the indicators contributing to the INVIA and the INTRIN constructs are also listed in the table. We see that INVIA_16 is the construct with the most missing values from its indicators, with a total of 3.2%. But since the missing values are spread over several indicators contributing to the same construct, we have as many as 19.4% of cases in the IB09 dataset having at least on indicator with missing value, and 11.0% of the cases for the IB16 dataset.

Table 1 Missing values for the constructs of the base models

Dataset	INVIA	INTRIN	Cases with missing values for at least one indicator
IB09	3.1%	2.9%	19.4%
IB16	3.2%	0.8%	11.0%

Hair, Hult et al. (2022) reports that mean replacement of less than 5% missing values result in only slightly different PLS-SEM estimates. Since there were considerably less than 5% individual missing indicator values for the constructs we are looking at, we applied mean replacement when analyzing the base models.

When analyzing all the indicators which are contributing to the higher order construct INSTRAT_09, there are a total of 5.8% missing values for these indicators. Grimm and Wagner (2020) show that PLS-SEM estimates are very stable when using casewise deletion on data sets with up to 9% missing values. We therefore applied casewise deletion when analyzing the full IB09 based model moderated by INSTRAT_09.

The IB16 survey is organized quite differently than IB09. IB16 only asks questions Q9 and Q10a to those firms which replied in question Q7 that they actually invested in innovation. Only 7935 firms replied that they invested in innovation, so for IB16 we will only be looking at this subset of the data when considering moderation by innovation strategy. Looking at a subset containing only firms investing in innovation might affect the relationships in the base model. But it should not be problematic when considering the effect of an innovation strategy, as only firms investing in innovation are expected to have an innovation strategy. 2.4% of the indicators which are contributing to the higher order construct INSTRAT_16 have missing values. We also applied casewise deletion when analyzing the full IB16 based model moderated by INSTRAT_16.

4.2 Base model analysis

The IB09 and IB16 path models are structurally the same and is illustrated in Figure 4, but the measurement models differ between these two datasets, as described in chapters 3.5.2 and 3.5.3. Formative measurement models are evaluated based on convergent validity (redundancy analysis), indicator collinearity, statistical significance, and relevance of the indicator weights (Hair, Hult, Ringle, & Sarstedt, 2022). These analyses are described in detail in the following sections.

4.2.1 Evaluation of Measurement Models

4.2.1.1 Convergent Validity

To evaluate our formative measurement models, we first need to examine whether the formative constructs exhibit convergent validity. Convergent validity is the extent to which a measure correlates positively with other measures of the same construct using different indicators. To do so, we must carry out separate redundancy analyses for each construct by creating new models (Hair, Hult, Ringle, & Sarstedt, 2022). This type of analysis is also known as redundancy analysis (Chin, 1998).

A global single item is often included in primary surveys for the purpose of such analyses (Sarstedt M. , Ringle, Ramayah, & Ting, 2018). However, when the model is based on secondary data, a variable measuring a similar concept would be used if available. If a construct which is to be checked for convergent validity is “multidimensional”, the alternative measure must relate to at least one theoretically justified dimension (Houston, 2004). But alternative measures are not always available in secondary data, and then convergent validity cannot be assessed.

When examining the questions in IB09, no alternative measures could be identified, maybe except for INVIA_09. The Oslo Manual (2018) describes intangible assets as knowledge-based capital (KBC) and includes for example R&D activities and innovation management activities. It could then be argued that question Q2, regarding the percentage of the firm's turnover spent on all innovation activities, could be used as an alternative measure to check for convergent validity of INVIA_09. A potential problem with using this is that it is measured on a ratio scale while Q1 is constructed as a combination of binary indicators.

We used the software package SmartPLS 4 (Ringle, Wende, & Becker, 2022) and created a model to test for convergent validity. Hair et al. (2022) is recommending that the strength of the path coefficient linking the two constructs should be a minimum of 0.70 for convergent validity of the measurement model. We calculated the path coefficient to be 0.546, which is below the threshold. The main reason for this is probably that Q2 is not a suitable alternative measure for INVIA_09 and the previously mentioned issue with the differences in measurement scales. There is the same issue with lack of alternative measures in IB16, and we therefore conclude that convergent validity cannot be assessed for any of our measurement models used in the base models.

4.2.1.2 Indicator Collinearity

High correlations are not expected between items in formative measurement models, and high collinearity can prove problematic from a methodological and interpretational standpoint, such as problems with singular data matrices occurring during PLS model estimation when one indicator is a linear combination of another indicator (Hair, Hult, Ringle, & Sarstedt, 2022).

The variance inflation factor (VIF) is often used to evaluate collinearity among the indicators of formatively measured constructs (Hair, Risher, Sarstedt, & Ringle, 2019), and VIF values of 5 or above indicate critical collinearity issues. However, collinearity issues can also occur at VIF values as low as 3 (Mason & Perreault, 1991; Becker J.-M. , Ringle, Sarstedt, & Völckner, 2015), so VIF values should ideally be lower than 3.

To calculate VIF values, we did a full PLS-SEM calculation in SmartPLS 4 on the base models for IB09 and IB16 respectively. The results are shown in Table 2, and as seen, indicator q2_3, contributing to INTRIN_16, has the highest VIF value (1.430) of all the indicators. Hence, VIF values are uniformly below the threshold value of 5, and even well below the recommended value of 3. We therefore conclude that collinearity does not reach critical levels in any of the formative constructs and is not an issue for the estimation of any of the two base models.

4.2.1.3 Significance and relevance of indicators

In the final step of the evaluation of the measurement models, we should assess the indicator weights' statistical significance and relevance (Hair, Risher, Sarstedt, & Ringle, 2019). PLS-SEM is a nonparametric method, and bootstrapping, which is a nonparametric procedure, is therefore used to determine statistical significance (Chin, 1998). A bootstrapping procedure assesses a parameter's variability by examining the estimates' distribution by means of resampling from the available sample data instead of using parametric assumptions to assess the parameter's precision (Davison & Hinkley, 1997; Efron & Tibshirani, 1986). To do so, bootstrapping generates a large number of randomly drawn subsamples (with replacement) from the original data set. The model estimates obtained from these subsamples are then used for calculating confidence intervals and *p*-values. A *p*-value is the probability of erroneously rejecting a true null hypothesis, or assuming a significant effect when there is no significance (Hair, Hult, Ringle, & Sarstedt, 2022).

It is recommended to use the percentile method to construct bootstrap-based confidence intervals (Aguirre-Urreta & Rönkkö, 2018). If the confidence interval of an indicator weight includes zero, this indicates that the weight is not statistically significant, and the indicator should be considered for removal from the measurement model. To increase the bootstrap distribution's approximation precision and level out random variations in the estimates, it is recommended that at least 10,000 subsamples should be used (Becker, Hwa, Ghollamzadeh, Ringle, & Sarstedt, 2023).

We ran bootstrap calculations in SmartPLS 4 on the PLS-SEM base models for IB09 and IB16 respectively. For both calculations we used 50,000 subsamples, and due to the confirmatory intent of this part of the research we used a conservative 1% significance level. The calculations are summarized in Table 2, and as we can see, all the indicator weights are significant to within a 1% significance level. The endogenous latent variables ECONG_09 and ECON_16 are single item constructs, so they are not included in the table.

Table 2 Statistical analyses results for the measurement models of the base models of IB09 and IB16

Constructs	Indicators	VIF	Outer Weights	99% Confidence Interval	*p* Value	Significance (p < 0.01)?
INVIA_09	q1_a	1.340	0.289	[0.220,0.357]	0.000	Yes
	q1_b	1.231	0.165	[0.101,0.228]	0.000	Yes
	q1_c	1.100	0.294	[0.231,0.355]	0.000	Yes
	q1_d	1.250	0.126	[0.061,0.189]	0.000	Yes
	q1_e	1.184	0.330	[0.265,0.394]	0.000	Yes
	q1_f	1.228	0.334	[0.269,0.397]	0.000	Yes
	q1_g	1.290	0.131	[0.069,0.193]	0.000	Yes
INTRIN_09	q6_a	1.149	0.464	[0.401,0.525]	0.000	Yes
	q6_b	1.180	0.188	[0.122,0.253]	0.000	Yes
	q6_c	1.280	0.414	[0.350,0.476]	0.000	Yes
	q6_d	1.258	0.208	[0.142,0.274]	0.000	Yes
	q6_e	1.294	0.223	[0.156,0.290]	0.000	Yes
INVIA_16	q4_1	1.313	0.046	[0.000,0.091]	0.010	Yes
	q4_2	1.271	0.151	[0.106,0.196]	0.000	Yes
	q4_3	1.354	0.245	[0.197,0.293]	0.000	Yes
	q4_4	1.292	0.212	[0.164,0.258]	0.000	Yes
	q4_5	1.422	0.293	[0.244,0.340]	0.000	Yes
	q4_6	1.406	0.406	[0.356,0.455]	0.000	Yes
	q4_7	1.148	0.159	[0.115,0.203]	0.000	Yes
INTRIN_16	q2_1	1.235	0.237	[0.189,0.284]	0.000	Yes
	q2_2	1.354	0.339	[0.294,0.383]	0.000	Yes
	q2_3	1.430	0.305	[0.255,0.353]	0.000	Yes
	q2_4	1.338	0.253	[0.201,0.303]	0.000	Yes
	q2_5	1.392	0.291	[0.241,0.341]	0.000	Yes

It should be noted that indicator q4_1, contributing to INVIA_16, is calculated to be on the borderline of 1% significance. Due to the random nature of the bootstrap sampling, the bootstrapping calculations were run 3 times to check if the indicator weight of q4_1 retained its 1% significance level. In one of these calculations, the lover limit of the 99% percentile confidence interval was slightly below 0 (-0.00005). But due to 2 out of 3 calculations being above 0, the indicator was deemed significant within the 1% significance level.

After confirming the statistical significance of all the indicator weights, we then evaluated the indicator's relevance, as recommended by Hair, Hult et al. (2022). The values of the outer weights are standardized to values between -1 and +1 and can therefore be compared with each other. They express each indicator's relative contribution to the construct, or its relative importance to forming the construct. All indicators are calculated to be significant and all except q4_1 have an indicator weight higher than 0.1. Indicator q4_1 has an indicator weight of only 0.046, but since the loading of this variable is calculated to be 0.513, its absolute contribution to the INVIA_16 construct is therefore concluded to be of relevance, as per the guidelines of Hair, Hult et al. (2022). We therefore concluded that all indicators were significant and relevant for the measurement models used in the base models.

4.2.2 Evaluation of Structural Models

We assessed all the measurement models of the base models to be satisfactory, and the next step in evaluating the PLS-SEM results is then to assess the structural model (Hair, Hult, Ringle, & Sarstedt, 2022). Standard assessment criteria, which should be considered, include collinearity, the statistical significance and relevance of the path coefficients, explanatory power by the coefficient of determination (R^2), and out-of-sample predictive power by using the PLSpredict procedure analysis (Shmueli, Ray, Velasquez Estrada, & Chatla, 2016). These analyses are described in detail in the following sections.

4.2.2.1 Collinearity

We had already done a full PLS-SEM calculation in SmartPLS 4 on the base models for IB09 and IB16 respectively, and the relevant results for the structural models are reported in Table 3. As for the measurement models, VIF is also used as an indicator for collinearity in the structural models (Hair, Risher, Sarstedt, & Ringle, 2019). The highest calculated VIF is 1.420, which is well below the recommendation of 3. We can therefore conclude that collinearity has no substantial effect on the structural model estimates.

Table 3 Statistical analyses results for the structural models of the base models for of IB09 and IB16

Relationships	VIF	Path Coefficients	99% Confidence Intervals	*p* Value	Significance ($p < 0.01$)?
INVIA_09 → ECONG_09	1.420	0.193	[0.094,0.294]	0.000	Yes
INVIA_09 → INTRIN_09	1.000	0.580	[0.551,0.611]	0.000	Yes
INTRIN_09 → ECONG_09	1.420	0.168	[0.074,0.261]	0.000	Yes
INVIA_16 → ECONG_16	1.372	0.124	[0.096,0.152]	0.000	Yes
INVIA_16 → INTRIN_16	1.000	0.255	[0.246,0.263]	0.000	Yes
INTRIN_16 → ECONG_16	1.372	0.256	[0.201,0.312]	0.000	Yes

4.2.2.2 Significance and relevance of path coefficients

The calculated path coefficients for the structural model relationships, together with their 99% percentile confidence intervals and their *p*-Values, are summarized Table 3 for both the base models. The path coefficients, the R^2 values, and the *p*-Values are also shown in Figure 6. As can be seen, all the path coefficients are significant to within a 1% significance level. There are not many path relationships in the models, but all of them are considered to be of relevance since none of them are very small and they are all of comparable sizes.

It is worth noting that the relationship from investing in intangible assets to introducing new innovations is much stronger for IB09 than for IB16. But as described in chapter 3.5.2, the measurement models are different for INVIA_09 and INVIA_16, so quantitative comparison could not be done directly.

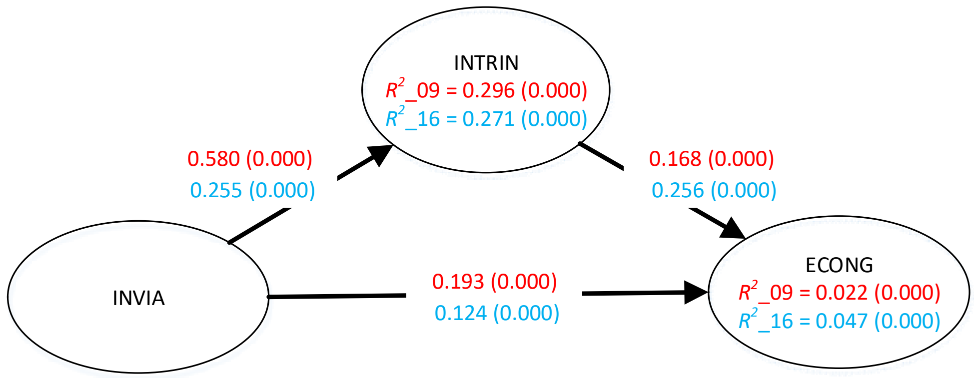

Figure 6 Path coefficients and R^2 values for IB09 in red and IB16 in blue, with p-Value in parentheses for each value

4.2.2.3 Assessing the Model's Explanatory Power

The most commonly used measure to evaluate the structural model's explanatory power is the coefficient of determination (R^2) value (Hair, Hult, Ringle, & Sarstedt, 2022). R^2 measures the explained variance in each of the endogenous constructs and is therefore a measure of the model's explanatory power (Shmueli & Koppius, 2011). R^2 is the portion of variation in a dependent variable that can be explained by variation in the independent variables, and its value ranges from 0 to 1, with higher levels indicating higher levels of explanatory power. As a guideline, R^2 values of 0.75, 0.50 and 0.25 can be considered substantial, moderate, and weak respectively, but acceptable R^2 values are based on the context (Hair, Risher, Sarstedt, & Ringle, 2019).

The R^2 values are shown in Table 3 and Figure 6. As we see, the models' explanatory power is very weak for the ECON constructs, as the R^2 values are only 0.022 for the IB09 model and 0.047 for the IB16 model. This is not unreasonable since we are not expecting to explain a firm's economic growth solely from its investments in intangibles assets, but just to confirm the contributing effect.

The INTRIN constructs have R^2 values of 0.296 for IB09 and 0.271 for IB16 respectively, and the explanatory power for these constructs could thus be considered weak to moderate. Overall, the models do not provide high explanatory power, as expected.

4.2.2.4 Assess the Model's Predictive Power

A PLS path model needs to produce generalizable findings to be useful for predictions and managerial decision-making. Producing generalizable findings requires assessing the model's out-of-sample predictive power (Sarstedt, Ringle, & Hair, 2022). The primary approach for assessing the predictive power of a PLS path model is by means of Shmueli, Ray, et al.'s $PLS_{predict}$ procedure (2016). In this procedure the overall data set is separated into training and holdout samples and uses model estimates from the training sample to generate predictions of the dependent constructs' indicators in the holdout. A small divergence between the actual and predicted values suggests the model has a high predictive power, while a large divergence indicates a low predictive power.

As detailed by Hair, Hult et al. (2022), we ran the $PLS_{predict}$ calculations in SmartPLS for both base models. Per equation 1 in chapter 3.6, the minimum path coefficient of 0.168 in the IB09 based model requires a minimum of 356 samples to have a statistical power of 80% for a significance level of 1%. After casewise deletion of missing values we had 4443 samples left, and this should allow for using 10 folds in the $PLS_{predict}$ calculations (356x11 < 4443). We therefore used default settings of 10 folds and 10 repetitions.

Since predictive power is not a main topic of interest in our research study, and as suggested by Shmueli, Sarstedt, et al. (2019), we only considered the very simplistic indicator-level average based statistic called $Q^2_{predict}$ as a naïve benchmark for the predictive power of our model (Hair, Hult, Ringle, & Sarstedt, 2022). $Q^2_{predict}$ equals one minus the quotient of the PLS path model's sum of the squared prediction errors in relation to the mean value's sum of the squared prediction errors (Hair, Hult, Ringle, & Sarstedt, 2022). A positive $Q^2_{predict}$ indicates that the PLS path model's prediction error is smaller than the prediction error given by the (most) naïve benchmark. A $Q^2_{predict}$ value of zero or less suggests the predictive power of the PLS-SEM analysis for that indicator does not even outperform the most naïve benchmark.

As the main focus in our study is on the general concepts (latent variables) and not on the individual indicators' contributions, we evaluated the $Q^2_{predict}$ values for the latent variable constructs. The $PLS_{predict}$ calculations gave the $Q^2_{predict}$ values shown in the table below.

Table 4 $Q^2_{predict}$ values for the based models' endogenous constructs

ECONG_09	ECONG_16	INTRIN_09	INTRIN_16
-0.035	0.036	0.671	0.114

These values show that the IB09 based model provides no predictive power for ECONG_09, but indicates a strong predictive power for INTRIN_09. The IB16 based model indicates a small predictive power for ECONG_16, and a stronger predictive power for INTRIN_16. We therefore conclude that the models provide low or no predictive power for economic growth (ECONG), but that they provide some predictive power for introduction of new innovations (INTRIN).

4.2.2.5 Mediating effect

As described in the preceding chapters, all required quality criteria of the measurement models and the structural models have been met, so we can now evaluate the mediation models. To evaluate the mediating effect, researchers should bootstrap the sampling distribution of the indirect effect via the mediator (Hair, Hult, Ringle, & Sarstedt, 2022). Direct, indirect and total effect (the sum of direct and indirect effects) of the bootstrap calculations done in chapter 4.2.1 is summarized in Table 5. We find that both indirect effects are significant within a significance level of 1%, and the direct effect is approximately twice as strong as the indirect effect for both the IB09 and the IB16 based models. The result suggests that the relationship between INVIA and ECONG is mediated by INTRIN.

Table 5 Direct, indirect and total effects to assess mediating effects.

Relationships	Direct Effect	99% Confidence Intervals	*p* Value	Significance ($p < 0.01$)?
INVIA_09 → ECONG_09	0.193	[0.094,0.294]	0.000	Yes
INVIA_16 → ECONG_16	0.124	[0.096,0.152]	0.000	Yes
	Indirect Effect			
INVIA_09 → INTRIN_09 → ECONG_09	0.098	[0.043,0.152]	0.000	Yes
INVIA_16 → INTRIN_16 → ECONG_16	0.065	[0.051,0.080]	0.000	Yes
	Total Effect			
INVIA_09 → ECONG_09	0.290	[0.208,0.373]	0.000	Yes
INVIA_16 → ECONG_16	0.190	[0.166,0.214]	0.000	Yes

Zhao, Lynch and Chen (2010) offer an approach to mediation analysis which is based on synthesis of prior research. The authors characterize several types of mediating effects, and according to their classification we have complementary mediation in our models, where the indirect effect and the direct effect are both significant and point in the same direction. This could also be called partial mediation according to Baron and Kenny’s (1986) terminology.

4.2.2.6 Robustness checks

Sarstedt, Ringle, et al. (2020) suggest that researchers should consider nonlinear effects, endogeneity and unobserved heterogeneity as robustness checks to safeguard the validity of the results of the structural model. Testing for endogeneity in a PLS-SEM analysis is primarily done when the main focus of the research is explanatory, and since that is not the case in this study, we did not do that. We also chose to not test for unobserved heterogeneity as we are only trying to find very general trends and averages in a diverse sample of firms and do not have any prior assumptions about a homogeneous population for this study.

When estimating PLS path models, researchers usually assume that the relationships between the constructs are linear by nature, but this is not always the case (Sarstedt M. , et al., 2020). To test whether relationships are nonlinear, researchers can establish a quadratic interaction term to map a nonlinear effect in the PLS-SEM model and test its statistical significance using bootstrapping (Svensson, et al., 2018). This quadratic term is similar to an interaction term, which comprises the exogenous construct's interaction with itself (Rigdon, Ringle, & Sarstedt, 2010). If the interaction term's effect is significant and positive (negative), the strength of the exogenous construct's effect increases (decreases) in the exogenous construct's higher values. Conversely, a nonsignificant interaction term offers evidence of the linear effect's robustness case (Sarstedt M. , et al., 2020).

For the analysis, we used the percentile method to construct bootstrap-based confidence intervals with 10,000 subsamples at a significance level of 1% by running the calculations in SmartPLS 4. We added a quadratic effect on one path coefficient at the time, and ran the bootstrap calculations separately for each relationship with added quadratic effect. The results are summarized in Table 6. As seen, all the first order linear effects became larger when a quadratic effect was added, at the same time as all the added quadratic effect was calculated to be negative. But not all quadratic effects were significant. The quadratic effect on the relationship between INTRIN and ECONG was insignificant for both IB09 and IB16, while the quadratic effect on the relationship between INVIA and INTRIN was significant for both. The quadratic effect on the relationship between INVIA and ECONG was insignificant for IB09, but significant for IB16.

We therefore conclude that the linear effects models are not robust, and several of the relationships should ideally have a quadratic term added to better model the reality. However, adding quadratic terms would complicate further analyses involving moderation and higher order constructs in the complete models discussed in the next chapter, so we decided to not include quadratic effects in any further analyses. Linear relationships generally approximate relations found in reality well, and since the quadratic effects in Table 6 are relatively much smaller than the linear effects, one could also argue that to be the case here as well.

Table 6 Quadratic effects of the relationships in the base models.

Relationships	Original Path Coef. of Linear Model	Quadratic effect models				
		Adjusted Linear Path Coefficients	Quadratic Effect (QE)	QE 99% Confidence Intervals	*QE p-Value*	QE Significance (p < 0.01)?
INVIA_09→ECONG_09	0.193	0.226	-0.018	[-0.205,0.168]	0.803	No
INVIA_09→INTRIN_09	0.580	0.723	-0.080	[-0.144,-0.017]	0.001	Yes
INTRIN_09→ECONG_09	0.168	0.252	-0.080	[-0.272,0.112]	0.288	No
INVIA_16→ ECONG_16	0.124	0.176	-0.040	[-0.059,-0.022]	0.000	Yes
INVIA_16→ INTRIN_16	0.255	0.318	-0.056	[-0.063,-0.048]	0.000	Yes
INTRIN_16→ECONG_16	0.256	0.401	-0.111	[-0.226,-0.005]	0.013	No

4.3 Analysis of full model moderated by innovation strategy

In our full structural model, as illustrated in Figure 5, we have hypothesized that a firm's innovation strategy is moderating the relationships in the base model, which is illustrated in Figure 4. However, the innovation strategy variables INSTRAT_09 and INSTRAT_16 are higher order constructs which each are built from very different lower order constructs, as described in chapter 3.5.3.

To validate higher order constructs, researchers need to consider two steps. First, as we did in 4.2.1, the lower order constructs' measurement models need to be validated by using the standard model evaluation criteria applied to standard constructs (Hair J. , Sarstedt, Ringle, & Gudergan, 2018). Then the higher-order models need to be estimated, and Becker, Hwa, et al. (2023) recommend a two-stage approach because such an approach finds ways around problems that occur in specific model constellations and because of the simple implementation in modern PLS-SEM software. Research has proposed two versions of the two-stage approach, (1) the embedded two-stage approach (Ringle, Sarstedt, & Straub, 2012) and (2) the disjoint two-stage approach (Agarwal & Karahanna, 2000). The embedded approach models the entire higher order construct in its first stage, while the disjoint approach models the lower order constructs separately in its first stage (Sarstedt M. , Hair, Cheah, Becker, & Ringle, 2019). The results of these two 2-step approaches do not differ significantly, so both could be used (Becker, Hwa, Ghollamzadeh, Ringle, & Sarstedt, 2023).

At the same time, researchers should also rely on a two-stage approach for moderation analysis (Becker, Hwa, Ghollamzadeh, Ringle, & Sarstedt, 2023). In a two-stage approach for moderation analysis, the construct scores from a model estimation without the interaction term from Stage 1 should be used as input to compute the interaction term in Stage 2. Since the higher order constructs are also the moderating variables in our models, and both require two stages for analyses, this complicates the analyses of our complete models.

We could not locate any literature on using higher-order constructs in moderation analysis. Becker, Klein and Wetzels (2012) covered this topic briefly in the future research section of their paper, but we could not identify any studies which have explicitly looked at this in detail. On the SmartPLS discussion forum (Becker J.-M. , 2018), the PLS-SEM research authority J. M. Becker advised that it would make sense to combine the two two-stage approaches into a three-stage approach, or to use the two-stage moderator approach with a repeated indicator (Sarstedt M. , Hair, Cheah, Becker, & Ringle, 2019) higher-order construct.

When calculating the results of a moderated model, SmartPLS 4 automatically performs the two-stage approach, which uses the latent variable scores of the latent predictor and latent moderator variable from the main effects model without the interaction term (SmartPLS GmbH, 2022). These latent variable scores are saved and used to calculate the product indicator for the second stage analysis that involves the interaction term in addition to the predictor and moderator variable.

In addition, Becker, Ringle, and Sarstedt (2018) examined the impact of different data treatment options on the performance of two-stage approach to moderation. Their results show that parameter recovery works best when standardizing the indicator data and the interaction term rather than working with unstandardized or mean-centered data, and they therefore recommended that researchers apply the two-stage approach with standardized data when conducting moderator analyses.

By combining the advice and inputs from these references with Hair, Hult et al.'s (2022) separate guidelines for higher order constructs and moderation analyses, the following approach seems most reasonable when the moderating term is a higher order construct:

Stage 1: The main effects model (i.e., without the moderating interactions), including the full lower order constructs with standardized data, and using the repeated indicator approach for the higher order construct, is estimated to obtain the scores of the latent variables. These latent variable scores are saved for further analysis in the second stage.

Stage 2: The model is modified to include moderating interactions, and all indicators and lower order constructs are substituted by latent variable scores from stage 1, as described by

Sarstedt, Hair, Cheah, et al. (2019) for stage two of the embedded two-stage approach. Since SmartPLS 4 automatically calculates two stages for moderation analysis, this should jointly be in line with the "three-stage approach" recommendation by J. M. Becker.

4.3.1 Evaluation of Measurement Models

The measurement models for innovation strategy, INSTRAT_09 and INSTRAT_16, were evaluated based on the main effect model in stage 1, as described above. These full PLS-SEM Stage 1 models are shown in Appendix C for IB09 and in Appendix D for IB16.

4.3.1.1 Convergent Validity

To evaluate whether the measurement models for the innovation strategy constructs in the IB09 and IB16 models respectively exhibit convergent validity, we must carry out redundancy analyses, as described previously. But when examining the questions in IB09 and IB16, no alternative measures could be identified for INSTRAT. We therefore conclude that convergent validity cannot be assessed for our INSTRAT measurement models.

4.3.1.2 Collinearity

As described previously, the measurement models for INSTRAT need to be evaluated for collinearity by calculating and evaluating the VIF values for all the constructs indicators. We ran full PLS calculations on the Stage 1 models, and the calculated indicator weights and VIF values are shown in Appendix E. The highest calculated VIF is 1.926 (for the indicator q13_d), which is well below the recommendation of 3. We can therefore conclude that collinearity has no substantial effect on estimates for the measurement models for the lower order constructs which the higher order constructs INSTRAT_09 and INSTRAT_16 are constructed from.

4.3.1.3 Significance and relevance of indicators

We ran bootstrap calculations in SmartPLS on the Stage 1 models for IB09 (Appendix C) and IB16 (Appendix D) respectively. For both calculations we used 50,000 subsamples and a less stringent significance level of 5% than the 1% significance level used for the base models. The reason for this less stringent significance level was due to the exploratory intent of this part of the research, as described previously. The calculations are summarized in Appendix E, and we found that all indicators contributing to these measurement models are significant within a significance level of 5%.

Considering relevance of the indicators, we see that all indicators have a relatively comparable contribution to the constructs which are related to INSTRAT_09, but for

INSTRAT_16 we see that q12.9 and q13.3 have noticeably lower weights than the other indicators. These two indicators are also the only indicators with a *p*-Value different from 0.000. However, due to the exploratory nature of this part of the study, and that we were not looking for any individual indicator's contribution to the higher order constructs of innovation strategy, we chose to keep them in the model. We therefore conclude that all indicators are significant and relevant for the measurement models used for the INSTRAT models.

4.3.2 Evaluation of Structural Models

Due to the exploratory nature of this part of the study, we are primarily interested in the concept or idea of an innovation strategy and its effects, not so much as how it is measured, or which lower constructs contribute to the higher order constructs of innovation strategies. In the following analyses we are therefore only considering the higher order constructs and the latent variables' scores, according to stage 2 described in chapter 4.3.

The model used for Stage 2 estimations, where we have substituted indicators and lower order constructs with latent variables, is shown in Figure 7 for IB09. The model for IB16 is structurally the same, but with different latent variables and scores.

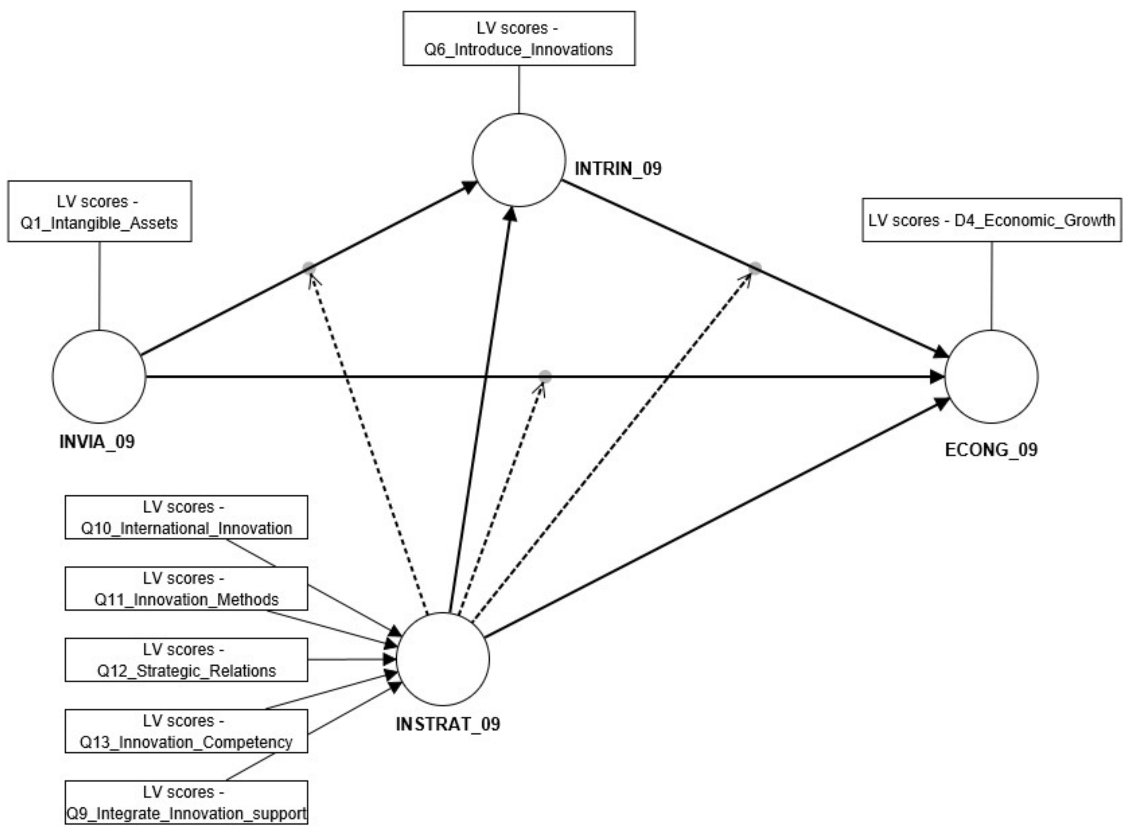

Figure 7 The full Stage 2 moderated model for IB09

Before doing further evaluations, we ran initial bootstrap calculations in SmartPLS on these full Stage 2 models, using 50,000 subsamples and a 5% significance level. These calculations are summarized in Appendix F.

From the calculations listed in Appendix F, and comparing with the results in Table 3, we observe that the path coefficients for all the relationships in the base model have been reduced by introducing innovation strategy as a moderator. We also see that:

- INSTRAT has a positive and significant direct effect on INTRIN for IB09 and IB16
- INSTRAT has a nonsignificant direct effect on ECONG for IB09, while the same relationship is significant but relatively small for IB16.
- The moderating effect of INSTRAT on the INVIA → ECONG relationship is insignificant for IB09 and small and barely significant for IB16.
- The moderating effect of INSTRAT on the INTRIN → ECONG relationship is insignificant for both IB09 and IB16.
- The moderating effect of INSTRAT on the INVIA → INTRIN relationship is negative and significant for both IB09 and IB16.

Based on these results, we simplified the Stage 2 models for the rest of the analyses and removed all relationships which were not significant for both IB09 and IB16. We then redid the calculations for the simplified Stage 2 models in SmartPLS 4 and used 50,000 subsamples and a 5% significance level. These models with calculated results are shown in Figure 8 for IB09 and in Figure 9 for IB16. The first numbers on the paths in the figures are path coefficients, and the second numbers in the parentheses are the *p*-Values for these path coefficients. The numbers inside the endogenous variables are the R^2 scores. These calculations are also summarized in Table 7.

Table 7 Bootstrap results for the simplified Stage 2 models

Relationships	VIF	Path Coefficients	95% Confidence Intervals	*p* Value	Significance (p < 0.05)?
INVIA_09 → ECONG_09	1,425	0.092	[0.048,0.136]	0.000	Yes
INVIA_09 → INTRIN_09	1,569	0.294	[0.257,0.329]	0.000	Yes
INTRIN_09 → ECONG_09	1,425	0.073	[0.029,0.117]	0.001	Yes
INSTRAT_09 → INTRIN_09	1,566	0.431	[0.397,0.467]	0.000	Yes
INSTRAT_09 x (INVIA_09 → INTRIN_09)	1,008	-0.075	[-0.100,-0.050]	0.000	Yes
INVIA_16 → ECONG_16	1,173	0.077	[0.051,0.103]	0.000	Yes
INVIA_16 → INTRIN_16	1,031	0.362	[0.341,0.382]	0.000	Yes
INTRIN_16 → ECONG_16	1,173	0.097	[0.071,0.122]	0.000	Yes
INSTRAT_16 → INTRIN_16	1,034	0.159	[0.138,0.182]	0.000	Yes
INSTRAT_16 x (INVIA_16 → INTRIN_16)	1,011	-0.048	[-0.067,-0.029]	0.000	Yes

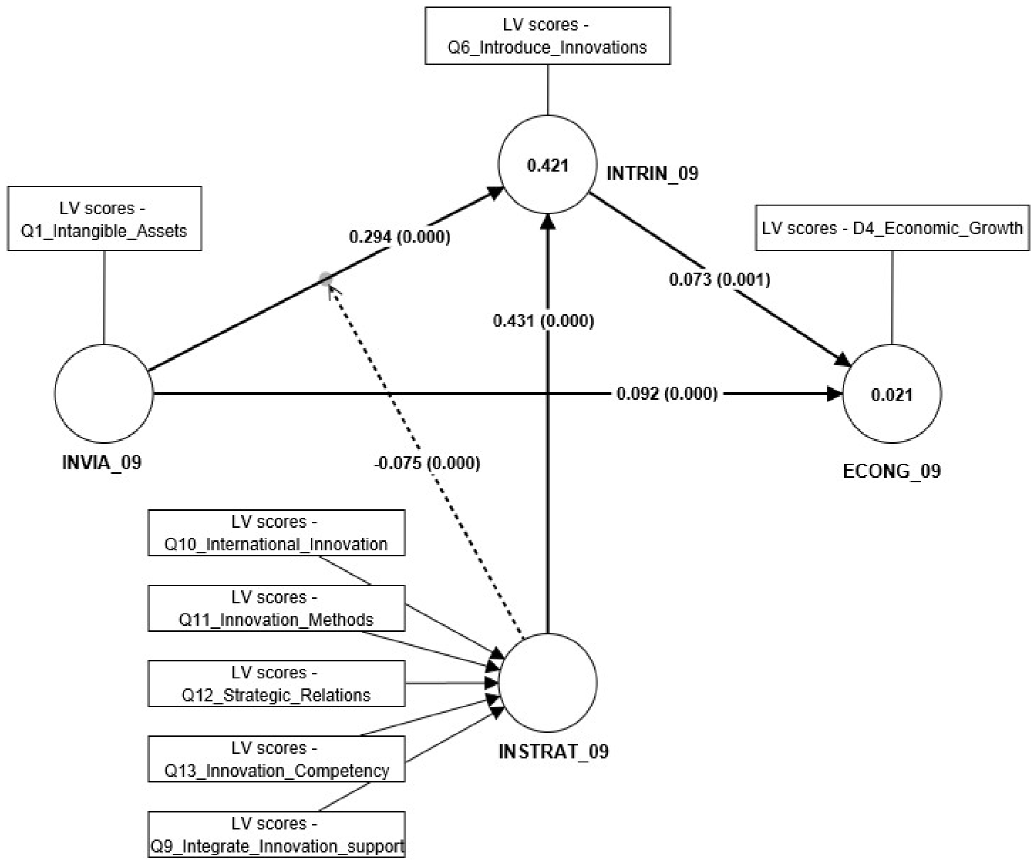

Figure 8 Simplified Stage 2 model for IB09 with bootstrap results for path coefficients, p-Values, and R^2 values.

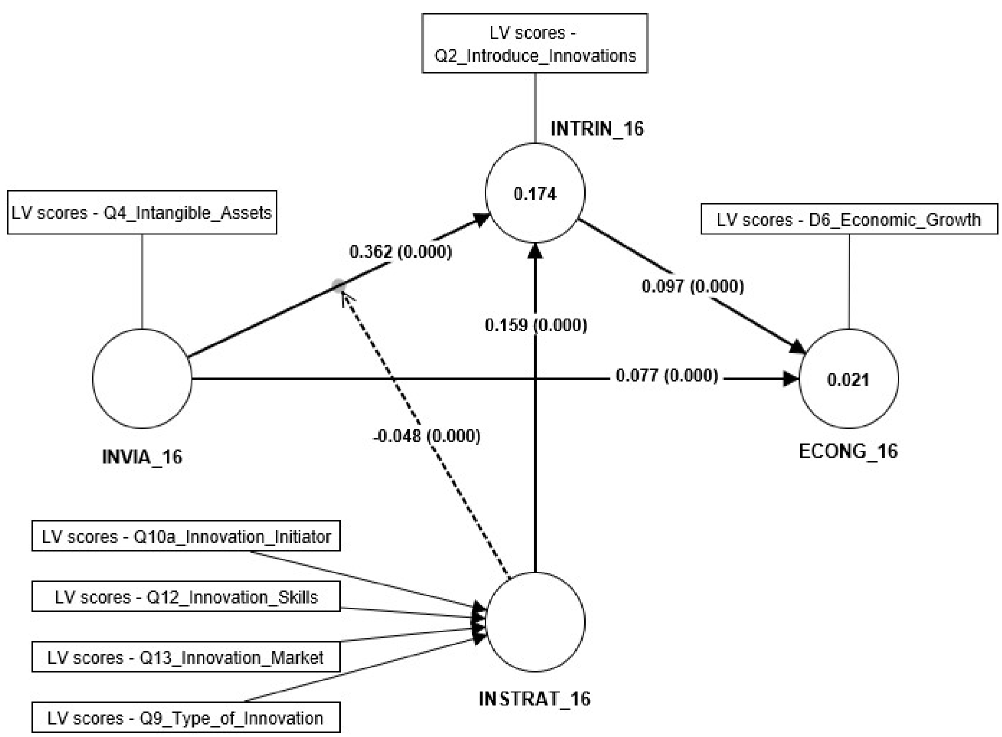

Figure 9 Simplified Stage 2 model for IB16 with bootstrap results for path coefficients, p-Values, and R^2 values.

4.3.2.1 Collinearity / VIF

VIF is also used as an indicator for collinearity in the Stage 2 models, which bootstrap estimates are summarized in Table 7. As the highest calculated VIF is 1.569, which is well below the recommendation of 3, we can therefore conclude that collinearity has no substantial effect on the structural model estimates.

4.3.2.2 Significance and relevance of path coefficients / bootstrap-based

The calculated path coefficients for the structural model relationships, together with their 95% percentile confidence intervals and their p-Values, are also summarized in Table 7 for the simplified Stage 2 models for both IB09 and IB16. The path coefficients are also shown in the path diagrams in Figure 8 and Figure 9. As can be seen, all the path coefficients are significant to well within a 5% significance level. There are not many path relationships in the models, but all of them are considered to be of relevance since none of them are very small and they are all of comparable sizes. We therefore conclude that all relationships in the structural models are significant and relevant.

4.3.2.3 Assessing the Models' Explanatory Power

As described previously, the coefficient of determination (R^2) is commonly used to evaluate the structural model's explanatory power. The R^2 values are shown inside the constructs in Figure 8 and Figure 9. As we see, the models' explanatory power is very weak for the ECONG constructs, as the R^2 values are only 0.021 for both models. The INTRIN constructs have R^2 values of 0.421 and 0.174 respectively, and the models' explanatory power for these constructs could thus be considered moderate and weak respectively.

4.3.2.4 Assessing the Moderating effect of innovation strategy

The main objective of a moderation analysis is to "measure and test the differential effect of the independent variable on the dependent variable as a function of the moderator" (Baron & Kenny, 1986). As seen in Figure 8 and Figure 9, INSTRAT has a significant positive direct effect on INTRIN for both IB09 and IB16, and a significant negative interaction effect on the INVIA→INTRIN relationship for both IB09 and IB16.

In addition to evaluating significance, we must calculate and report the effect size (f^2), which enables an assessment of the change in the R^2 as a function of the moderator when it is included or excluded from the model (Memon, et al., 2019; Hair, Hult, Ringle, & Sarstedt, 2022). Thus, the f^2 effect size indicates how much the moderation contributes to the explanation of the endogenous construct, and we can assess the relevance of the moderating effect. f^2 is included as a standard calculation in SmartPLS, so these estimations from the already performed bootstrap calculations are listen in Table 8 for both IB09 and IB16.

Table 8 Effect size f^2 for direct and moderating relationship of INSTRAT

Relationships	f^2	95% Confidence Intervals	*p* Value	Significance ($p < 0.05$)?
INSTRAT_09 → INTRIN_09	0.205	[0.169,0.248]	0.000	Yes
INSTRAT_09 x (INVIA_09 → INTRIN_09)	0.010	[0.004,0.018]	0.004	Yes
INSTRAT_16 → INTRIN_16	0.030	[0.022,0.039]	0.000	Yes
INSTRAT_16 x (INVIA_16 → INTRIN_16)	0.003	[0.001,0.006]	0.014	Yes

Kenny (2018) proposes that effect sizes of 0.005, 0.01, and 0.025 represent small, medium, and large effect sizes respectively. Using these values, the effect size of the direct effect of INSTRAT on INTRIN is large for both IB09 and IB16. And the effect size of the moderating interaction term of INSTRAT on the INVIA→INTRIN relationship is medium for IB09 and small for IB16.

To better understand the nature of these interactions, we followed recommendations by Aiken, West and Reno (1991) to plot the effect of a firm's investment in intangible assets (INVIA) on the firm's introduction of new innovations (INTRIN) at low (-1 standard deviation (SD)), medium (mean) and high (+1 SD) degree of innovation strategies (INSTRAT). These simple slope plots are shown in Figure 10 for both IB09 and IB16 for standardized values of INVIA, INTRIN and INSTRAT. From the plots we see visually that INSTRAT has a positive direct effect on INTRIN since INTRIN is higher at higher INSTRAT, but also that INSTRAT has a negative moderating effect (a dampening effect) on the INVIA → INTRIN relationship since INTRIN as a function of INVIA is flatter at higher INSTRAT.

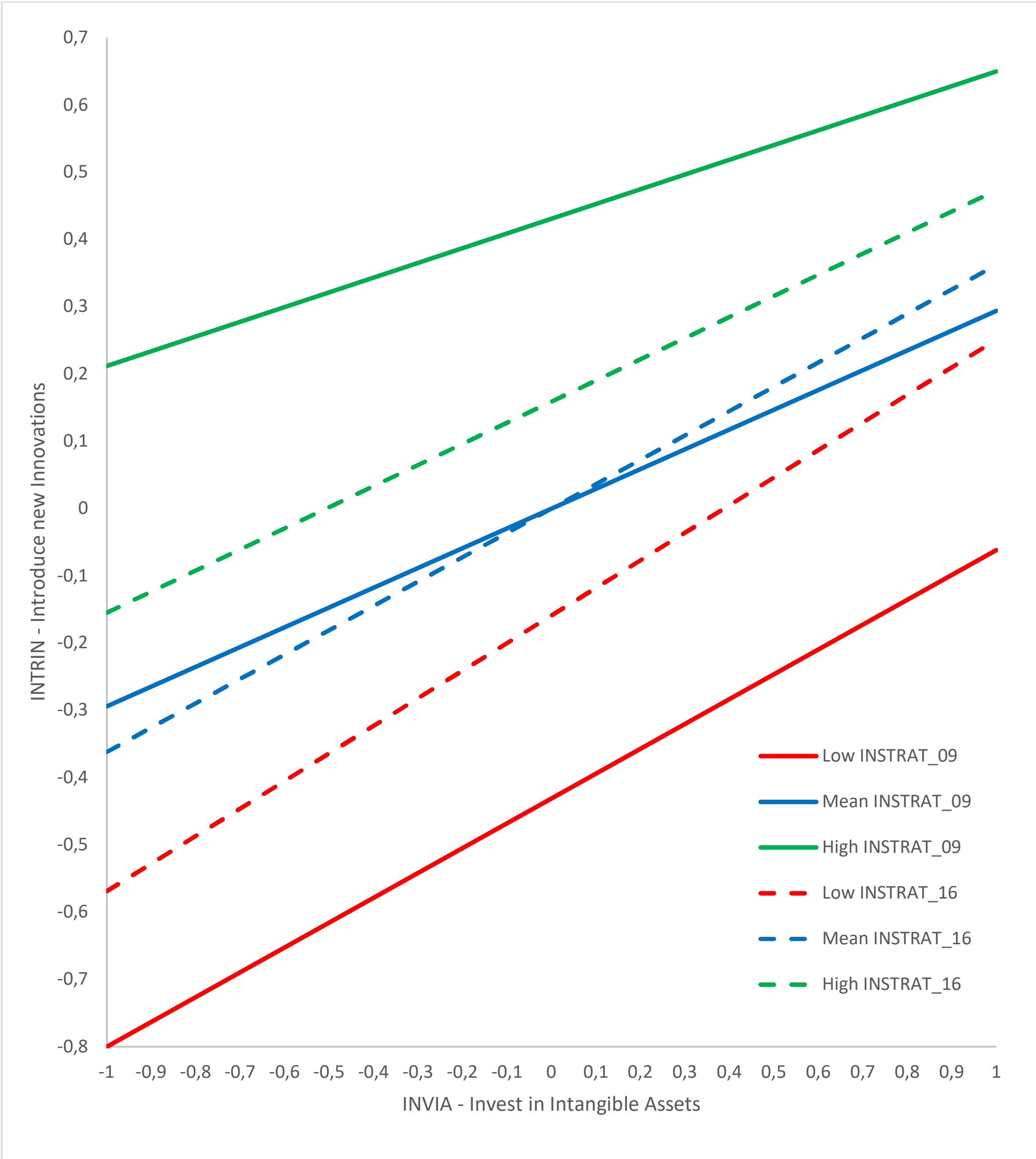

Figure 10 Simple slope plots for Low, Mean and High degree of innovation strategy (INSTRAT) on the relationship between a firm's investments in intangible assets (INVIA) and its introduction of new innovations (INTRIN).

5 Discussion

In this section we are evaluating and discussing our empirical findings presented in chapter 4 with relevant theory from chapter 2, and the relevant discussions are categorized under each hypothesis.

5.1 H1: Firm's investments in intangible assets have a positive relationship with the firm's economic growth.

In order to compare previous studies with our research results, it's relevant to reiterate how this paper has studied the relationship between IA and economic growth, and our hypothesis that INVIA (a firm's investment in IA) has a positive relationship on ECONG (a firm's economic growth). As Figure 6 illustrates, our structural model's explanatory power is relatively weak for the ECONG constructs, with R^2 values of 0.022 for the IB09 model and 0.047 for the IB16 model. This is considered reasonable since we were not expecting to fully explain a firm's economic growth solely from its investments in IA. Our findings in chapter 4.2.2.3 show that the IB09 based model provides no predictive power for ECONG_09 and a small predictive power for IB16 on the ECONG_16 construct. Also, as illustrated in Figure 6, the path coefficient between INVIA and ECONG is significant to within a 1% significance level and the calculated path coefficient is 0.193 and 0.124 for IB09 and IB16 respectively. The findings are considered to be of relevance since none of the coefficient are very small, and they are all of comparable sizes.

Hypothesis H1 is supported by our findings.

In the theoretical review done in chapter 2 we presented earlier research looking into how IA affect firms' economic performance. The role of IA has been studied across European countries in research projects such as INNODRIVE, COINVEST, IDICSER and IAREG focusing on different forms of IA and the relationship to economic growth (Montresor & Vezzani, 2016). These studies mostly focus on macro-level trends within Europe and does not go too far into firm specific results as our analysis. The term IA also heavily focuses on the R&D and "knowledge" part (earlier referred to as ICT) of intangibles.

During the last fifty years a popular research angle for looking at this relationship has been a total productivity factor function, where researchers has tried to showcase the residual growth factor in production that is not explained by physical assets such as labor and capital (Hall & Rosenberg, 2010). Using the product function, researchers have found a strong correlation between investing in IA and a firm's returns (Hall, Foray, & Mairesse, 2007; Rogers, 2009;

Griffith, Harrison, & Van Reenen, 2006; Kafouros, 2005; Mairesse, Mohnen, & Kremp, 2005). In developed countries, the rate of return from R&D activities have been strongly positive, and most likely in the 20-30% range (Hall & Rosenberg, 2010). In contrast we have also presented studies that did not find a proven link between IA and a firm's business performance (Fernando, Jabbour, & Wah, 2019; Weqar, Khan, Raushan, & Haque, 2020; Miala, et al., 2021).

We did not find a high explanatory power in the relationship between INVIA and ECONG. One reasoning can be that we have not accounted for spillovers or done any sector, or macro adjustments. We have also not considered control variables, and there are several omitted variables which would contribute to explaining ECONG. Another factor discussed in chapter 3.5.2 that might skew our results is that ECONG_09 and ECONG_16 is measured slightly differently, where ECONG_09 uses the term "turnover" and ECONG_16 is using the term revenue. Even if these are often used interchangeably, they refer to different terminology within finance and might be an uncertainty factor as to if firms had the same understanding of the terminology.

Another difference in the datasets are how they differentiate to what degree a firm has invested in IA or not. For INVIA_09 it is asked whether a firm has had "any expenditures to support innovation", while for INVIA_16 it is asked what percentage of revenue the firm has invested in the different categories of IA. These are significantly different measurement scales and will cause some problems, as firms with even the tiniest investment in IA could be answering that they have done activities to support innovation in IB09.

Lastly, we should include the empirical work from Piyush & Leung (2021) and Rui, Li, & Wei, (2022) that concludes that investing in IA might hurt a firm's growth short term. As mentioned in chapter 3.5.2, both IB09 and IB16 economic growth is compared from year zero to three years after. In contrast, investment in IA is measured "during" this three-year period. This might not be enough time from investment to see the full gains on return. In addition to this, there is no indications provided by the studies whether the numbers for turnover/revenue are adjusted for inflation or not, something which will also be of importance when considering real growth.

5.2 H2: Firms investing in intangible assets are introducing more new innovations

In order to understand the relationship between IA and economic growth, based on the theory presented in chapter 2.2, we have included the introduction of innovation as a mediator to further explain the relationship. This led to the hypothesis that INVIA (a firm's investment in IA) has a positive relationship with INTRIN (introduction of new innovations)

When evaluating the effect investing in IA has on the introduction of more new innovations it is important to mention the difference in measuring INVIA for this construct also provides some issues as mentioned in chapter 5.1. On the other hand, the constructs INTRIN_09 and INTRIN_16 are measured almost identical in chapter 3.5.2.5. While the newer 2018 edition of the Oslo Manual is only differentiating between two main types of innovations: product innovations and business process innovations (OECD /Eurostat, 2018), IB09 and IB16 are differentiating between 5 types of innovation types, in accordance with the 2005 edition of the Oslo manual (2005).

As illustrated in Figure 6, chapter 4.2.2.3, our structural model's explanatory power for the INTRIN constructs have R^2 values of 0.296 for IB09 and 0.271 for IB16 respectively, and are considered weak to moderate. It is important to note that the INTRIN variables were constructed to measure how many types of different innovations a firm has introduced. Rather than measuring the number or sizes of the innovations, it was measured in how many different categories a firm has introduced innovations. This is not an optimal measure for innovation, but represents a typical challenge with using secondary data.

The relationship between resources and innovation has always been a key focus area for research within innovation and strategic management (Fang, Marshal, & Yugang, 2023). Several studies show a positive relationship from investing in IA and innovation (Chen & Huang, 2009; Khan, Atlas, Ghani, Akhtar, & Khan, 2020; Liu, Kim, & Yoo, 2019; Roberts & Dowling, 2002). However other researchers (Cox Pahnke, Mcdonald, Wang, & Hallen, 2015; Dahlander, O`mahony, & Gann, 2016) find a negative relationship. Fang et al. (2023) illustrates that existing literature and research doesn't adequately explain the inconsistency, and showcased a framework to analyze how and why IA can impact firms' innovation. Fang et al. (2023) presents a U-shape in how investing in intangible resources will affect a firm's innovation. In chapter 4.2.2.6 we checked for nonlinear effects and found significant quadratic effect on the relationship between INVIA and INTRIN that might be supporting a U-shape in the relationship.

We introduced INTRIN as a mediator to better explain the relationship between investing in IA and economic growth. This is supported by the well-known CDM model (Crepon, Duguet, & Mairesse, 1998) presented in chapter 2.2.4. This model is the most used model for explaining the economics of innovation (Fedyunina & Radosevic, 2022) and predicts that investing in IA leads to innovation. However, there are several different ways to look at the definitions for innovation, and there is no clear consensus (Chesbrough, 2003; Schumpeter, 1934; OECD/Eurostat, 2005; OECD /Eurostat, 2018). The constructs INVIA_09 and INVIA_16 are measured very differently, something which probably could explain why the link between INVIA and INTRIN is so much stronger in IB09 than in IB16.

The Innobarometer surveys follows the Oslo manual as to describing "what" innovation is. The Oslo manual (OECD/Eurostat, 2005), based on Schumpeter's (1934) definitions of innovations, describes innovation as introduction of a new product, process innovation new to an industry, the opening of a new marked, development of new sources of supply or changes in industrial organization as the different types of innovation. Innovation, represented by the constructs INTRIN_09 and INTRIN_16 are measured almost identical, as described in chapter 3.5.2.5, but there are nuances in wording between them. One could argue that the definitions of "what" innovation is differs somewhat between literature and what is captured in the two Innobarometer reports, something which could contribute to slight differences in results.

In Table 3 we found that the path coefficient between INVIA and INTRIN were significant to within a 1% significance level and the calculated path coefficient were 0.580 and 0.255 for IB09 and IB16 respectively. It is worth noting that the relationship from investing in IA to introducing new innovations were much stronger for IB09 than for IB16. But as described in chapter 3.5.2, the measurement models are different for INVIA_09 and INVIA_16, so quantitative comparison could not be done directly. In chapter 4.2.2.4 we concluded that the base models provided some predictive power for introduction of new innovations (INTRIN), and overall, we conclude that;

Hypothesis H2 is supported by our findings.

5.3 H3: Firms Introducing more innovations have greater economic growth

After introducing H2, that firms investing in IA would introduce more innovations, we presented H3, that the same firms would have a higher economic growth to further describe the mediating effect of innovations. As mentioned in chapter 2.3.2, innovation is widely regarded to have an important role in firms' economic performance.

In our analysis we found a significant positive relationship in economic growth for companies introducing innovations, although with a weak explanatory power, as discussed previously.

We could compare the direct effect of INVIA on ECONG with the indirect effect via INTRIN as a mediator, as shown in Figure 6. Direct, indirect and total effect of the constructs of the base models are summarized in Table 5, and we found that the indirect effects were significant within a significance level of 1%, and that the direct effect is approximately twice as strong as the indirect effect for both the IB09 and the IB16 base models. The result suggests that the relationship between INVIA and ECONG is mediated by INTRIN, and since the indirect effect and the direct effect were both significant and pointed in the same direction, we have complementary mediation in our models. It is worth mentioning that, according to Neely et al. (2001) the introduction of innovations affects business performance through other mediating factors. When firms introduce innovation, this would lead to business performance either through return on investment, increased market share, a stronger competitive position or increased value to customers. As presented in Figure 3 this increase in performance would be through the mediating effects lower cost, enhancements to existing products, extensions to product range or better customer service (Neely, Filippini, Forza, & Vinelli, 2001).

Several researchers have found a clear link between innovation and economic performance. In chapter 2.3.1 we introduced some literature which found that the more innovative a firm is, the more likely they are to achieve higher performance (Shouyu, 2017), the study by Roberts (1999) who found that innovation has a direct positive return of investments, and the study by Cho and Pucik (2005) which found a positive relationship between innovation, profitability, and growth. However, a lot of the research is focused on economic performance, and in this paper, we have focused on economic growth, rather than gross income. Most companies have growth ambitions, but the most important goal for shareholder value would be the bottom line, and not growth specific increasements.

As seen in Table 3, we found that the relationships between INTRIN and ECONG were positive and significant to within a significance level of 1%, and we therefore confirmed a clear link between innovation and economic performance in our study. We found a somewhat stronger relationship for IB16 data than for IB09 data. This might to some degree be explained be the 2008 financial crisis affecting the IB09 numbers. Overall, we can conclude that our findings confirm that companies introducing more new innovations have a higher degree of economic growth.

Hypothesis H3 is supported by our study.

5.4 The direct effect of innovation strategy on our base model

When evaluating the direct effect innovation strategy has on the relationships in our base model, it's important to note that there are differences in how the two surveys measure the firm's innovation strategy, as we discussed in chapter 3.5.3.2. Specifically, INSTRAT_09 focuses on the respondent's innovation strategies for the last three years, in line with the rest of the survey questions, whereas INSTRAT_16 focuses on the future, with perspective ranging from twelve months to five years. The constructs are also built upon different questions, and thus INSTRAT_09 and INSTRAT_16 are measured completely different in the surveys. The questions in INSTRAT_09 focuses on internal and international activities to support innovation, strategic relationships and training and recruitment whereas INSTRAT_ 16 focuses on investments in innovation, skills required and the impact of the firm's innovations. We therefore base our analysis on different indicators to measure innovation strategy, and this might lead to inconsistent results. For INSTRAT_16 we make the assumption that firms with an innovation strategy for the future also had it in the past, specifically during the same period as the other questions in the survey are based upon. Even though we make this assumption, we cannot rule out that this may influence our findings as firms may have answered optimistically with regards to their own future innovation strategy, and not necessarily in accordance with the current strategy.

When looking into the results from our analysis we found that an innovation strategy has a direct effect on INTRIN that is strong and positive. This can be seen by the path coefficients in Figure 8 for IB09 and Figure 9 for IB16. We also found the effect size of the direct effect of INSTRAT on INTRIN to be large for both IB09 and IB16, as shown in Table 7. The direct effect an innovation strategy has on a firm's introduction of new innovations can also be seen in Figure 10, where we see that INTRIN is at a higher level at higher INSTRAT, as shown by the green curves being on a higher level than the red curves. For ECONG we found in chapter 4.3.2 that innovation strategy has a nonsignificant direct effect on ECONG for IB09, while the same relationship is significant but relatively small for IB16.

The large direct effect of INSTRAT on INTRIN for both IB09 and IB16 suggests that a higher degree of innovation strategy will give a higher degree of introduction of new innovations. This corresponds with theory presented in chapter 2.4.2, showing a positive link between activities in line with the firm's innovation strategy and the firm's innovation performance (Verhees & Meulenberg, 2004), and that innovation strategy and formal structure are drivers for innovation. Implementing these could improve firm performance (Terziovski, 2010). This again is further supported by Seclen-Luna, Moya-Fernández and

Pereira (2021) who shows that developing innovation strategies will have a positive effect on a firm's productivity.

We found no significant direct effect of innovation strategy on ECONG for IB09, while the same relationship is significant but relatively small for IB16. In chapter 2.4.2 we presented theory stating that innovation strategy would help increase firm value and create competitive advantages for a firm (Dodgson, Gann, & Salter, 2008). It was also proposed that managing IA is taking an increasingly bigger part of the foundation of where a firm builds its competitive advantage compared to managing tangible ones, which have traditionally been dominant (Lev, 2008; Haskel & Westlake, 2018). And Surya et al. (2021) indicated that an economic growth strategy linked with a firm's technological innovation would increases the firm's productivity. There is therefore a dissonance between our findings and presented literature. However, we did not expect to explain a firm's economic growth by innovation strategy on its own, merely to show the influence it might have. This is supported for IB16, as innovation strategy has a significant direct effect, although a relatively small one. We therefore propose that having an innovation strategy alone will not have a significant impact directly on a firm's economic performance. This might very well be because one cannot use innovation strategy on its own to gain economic growth. At the same time, due to the previously mentioned large direct effect innovation strategy has on INTRIN, and INTRIN being a mediator between INVIA and ECONG as shown in chapter 4.2.2.5, Table 5, innovation strategy can yield increased economic growth. This corresponds with theory presented in chapter 2.2.1 where we described that the relationship between a firm's investments in IA and the firm's growth is thought to be due to the mediating effect of innovations (Piyush & Leung, 2021).

Our findings therefore suggests that firms who develop an innovation strategy will experience a positive effect on the firm's ability to introduce new innovations, which will in turn lead to increased economic growth.

5.5 The moderating effect of innovation strategy on our base model

In chapter 2.4.2 we presented theory on the effect an innovation strategy has on the relation between investing in IA and economic growth, showing that the management of IA is taking an increasingly bigger part in creating a firm's competitive advantage (Huang, Mei-Chi, & Lin, 2011). In addition, we stated that for a firm to gain economic value from intellectual assets depends significantly on the firm's management capabilities and the implementation of appropriate business strategies. We also included that Purnamawati et al. (2022) argued that it is the strategic decision a firm makes to dedicate internal resources that will give an effect, not necessarily the investments in IA on its own. This shows that a strategic intent could be much more impactful than the act of investing. From this we can derive that for a firm to gain value from their investments in IA it is paramount that the firm manages their assets in line with the overall strategic intent, and having a clearly stated innovation strategy will assist the firm's management in doing so. Yet our calculations presented in Appendix F shows the moderating effect innovation strategy has on the relation between investment in IA and a firm's economic growth to be insignificant for IB09, and small and barely significant for IB16 and thus we found no support for H4. The observed outcome could be a result of the intermediary influence of introducing new innovations into our base model. When investments in IA lead to the creation of new innovations, the company gains the potential for economic growth. This potential is not created by investing in IA alone, but is instead rooted in having an innovation strategy. In this manner, an innovation strategy has the capacity to serve as a valuable tool in enhancing the overall impact of innovation processes within a firm.

Hypothesis H4 is not supported by our study.

In chapter 2.4.3 we showed the effect an innovation strategy has on the relation between a firm's introduction of new innovations and economic growth, stating that having a strategic focus, and defined priorities aligned with the firm's goals would be essential to gain a successful output from ones innovations (Si, Loch, & Stelios, 2023). We also showed research indicating that the speed of innovation is crucial to increasing one's own economic performance (Purnamawati, Jie, Hong, & Yuniarta, 2022), and that developing an innovation strategy will have a positive effect on a firms productivity (Seclen-Luna, Moya-Fernández, & Pereira, 2021), and thus increase economic growth. The theory therefore suggests that an innovation strategy would increase the gain a firm would have from introducing new innovations. This is on the other hand not supported by our findings. Appendix F shows the moderating effect innovation strategy has on the relation between the introduction of new innovations and a firm's economic growth to be insignificant for both IB09 and IB16, and thus we found no support for H6. This might be because an innovation strategy primarily focuses on the process of innovation and making a firm more successful with its innovations, not necessarily on how a firm would introduce new products to the market. Or as Calantone, Chan and Cui (2006) stated, products and services that are less innovative are less uncertain and may possess more synergy, leading them to be more successful, and thus creating more economic growth for the firm.

Hypothesis H6 is not supported by our study.

As we found both H4 and H6 to not be supported by our study, we simplified the model by leaving them out, and then ran new PLS-SEM calculations. As shown by the path coefficients in Figure 8 for IB09 and in Figure 9 for IB16, and as summarized in Table 7, we found a negative moderating effect of an innovation strategy on the relationships between INVIA and INTRIN to within the tested significance level of 5%. As summarized in Table 8, we found the effect size of the moderating interaction term of INSTRAT on the INVIA→INTRIN relationship to be medium for IB09 and small for IB16. Hypotheses could be considered partially supported if one aspect of the hypothesis is supported, but not others (Cairo, Green, Forsyth, Behler, & Raldiris, 2020). We found significant moderation for both IB09 and IB16, but negative instead of the hypothesized positive moderation, and we therefore found partial support for H5.

Hypothesis H5 is partially supported by our study.

In chapter 2.4.3 we elaborated on research looking into the effect an innovation strategy has on the relation between a firm's investments in IA and its introduction of new innovations. It was suggested that it's the strategic decision made to commit internal resources in a firm to develop their IA that increase a firms ability to introduce new innovations, not the investment in IA on its own (Montresor & Vezzani, 2016). The partial support for H5 shows that innovation strategy affects the relationship between IA and the introduction of new innovations. This is in line with current theory showing that being strategic with investments in IA will affect how the firm performs with its innovations. By increasing its investments in IA, the firm's ability to innovate will increase (Montresor & Vezzani, 2016), and as Terziovski (2010) found; innovation strategy and formal structure in a firm are key drivers for innovation and that by implementing these the firm has the possibility to improve firm performance. Yet, the support shown in chapter 4.3.2. is only partial, as we find the moderating effect to be negative, and for IB09 the effect size of the moderation interaction term is medium, and for IB16 it is small.

Firms generally introduce more new innovations with increasing investments in intangible assets. In addition, having an innovation strategy will lead to an increase in the introduction of new innovations due to the direct effect of innovation strategy. The partial support for H5 we found means that an innovation strategy is negatively moderating the relationship between a firm's investments in intangible assets and its introduction of new innovations. The moderating effect is visualized in Figure 10, where we can see that INTRIN as a function of

INVIA is flatter at higher INSTRAT. Due to the moderating effect being negative, firms who have an innovation strategy will experience that there is less increase in introduction of new innovations per investment in intangible assets; the introduction of new innovations will be dampened as they increase their investments in intangible assets. This could probably be explained by the strong direct effect of an innovation strategy, and one could say that the effect of the innovation strategy is being saturated as the firm increases its investments in intangible assets.

Our findings therefore suggests that it is important for firms to have a clearly stated innovation strategy, as it will help firms make the most out of their investments in intangible assets and have a positive effect on a firm's ability to introduce new innovations.

6 Conclusions and limitations

In this study we have sought to answer the following research question:

"How does an innovation strategy impact the relationship between a firm's investments in intangible assets and the firm's economic growth?"

In order to answer this, we did a PLS-SEM analysis to research the relationships between intangible assets, innovation and economic growth. We found our research on these relationships to be aligned with existing theory in the field, and confirmed that a firm's investments in intangible assets have a positive relationship with the firm's economic growth. Furthermore, we confirmed that firms investing in intangible assets are introducing more new innovations and that firms introducing more innovations have greater economic growth.

To provide an answer to our research question we continued the PLS-SEM analysis to research the moderating effects an innovation strategy has on the previously mentioned relationships between intangible assets, innovation and economic growth. We did neither find sufficient support for an innovation strategy's moderating effect on the relationship between a firm's investments in intangible assets and its economic growth, nor did we find sufficient support for an innovation strategy's moderating effect on the relationship between a firm's introduction of new innovations and its economic growth.

We found a strong and significant direct effect of a firm's innovation strategy: a higher degree of presence of an innovation strategy correlates with more new innovations being introduced. Intriguingly, we found that an innovation strategy is negatively moderating the relationship between a firm's investments in intangible assets and its introduction of new innovations. As the degree of the firm's innovation strategy increases, there is less increase in introduction of new innovations per investment in intangible assets. We had hypothesized this to be a positive moderating effect, but found that it was negative, probably due to the strong direct effect of an innovation strategy.

This suggests that firms with an innovation strategy will introduce more new innovations from their investments in intangible assets than firms without an innovation strategy. But due to the negative moderating effect, the relation between firms' investments in intangible assets and their introduction of new innovations will flatten. Firms with a high degree of innovation strategy will have a less increasing rate of introduction of new innovations per investment in intangible assets compared to those with low degrees, although at a higher level. Having an innovation strategy could thus help firms unlocking higher returns from their investments in intangible assets.

As in all empirical research there are limitations in our study, but it also presents some new opportunities for future research. We have for example not looked at all theory which could be relevant for our study, both because it is challenging to identify theory of relevance and challenging to make a selection of theory to include in the study, and the study therefore has theoretical limitations in scope, depth, and applicability.

We also have some methodological limitations, for example in deciding to not include control variables, in using a method for analysis of moderation with higher order constructs without well-established support in the literature, and in using two different constructs to measure innovation strategy, both which were constructed by a bottom-up approach, and both which were lacking solid support in the literature. For future research we therefore suggest establishing the theoretical basis for using higher-order constructs in moderation analysis. We also suggest constructing and validating a scale for measurement of innovation strategy.

As most studies that go into the drivers for a firms' innovation primarily focus on the drivers for product and process innovation, and a combination of these (Cabagnols & Le Bas, 2002; Du, Love, & Roper, 2007), we further suggest that future research take on a broader take on innovation and its drivers to gain a fuller understanding of what drives innovation in a firm. We also found a gap in studies looking collectively into the effect of intangible assets on performance, competitive advantage, and sustainability in a firm. We therefore suggest looking into these three collectively, to gain increased insight on how intangible assets influence these key parameters.

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Appendix A The indicators from Innobarometer 2009 used in this study.

Here are the questions and corresponding indicators listed which are used to make the constructs of the IB09 based model in this study.

ECONG_09: A firm's economic growth	
D4: Comparing your turnover of 2008 to that of 2006, did the annual turnover of your company decrease, increase, or remain approximately the same (within plus or minus 5%)?	
d4_a	Decreased
d4_b	Increased
d4_c	Approximately the same
D4a: FROM 2006 TO 2008, DID TURNOVER DECREASE …	
d4a_a	… by less than 5%
d4a_b	… by 5% to 25%
d4a_c	… by more than 25%
D4b: FROM 2006 TO 2008, DID TURNOVER INCREASE …	
d4b_a	… by less than 10%
d4b_b	… by 10% to 50%
d4b_c	… by more than 50%

INVIA_09: A firm's investment in intangible assets Q1: Has your company had expenditures on any of the following activities to support innovation since 2006?	
q1_a	Research & development within your company
q1_b	Research and development performed for your company by other enterprises or research organizations
q1_c	Acquisition of new or significantly improved machinery, equipment, and software
q1_d	Purchase or licensing of patents, inventions, know-how, and other types of knowledge
q1_e	Training to support innovative activities
q1_f	Design (graphic, packaging, process, product, service or industrial design)
q1_g	Application for a patent or registration of a design

INTRIN_09: A firm's introduction of new innovations Q6: Has your company introduced any of the following innovations since 2006?	
q6_a	New or significantly improved products
q6_b	New or significantly improved services
q6_c	New or significantly improved processes (e.g. production processes, distribution methods, support activities)
q6_d	New or significantly improved marketing strategies
q6_e	New or significantly improved organizational structures

INSTRAT_09: A firm's innovation strategy	
Q9: Since 2006, has your company started or increased any of the following initiatives to integrate different company activities (R&D, design, marketing/sales, production etc.) in support of innovation?	
q9_a	Knowledge management systems
q9_b	Internal mechanisms for employees to submit innovative ideas
q9_c	Staff rotations or secondments between different functions
q9_d	Creation of cross-functional or cross-departmental teams on innovation projects
Q10: Since 2006, has your firm started or increased to perform any of the following international activities in support of innovation?	
q10_a	Outsourcing of tasks to companies located in other countries
q10_b	Investments in companies located in other countries
q10_c	Other cooperation with local partners in other countries
q10_d	Recruitment of employees from other countries on a permanent or temporary basis
q10_e	Market-testing of your innovative products in other countries
Q11: Since 2006, has your company used any of the following methods to support its innovative activities?	
q11_a	Create or participate in internet-based discussion forums
q11_b	Give away or allow free access to test products or services to potential users
q11_c	Involve potential users in your in-house innovation activities
q11_d	Share or exchange your intellectual property
Q12: Since 2006, has your company developed any strategic relationships in support of your innovation activities with…?	
q12_a	…some specific customers or clients
q12_b	…suppliers
q12_c	…other companies active in your field
q12_d	…research institutes
q12_e	…educational institutions
Q13: Since 2006, has your company targeted any of the following competences in its training or recruitment activities to support innovation?	
q13_a	Team working capacity
q13_b	Negotiation skills
q13_c	Ability of successful communication with people of other cultures
q13_d	General communication skills
q13_e	Creativity (e.g. problem-solving, originality of thought)

Appendix B The indicators from Innobarometer 2016 used in this study.

Here are the questions and corresponding indicators listed which are used to make the constructs of the IB16 based model in this study.

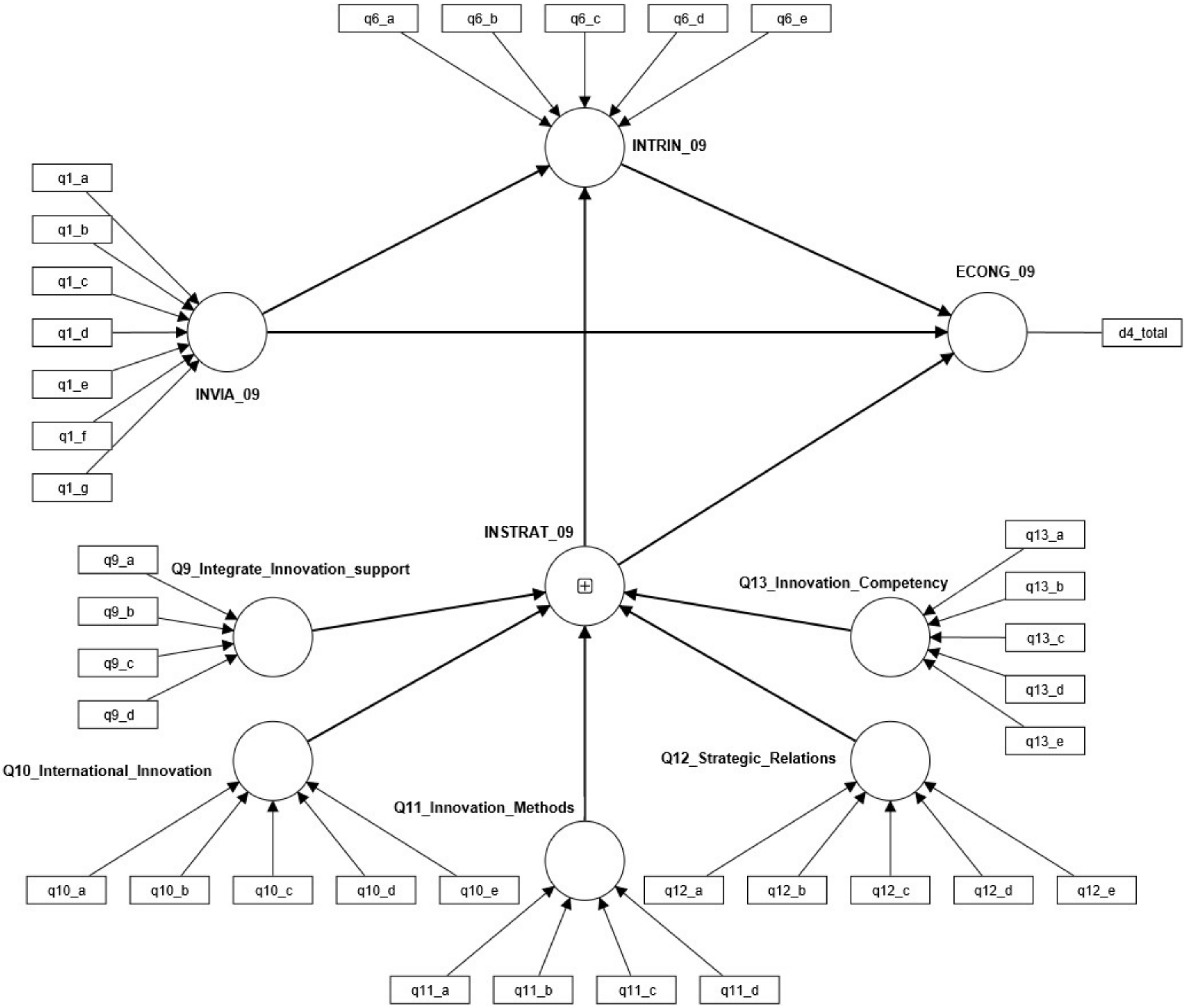
ECONG_16: A firm's economic growth	
D6: Since January 2013 has your company's revenue … ?	
d6_1	Risen by more than 25%
d6_2	Risen by between 5% and 25%
d6_3	Remained approximately the same
d6_4	Fallen by between 5% and 25%
d6_5	Fallen by more than 25%

INVIA_16: A firm's investment in intangible assets Q4: Since January 2013, what percentage of its total revenue has your company invested in each of the following activities? Alternatives: 0%, 0.5%, 3%, or 8%	
q4_1	Training
q4_2	Software development
q4_3	Company reputation and branding, including web design
q4_4	Research and development (R&D)
q4_5	Design of products and services
q4_6	Organization or business process improvements
q4_7	Acquisition of machines, equipment, software or licenses

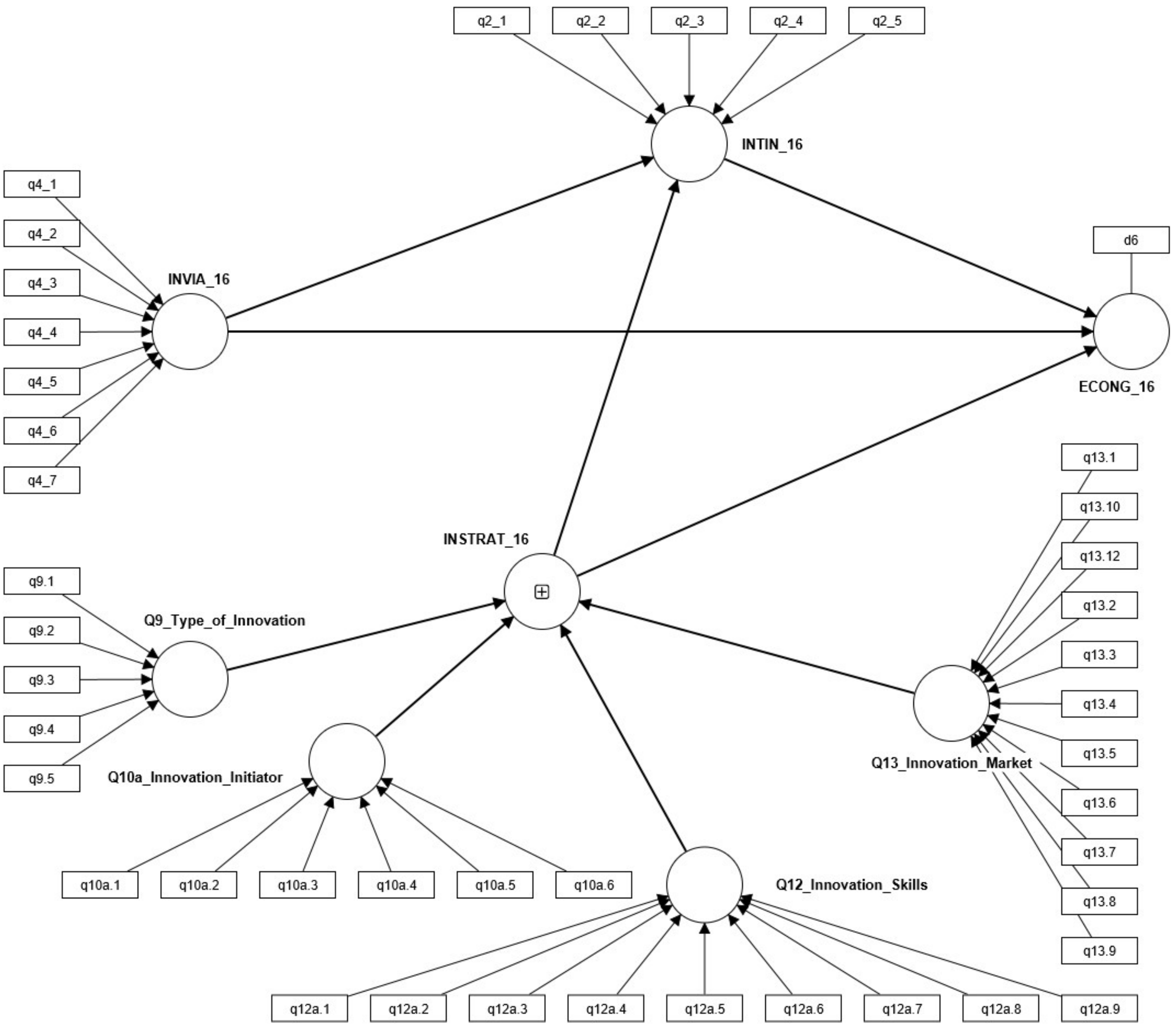
INTRIN_16: A firm's introduction of new innovations Q2: Has your company introduced any of the following innovations since January 2013?	
q6_a	New or significantly improved goods
q6_b	New or significantly improved services
q6_c	New or significantly improved processes (e.g. production processes or distribution methods)
q6_d	New or significantly improved marketing strategies (e.g. packaging, product promotion or placement, or pricing strategies)
q6_e	New or significantly improved organizational methods

INSTRAT_16: A firm's innovation strategy	
Q9: What will be the focus of your planned investment in innovation in the next 12 months?	
q9_1	Goods
q9_2	Services
q9_3	Processes (e.g. production processes or distribution methods)
q9_4	Marketing strategies (e.g. packaging, product promotion or placement or pricing strategies)
q9_5	Organizational methods
Q10a: What are the 2 main reasons why your company decided to invest in innovation in the next 12 months?	
q10a_1	Market potential
q10a_2	Customer request
q10a_3	Increased competition
q10a_4	Supplier offering a new feature or business solution
q10a_5	New legal or administrative requirements coming into force in the coming years
q10a_6	Other
Q12=Q12A+Q12B: Which two of the following skills could help improve/kick-start and support your company's innovation activities over the next two years?	
q12_1	Technical skills needed in your sector
q12_2	Engineering skills
q12_3	Organizational and leadership skills
q12_4	Skills linked to IT and the digital economy
q12_5	Creativity, inventiveness, experimentation
q12_6	Soft skills like flexibility, relationship building, resilience, etc.
q12_7	Marketing skills
q12_8	Financial skills relating to investment and access to finance
q12_9	Other
Q13: Thinking about your company's innovation activities 5 years from now, in which of the following areas do you think your innovations could make a positive impact?	
q13_1	Job creation
q13_2	IT and the digital economy
q13_3	Resource efficiency (e.g. more efficient use of raw materials)
q13_4	Lifelong learning and skills improvement
q13_5	Environmental protection
q13_6	Construction solutions for future smart cities
q13_7	Space applications
q13_8	Health and medical care
q13_9	Transport and transport infrastructures
q13_10	Availability and quality of food
q13_12	Other

Appendix C Full PLS-SEM model for IB09, Stage 1 of moderation by HOC



Appendix D Full PLS-SEM model for IB16, Stage 1 of moderation by HOC



Appendix E Estimates for measurement models contributing to INSTRAT

Bootstrapped PLS-SEM estimates for measurement models contributing to INSTRAT_09, as calculated from the model in Appendix C:

Constructs	Indicators	VIF	Outer Weights	95% Confidence Interval	*p* Value	Significance ($p < 0.05$)?
Q9_Integrate_Innovation_ support	q9_a	1.178	0.384	[0.337,0.431]	0.000	Yes
	q9_b	1.257	0.358	[0.309,0.404]	0.000	Yes
	q9_c	1.141	0.247	[0.201,0.293]	0.000	Yes
	q9_d	1.263	0.450	[0.401,0.499]	0.000	Yes
Q10_International_Innovation	q10_a	1.320	0.148	[0.074,0.221]	0.000	Yes
	q10_b	1.293	0.083	[0.014,0.151]	0.018	Yes
	q10_c	1.385	0.352	[0.276,0.425]	0.000	Yes
	q10_d	1.179	0.335	[0.262,0.406]	0.000	Yes
	q10_e	1.282	0.501	[0.432,0.566]	0.000	Yes
Q11_Innovation_Methods	q11_a	1.083	0.269	[0.206,0.330]	0.000	Yes
	q11_b	1.177	0.241	[0.175,0.306]	0.000	Yes
	q11_c	1.227	0.565	[0.504,0.623]	0.000	Yes
	q11_d	1.153	0.385	[0.320,0.449]	0.000	Yes
Q12_Strategic_Relations	q12_a	1.340	0.402	[0.349,0.454]	0.000	Yes
	q12_b	1.277	0.355	[0.303,0.408]	0.000	Yes
	q12_c	1.233	0.165	[0.109,0.219]	0.000	Yes
	q12_d	1.373	0.283	[0.225,0.341]	0.000	Yes
	q12_e	1.400	0.275	[0.217,0.331]	0.000	Yes
Q13_Innovation_Competency	q13_a	1.618	0.400	[0.331,0.467]	0.000	Yes
	q13_b	1.686	0.093	[0.021,0.166]	0.012	Yes
	q13_c	1.415	0.223	[0.154,0.289]	0.000	Yes
	q13_d	1.926	0.196	[0.122,0.270]	0.000	Yes
	q13_e	1.701	0.372	[0.302,0.439]	0.000	Yes

PLS-SEM estimates for measurement models contributing to INSTRAT_16, as calculated from the model in Appendix D:

Constructs	Indicators	VIF	Outer Weights	95% Confidence Interval	*p* Value	Significance (p < 0.05)?
Q9_Type_of_Innovation	q9.1	1.000	0.241	[0.096,0.355]	0.000	Yes
	q9.2	1.006	0.412	[0.314,0.499]	0.000	Yes
	q9.3	1.025	0.485	[0.368,0.580]	0.000	Yes
	q9.4	1.006	0.623	[0.495,0.750]	0.000	Yes
	q9.5	1.028	0.332	[0.244,0.416]	0.000	Yes
Q10a_Innovation_Initiator	q10a.1	1.489	1.069	[1.024,1.107]	0.000	Yes
	q10a.2	1.362	0.731	[0.658,0.792]	0.000	Yes
	q10a.3	1.435	0.837	[0.774,0.892]	0.000	Yes
	q10a.4	1.157	0.575	[0.510,0.633]	0.000	Yes
	q10a.5	1.211	0.520	[0.433,0.598]	0.000	Yes
	q10a.6	1.489	0.279	[0.207,0.348]	0.000	Yes
Q12_Innovation_Skills	q12.1	1.462	0.589	[0.459,0.683]	0.000	Yes
	q12.2	1.234	0.396	[0.262,0.497]	0.000	Yes
	q12.3	1.341	0.797	[0.699,0.872]	0.000	Yes
	q12.4	1.341	0.837	[0.741,0.906]	0.000	Yes
	q12.5	1.332	0.699	[0.601,0.769]	0.000	Yes
	q12.6	1.305	0.628	[0.531,0.698]	0.000	Yes
	q12.7	1.438	0.885	[0.769,0.981]	0.000	Yes
	q12.8	1.398	0.613	[0.520,0.685]	0.000	Yes
	q12.9	1.039	0.092	[0.021,0.168]	0.014	Yes
Q13_Innovation_Market	q13.1	1.146	0.569	[0.475,0.647]	0.000	Yes
	q13.2	1.101	0.536	[0.416,0.638]	0.000	Yes
	q13.3	1.071	0.108	[0.020,0.193]	0.014	Yes
	q13.4	1.173	0.784	[0.682,0.859]	0.000	Yes
	q13.5	1.109	0.513	[0.392,0.604]	0.000	Yes
	q13.6	1.110	0.498	[0.398,0.577]	0.000	Yes
	q13.7	1.098	0.338	[0.231,0.423]	0.000	Yes
	q13.8	1.109	0.323	[0.217,0.414]	0.000	Yes
	q13.9	1.011	0.241	[0.146,0.334]	0.000	Yes
	q13.10	1.057	0.370	[0.264,0.459]	0.000	Yes
	q13.12	1.103	0.315	[0.192,0.418]	0.000	Yes

Appendix F Bootstrap estimates for full Stage 2 models

PLS-SEM bootstrap estimates for full Stage 2 models for both IB09 and IB16.

Relationships	Path Coefficients	95% Confidence Intervals	*p* Value	Significance ($p < 0.05$)?
INVIA_09 → ECONG_09	0.073	[0.025,0.121]	0.003	Yes
INVIA_09 → INTRIN_09	0.293	[0.257,0.329]	0.000	Yes
INTRIN_09 → ECONG_09	0.055	[0.006,0.103]	0.026	Yes
INSTRAT_09 → INTRIN_09	0.431	[0.397,0.467]	0.000	Yes
INSTRAT_09 → ECONG_09	0.047	[-0.001,0.096]	0.058	No
INSTRAT_09 x (INVIA_09 → ECONG_09)	0.004	[-0.039,0.049]	0.842	No
INSTRAT_09 x (INVIA_09 → INTRIN_09)	-0.077	[-0.102,-0.052]	0.000	Yes
INSTRAT_09 x (INTRIN_09 → ECONG_09)	-0.004	[-0.051,0.042]	0.851	No
INVIA_16 → ECONG_16	0.067	[0.041,0.093]	0.000	Yes
INVIA_16 → INTRIN_16	0.361	[0.341,0.382]	0.000	Yes
INTRIN_16 → ECONG_16	0.083	[0.057,0.109]	0.000	Yes
INSTRAT_16 → INTRIN_16	0.158	[0.136,0.181]	0.000	Yes
INSTRAT_16 → ECONG_16	0.083	[0.059,0.108]	0.000	Yes
INSTRAT_16 x (INVIA_16 → ECONG_16)	0.025	[0.000,0.049]	0.043	Yes
INSTRAT_16 x (INVIA_16 → INTRIN_16)	-0.047	[-0.066,-0.029]	0.000	Yes
INSTRAT_16 x (INTRIN_16 → ECONG_16)	-0.006	[-0.031,0.020]	0.669	No