How does a firm's position in a research network affect its innovation outcome?

A multi-sectoral study of a Norwegian publicly funded research network

Joar Kvamsås

Master's thesis

TIK Centre for Technology, Innovation and Culture

UNIVERSITY OF OSLO

05.10.2018

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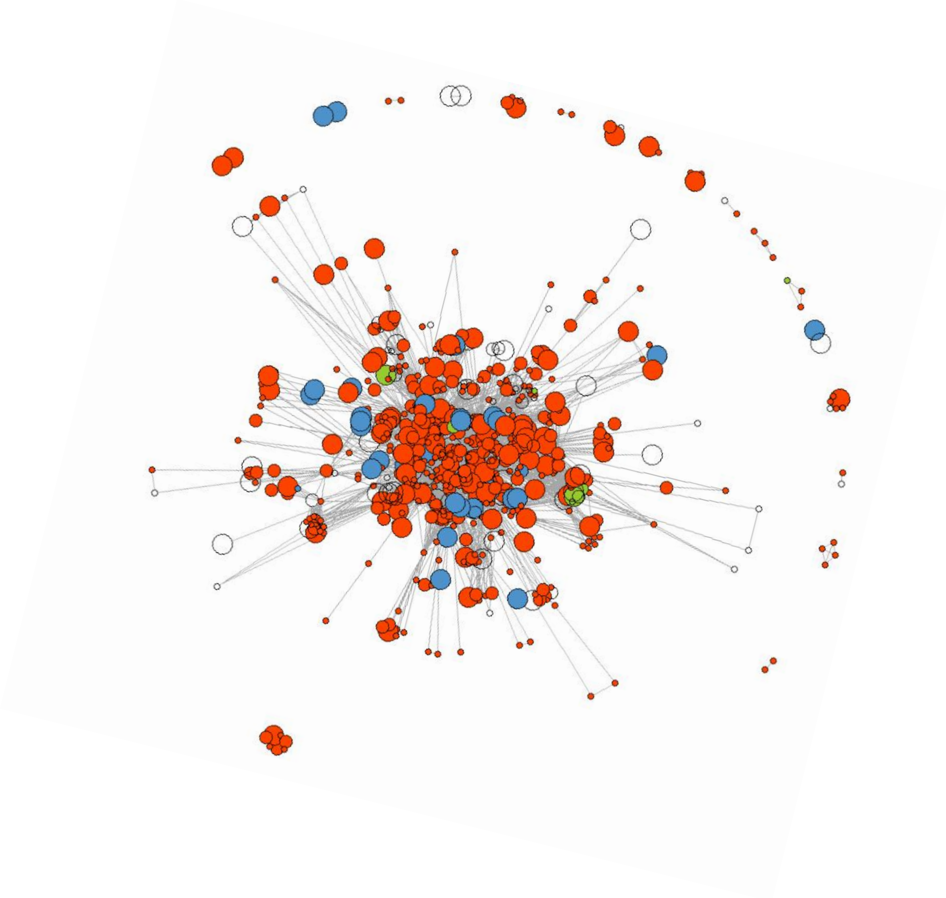

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Abstract

As interorganisational collaboration is increasingly seen as a crucial nexus of innovation by scholars and policymakers alike, it is important to investigate whether and in what way research collaboration networks affect innovation outcome. Answering the research question "How does a firm's position in a research network affect its innovation outcome?" this thesis employs a novel combination of data sources to test the innovation effects of three variables related to firm network position: Node strength, reach, and ego-network redundancy. Using a network constructed from a database of publicly funded research collaboration projects from the Research Council of Norway (RCN), the effect of network variables are tested on variables from firm-level data from the 2014 Norwegian Community Innovation Survey that indicate process and product innovation, as well as new-to-firm and new-to-market innovation.

Using the unique RCN dataset, the thesis implements a few novel methodological approaches, such as delineating sectoral network by tags denoting knowledge areas, and weighting the network ties according to project budget.

The findings indicate that while a firm's research network position has significant effects on product innovation, it does not significantly affect process innovation. Furthermore, while both node strength and reach are positively associated with innovation outcome, the effect of the former is heavily dependent upon the firm's R&D-intensity. These results are explained in light of both the network and modes of innovation literature, which both emphasise the different nature of the knowledge being created and exchanged in different innovation processes. Meanwhile, the effects of ego-network redundancy on innovation outcome are inconsistent, as a significant positive effect is found for innovation in general, but no effect can be found for new-to-market innovation. The ambiguous results are used as the basis for an exploratory reflection on how the effects of knowledge creation and diffusion may be inhibited by imitative behaviour in dense ego-networks.

Acknowledgments

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1 Introduction

1.1.1 Thesis aims

In order to boost technology development and economic growth, governments are increasingly funding collaboration activities between enterprises, universities and research institutes in order to facilitate the creation, diffusion and utilisation of scientific knowledge (Liang and Liu, 2018, Czarnitzki et al., 2007, Protogerou et al., 2013). It is therefore important to understand how government-sponsored collaboration networks influence innovation performance and to provide empirical evidence of the tangible outcomes of this public funding (Liang and Liu, 2018).

Answering the research question "How does a firm's position in a research network affect its innovation outcome?" this thesis has a twofold mission. Primarily, I use a novel combination of data sources to test established theories from the innovation network literature on how firm network position affects tangible innovation outcomes. In particular, I test hypotheses regarding the effects of direct ties, indirect ties and ego-network redundancy on innovation output, as well as the role of R&D intensity in moderating these effects. These are all factors that explain how and in which contexts research collaboration networks yield innovation outcome benefits that are greater than the sum of their parts.

Secondly, I also make use of the thesis' novel combination of data sources to explore how these network effects have different impacts on different measures of innovation outcome. The innovation outcomes studied are product and process innovation, as well as whether the innovation is new to the market or only new to the firm, each of which have different relations to how they are affected by R&D subsidies, different modes of innovation and network dynamics relating to radical and incremental innovation, as well as imitation and deviance.

While there is a growing literature that successfully establishes an empirical connection between a firm's position in innovation networks and their subsequent innovation performance, virtually all of these studies have relied on the use of citation and patent data to measure innovation output. While patent data have many advantages, such as their relative abundance and availability, they are, strictly, a measure of *invention* rather than *innovation* per se, and calls have long been made for studies of network effects on innovation outcome that do not depend on this proxy (Smith, 2005, Powell and Grodal, 2005). In this thesis, I employ a unique database of publicly funded research collaboration projects from the Research Council of Norway and combine it with data on innovation performance from the Norwegian Community Innovation Survey (CIS). In so doing, I use an entirely novel combination of data sources to investigate the association between firm position in a large and diverse research network, and innovation output as reported by the firm to the CIS.

I apply a stepwise model of logistic regressions to test the effect of network variables on the likelihood of whether firm has achieved a specific form of innovation outcome in the survey period. The results confirm previous findings of positive effects on innovation of direct ties and indirect ties, though only for product innovation. I also find that network effects on innovation outcome depend greatly on firm R&D intensity. Lastly, I find that the effects of network position on different innovation outcomes vary significantly, and discuss some potential reasons why this might be and point to potential areas for future research.

1.1.2 The innovation network literature and research gap

Collaboration between different organisations is increasingly being positioned at the core of innovation policy. In order to boost both the creation, spread and real-world application of new technology and scientific knowledge, governments are working to link firms together with knowledge-based organisations such as universities and research institutes through the funding of R&D collaboration (Autio et al., 2008, Heinze and Kuhlmann, 2008, Poirier et al., 2016). These links form growing collaboration networks that affect the way that knowledge is created and diffused through the interaction of different organisations. (Protogerou et al., 2013). For this reason, it is important to explore and understand the relationships between research networks and innovative output. In the innovation field, it is of prime interest to contribute to the understanding of how the positions and structures of complex networks affect actors' creation, absorption, and utilisation of new knowledge. This is also an important question for governments and policymakers, and the results contribute to the understanding of innovation in research networks, leading to meaningful implications for innovation policy.

The innovation network literature has primarily dealt with two aspects of collaboration networks: (1) what determines how networks are formed and develop over time? and (2) how do these structures affect innovation performance? This thesis falls within the second category, as it seeks to measure the association between firms' position in a Norwegian government-funded research network and their innovation output. Three measures of network position are examined: (1) The number and intensity of direct network ties, (2) the number of indirect ties and (3) the relative efficiency or redundancy of an actor's immediate ego network. While the first of these measures are generally thought to have a positive or inverted-U shape relationship with innovation output, the two subsequent measures have shown varying results in the literature (Ahuja, 2000, Baum et al., 2000, Schilling and Phelps, 2007, Liang and Liu, 2018).

Previous contributions to the literature on network effects of innovation have mainly used patent data to operationalise innovation output (Liang and Liu, 2018, Guan and Liu, 2016). However, patenting is more of an indicator of invention than innovation, which is an important distinction. While invention is the first occurrence of an idea for a new product or process, innovation is the first attempt to carry it out into practice (Fagerberg 2005). Some types of technology are not patentable and a substantial share of patents are never translated into commercially viable products or processes. Moreover, the use of patenting can be have purely strategic goals, such as preventing others from commercialising a technology (Smith, 2005, Kleinknecht et al., 2002). When conceptualising innovation not as the generation of new technology, but rather as the introduction of novelty into the economic sphere, the link between research collaboration networks and innovation might be less straightforward than patent-based studies would have you believe. This study contributes to filling that gap, and in it I find that while both direct ties and indirect ties positively affect innovation outcome, the effect of direct ties in particular are highly dependent upon the firm's level of R&D intensity. As for ego-network redundancy, the results are characteristically ambiguous, showing a positive effect for innovation in general, but no significant effect for new-to-market innovation.

In addition to using improved measures to test established hypotheses, I also explore how research network position affect different types of innovation outcome differently. In addition to using the established theoretical and methodological framework of the innovation network literature, I also employ the concept of modes of innovation as first introduced by Jensen et al. (2007). I use insights from the modes of innovation literature to predict and explain why certain types of innovation outcome are strongly affected by research network position, while others less so. The main argument put forward is that as the Science and Technology Innovation mode (STI) is more tightly linked to product innovation than process innovation, research network position will primarily affect product innovation, a proposition that is confirmed by the final regression results. Moreover, the network effects observed for new-to-firm and new-to-market innovation have certain patterns that reveal potentially different dynamics relating to each outcome. This includes varying results for the effects of ego-network redundancy on innovation output but also encompasses different strengths of the effects observed for the other independent variables. Rather than test explicit hypotheses on these issues, I use the results as the basis for an explorative discussion that draws upon literature relating to radical and incremental innovation, as well as network effects on product imitation and deviation. From this discussion, I conclude that distinctions between radical and incremental innovation do not appear to fit well with the results, whereas the imitation/deviation distinction might have more explanatory power, and is a potential avenue for future research.

1.1.3 Novel data source and methodological development

In this thesis, I make use of a unique dataset from the Research Council of Norway (RCN), which encompasses data on each project funded by the Research Council in the period 2005-2015, including the identity of their participants. This data is used to map the full structure of the research networks for four important sectors: oil and gas, maritime, marine and biotechnology; during a 5-year period from 2008-2013. These networks are then used to extract data on the network positions of each node in the network for this period, and these data are then matched with the Norwegian CIS of 2014.

The RCN dataset enables some methodological approaches that are uncommon in previous innovation network studies. First and foremost, by using a variable for project budgets as a proxy for tie intensity, I model a weighted network for the calculation of the network variables. Furthermore, as this dataset includes actors from all disciplines and sectors of industry found in Norway, I a combine data from different sectors in the final analysis in order to obtain results that are more generalisable than previous studies that focus on only a single sector.

The empirical basis of this thesis is a very particular kind of research network, namely one made up of partly publicly funded research projects in Norway. The Norwegian innovation system has certain peculiarities when it comes to public versus private R&D funding, and so the network effects found here are not immediately generalisable to equivalent networks in other countries – not to mention other networks constructed from patents, citations or strategic alliance data. This thesis offers useful complementary evidence to these previous studies and makes a meaningful contribution to the literature both by new empirical findings, as well as the development of novel methodological approaches in the study of innovation networks.

1.2 Empirical research context

1.2.1 The Norwegian innovation system and the Research Council of Norway

Analysing the network effects of government-funded research collaborations requires that one take into account certain peculiarities of the Norwegian innovation system. Fagerberg et al. (2009) describe in detail the historical developments and economic processes that have led to the current structures of innovation in Norway. In summary, Norway's innovation system has been a laggard in terms its formal R&D efforts, as firms across sectors have turned to local sourcing of innovation, and focused on incremental improvements to their production process rather than introducing radically different technologies and products. The relative private R&D expenditure among Norwegian firms has been far lower than what is found in other comparable European economies. Despite this, Norwegian firms enjoy a high level of productivity, part of what has been labelled by the OECD (2007) as the "Norwegian Paradox". This paradox is commonly explained by Norway being an economy reliant on natural resources, favouring frequent process innovations over radical product innovations (Fagerberg et al. 2009). According to Fagerberg et al., Norwegian firms have tended to be able to rely on the import of foreign technologies in most sectors, and only when reaching the forefront of international research (such as in the petroleum sector) have companies shifted to increase their internal R&D intensity.

In response to this perceived neglect of R&D among Norwegian companies, policymakers have prioritised increased collaboration between firms and public universities and research institutes (Thune, 2007, Gulbrandsen and Nerdrum, 2009). Much of this comes via research calls from the Research Council of Norway, which next to basic research funding for research institutions and institutions of higher education is one of the main sources of public research funding in Norway (Regjeringen.no, 2014).

Half of the Research Council's funds come from the Ministry of Education and Research and the Ministry of Trade and Industry, the former being the ministry under which the research council serves. The stated purpose of the Norwegian Research council, as found on their website, is:

The Research Council provides advice on how and in which areas to target investments in Norwegian research efforts. We have been charged with strengthening the knowledge base and encouraging research that can help to solve the Grand Challenges. The Research Council of Norway works to add value to the research system by facilitating research that actors in the system could not successfully achieve working on their own.

(Forskningsrådet, 2018)

The Research Council of Norway has been a major driver to support knowledge creation and exchange between science and industry. Fagerberg et al. (2009) note that such R&D support has been most effective at spurring radical innovation and product innovations, as is predicted by innovation theory.

1.2.2 Sectors in the Norwegian research network

This thesis samples four sectors of the Norwegian innovation system: Oil and gas, marine, maritime and biotechnology. The first three sectors have been described as the only sectors in Norway which are internationally competitive (Reve and Sasson, 2012, Simensen and Abbasiharofteh, forthcoming), and are the three industry-specific sectors that are mentioned in the public long-term plan for Norwegian research. (Regjeringen.no, 2014).

Since the 1970's, the oil and gas sector has been very important in shaping the Norwegian economy and industry structure. As well as the companies that engage in direct offshore oil extraction, the sector includes all firms that supply the sector with products and services. Over the last half-century, much of Norwegian industrial structure has moved to become either directly or indirectly involved in the sector's activities. This is reflected in the oil and gas firms' position in the Norwegian research network as a whole, as companies are connected with universities and public research institutions, as well as actors from other sectors.

A primary example of this is the Norwegian maritime sector. Norway has the second largest offshore fleet in the world, and the maritime sector is the second largest export sector in Norway after oil and gas. The maritime sector has deep roots in Norwegian industrial history, and to this day represent a stable and significant share of the Norwegian economy (Maritimt Forum, 2017). In particular, the maritime sector is relatively highly interdependent with the oil and gas industry, as it supplies offshore oil activities with vessels and solutions. Most of the growth in this sector in later years has been related to the oil and gas sector.

The marine sector in Norway encompasses all production of seafood, including both fisheries and aquaculture. The sector has experienced strong growth in recent years, accompanied by a steep increase in export value (Norwegian Seafood Council, 2017) Meanwhile, the industry’s growth, in particular that of acquaculture, has been hampered by complications and problems related to salmon lice, pollution and escape of fish stock (Hersoug, 2015). In order to find solutions to these problems, the industry has turned to broader knowledge sources such as marine ecology, nutrition science, breeding, artificial intelligence and medicine/pharmaceuticals.

Next to these major industrial sectors, medicine and health represent one of the largest research areas in the Norwegian system. However, the health sector is dominated by public actors that do not report innovation statistics in terms of product innovation. Meanwhile, the sector of biotechnology is highly connected to the health sector and is characterised by a large amount of small and innovative start-ups (Forskningsrådet 2018). When it comes to industry, the biotechnology sector has strong links to the aquaculture industry, particularly the health and environmental issues connected to salmon farming (Forskningsrådet, 2016).

While the biotech sector cannot be characterised as a particularly significant part of the Norwegian economy, it does receive extensive research funding and its number of actors in the RCN research network rivals those of both the petroleum and maritime sectors. Biotechnology is also a sector that is often the object of study in innovation network research (Owen-Smith and Powell, 2004, Liebeskind et al., 1996, Shan et al., 1994), as it is highly dependent upon formal and R&D linkages between universities, hospitals, and industry actors.

Together, this is a collection of sectors that are central to the Norwegian economy and innovation system, and that are prominent in the collaboration network made up of publicly funded research (Simensen and Abbasiharofteh, forthcoming). The sectors are large and diverse both in terms of their actors and knowledge areas, while also being interconnected with each other to various degrees. In a multi-sectoral analysis such as this one, these sectors represent a wide and heterogeneous sample of actors and knowledge areas that are central to the Norwegian economy and to the Norwegian innovation system.

1.3 Thesis structure

This thesis is divided into chapters that cover the thesis' theoretical framework, data, and methodology, empirical results, discussion of findings and a final conclusion.

Chapter 2: Theoretical framework has four sections. The first section outlines the general theories that relate to how innovation is spurred by new knowledge, and how collaboration between actors can lead to innovation through increased knowledge heterogeneity and the combinatorial potentials that arise from the merging of internal and external knowledge. It further goes on to discuss how a firm's characteristics moderates its ability to absorb and make use of external knowledge, and how this in turn affects innovation outcome. The second section focuses on the role of R&D in the innovation process, in order to explain what kind of innovation outcome effects one would expect to see from a firm's position in a research network. This section outlines theories behind different modes of innovation, and uses this to explain why position in a research collaboration network will affect certain types of innovation outcomes rather than others. In particular, it argues that research network activities will affect product innovations over process innovations, due to the mode of innovation and knowledge types that are involved in research collaborations. It further argues that these effects are strengthened by the public funding that forms the basis for the research projects that make up the network. The third section outlines the main strands of the network literature and presents relevant theories and recent findings that form the basis for the hypotheses related to how network position affects innovation outcomes. It focuses on three aspects of network position that are prominent in the literature: Direct ties, indirect ties, and the redundancy among ties. The fourth section summarises and synthesises the main arguments derived from the literature, and presents the hypotheses to be tested in the empirical analysis.

Chapter 3: Methodology and data has three sections. The first section describes the empirical data sources used to test the hypotheses, and discusses the possibilities and constraints that these data present for the analysis. It also provides a detailed description of the gathering, matching and cleaning of the data, and gives insight into the theoretical, methodological and pragmatic considerations that shaped this process. The second section describes each variable that is included in the analysis, and gives detailed theoretical and methodological justifications for their operationalisation. The third and final section describes the statistical model employed, and provides theoretical and methodological justifications for the model selection and specifications.

Chapter 4: Results has three sections. The first presents the descriptive statistics, as well as the tests performed to ensure that the regression results are not compromised by issues such as high collinearity between independent variables. The second section presents graphic visualisations of the four sectoral networks, and discusses whether sectoral differences can affect the final results. The third section presents the full stepwise regression results for product innovation, new-to-market product innovation, process innovation and new-to-market process innovation. It compares the goodness of fit between the models estimated, and discusses the robustness of findings across models.

Chapter 5: Discussion has two sections. The first deals with the hypotheses laid out in chapter 2.4 and discusses whether and in which contexts each hypothesis is confirmed by the results. This section focuses mainly on the results regarding product innovation, since as described in chapter 2.2, these are seen as the most relevant variables to test the hypotheses. The second section is an explorative discussion that compares the results for all four dependent variables, pointing to potential interpretations and possibilities for further research. This section considers whether the observed results fit well within an explanatory framework of radical/incremental innovation and suggests that a less commonly applied framework of creativity and imitation in networks could beneficially be applied to understand the regression outcomes.

Chapter 6: Conclusion has two sections. The first summarises the extent to which the thesis has achieved its theoretical, empirical and methodological goals. It argues that both the testing of the hypotheses and the exploratory discussion of the different results make meaningful contributions to the literature, before pointing to some methodological developments that can be extended further. The second section outlines the limitations of the thesis, and suggests how the data and methodology and the insights gained from the thesis can be applied in future research.

2 Theoretical framework

While the focus on networks and their importance to the creation of new knowledge goes far back in the innovation literature (Merton, 1957, Granovetter, 1985), it is only in the last decades that its popularity has surged. The development of methods and tools for social network analysis (SNA) and the increasing availability of large and complex data sets has led to an increasing amount of quantitative empirical studies of innovation in interorganisational networks. In addition to looking at how innovation networks form (Boschma and Frenken, 2010) and how network positioning can be utilized in business strategy (Ritter et al., 2004), there is also a growing strand of the literature focusing on how interorgansational networks contribute to innovation by enabling the creation and transfer of new knowledge. These studies examine networks of collaboration created by inter-firm technological alliances (Hagedoorn and Schakenraad, 1994, Reuer et al., 2002), or firms collaborating with heterogeneous actors such as universities, research institutes and government agencies (Baum et al., 2000, Faems et al., 2005).

The main topic of interest in these studies is how network positions connect organisations to external knowledge sources, and how this affects innovation outcomes and performance. This includes how knowledge flows changes with the level of connectedness in the network, as well as how the heterogeneity of the knowledge flows are affected by whether firms occupy positions that bridge structural holes in the network (Burt, 1992, Ahuja, 2000). Furthermore, there are debates about whether the knowledge governance of firms is influenced by network structures that have the potential to increase the risk of unintended knowledge spillovers and free-riding (Ahuja, 2000, Vanhaverbeke et al., 2012).

Recent studies on the network effects on innovation outcome indicate that occupying a central position in the network generally has a positive effect on innovation outcomes (Liang and Liu, 2018, Guan and Liu, 2016, McKelvey and Rake, 2016, Mazzola et al., 2015, Wang and Wang, 2012), while results regarding the innovation effects of bridging structural holes are far more mixed (Mazzola et al., 2015, Helena Chiu and Lee, 2012, Guan and Liu, 2016). Meanwhile, the vast majority of these studies use either patent or citation data in order to measure network effects on innovation. The use of patent data as a measure of innovation has many problematic aspects, and more studies that can tie network structures to other innovation indicators have been requested (Smith, 2005, Powell and Grodal, 2005). While there are some studies that have used small-scale surveys and structured interviews to measure network position and innovation outcome (Salman and Saives, 2005, Helena Chiu and Lee, 2012, Dolfsma and van der Eijk, 2017), there are to my knowledge no previous studies that have linked a complete cross-sectoral database on a research network to a large-scale national survey that measures innovation output.

This unique empirical material provides a new setting to test reigning theories on how network structure is tied to innovation. This work centers on Ahuja's (2000) three main network position characteristics that affect innovation outcome: direct ties, indirect ties, and redundancy among ties. The data enables new means by which to examine central concepts, such as measuring the influence of direct ties in terms of node strength rather than degree centrality by using a weighted network. The micro-data from the survey material also enable the analysis to control for variables such as size and R&D-intensity, as well as providing an avenue to examine how R&D-intensity affects absorptive capacity and thus moderates the effects of network position on innovation outcome. Furthermore, the survey data includes several indicators of innovation output, and so enables an exploration of how network position affect different kinds of innovation outcome.

In order to measure how network position affects innovation outcome, it is important to understand how the type of network studied affects the kind of innovation outcomes that will likely be most affected. Specifically, the object of study is a network consisting of publicly funded collaborative research projects. According to Jensen et al. (2007) such research projects belong to the mode of innovation "STI", which is characterised by highly complex and codified scientific knowledge. Previous studies have found that this type of innovation is more associated with product innovation than process innovation (Apanasovich, 2016, Parrilli and Elola, 2012). Also, as the network consists of projects that are partially or fully funded by public money, the effects that this aspect has on how position in such a network affects innovation is a question worth investigating. The essence of the argument put forward is that the public funding of the projects mitigates issues of cost, risk and free-rider problems that can impact the effect of network position on innovation outcome.

2.1 Knowledge creation, transfer and absorption

2.1.1 Knowledge diversity and innovation

The idea that collaboration is a vital component of the innovation process stems from the Schumpeterean view that innovation arises from a diversity of knowledge. According to Schumpeter (1939), innovations occur when novel combinations emerge from a 'variety in cognition', such variety being a requisite for firms to break away from dominant designs and path-dependence. In addition to the R&D work committed to extending a firm's knowledge stock, novel combinations can be spurred by accessing new and external sources of knowledge (March, 1991). This idea is also central to Nelson and Winter's (1982) evolutionary theory of economic change, in which firm's knowledge base is broadened by accessing heterogeneous sources of knowledge (Nooteboom, 2000), allowing firms to generate the diversity that is necessary for the evolutionary "diversity/selection"-model of technological development and economic growth. Whether or not one adheres to Nelson and Winter's premise of an evolutionary model of economic growth, there is a general consensus in the literature that innovation is, in some form or other, an outcome of new knowledge (Cohen and Levinthal, 1990, Trippl et al., 2009).

One way that a firm can generate new knowledge is by a process of internal knowledge creation, wherein the organization draws on the skills, knowledge and experiences of their employees. This process of increasing the existing knowledge stock by creating, processing and disseminating knowledge within the firm boundaries is what defines the firm's internal knowledge capability (Bierly and Chakrabarti, 1996, Bontis et al., 2002, Danneels and Kleinschmidt, 2001). This capability can then be combined with, complemented by and even enhanced by external sources of knowledge. One such external knowledge source are other organisations that firms interact with, for example through research collaboration.

2.1.2 Knowledge sourcing

Historically, firms organised their knowledge acquisition by relying on in-house R&D departments, and turned to external contract research only for relatively simple products or other functions (Mowery, 1983, Nelson, 1990). This has changed, however, as knowledge processes have become increasingly complex (Becker and Dietz, 2004). Firms will increasingly do external searches for skills and knowledge that add to and complement their own capabilities. Effective innovation is less and less reliant on internal R&D efforts working in isolation, and instead favours a more open innovation model, along the lines of Chesbrough (2003), (Laursen and Salter, 2006).

In Chesbrough's open innovation model, innovation is a product of combining ideas from internal and external sources. By engaging in collaborative activities or alliances, firms find themselves having denser knowledge flows than firms that operate in isolation (Gomes (Gomes-Casseres et al., 2006). By engaging in this intensive knowledge exchange, firms are able to combine complementary assets and achieve economies of scale and scope, cost sharing and risk spreading (Ahuja, 2000, Cassiman and Veugelers, 2002, Hagedoorn, 2002), the latter being of particular importance considering the great risks that are involved in innovative ventures. In addition to risk sharing and pooling of complementary skills, firms are also increasingly collaborating in order to access new markets and technologies, as well as speeding products to market (Kogut, 1989, Kleinknecht and Reijnen, 1992, Hagedoorn, 1993, Mowery and Teece, 1993, Eisenhardt and Schoonhoven, 1996).

2.1.3 Absorptive capacity

The ability to successfully transfer and retain new knowledge from external sources is most commonly referred to as 'absorptive capacity', defined by Cohen and Levinthal (1990, p.218) as the 'ability of a firm to recognise the value of new external information, assimilate it and apply it to commercial ends.' Cohen and Levinthal (1989, 1990) emphasise the importance of a firm's existing R&D efforts to this capability, claiming that prior knowledge and R&D expenditure interact with a firm's interdependence on other actors. Rosenberg (1990, p. 171) also focuses on this point, writing: "it requires a substantial research capability to understand, interpret and to appraise knowledge that has been placed upon the shelf – whether basic or applied."

Elaborating upon Cohen and Levinthal's ideas, Escribano et al. (2009) outline how a firm's absorptive capacity depends on its existing stock of knowledge, which by and large is embedded in its products, its processes, and its employees and managers. Particularly the last two of these elements have gained a lot of traction in the literature on absorptive capacity. Olmos-Peñuela et al. (2017) emphasise how a firm's potential innovation gains from a diverse set of collaboration partners are determined by its R&D human capital, defined as the knowledge, skills and abilities residing in and used by individuals (Subramaniam and Youndt, 2005). According to human capital theory, such skills and abilities can be built through both education and experience (Becker, 1964), and a better educated and trained staff will have a higher ability to apply and integrate the knowledge that is coming in from external sources (Spithoven and Teirlinck, 2010, Caloghirou et al., 2003). Teixeira and Tavares-Lehmann (2014) emphasise that innovation strategies that rely on the open sourcing of knowledge require high levels of human capital. Rothwell and Dodgson (1991) further claim that the human capital aspect of a firm's internal knowledge capabilities is particularly important when it comes to integrating and applying scientific knowledge.

However, the manner in which absorptive capacity has come to be treated in the innovation literature has drawn some recent criticism. Forés and Camisón (2016) lament the way in which studies tend to characterise absorptive capacity as a one-dimensional construct, such as by operationalising it using R&D variables or simple proxies. They claim that this moves the study of absorptive capacity away from Cohen and Levinthal's original multidimensional construct. Indeed, Cohen and Levinthal (1990) did make distinctions such as "inward-looking" and "outward-looking" absorptive capacities, claiming there was a trade-off between "the efficiency of internal communication against the ability of the subunit to assimilate and exploit information originating from other subunits or the environment". Zahra and George (2002, p. 185) further build upon these ideas as they reconceptualise the construct into "potential" and "realised" absorptive capacities, wherein "potential capacity comprises knowledge acquisition and assimilation capabilities, and realised capacity centers on knowledge transformation and exploitation". They further develop a multi-dimensional construct that outlines a series of conditions under which potential and realised capacities sustains a firm's competitive advantage. Lane 's (2006) critical review of the absorptive capacity concept again underscores the need to treat absorptive capacity as a multi-dimensional concept.

When attempting to measure the effects of research network position on innovation outcome, it is most likely not advantageous to apply as highly complex a conceptualisation of absorptive capacity as might be appropriate within the innovation management literature. This would present problems not only with the practicalities of operationaling the many dimensions of absorptive capacity, but would also make for a final model that would be overly complex; for example, Forés and Camisón (2016) operate with a total of six different dimensions measuring absorptive capacity, derived from a factor analysis of 19 different survey items. However, the debate around the uni-dimensionality versus multi-dimensionality of absorptive capacity can inform how a one-dimensional conceptualisation of absorptive capacity's effect should be hypothesised to interact with network effects, as well as how it should operationalised and interpreted. The most important takeaway is that the interpreter of an R&D-based conceptualisation of absorptive capacity should be mindful of its failure to take into account potentially important managerial dimensions that could affect absorptive capacity.

2.2 R&D and innovation outcome

2.2.1 Modes of innovation

In their seminal work on innovation modes, Jensen et al. (2007) introduced the concepts of Science and technology-based innovation (STI), and the doing-using-interacting mode of innovation (DUI). Jensen et al. (2007) strove to combine two rivalling approaches in the study of national systems of innovation. The first was the traditional approach based on the linear model of innovation, which focuses on formal processes of R&D that produce explicit and codified knowledge, the science-based R&D laboratory being the main engine of innovation. The second approach, developed by scholars such as Freeman (1987), Kline and Rosenberg (1986), and Lundvall (1988), was based on a more complex model of the innovation process which emphasises the importance of the learning that occurs through interaction between and within organisations that can often be informal and include many tacit elements.

According to Jensen et al., these two approaches characterise two complementary modes of innovation, which both serve different functions in the innovation process. STI deals with the creation of highly global, codified knowledge of the know-what and know-why varieties. Meanwhile, DUI is more dependent upon forms of knowledge like know-how and know-who, which are characterised as tacit, local, and embedded in social bonds and experience.

This knowledge classification is based on a taxonomy of Lundvall and Johnson (1994), wherein know-what and know-why refer to the knowledge of facts and the general relationships derived from natural or social science. These are said to be ‘codified’, which is to say they can be articulated and written down. Know-how refers to the knowledge of skills, which can be difficult to codify and is therefore more silent, or *tacit*. Know-who is the type of knowledge that is embedded within close social bonds, including knowledge about who knows what and who can do what, a crucial form of knowledge for innovation at the strategic level. Because of its social dimension, know-who is difficult to codify and so falls within the more tacit category.

The activities and effects of a research network fall comfortably within the STI mode of innovation. The STI mode is mainly based on R&D, is dependent on a high level of human capital and can be enhanced through research collaborations (Apanasovich, 2016). Common partners for STI-mode collaboration include external researchers, universities and research organisations (Isaksen and Karlsen, 2012, Jensen et al., 2007, Parrilli and Elola, 2012, Fitjar and Rodríguez-Pose, 2013). DUI, on the other hand, relies more on practical problem solving based on experience, which requires proximity, frequency of interactions and often hands-on applications (Lundvall, 1988, Nonaka and Takeuchi, 1995). DUI is spurred by cooperation with customers, suppliers, distributors and competitors (Apanasovich, 2016) and is seen as more “user-driven”, as it tends to support the development of new products and services in compliance with the needs of the market (Isaksen and Nilsson, 2013). Whereas STI innovation is more prominent in science-intensive industries, DUI is more dominant in traditional manufacturing.

Although R&D activities are dominated by STI-mode innovation, Jensen et al. (2007) make sure to point out that know-how, know-who and tacit knowledge still make up an important part of firms’ R&D process. Johnson et al. (2002) emphasise the interdependence of tacit and explicit knowledge, pointing out that even knowledge within domains that are considered highly “codifiable” may only partly actually be so. As they illustratively state: “there will always remain irreducible differences between the skills of a heart surgeon and the code-book she uses” (p.251). This is important to keep in mind when looking at centralities within a research network, as tacit knowledge, direct interaction and social bonds will have an impact on how network structures affect innovation.

It is, however, important to note that research collaborations are precisely the kind of social and institutional context where there is a definite push to *make* otherwise tacit knowledge explicit. For example, common practices such as publishing, licensing and patenting disembodies knowledge and eases its transfer. As knowledge from research collaborations is often made with the explicit intention that it travel within or between organisations, great efforts are made to appeal to knowledge that is global, as well as making local knowledge (for example embodied in specific scientists or equipment) global by codifying it. However, Jensen et al. (2007) make a point of emphasising that while such knowledge can more easily travel, it is not automatically absorbed. Scientific texts only make sense to scientists – a prime example of how even the most codified of know-what and know-why can be locally embodied in people. This contributes to the importance of the role that R&D intensity and R&D human capital play for absorptive capacity when it comes to scientific knowledge.

2.2.2 STI, product innovation and process innovation

In its investigation of how network position affect innovation outcome, this thesis takes advantage of the different indicators for innovation outcome to test network effects on both product and process innovation. However, due to the network being made up of research collaboration projects, network position is expected primarily to affect firms' product innovation. This is based on previous findings from the literature on modes of innovation, which finds that a firm's STI efforts tends to have more of an impact on product innovation than process innovation.

Product innovation can be defined as a firm's introduction of a new or markedly improved product, while process innovation is defined as the introduction of new or improved methods to a firm's production processes, service operations or distribution models (Reichstein and Salter, 2006, Un and Asakawa, 2015). STI and DUI affect product and process innovations differently, in large part due to the different roles that radical and incremental innovation plays to each type of innovation outcome. The distinction between incremental and radical innovation stems from the literature on the product cycle and dominant designs elaborated by Abernathy and Utterback (1975, 1978). Utterback and Suárez (1993) define radical innovation as innovation that either introduces new core technologies, or that integrates core technologies in new ways resulting in a product with different capabilities.[1] Once certain designs and

[1] This latter form of innovation is referred to by Henderson and Clark (1990) as "architectural innovation" in their more complex four-part taxonomy of innovation types. While Henderson

technologies gain dominance, producers specialise in optimising the product and production process.

Whereas product innovation tends to involve more radical change, relying on the introduction and recombination of designs and technologies, process innovation is usually characterised by incremental improvements in operational efficiency that provide increased capacity and flexibility, and decreases labour, capital and other costs by rationalizing the production process (Hervas-Oliver et al., 2014, Stadler, 2011). As opposed to the more radical product innovation, process innovation tends to some degree to be the result of incremental innovation that makes processes more efficient, rather than fundamentally changed (Stadler, 2011, Un and Asakawa, 2015).

In her overview of the literature on the effects of STI and DUI, Apanasovich (2016) finds that while results are somewhat mixed, there are certain trends that seem to confirm that product and process innovation are differently affected by STI and DUI. While a series of studies find that innovation in general is best enhanced by a combination of STI and DUI modes (Apanasovich, 2014, González-Pernía et al., 2015, Isaksen and Karlsen, 2012, Isaksen and Nilsson, 2013), there are also several studies that find that STI mode is more closely associated with product innovation (Parrilli and Elola, 2012, Gonzalez-Pernia et al., 2013), as well as some that find the DUI mode more closely associated with process and organisational innovation (Gonzalez-Pernia et al., 2013, González-Pernía et al., 2015, Apanasovich, 2014).

These findings show that while innovation as a whole depends on a combination of STI and DUI, one should expect STI mode innovation to plays a more central role in producing product innovations than process innovations. When testing hypotheses related to how different research network properties affect innovation outcomes, it is therefore natural to focus on product innovation, as this is where the effect will primarily be. The other measures enable a comparison between network effects on product and process innovation as well as new-to-firm

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and Clark's more complex conceptualisation can be advantageous in certain research setting, the incremental-radical dichotomy is both more intuitive and easier to operationalise, and seems to have gained standard use in quantitative studies of innovation outcomes, including this one.

and new-to-market innovation, which enables an explorative discussion of the potential network dynamics that could be causing differences in outcome.

2.2.3 Subsidised research and innovation outcome

The focus on product innovations is also supported by the fact that the links in the research network in question is made up of research programs that are partly or fully publicly funded. According to the underlying economic rationale behind R&D subsidies, the difficulties of capturing the full profits of R&D processes that are both costly and risk-laden cause firms to invest in R&D below what is socially optimal (Nelson, 1959, Arrow, 1962, Bloom et al., 2010). Public policies are designed to correct for this market failure by reducing R&D costs. Greater investment requirements and uncertainties lead to greater market failure, and thus a greater potential for R&D subsidies to affect innovation outcome.

Product innovation creates market uncertainties and investment requirements that firms seek to reduce with the help of their partners (Sainio et al., 2012, Ritala, 2012). The uncertainties bring ambiguity and ambivalence, generating high tensions between collaboration partners (Raza-Ullah et al., 2014). Subsidising collaborations can therefore be expected to have the greatest effect on the output of innovation that brings with it the highest levels of uncertainty. Introducing new products to market or radically transforming technologies will in general bring more uncertainties than creating incremental process or product improvements to products with established markets. It is therefore likely that the more STI-driven radical innovation and product innovation will be more greatly affected by a firm's position in a publicly funded R&D network, which is supported by the findings of Beck et al. (2016) and Sakikaba (2001), who both link R&D subsidies primarily to product innovation.

2.3 Network effects

In Granovetter's (1973) seminal contribution to social network analysis, he focused on the nature of the ties that an actor had to others, ranging them on a scale from strong to weak. Granovetter's concept of strength had many dimensions, being a function of the amount of time, emotional intensity, intimacy and reciprocity within a relationship between network actors.

Granovetter used the distinction between strong and weak ties to infer a series of attributes about the actors involved and the structure of their immediate local networks, or *ego networks*. His main argument was that weak ties are more likely to connect actors from different social circles or local networks, and as such would be more valuable for bringing in relevant new information. He thus connected the strength of ties to information flow by claiming that a preponderance of strong ties was an indicator of tie redundancy (Granovetter, 1973, Burt, 1992). Granovetter posited that a weak tie between two companies is an indicator that the companies in question are more likely to be distant to each other, and as such dissimilar in terms of their information, perspectives, activities and problem-solving styles (Granovetter, 1982, Ruef, 2002).

Granovetter's ideas have been highly influential to both the innovation and social network literatures, and many tools have since been developed within SNA to measure network centralities, network efficiencies and structural holes. The social network analyses that focus on innovation at the firm-level have tended to focus on two general aspects of network positions, operationalised in a few different ways. The first aspect is an actor's overall connectedness in terms of its direct or indirect ties, and the second is to what extent the actor bridges structural holes in the network. Direct and indirect ties are focused upon because they are assumed to indicate the volume of different knowledge flows and resources that the focal node has access to. Bridging structural holes is important as it says something about the heterogeneity of the knowledge sources that the focal node has access to through the network. This study follows the line of Ahuja (2000) as well as some more recent papers (Guan and Liu, 2016, Liang and Liu, 2018) and looks at direct ties and indirect ties as indicators of general connectedness, and the level of ego-network redundancy to look at the effect of structural holes.

Network centralities and the bridging of structural holes can be operationalised using a set of different network measures. However, rather than being mere practical operationalisations of well-established theoretical properties, these network measures in themselves embody conceptualisations about the nature of the properties they measure. The following discussion therefore includes discussions of different network measures and why they are used, insofar as they are integral to the hypotheses put forward. This makes the conceptual framework more thorough while leaving it to the methodology chapter to specify more precisely how these different measures are calculated.

2.3.1 Direct ties

The first measure of interest when studying network structure effects on innovation is the number of direct ties an actor has, as well as the intensity these ties have. In SNA terminology, the number of ties of the focal actor is known as its degree centrality. Earlier uses of social network analysis to assess network effects on innovation outcome often utilize degree centrality, i.e. the measure that counts the number of a node's direct ties. This includes Ahuja (2000), Stuart (2000), Rothaermel and Deeds (2004) and Salman and Saives (2005), who all find generally positive relationships between degree centrality and various measures of innovation outcomes.

Ahuja (2000) is one of many authors (Porter, 1990, Prahalad and Hamel, 1994, Grabher, 1993, Hagedoorn, 1993, Hagedoorn and Schakenraad, 1994, Ring and Van De Ven, 1994, Grandori, 1997, Lambe and Spekman, 1997, Uzzi, 1997, Nooteboom, 2000, Nooteboom, 1999, Rowley et al., 2000) who all emphasise how actors can increase the innovation yield of their own knowledge stock by combining and integrating it with complementary knowledge and capabilities from a heterogeneous set of collaboration partners. Direct ties in a research network can provide access to other organisations' knowledge elements, and foster innovation by exploiting the recombinatoral potential of heterogeneous knowledge stocks (Wang et al., 2014a). In addition to speeding up a firm's innovation process, access to complementary knowledge and skills can enable firms to better evaluate the quality and relevance of their internally developed expertise (Dyer and Nobeoka, 2000, Powell and Brantley, 1992). As Ahuja (2000) emphasises, direct ties can also spur innovation because they allow firms to share the risk and costs of innovation. Meanwhile, as the knowledge created is a nonrivalrous good, each party involved can make full use of its yield.

As the network in this study is a publicly funded research network, this cost and risk sharing comes in addition to the cost alleviation provided by the public funding in the first place, making direct ties in this network particularly effective in boosting innovation processes that are marred by uncertainty. In addition, in a research network, direct ties are sites with high potential for STI learning. It is a nexus in which high amounts of codified know-what and know-why can be exchanged, in conjunction with the types of sophisticated tacit know-how that is generated and transferred when scientists and other highly competent practitioners collaborate to reach common goals. Vanhaverbeke et al. (2012) emphasise how the access and/or joint development of specific, fine-grained knowledge allows firms to improve their core technologies, as the close interaction allow little room for noise, distortion or misinterpretation of information.

In addition to the avenues by which network ties can enhance a firm's knowledge stock, Vanhaverbeke et al. (2012) also point out that a firm's position in a collaboration network will also have implications for their need to govern their knowledge. Fundamentally, as firms' knowledge stock in knowledge-intensive sectors are important to their competitive advantage, the unintended knowledge spillovers that a collaboration network enables could potentially damage this competitive advantage and disincentivise knowledge creation due to free-rider problems. However, in the case of direct ties, this is not seen as a major issue, as direct partnerships allow strong, trust-based relationships to develop (Bstieler, 2006, Rowley et al., 2000). The direct links allow for a strict control of knowledge flows, and limits the room for freeridership (Dhanaraj and Parkhe, 2006), for example by having firms collaborate with universities or suppliers rather than direct competitors in projects involving sensitive technologies.

It is, however, worth noting that while more intense research collaboration will generally yield higher innovation output, there are also several theories that indicate that too many collaboration partners might be detrimental to a firm's innovation performance. Ahuja and Katila (2004) claim that if a firm has many unfamiliar knowledge streams, they will become increasingly difficult to manage. propose that the combinatorial potential of any knowledge element has an upper limit, the implication being that there are decreasing marginal returns to forming new collaboration ties. Deeds and Hill (1996) show that a firm's effectiveness in managing collaboration will decline with the number of their alliances, while Duysters and De Man (2003) go so far as to claim there can be diseconomies of scale to direct ties, as management attention and integration costs may grow exponentially with an increase in collaboration ties. Recent studies have shown degree centrality to have either a positive effect (Mazzola et al., 2015, Wong and Boh, 2014, Dolfsma and van der Eijk, 2017) or an inverted U-shaped effect (Guan and Liu, 2016, Liang and Liu, 2018) on innovation outcome.

While many studies investigating network effects on innovation outcome have used the strength of ties as independent variables in line with Granovetter (Ruef, 2002, Capaldo, 2007), few studies have looked at the intensity of ties by using a weighted social network. While the dominant use of simple rather than weighted degree centrality is partly due to it indicating combinatorial potential via the number of different sources of external knowledge, the prominent use of simple degree stems in large part from the fact that most previous studies have relied on count data, such as number of co-published papers or patents. Meanwhile, the RCN dataset used in this thesis enables one to weigh tie intensity by the budget of research projects. Instead of measuring degree centrality, direct ties can be measured by weighted degree centrality, also known as node strength. [2] I would argue that despite it being unconventional, using node strength would be a better way to conceptualise the role that direct ties play in the innovation process.

Focusing on combined direct tie strength does obscure the exact number of different collaboration partners a firm has, and one could argue that this limits the indicator's ability to gauge the diversity of information coming into the firm. However, measuring degree centrality, wherein all connections count as equal, would inflate the importance of rather trivial connections, and fail to reflect the cumulative benefits of intense and persistent research collaboration. Seeing as this is a research network, and as such characterised by the creation and exchange of complex scientific knowledge, the combined amount of resources that direct ties encompass should be a better indicator of the amount and value of external knowledge flowing into a firm than the mere number of direct ties.

Furthermore, a strong argument for the use of node strength over degree centrality is Ahuja 's (2000) idea that direct ties are not just an indicator of external knowledge sources, but also a source of cost reduction and risk sharing in the innovation process. In order to properly account for this cost-reduction effect, using a network weighted by project budgets is appropriate.

2.3.2 Indirect ties

Indirect ties are defined as ties to "actors the focal actor can reach in the network through its partners and their partners" (Gulati and Gargiulo, 1999). The amount of indirect ties a firm has

[2] This concept of node strength should not be confounded with Granovetter's multi-faceted concept of tie strength, as in modern social network analysis, networks weights are usually defined by a single variable that is a functional operationalisation of tie importance or intensity. In this study, two actors have a direct tie if they both participate in the same research project, and the tie intensity is measured by the amount of resources that go into that research project per actor involved – there will be more on this in the methodology section.

is also a characteristic of what Granovetter (1985) referred to as "structural embeddedness". Structural embeddedness has been conceptualised using various network measures in the innovation literature, depending on the underlying research aims of the study in question. For instance, studies in the innovation management literature often use the measure eigenvector centrality, which accounts for how important a firm's direct partners are in terms of how many (and how important) ties their partners have in relation to the network as a whole (McKelvey and Rake, 2016). Eigenvector centrality focuses on determining how important firms are in the network and is often used in studies that focus on innovation as an intermediary variable between network position and firm performance, while also taking into account the strategic benefits of being a relatively powerful actor in a network.

However, this thesis focuses on knowledge exchange and innovation outcome rather than network strategy and firm performance, and so the eigenvector conceptualisation of indirect ties is inappropriate. Ahuja (2000) makes use of a different measure of indirect ties, namely reach, in order to focus on indirect ties as a source of knowledge as opposed to an indicator of strategic advantage. While direct and indirect ties both impact the amount of external knowledge that a firm has access to, Ahuja prefers the conceptualisation of indirect ties measured by reach under the assumption that the innovation benefits that actors can gain from their indirect ties are qualitatively different from those gained from direct ties. Ahuja (2000) theorises that indirect ties are primarily sources of information and not resources like direct ties. Gulati (1995) also characterise indirect ties primarily as "channels of information". The focal firm can receive information about ongoing innovation projects far beyond the reach of its direct partners, and as such have a 'radar' function that brings in more general information about technological development. Wang et al. (2014b) emphasise the social nature of the knowledge that becomes available through network ties, such as information related to knowledge distribution among inventors, information pertaining to the latest development trends of research and information bearing on the inventors and the interactions among them.

A number of scholars claim that in contrast to knowledge coming from direct ties, information received by indirect ties is highly prone to 'noise', leading to limited understanding, misunderstandings and an overreliance on the interpretations and filters of mediating actors (Vanhaverbeke et al., 2012, Hansen, 2002, Kogut and Zander, 1993). Indirect ties do not yield information and knowledge that is specific and fine-grained enough to have the same effects that direct ties can have, particularly when it comes to the development of core technologies

(Vanhaverbeke et al., 2012, Gilsing and Nooteboom, 2006). The other side of that equation is that indirect ties cast a wider net when sourcing external knowledge, and so provide the firm with a more comprehensive view of unfamiliar domains and ensure that the firm does not miss out on key new developments. This is particularly important for the development of non-core technologies, which themselves may not be as dependent on knowledge that is specific and noise-free (Vanhaverbeke et al., 2012).

Indirect ties are also fundamentally different from direct ties when it comes to knowledge governance. The knowledge advantages that a firm gains from its indirect ties also go in the opposite direction (Gulati and Gargiulo, 1999). Structural embeddedness therefore increases the risk of unintended spillovers and freeridership, as knowledge shared with partners may in turn be shared with and benefit partners' partners (Vanhaverbeke et al., 2012). Unlike direct ties, firms do not have the same ability to govern the knowledge flows of indirect ties. For example, even though firms collaborate only with suppliers or universities on projects relating to sensitive technologies, there is always the possibility that the knowledge and competencies that are developed and exchanged will in turn find its way to their competitors by way of indirect ties. So while being deeply structurally embedded allows access to a wide range of knowledge flows, it might also disincentivise or hamper the capitalisation of in-house innovation.

The effects of indirect ties measured by reach found so far in the literature have been generally positive, though not unambiguously so. Ahuja (2000) finds a positive relationship between indirect ties and innovation outcome, and a recent study by Liang and Liu (2018) confirms this relationship when controlling for geographic, institutional and technological proximities. Meanwhile, Guan and Liu (2016) find that indirect ties in a collaboration network have effects on explorative innovation only, not exploitative innovation. This seems to confirm Vanhaverbeke , Gilsing and Duyster's (2012) findings that indirect ties play a positive role mostly in the development of non-core technologies.

2.3.3 Ego-network redundancy

Besides indicating the volume and quality of knowledge an actor has access to, network positions can also tell us something about whether the knowledge that is being accessed is highly heterogeneous. This is often done by seeing to what extent the focal node bridges structural holes in the network, which is to say that they connect to different sections of the network that generally have little communication between each other. A common measure by which to indicate structural holes is betweenness centrality, which measures the number of shortest paths between all node pairings of a network that a node is part of. Betweenness centrality has been found to be positively related to innovation outcome in several earlier studies (Owen-Smith and Powell, 2004, Shan et al., 1994, Salman and Saives, 2005), and degree centrality has also been found to be positively related to the success of innovative products (McKelvey and Rake, 2016). However, like eigenvector centrality, betweenness centrality measures how important an actor is in relation to the entire network as a whole, and is often used to indicate actors that are in a brokerage position, which can be used to their strategic advantage.

There is however a different measure relating to bridging structural holes which focuses specifically on how structural holes impact the information access of an actor. This is done by looking at to what extent ties in a focal node's ego-network are made redundant by each other in terms of how much novel knowledge they are likely to bring in. The concept of redundancies among ties in an actor's ego-network was brought to the forefront of the SNA literature by Burt (1992, 2004), and is measured by what is now known as the "Burt's constraint". According to Burt (1992), whether a firm's direct contacts have many ties among themselves will have an effect on how valuable the firm's network position is to access heterogeneous knowledge and information. Firms can reap knowledge rents from having contacts that do not have ties between them, but on the other hand, firms will be able to gain more information about their partners more quickly if they have more redundant ties in their immediate ego-network (Burt, 1992, Powell et al., 1996, Uzzi, 1997). According to Burt (1992), having a low level of redundancy makes the network more efficient, as it is an indicator of both having a heterogeneous collection of ties (and thus novel knowledge), as well as having a key position between them that can be leveraged to the focal firm's advantage.

However, Burt's view conflicts with Coleman's (1990, 1988) theory of social capital, in which he proposes that tie density (or 'closure') facilitates conditions that are necessary for the efficient exchange of knowledge and information, such as building a reputation, trust, social norms and the execution of social control. This could prevent the kind of opportunistic behaviour that hampers firms' tendency to divide the costs and share the yields of collaboratively generated knowledge.

The idea of closure is not only beneficial when it comes to knowledge management. Gilsing and Nooteboom (2005) claim that redundant ties may be important to enhance absorptive capacity. If some knowledge is too different or advanced to be absorbed by one actor, two actors sharing the same network ties may be able to make use of it through their combined absorptive capacities. Rowley et al. (2000) notes how the problem of noise is reduced in the presence of redundant ties, as third parties can be used to test the reliability of information by triangulation. This idea goes back to basic information theory as laid out by Shannon (1948). Dyer and Nobeoka (2000) and Kogut (2000) find that tie redundancy is particularly important when it comes to improving the transfer of tacit knowledge, tacit knowledge being particularly difficult to convey and prone to noise.

In the context of a research network, the impact that network redundancy has for innovation will in large part depend upon how redundancy affects STI. As high levels of redundancy enhance the transfer of highly complex, noise-prone and often tacit knowledge, it should have a positive effect on STI. According to Coleman's social capital theory, the shared trust in a denser network will also be more conducive to success in more uncertain ventures. However, STI innovation also depends upon a heterogeneity of knowledge flows, and it is not a given that the benefits of a more redundant ego-network outweigh the benefits of ego-network efficiency.

The evidence of whether tie redundancy has a negative or positive effect on innovation has so far been mixed (McEvily and Zaheer, 1999, Ahuja, 2000, Walker et al., 1997). Much of the literature suggests that the effect of tie density have to be seen in the context of the environmental factors that influence it, mainly the technological dynamism of the sector that is involved, and whether a wider or narrower search process is more optimal (Podolny and Baron, 1996, Rowley et al., 2000, Podolny, 2001, Hagedoorn and Duysters, 2002, Gilsing and Nooteboom, 2005). This is partly confirmed in a more recent study by Guan and Liu (2016), in which non-redundancy has been found to have a positive effect on exploitative innovation, though not finding any conclusive effect on explorative innovation.

2.4 Hypotheses

In the literature, there are varying results on the effects that network measures have in different contexts. In order to form hypotheses, it is necessary to see how these theories and findings should be applied in the context of a publicly funded research network.

There is a wide consensus in the literature that direct ties have a positive effect on innovation outcome, both due to cost and risk sharing, as well as the increased external information that can be accessed via relatively easy-to-govern knowledge flows. There is some discussion about whether the finite recombinant possibilities of firm knowledge stock increasing management costs of new knowledge lead to diseconomies of scale from when degree centrality gets very high, as several findings suggest.

However, the inverted U-shaped relationship between direct ties and innovation outcome has been found in studies using unweighted networks, and so the diseconomies of scale are indicating that spreading R&D collaboration efforts between too many collaborators is disadvantageous. However, this study uses a weighted network, and there is no a priori reason to assume that an increasing total intensity of collaboration should lead to an inverted U-shaped relationship between direct ties and innovation outcome. This leads to the first hypothesis:

H1: Node strength has a positive effect on product innovation.

As for indirect ties, there is a consensus in the literature that they too have a positive effect on innovation by increasing information coming into the firm, though the information is of a lower quality and accuracy than the information coming from direct ties. The contention in the literature revolves around the idea that deeply embedded firms have a more difficult time controlling for unintended knowledge spillovers, and so would exchange less knowledge through their ties as a result. However, this is precisely the kind of market failure that is the very rationale behind the public support for research collaborations in the first place. Research collaborations will include large amounts of knowledge transfer, and one would assume that public funds make up for the spillover costs involved even for firms that are deeply embedded in the network. This leads to the second hypothesis:

H2: Node reach have a positive effect on product innovation

The most contentious issue when it comes to network position's effect on innovation output is the role of structural holes. The literature is split on this topic, some finding that Burt's emphasis on an efficient and low-density ego network brings innovation effects by heterogenety of information, others finding that Coleman's idea of a cohesive community more conducive to efficient knowledge transfer. Either of these two considerations is valid in the context of a research network, and without introducing some kind of mediating variables, one is left with a split third hypothesis:

H3a: Ego-network redundancy has a positive effect on product innovation

H3b: Ego-network redundancy has a negative effect on product innovation

The fourth and final hypothesis relates to the role of absorptive capacity. Absorptive capacity has many dimensions, and there are contexts wherein R&D intensity is not highly important to a firm's ability to absorb and make use of new knowledge. However, in the context of a research collaboration network, the prominent position of STI means that R&D intensity will have a major impact on a firm's absorptive capacity. This absorptive capacity will moderate the effect that networks have on innovation outcome, leading to the fourth and final hypothesis:

H4: Network effects on product innovation are strengthened by the firm's R&D intensity

3 Data and methods

3.1 Empirical materials

3.1.1 Research Council of Norway database

The network variables in this study are derived using a unique dataset which contains complete data on all projects funded by the Research Council of Norway in the period 2005-2015. The dataset includes each collaboration partner for each research project with a unique name and/or organisational number. While most collaboration partners are firms or educational or scientific institutions, the dataset also includes research groups, public institutions such as municipalities and government departments, trade unions, and industry associations to name a few. Furthermore, the dataset includes qualitative descriptions of each research project, the total budgets and the start and end year of every project, as well as the name of the head of each project.

In addition to this, the Research Council of Norway has provided a separate database which links each project to a series of tags denoting the different spheres of science and research that it involves. There are a total of 129 of these tags, (for a full overview see Appendix 1) and there is no limitation on how many tags a single project can have. This database has been merged with the existing database by project number so that each research project is associated with tags denoting general areas of science and research.

This is an administrative database, which required a substantial amount of preparation in order to be useful to a network study. The foremost issue has been inconsistencies in organisational numbers and names: names of organisations were often incomplete or inconsistent, and many organisational numbers were missing. By matching partial name overlaps and assigning new unique values to the organisations that lacked organisational numbers, we were able to create a database in which each organisation could be identified by a unique organisational number, and tied to the projects it was part of. This data cleaning entailed a large amount of semi-automised and manual labour and resulted in a database that includes 4,600 organisations involved in 35,664 research projects over a 10-year period.

3.1.2 Brønnøysund Register and Proff forvalt

In order to supplement and complete the information about organsations in the RCN database, additional information on actors has been gathered from the Brønnøysund Register, as well as the Proff Forvalt market information service by Proff AS.

Brønnøysund provides information such as company names, organisational numbers, locations and numbers of employees through their publicly available API of Enhetsregisteret and Underenhetsregisteret (the unit and sub-unit registries.) This includes data on all registered organisations within Norway that are still in the registry.

As entries are deleted from the Brønnøysund Register after an organisation ceases to exist, the Proff Forvalt service was used to fill in information for companies going back to 2010. However, the RCN database includes many organisations that were deleted before this year. Fortunately, the Brønnøysund webpages include a register of announcements (Kunngjøringsregisteret), which contains announcements on organisations that have been deleted from the main register. This announcement information is searchable by both name and organisational number, and includes information on location and size. As the announcement registry does not have a publicly available API, I constructed a web scraper in Python that crawled the online search results and gathered the relevant information.

Through the use of Proff Forvalt's services, Brønnøysund's API and the web scraper, I was able to supply many of the missing organisational numbers in the RCN database. I was also able to gather data on firms' number of employees and location. However, as this data was taken from several different sources, as well as reported from many different reference years, the resulting data was highly inconsistent and unreliable. The sizes gathered from these disparate sources are therefore collapsed into three wide categories: Small (<50 employees), medium (51-250 employees) and large (>250 employees). These size categories are only used in the visualisation of the network graph, determining the size of the circles that represent each node.

3.1.3 Network construction

The network variables were estimated by creating an edgelist of every organisation's link to any other organisation. In this analysis, two organisations have a link between them if they are involved in the same research project. Before constructing the nodelist, the RCN dataset was subsetted into smaller networks based on knowledge sectors. This was done in order that knowledge institutions that span many disciplines, mainly universities, would not inflate the indirect ties of their collaboration partners. Large and diverse actors such as universities are coded as singular nodes in the network, which is problematic due to their breadth of involvement in different knowledge areas. A firm that collaborates with a particular institute within one university department would, according to the full network graph, be only a single degree of separation away from a staggering amount of different firms and research organisations involved in collaboration projects within entirely unrelated disciplines. It is difficult to sub-divide the university into smaller units, as departments, research centers and institutes will have varying levels of interaction and information flow going through them, and it is not obvious that there is one level of aggregation that is optimal across disciplines and institutions.

In order to solve this problem, the network was divided into sub-networks delineated by knowledge areas defined by the tags in the RCN datasets. Four sectors were chosen: Oil and gas, marine, maritime and biotechnology. These sectors were chosen because of their relative science and technology intensity and their central role in the Norwegian research system (see chapter 1.3). Each sector delineates a broad sphere of scientific and technological knowledge. This enables each network to capture the dynamics of knowledge exchange between diverse collaboration partners while ensuring that all links represent collaborations that are relevant to the general knowledge area.

While subsetting the networks in this way has many benefits, it also introduces certain limitations. The delineation fits well with the overarching goals of performing an analysis that spans several sectors, giving highly generalisable results. However, this entails that once network variables have been calculated from the four sub-networks, the actors then need to be combined into a single dataset for the final analysis.[3]

Combining network centrality data from different networks is uncommon, as many network centrality measures depend upon the structure of the entire network for their calculation. This includes the commonly used betweenness-centrality, measuring the bridging of structural holes, and eigenvector centrality, which measures a node's relative importance in the network. These measures are ratios that depend upon the size and the density of the entire network for their calculation, and so it would not make sense to compare such measures taken from separate networks with different overall properties.

Fortunately, the network measures that are commonly used in the analysis of innovation networks are focused on each node's ego-network. This is particularly true for the measure of node strength, which only takes into account each actor's direct ties, and Burt's constraint, which expresses the relative network density within the network created by the actor's direct ties. Neither of these depends on the overall network structure, only the local network directly around each actor. The measure of indirect ties, reach, is more affected by the overall size and density of the network, but this does not necessarily invalidate comparisons between nodes of different networks. Unlike eigenvector centrality, reach is a measure weighted by each node's degree of separation to the focal node. As such, an actor's reach is not arbitrarily skewed by the structure of the entire network, but instead is most affected by the network density a few degrees of separation away from the focal node. Naturally, a larger and denser network will have a higher level of reach among the nodes, but this should be seen as an accurate reflection of these nodes' larger number of indirect connections, rather than an arbitrary bias created by the way the network measure is calculated. Nevertheless, as combining data from differently sized networks could introduce biases if the tag-based network delineation is highly arbitrary, I have

[3] In addition to attaining the goal of generalisability, this was also done for practical reasons. While it would have been interesting to analyse and compare each sector separately, once the network data was matched with the CIS survey for 2014, it was clear that the matches between them were so sparse that no sector had a large enough number of observations to make statistically significant coefficients for the main explanatory variables. This was an additional reason why a more general research design was chosen.

included a separate analysis that tests for interaction effects between sectors and indirect ties in Appendix 3.

Of course, defining network delineations – that is, determining which nodes and ties belong inside and outside the network – will always lead to certain biases and limitations. One, which is pretty much inescapable, is that a node which is peripheral to one network might in fact be highly central a different network, and have the innovation characteristics of a highly central node. For example, a node that is peripheral in the biotechnology sector might be highly central within chemical engineering, but this would not be reflected in the biotechnology network variables.

This also brings up the issue of nodes shared between networks. Some networks will partially overlap, particularly as the maritime sector is a supplier to both the marine and the oil and gas sectors. Biotechnology also has important interconnections with the marine sector when it comes to research. These overlaps and actors' betweenness centrality are interesting as a subject of study in and of themselves, but this is outside of the scope of this thesis. In the final network analysis, each overlapping company is defined as belonging to the network in which it has the highest strength. This assumes that a higher strength indicates that this is the sector which characterises the brunt of the firm's activities, and that they have a more peripheral role in the sectors where their strength is weaker. The centrality scores in this sector therefore best represent the position of the node. The lower network centrality scores are discarded, avoiding double counting of units in the final regression analysis.

There are other delineations that also introduce limitations that cannot easily be controlled for statistically. For example, the RCN database only includes Norwegian actors, so it might show bias against companies that source their R&D internationally. And of course, the database only includes research collaboration projects that are publicly funded, and entirely ignores privately funded collaboration projects, which may have unmeasured effects of supplication or substitution that could skew results in various directions. Seeing as there are no good data sources to hand by which to mitigate these biases by statistical controls, there is no recourse but to interpret the final results with these limitations in mind.

3.1.4 Community Innovation Survey

While previous networks studies have often used citation and patent data as dependent variables, this thesis takes advantage of the fact that the RCN data can be matched with the Norwegian CIS in order to link network position to innovation outcomes. Seeing as the CIS have direct indicators of whether firms introduce new products or implement new processes, this data source can potentially give better operationalisations of innovation output than citation and patent-based studies have been able to provide.

Of course, survey data comes with its own limitations. As with all surveys, responses to questions will be sensitive to their interpretation by the respondent. Although the Norwegian CIS includes a guide to help respondents interpret the questions and terminology, interpretations will always be influenced by the questions' context, as well as limited by the respondent's knowledge. Complex queries, such as estimating the percentage of total turnover that is made from innovative products, is difficult for a respondent to come up with on the spot, and responses reflect this by reporting estimates within 5% intervals (Eurostat, 2016). Other questions, such as whether an innovation is new to the market or just new to the firm, require that the respondent knows a great deal about her market. Innovation surveys may be particularly sensitive to issues of interpretation, as the definitions of what constitutes "new" or "significantly improved" products or processes are inherently ambiguous and fuzzy. They can also vary greatly depending on the industry or technology in question.

For these reasons, I find it most prudent to utilise the simplest and most easily interpretable questions to measure innovation outcome. These amount to binary yes/no questions on whether companies have introduced improved or new products or processes, and whether or not these were new to the market.

While this might seem like an overemphasis of limitations that are common to most survey data, the change between the survey procedure between the 2012 and 2014 Norwegian CIS revealed how sensitive responses in these surveys are to context and interpretation. Up until 2012, the Norwegian CIS consisted of a single survey on both R&D performance and innovation outcomes. Since 2014, R&D and innovation have been measured in separate surveys. The result was a jump in the reported measures of innovation in 2014 from the 2012 and previous surveys. (Wilhelmsen, 2016) This seems to indicate that when the two were combined in a single survey, respondents tended to think of innovation in the context of R&D, neglecting to report innovations that were not R&D-related.

This change has two implications for how to use Norwegian CIS data. Firstly, the change in the survey practice makes data from 2014 onwards incompatible with data from 2012 and before. This particular limitation is not unique to the Norwegian CIS, as stratified sampling in other European countries also makes the CIS a poor resource for panel data (Eurostat, 2016). Secondly, seeing as one aim of this thesis is to examine the how R&D intensity moderates network effects on innovation outcome, the Norwegian CIS from 2012 and before are inappropriate for this purpose due to their relative bias against innovation that is not associated with R&D.

Furthermore, while the CIS goes out to all businesses with 10 or more employees in Norway, it also suffers from response bias, resulting in a sample that of firms that are both larger and more likely to engage in R&D activities and innovation than the average firm. In addition to this, the final sample consists of firms that are matched across the 2014 CIS and the RCN database, further skewing the sample heavily towards large and R&D-intensive firms. This puts a major limitation on the generalisability of the results, as the findings will fit large R&D-intensive firms better than small or medium-sized enterprises.

One weakness that survey data has in comparison to patent data is that survey data contains little fine-grained information about the technologies that are involved. Unlike previous studies that have focused on network effects on knowledge stocks (Guan and Liu, 2016, Vanhaverbeke et al., 2012), this thesis cannot account for the more detailed technological nature of the innovations introduced. However, surveys do give indications of what type of innovation that a company introduces in terms of product/process innovation, and whether innovation is new to the market, which itself can be a starting point to make inferences about the different effects networks have on different innovation outcomes.

3.2 Measure of variables

3.2.1 Dependent variables

In line with previous scholars who study innovation outcomes (Fitjar and Rodríguez-Pose, 2013, Archibugi et al., 2013, Frenz and Ietto-Gillies, 2009), this study uses answers to the Norwegian CIS survey to measure different innovation outcomes. Each dependent variable is dichotomous, taking either the value 1 or 0.

The first dependent variable measures whether the firm has engaged in product innovation during the survey period. This takes a value of 1 if the respondent reports that the firm has introduced product innovation by either introducing a new product or service to the market in the survey period, otherwise it is 0.

The second dependent variable measures whether the firm has engaged in new-to-market product innovation during the survey period. This takes the value 1 if the respondent reports that the firm has introduced a product innovation that is new to the market in the survey period (as opposed to new for the firm only) during the survey period, otherwise it takes the value 0.

The third dependent variable measures whether the firm has engaged in process innovation during the survey period. This takes the value 1 if the respondent reports that the firm has introduced a process innovation by significantly improving their production process, including improvements related to organisation and logistics. It takes the value 0 otherwise.

The fourth dependent variable measures whether the firm has engaged in new-to-market process innovation during the survey period. This takes the value 1 if the respondent reports that the firm has introduced a process innovation that is new to the market in the survey period, otherwise it takes the value 0.

3.2.2 Independent variables

The independent variables in this study are direct ties, indirect ties, and network redundancies. These variables are calculated from network graphs created using the iGraph package in R, except for weighted reach, which is taken from Shizuka (2018). The network is non-directed, and each tie is weighted by the total project budget divided by the number of partners. Tie strength and network efficiency are measured using igraph functions, while weighted reach is measured using a specially constructed function from Shizuka (2018). In the final analysis, independent variables have all been standardised.

The measure is based on Ahuja's (2000) conceptualisation of direct ties as a way to share resources, as opposed to just exchanging information. The weighting of the network was estimated with this in mind. While each project that has several partners in it will have a budget divided between them, the network is weighted so that each of the partners in the project will receive the innovation benefits of the full project. This is done by weighting each tie according to the formula B/(n-1), where B is the total project budget and n is the number of participating organisations. As each project will provide each node with n-1 ties in the network graph, the sum of the weight that a node receives from each project will equal the full budget of that project. Due to a paucity of data that could indicate otherwise, it also makes the rather unrealistic assumption that each dyadic relationship is equally important in any multi-party research collaboration.

In order to check that the weighting of the graph did not skew the results in an unforeseen way, a set of regression results were also produced using network measures derived from an unweighted graph, and these have been included in Appendix 2.

3.2.3 Direct ties

The most common measure of direct ties is degree centrality, which is a measure of the number of direct ties that a node has. This is a measure of the number of collaboration partners an organisation has in the period, but does not take into account the time and resources that actually went into each collaboration. In order to gain a better measure of actual research collaboration intensity, instead of degree centrality I have chosen to use the measure node strength, which is the sum of the weights of all direct ties to other organisations.

While degree centrality and node strength are highly correlated, there is a trade-off to using one over the other. Degree is best to use when the main subject of interest is the diversity of information, the idea being that a higher number of ties to different organisations brings in a higher diversity of information. However, there is nothing in the measure itself that indicates to what extent different organisations that are part of the focal node's ego network are actually diverse along technological, cognitive, organisational or other dimensions. Without combining it with some kind of attributes (as is done in Liang and Liu (2018)), it is of limited value as a measure of diversity.

Meanwhile, node strength measures the total intensity of all direct collaborations. The intensity of each tie is operationalised using the weighting system described above. This weighting works under the Ahujan assumption that the knowledge created from a collaborative project is a non-discriminatory good, i.e. that each partner has full use of the total knowledge created by the project. As projects included in the RCN dataset vary greatly in their budgets, it seems straightforward to assume that the importance of the collaboration ties that constitute them vary as well. Node strength is therefore used instead of degree centrality, as it will be a better predictor of the effect that these network ties will have.

3.2.4 **Indirect ties**

The variable called ‘reach’ measures the number of partners the focal actor can reach indirectly. While there are several ways to operationalise indirect ties, this study follows the trend of prior researches (Ahuja, 2000, Guan and Liu, 2016, Vanhaverbeke et al., 2007) and makes use of a variable that measures the impact of indirect ties while also taking account that tie strength declines as ties become more distant to the focal node. Indirect ties are operationalised using a distance-weighted reach (Everett and Borgatti, 1999). The variable for distance-weighted reach is calculated by summing the (weighted) ties at several distances weighted by their path distances. This is equal to the sum of the actors that can be reached in k steps divided by k. As indirect ties for $k = 1$ is equal to direct ties, which are already measured by strength, reach only calculates the number of actors in the network that the focal actor can reach in two or more steps, which is to say $k >= 2$. The result is a measure by which collaboration partners receive smaller weights the higher the degrees of separation between them and other actors.

As with direct ties, indirect ties are measured using the weighted graph measures. This is done under the assumption that the weight of a tie is an indication of the amount of interaction that tie represents, which again affects the amount of information one can expect to flow through that tie.

3.2.5 Redundancy

Network redundancy (often referred to by it symmetrically opposite term *network efficiency*) has been used extensively in previous literature on innovation networks (Ahuja, 2000, Phelps, 2010, Liang and Liu, 2018). Network redundancy measures the number of ties that exist in a node's ego-network compared to the number of ties that potentially could exist in that same ego-network. In other words, to what extent does an actor's collaboration partners themselves collaborate with each other? Network redundancy is measured by Burt's constraint, using the igraph constraint function. In Burt's measure of constraint, *C[i]*, of node *i*'s ego network *V[i]*, is defined for directed and valued graphs

C[i] = sum([sum(p[i,j] + p[i,q] p[q,j], q in V[i], q != i,j)]^2, j in V[i], j != i)

This is for a graph of order (i.e. Number of nodes) N, where proportional tie strengths are defined as

p[i,j]=(a[i,j]+a[j,i]) / sum(a[i,k]+a[k,i], k in V[i], k != i)

(Csardi, 2018)

A higher value indicates that there is a high level of redundancy, and so that there are fewer structural holes. A lower value indicates a higher level of efficiency, which is to say less collaboration between direct partners and more structural holes in the focal node's ego network.

3.2.6 Control variables and interaction variables

This analysis controls for two variables that are expected to be highly predictive of innovation outcome, namely R&D intensity and firm size. Admittedly, this is a relatively small number of controls to use in such an analysis, considering the amount of different factors that can affect innovation outcome. The limited number of control variables is explained in part by a paucity in reliable data for other variables, but also with the goal of parsimony in mind. For example, the absence of any geographical controls might appear conspicuous, considering the well-established association between geographic location and innovation (Asheim and Gertler, 2005). This is possible to control for with the data sources at hand, but so much of the innovation effect of geographical location has to do with the way geographical proximity encourage knowledge transfer through collaboration and interaction. The interactions between collaboration network variables and geographical factors is an interesting topic in its own right, but it is a large and complex topic of research that goes beyond the scope of this thesis. For this reason, the model is limited to controlling for size and R&D intensity, the latter also being interacted with the network variables.

3.2.7 R&D intensity

R&D intensity is calculated by numbers taken from the CIS survey. In the CIS survey, both total turnover and internal R&D costs are provided by the respondent. R&D intensity is therefore defined as internal R&D costs divided by total turnover. This is a common operationalisation of R&D intensity in studies making use of CIS data (Lhuillery and Pfister, 2009, Hölzl, 2009).

However, seeing as this study has a particular focus on research networks and effects related to STI and DUI, it also employs an R&D-focused conceptualisation of absorptive capacity. Many studies which use CIS data (Kostopoulos et al., 2011, Escribano et al., 2009) use measures related to human resources in order to gauge firms' absorptive capacity, but in the context of this thesis absorptive capacity is best operationalized using the measure of R&D intensity itself. R&D intensity is calculated using the total costs that go into R&D, which includes technologies and capital not reflected in education statistics. Measuring absorptive capacity in total R&D costs and not educational attainments comes with its own benefits. The role of particular levels of educational attainment may have arbitrary differences across disciplines and industries. Depending on the discipline, it will also have a varying association with R&D and the STI-mode. In addition to this, using R&D intensity instead of a separate human capital indicator to operationalise absorptive capacity leads to a more parsimonious model.

In order to treat R&D intensity as a modifying capability, the measure is used as an interactive term with the three network variables being tested.

3.2.8 Size

The size of a firm is measured by its number of employees as reported by the CIS survey. While the dataset from which the network visualisations were created had its own measure of size, these measures were taken from disparate sources and were relatively uncertain and incomplete.

This works for a purely descriptive network visualization, as in this visualisation the sizes could be divided into three rough categories of small, medium-sized and large.

However, for the firms for which CIS data is available, the survey data includes a number of employees variable retrieved from a single source, and which is complete for all the units included in the final regression model. For this reason, while various Brønnøysund and Forvalt numbers were used for the purely descriptive network visualisations, CIS data were used in the final regression analysis.

3.3 Model estimation

In order to estimate the statistical effects that networks position has on innovation, this thesis follows a combination of methods used by Liang and Liu (2018) and Fitjar and Rodríguez-Pose (2013), and uses binomial regression models to test how networks measure predict the likelihood that a firm will introduce an innovation in the survey period. Four analyses are conducted: one for each of the four dependent variables. All these dependent variables are dichotomous and the coefficients indicate the logarithm of the odds that the dependent variable will be 1 rather than 0. Positive coefficients imply an increase the likelihood that firms will introduce an innovation, while negative coefficients imply a decrease.

In order to check the robustness of these analyses, a stepwise model is used, and each model has five different estimations. The first is a simple model including only the control variables. The model controls for each firm's R&D intensity, its size in terms of the number of employees logarithmically transformed, and has a dummy variable for the sector to which it belongs.

The second includes all three dependent variables, but without interaction terms that test the effects of absorptive capacity. The third model includes an interaction term for strength and R&D intensity, in order to test the role of absorptive capacity. The fourth and fifth models each include an interaction term between R&D intensity and reach and redundancy, respectively, and the sixth includes the full model with R&D intensity interaction terms for all network variables.

As the network measures, R&D intensity and number of employees all have different scales, and few of those scales have simple intuitive direct interpretations, all independent variables have been standardised. This means that the beta coefficients each report the change in log odds for the dependent variables per change of one standard deviation of the independent variable.

In order to test the goodness of fit of the models, the regression analyses are reported with log likelihood values, as well as a McFadden pseudo R^2 score. However, as the goodness of fit of these measures tend to increase indiscriminately when more variables are included, the Akaike information criterion (AIC) for each model is also included, a measure which penalises the fit of model for introducing more independent variables. For model estimations that have similar levels of fit, a likelihood ratio test is used on pairs of nested models to see if the improvement in fit between the two models is statistically significant.

In order to test the hypotheses laid out in chapter 2.4, it would be desirable to minimise as much as possible the potential for biases created by endogenous processes and omitted variables. Endogeneity is a particularly difficult issue when studying effects on innovation outcome, as the innovation process is recognised as being highly complex and affected by feedback loops. For example, innovation outcomes might affect firm's predilections to form more research collaborations, and so it is difficult to infer the nature of the causal relationship between the two just from a statistical correlation. This study mitigates this problem by introducing a temporal lag, wherein innovation CIS outcomes are measured against network position in the 5-year period prior to the survey year. However, this method does have two major weaknesses. First, network formation and positioning is part of companies' strategic decisions, which encompass their expectations about the future. A temporal lag is therefore a relatively weak control for endogeneity in this context, as there is not a clear-cut temporal sequence between causes and effects (Hays et al., 2010). Second, the analysis does not control for prior innovation outcomes. Other studies (Liang and Liu, 2018) have employed panel data in order to test for time-invariant effects, and in so doing are able to test the correlation between variables by seeing how they change over time. A panel study is unfortunately not applied in this study, due to the limitations of the CIS data described in chapter 3.1.4.

Other studies (Soda and Bizzi, 2012) have tried to deal with the difficulties of inferring causal relationships between network effects and innovation outcomes by applying a Two Step Least Square model (2SLS) in order to "tease out" the different causal relationships from the data. However, such a research design would require some exogenous factor or event that could function as an instrumental variable, which is particularly difficult to come by in this case seeing as there is no time-series data available. While a more sophisticated design for inferring causal relationships between network position and innovation outcome would be desirable, this study has to resign itself to discuss the simple statistical correlation between network position and innovation outcome and rely on previous theory and empirical literature to make inferences about the causal relationships they may reflect.

4 Results

4.1 Descriptive statistics

From the descriptive statistics reported in Table 1, one can immediately see that the sample is skewed towards large firms. The mean number of employees is 457, and the standard deviation of 853 is evidence that this variable has a strong right skew, with the largest company in the sample having 6120 employees. The smallest firm in the sample has 11 employees, reflecting the CIS practice of only surveying firms that have more than 10 employees. The sample is thus also skewed towards firms that have a high likelihood of innovating, as 77% of firms in the sample introduced new products in the sample period, with 66% of firms in the sample introducing products that were new to the market.

As can be expected, node strength also has a considerable right skew in the sample, with a standard deviation over twice as high as its mean, and a high maximum value. Weighted reach is not as skewed as node strength, with a standard deviation lower than its mean, and Burt's constraint even less so as its maximum value is capped at 1. As can be expected for actors in a research network, firms in the sample have a relatively high degree of R&D intensity, with a mean proportion of 9% in R&D costs of total turnover, and one actor reaching as far as 94%.

Table 1 Descriptive statistics for sample, N = 490

Variable name	Mean	Min	Max	St Dev
Node strength	40,65395	0,06024	932,4912	89,03869
Weighted reach	981,7577	1,300907	4460,218	775,3062
Burt's constraint	0,360936	0,061427	1	0,261238
R&D intensity	0,093562	1,53E-05	0,949632	0,177849
Employees	457,4163	11	6120	852,6255
Product innovation	0,771429	0	1	0,420342
New-to-market product innovation	0,659184	0	1	0,474468
Process innovation	0,530612	0	1	0,499572
New-to-market process innovation	0,259184	0	1	0,438634

Table 2: Correlation matrix of independent variables

	Strength	Weighted reach	Burt's constraint	R&D intensity
Strength				
Weighted reach	0,23825			
Burt's constraint	-0,32699	-0,33534		
R&D intensity	-0,06861	-0,11958	0,253209	
Employees	0,230089	0,149006	-0,21811	-0,18608

From Table 2 we can see that firm size is negatively correlated with R&D intensity, while being positively correlated with both strength and weighted reach. This could indicate that while large companies are relatively important and central actors in the research network, the volume of their turnover so much outweighs their R&D costs in comparison with smaller firms that the relationship between size and R&D intensity is negative. Meanwhile, both size, strength and weighted reach are negatively correlated with Burt's constraint. This seems logical, as larger and more highly embedded firms have larger ego-networks, and as ego-networks grow, the number of potential ties will increase faster than the number of actual ties.

Meanwhile, Table 2 shows that the levels of collinearity between independent variables are relatively low, the highest being the negative correlation -0.34 between weighted reach and Burt's constraint. To test for potential mutli-collinearity, variance inflation factors (VIF) were estimated for each independent variable. The results show that the maximum variance inflation factor is 1.73, which is well below the recommended threshold level of 10 (Powers and McDougall, 2005). Multi-collinearity is therefore not expected to be a major issue in the interpretation of the regression results.

4.2 Network visualisations and sector-level descriptive data

In addition to looking at the descriptive data from the whole sample, it is also enlightening to compare the graphical representations of the sectoral networks. Network graphs give an overview of the structure of the network as a whole, and as the sample is drawn from four different networks each representing one of four sectors, examining and comparing these networks graphically can say something about the structural differences and commonalities between the various sectors.

The network graphs in this thesis are all generated using the igraph package in R. In each graph, each actor is a node in the network represented by a circle. All nodes in the graph repel each other, but the number and weight of ties between any two nodes bring them closer together. This results in a graph where the most deeply embedded nodes end up in the center of the graph, while those less connected end up at the periphery, while isolated dyads and cliques form satellites around the main cluster or clusters. Ties are represented by the grey lines connecting the nodes, though for the sake of readability they are the same width regardless of their weight.

In addition to node ties and positions, the network graphs also include some indications of node-level metadata. The type of institution, be it private firm, public research institute or university, is indicated by the colour of each node. The size of the firm, meaning whether the firm is small (≤ 50 employees), medium (51 - 250 employees) or large (> 250 employees) is indicated by the size of the diameter of the circle representing the node.

Each of the graphs shows the full sectoral network generated using the RCN database. In addition to firms, this includes universities, research institutes and other organisations. To shed additional light on what the graphs reveal, each graph is accompanied with descriptive statistics for that sector. These are statistics taken from the firms that were successfully matched with the CIS data, and so only represent a limited sample of the total number of firms depicted in the network graph.

4.2.1 Oil and gas

Figure 1 shows the full research network of the oil and gas sector. When compared to the other networks, particularly the networks of the marine and biotechnology sectors, the oil and gas network is dominated by a number of highly central large firms that cluster at the centre of the graph. This is reflected in the descriptive data in table 3, where one can see that both average actor size and average actor strength is higher in the oil and gas sector than in the sample average. The network also has the smallest number of nodes of the four networks and has relatively few isolated cliques forming satellites around the main cluster. Meanwhile, public research institutions and universities are an integral part of the main cluster, but have a slightly more peripheral role than the large deeply embedded companies that occupy the core of the network.

Altogether, the research network of the oil and gas sector is characterised by a centrality of highly connected large firms. From the descriptive data, the oil and gas sector has a rate of innovation that is pretty much within a hair's breadth of the average of the whole sample.

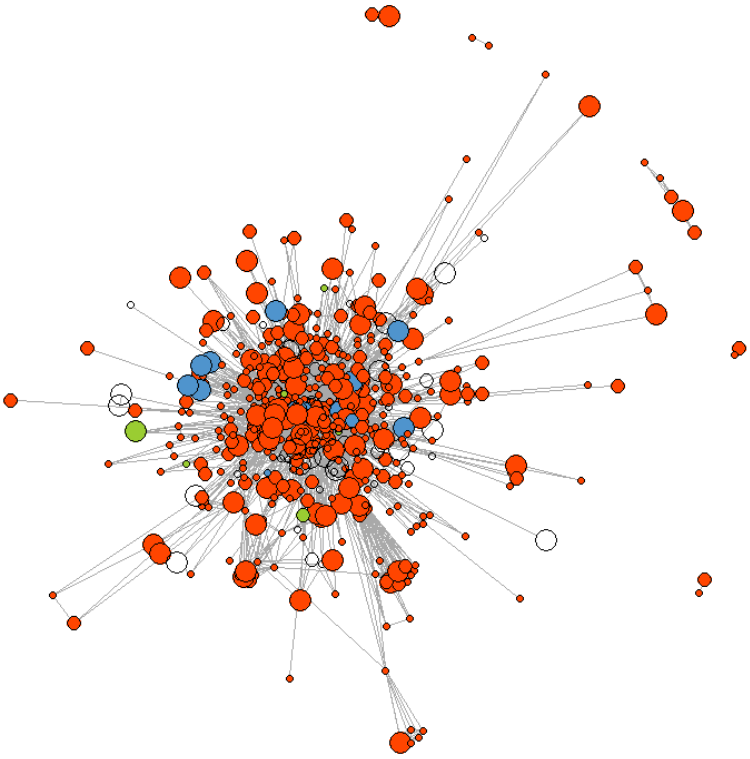

Figure 1: Network graph of R&D collaborators in the oil and gas sector. N = 527.

Red = firms, blue = educational institutions, green = public research institutes, opaque = other

Table 3: Descriptive data for firms in oil and gas sector, N = 97

Variable name	Mean	Min	Max	St Dev
Node strength	50,99993	0,144491	608,6279	99,76725
Weighted reach	578,0617	1,300907	1573,387	337,6085
Burt's constraint	0,354155	0,074229	1	0,265837
R&D intensity	0,112735	1,53E-05	0,949632	0,205942
Employees	542,1546	12	3704	841,7181
Product innovation	0,752577	0	1	0,433756
New-to-market product innovation	0,639175	0	1	0,482735
Process innovation	0,505155	0	1	0,502571
New-to-market process innovation	0,257732	0	1	0,439658

4.2.2 Marine sector

The marine sector research network stands out from the other three in mainly one respect: Its size. It has almost twice as many nodes as the second-largest network, which explains why the graph looks different from the other three. The high number of nodes means nodes will get more clustered in the graph. Also, the graph reveals branching sub-communities that are more loosely tied to the centre. Isolated cliques and dyads look like isolates, but this is due to the limitation of the visualisation software, which works best for networks with numbers of nodes N < 1000.

As anticipated, the sheer size of the network population does appear to have an impact on the reach, as mean weighted reach is just about twice as high as the second-most populous network, biotechnology. Meanwhile, strength and Burt's constraint have similar mean values and standard deviations to the mean of the full sample, though the high maximum value of node strength indicates that the size of the network allows for some very high values of degree centrality among the very most central nodes.

Now, the size of the network and its effect on network variables should not give skewed results as long as the variables have been properly operationalised (see chapter 3.1.3). However, the sector-level descriptive data do indicate that if the delineations of the networks are problematic, which is to say that the tags used to delineate the network are not accurate reflections of the size of the sector but instead are highly arbitrary, this could have consequences in the final analysis. In the final regression analysis, sector dummies control for between-network differences. However, the data from the marine sector appear to indicate that the measure for weighted reach might be more sensitive to changes in network size than measures that are based solely on ego-networks such as strength and Burt's constraint. To control for this potentiality, an auxiliary set of regressions were run which in addition to sector dummies include interaction terms between sector and reach, the results of which are included in Appendix 3.

Meanwhile, firm size mean in the sector is close to the full sample mean, as is R&D intensity. Rates of product innovation are very similar to the oil and gas sector, sitting just below the mean of the full sample.

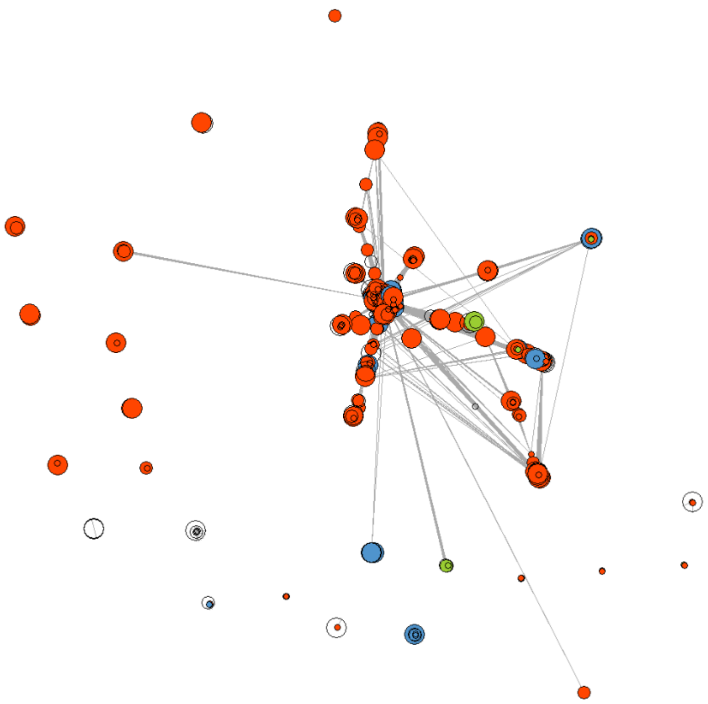

Figure 2: Network graph of R&D collaborators in the marine sector. N = 1310

Red = firms, blue = educational institutions, green = public research institutes, opaque = other

Table 4: Descriptive statistics for firms in marine sector. N = 204

Variable name	Mean	Min	Max	St Dev
Node strength	42,19754	0,06024	932,4912	96,53616
Weighted reach	1483,771	2,074438	4460,218	894,9213
Burt's constraint	0,349637	0,061427	1	0,256465
R&D intensity	0,0921	1,53E-05	0,949632	0,176037
Employees	435,9314	11	6120	862,4065
Product innovation	0,764706	0	1	0,425226
New-to-market product innovation	0,647059	0	1	0,47906
Process innovation	0,514706	0	1	0,501013
New-to-market process innovation	0,240196	0	1	0,428253

4.2.3 Maritime sector

The mean of actor size in the maritime sector is lower than the full sample mean, while R&D intensity is below but very close to the mean for the full sample. Mean node strength is somewhat below the full sample mean, and we can see that in comparison to for example the oil sector, the maritime sector is less dominated by highly central large firms. Looking at the graph, one can also see a dense sector cluster of firms connected to highly central large firms. However, in the maritime networks cluster universities seem to take a more prominent role, most integrated in the core and around the close periphery, as well as the in disconnected dyads and cliques circling the main cluster. In general, the network graph takes on a more dispersed structure and is more characterised by small actors that take up peripheral positions, including more satellites of clusters and dyads.

The rate of product innovation is pretty much the same as the full sample mean, while the rate of new-to-market product innovation is significantly higher than in the full sample.

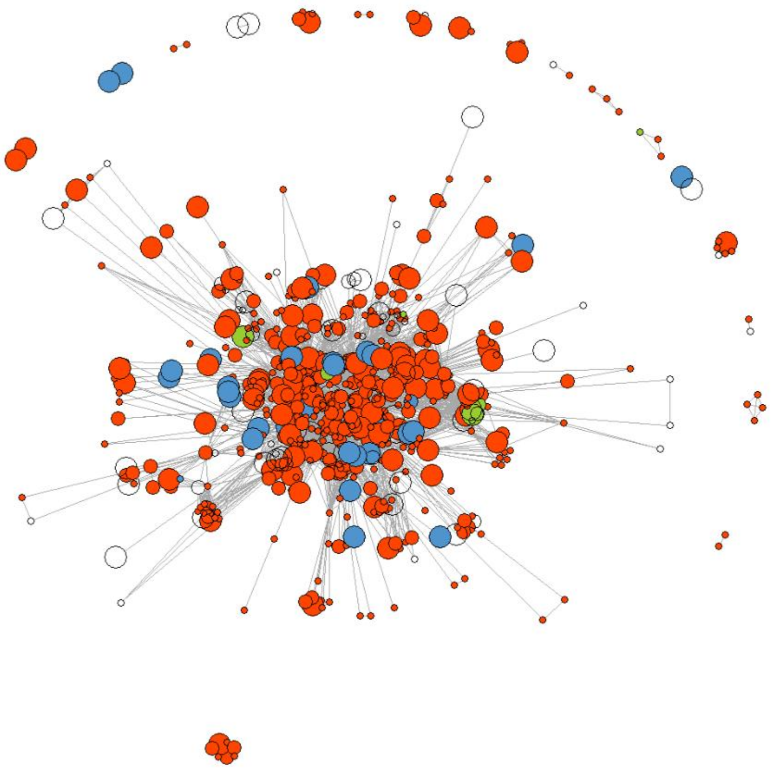

Figure 3: Network graph of R&D collaborators in the maritime sector. N = 643

Red = firms, blue = educational institutions, green = public research institutes, opaque = other

Table 5: Descriptive statistics for firms in the maritime sector. N =103

Variable name	Mean	Min	Max	St Dev
Node strength	38,49727	0,075109	890,5214	94,68927
Weighted reach	595,0805	2,042167	1919,797	399,1075
Burt's constraint	0,387645	0,08545	1	0,268185
R&D intensity	0,082623	4,15E-05	0,888959	0,168429
Employees	395,4712	13	3704	671,3628
Product innovation	0,778846	0	1	0,417034
New-to-market product innovation	0,682692	0	1	0,467682
Process innovation	0,538462	0	1	0,500933
New-to-market process innovation	0,240385	0	1	0,429386

4.2.4 Biotechnology

The Biotechnology research network might be the one that has the starkest differences from the other three. Mean firm size is significantly lower than the full sample mean, and the network has the lowest mean node strength of the four sectors. The standard deviation for size is also lower than in the other sectors, implying that the right skew is not as strong in the biotechnology network as in the full sample. Meanwhile, one can see that universities and university colleges have prominent positions throughout the network, some of them forming a research cluster on their own that are not closely tied to any firms.

While mean node strength is relatively low, the weighted reach is high. All in all, this reflects the structure of the biotechnology sectors, which is characterised by smaller firms that work in close collaboration with research institutions and universities. In addition, many of the important research collaborations are to a greater degree between academic institutions, rather than industry-academia, as compared to the other networks.

This sector also has the highest rate of product innovation of the four in the sample, and the new-to-market product innovation is also high, matching that of the marine sector.

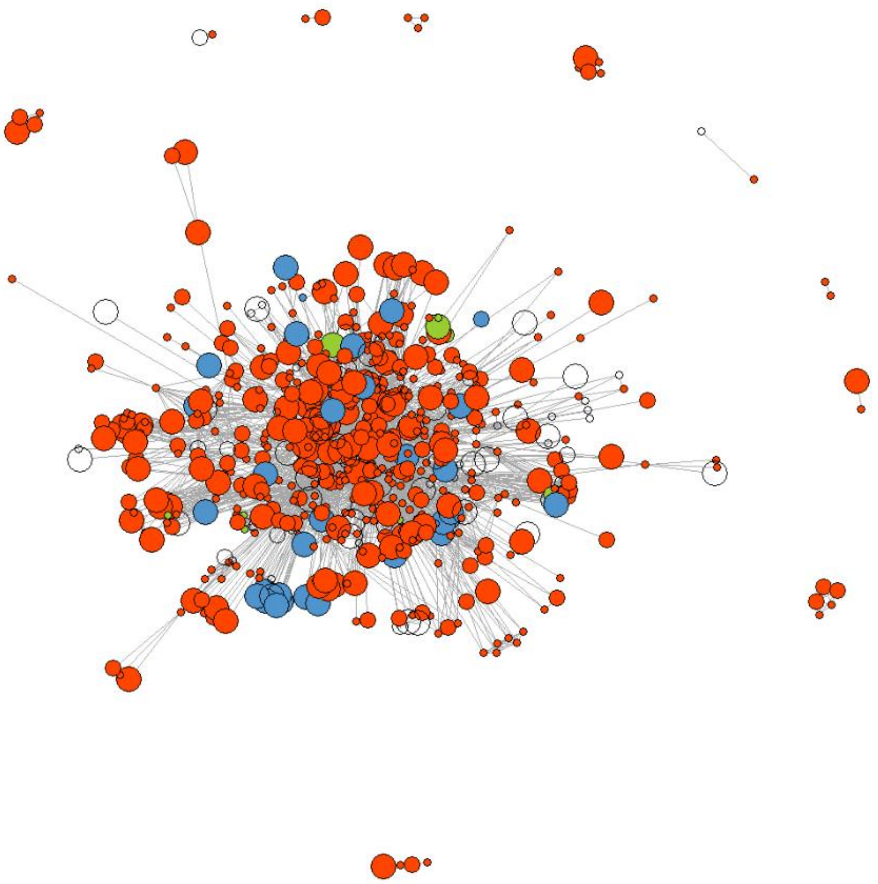

Figure 4: Network graph of R&D collaborators in the biotechnology sector. N = 682

Red = firms, blue = educational institutions, green = public research institutes, opaque = other

Table 6: Descriptive statistics for firms in the biotechnology sector. N = 85

Variable name	Mean	Min	Max	St Dev
Node strength	27,78153	0,692088	97,41151	30,94866
Weighted reach	714,1951	6,838694	1728,706	430,0864
Burt's constraint	0,362901	0,081774	1	0,261012
R&D intensity	0,088572	1,53E-05	0,83871	0,15932
Employees	488,0706	12	6120	1028,167
Product innovation	0,8	0	1	0,402374
New-to-market product innovation	0,682353	0	1	0,468324
Process innovation	0,588235	0	1	0,495074
New-to-market process innovation	0,329412	0	1	0,472789

4.3 Regression results

4.3.1 Network effects on product innovation

Table 6 summarises six models of the effect of network measures on the likelihood for a firm to introduce a new product or service during the survey period. Model 1 is the baseline model including only control variables, model 2 includes the three network variables, and models 3 through 6 include various combinations of interaction variables between network variables and R&D intensity. All models are nested stepwise within each other, with the exception of models 4 and 5, which each include an interaction term the other does not.

Model one gives the results one would expect. R&D intensity has a moderate positive effect on innovation outcome, with a significance level of $p<0.01$. Size has a weak positive effect on innovation outcome, though only at a significance level of $p<0.1$. However, this relationship is stronger and gains a level of significance $p<0.5$ in model 2, wherein the network variables are included. In models 2 through 6, both R&D intensity and size remain positive and significant, as well as increasing with the increased level of fit with the model. Sector dummies for marine, maritime and oil and gas all have negative but insignificant effects on innovation outcome in model 1, with biotechnology as the baseline.

The first model to include network variables, model 2, shows an unexpected relationship between node strength and innovation outcome, namely a weak but statistically significant negative effect. However, this effect changes sign in model 3, which controls for the interaction effect between node strength and R&D intensity. Model 3 shows both a strong positive effect of node strength on innovation outcome, as well as a several-times stronger positive effect of the interaction term between strength and R&D intensity. Meanwhile, controlling for this interaction also strengthens the relationship between R&D intensity and innovation outcome. The effects of strength, R&D intensity and their interaction term are all significant at a level of $p<0.01$, and a likelihood ratio test between model 2 and model 3 reveals that the improved fit of model 3 is statistically significant at a level of $p<0.001$. The positive effect of strength and the interaction effect between strength and R&D remain relatively stable and significant in models 3 through 6, showing a relationship robust to other specifications of interaction terms.

Reach shows a moderate positive effect in models 2 through 6. While interaction variables have a moderate positive effect for reach in models 4 and 6, neither of these are statistically significant at a level of $p<0.05$. Furthermore, likelihood ratio tests show that model 4 and model 6 improve upon the fit from model 3 only at a level of significance $p<0.1$, and so while there are some tendencies in the results hinting at an interaction effect between reach and R&D intensity, it is not statistically significant.

Burt's constraint shows a weak-to-moderate positive effect on innovation in all models. It is not significantly affected by interaction with R&D intensity, and in models 3 through 6 the magnitude of the effect remains stable and significant at a level of $p< 0.05$.

In summary, the results presented in Table 6 show that the effect of direct ties on innovation outcome can be strongly positive, but it will mainly depend on a high level of R&D intensity in the firm. Furthermore, indirect ties have a positive effect on innovation outcome, though not as strong as direct ties, and they are not shown to be significantly dependent upon R&D intensity. Burt's constraint also has a positive effect on innovation outcome, but this effect is weaker still and does not appear to be moderated by R&D intensity.

Table 6: Logistic regression of the effect of network position on product innovation

	Dependent variable:					
	Product innovation					
	(1)	(2)	(3)	(4)	(5)	(6)
Strength		-0.278**	2.140***	1.960**	2.174**	2.240**
		(0.128)	(0.816)	(0.814)	(0.850)	(0.877)
Reach		0.586***	0.606***	0.764***	0.606***	0.914***
		(0.172)	(0.181)	(0.218)	(0.181)	(0.260)
Burt's constraint		0.237*	0.318**	0.343**	0.318**	0.370**
		(0.137)	(0.150)	(0.155)	(0.149)	(0.155)
R&D intensity	0.573***	0.493***	2.590***	2.777***	2.601***	3.040***
	(0.186)	(0.181)	(0.678)	(0.687)	(0.684)	(0.743)
Employees (log)	0.239*	0.351**	0.450***	0.484***	0.447***	0.466***
	(0.123)	(0.143)	(0.152)	(0.154)	(0.153)	(0.153)
Sector Marine	-0.187	-0.725**	-0.605*	-0.611*	-0.605*	-0.629*
	(0.291)	(0.355)	(0.363)	(0.364)	(0.363)	(0.365)
Sector Maritime	-0.075	-0.009	0.054	0.049	0.054	0.048
	(0.331)	(0.369)	(0.377)	(0.378)	(0.377)	(0.377)
Sector Oil and Gas	-0.174	-0.278	-0.055	-0.066	-0.051	-0.008
	(0.341)	(0.372)	(0.385)	(0.385)	(0.386)	(0.388)
Strength*R&D intensity			5.837***	5.378***	5.920***	6.045***
			(1.656)	(1.665)	(1.752)	(1.812)
Reach*R&D intensity				0.500		0.885*
				(0.322)		(0.459)
					0.019	0.225
Burt's constraint*R&D intensity					(0.120)	(0.154)
Constant	1.303***	1.564***	2.293***	2.349***	2.298***	2.461***
	(0.251)	(0.291)	(0.402)	(0.401)	(0.405)	(0.421)
Observations	563	484	484	484	484	484
Pseudo R2 (McFadden)	0.5431	0.6255	0.6458	0.6480	0.6458	0.6497
Log Likelihood	-301.314	-246.954	-233.586	-232.078	-233.574	-230.987
Akaike Inf. Crit.	614.628	511.908	487.172	486.157	489.148	485.974
Note:				*p<0.1; **p<0.05; ***p<0.01		

4.3.2 Network effects on new-to-market product innovation

Table 7 shows that the network effects on new-to-market product innovation are similar to the effects on general product innovation, although the models show slightly different results. For one, company size's positive effect remains stable and significant at a level of $p<0.01$ throughout models 1 through 6, and does not change much with the introduction of network and interaction variables.

The effect of strength behaves the same for new-to-market innovation as it does for innovation in general, starting out negative (though this time not statistically significant) and changing sign once interacted with R&D intensity, having a positive effect with statistical significance at level $p<0.05$ for model 2, but then dropping below that threshold to a level $p<0.1$ for models 3 through 6. The interaction term of strength and R&D intensity still has the strongest effect on innovation outcome, though this effect too is weaker for new-to-market innovation than for innovation as a whole.

The most consistent between the effects on the two dependent variables is the coefficient for reach. This has a similar magnitude and significance level $p<0.01$ as in the previous model, however the coefficients for the interaction term between reach and R&D intensity in model 4 and 6 are more consistent with each other, and are have significance levels of $p<0.05$ and $p<0.1$, respectively. And while there is no statistically significant improvement of fit between model 4 and 6, both models have an improved fit from model 3 with a statistical significance at level $p<0.05$.

Finally, the most prominent difference between table 6 and 7 is that there is no longer any significant effect of Burt's constraint on innovation output in any of the specified models.

Between the two specifications of the dependent variable, the most robust effect seems to be the modest but consistent effect that indirect ties have on innovation output. While there is some suggestion of an interaction effect, the evidence is relatively weak and inconsistent. Both models show that the positive effect of strength is strong, but heavily dependent upon R&D intensity. And while Burt's constraint shows a consistent positive effect for general product innovation, this effect cannot be found for new-to-market product innovation.

Table 7: Logistic regression of the effect of network position on product innovation

	Dependent variable:					
	New-to-market product innovation					
	(1)	(2)	(3)	(4)	(5)	(6)
Strength		-0.196	1.093**	0.906*	0.889*	0.900*
		(0.125)	(0.528)	(0.534)	(0.531)	(0.544)
Reach		0.510***	0.509***	0.704***	0.508***	0.700***
		(0.146)	(0.151)	(0.187)	(0.151)	(0.199)
Burt's constraint		0.038	0.082	0.104	0.076	0.103
		(0.114)	(0.122)	(0.126)	(0.124)	(0.127)
R&D intensity	0.549***	0.525***	1.710***	1.988***	1.742***	1.985***
	(0.148)	(0.149)	(0.434)	(0.460)	(0.432)	(0.463)
Employees (log)	0.302***	0.344***	0.397***	0.440***	0.424***	0.441***
	(0.110)	(0.126)	(0.130)	(0.132)	(0.133)	(0.133)
Sector Marine	-0.164	-0.621**	-0.527*	-0.531*	-0.519	-0.530*
	(0.258)	(0.311)	(0.317)	(0.319)	(0.317)	(0.320)
Sector Maritime	0.047	0.122	0.156	0.152	0.164	0.152
	(0.295)	(0.323)	(0.328)	(0.329)	(0.328)	(0.329)
Sector Oil and Gas	-0.159	-0.192	-0.031	-0.036	-0.058	-0.038
	(0.302)	(0.328)	(0.336)	(0.336)	(0.337)	(0.337)
Strength*R&D intensity			3.409***	2.908***	2.863***	2.894**
			(1.071)	(1.096)	(1.103)	(1.131)
Reach*R&D intensity				0.643**		0.633*
				(0.288)		(0.349)
Burt's constraint*R&D intensity					-0.164	-0.007
					(0.114)	(0.136)
Constant	0.695***	0.895***	1.254***	1.334***	1.249***	1.332***
	(0.220)	(0.249)	(0.297)	(0.302)	(0.295)	(0.303)
Observations	563	484	484	484	484	484
Pseudo R2 (McFadden)	0.4824	0.5687	0.5824	0.5872	0.5841	0.5872
Log Likelihood	-352.903	-294.037	-284.697	-281.439	-283.575	-281.437
Akaike Inf. Crit.	717.807	606.074	589.393	584.877	589.149	586.875
Note:				*p<0.1; **p<0.05; ***p<0.01		

4.3.3 Process innovation (general and new-to-market)

Tables 8 and 9 show regression results for process innovation and new-to-market process innovation, respectively. Both regression tables show that network centrality in terms of reach and strength do not have significant effects on process innovation, even when interaction terms for R&D intensity are taken into account. In fact, when it comes to process innovation in general, R&D intensity cannot be shown to have a statistically significant positive effect on innovation outcome at all. This is in contrast to new-to-market process innovation, wherein R&D intensity does seem to have a modest positive effect. However, this effect is only statistically significant at a level $p<0.001$ in models 1 and 2, and decreases to a level of $p<0.1$ in all models where R&D intensity is interacted with network variables.

In table 8 one can see a modest interaction effect between reach and R&D intensity, significant at a level of $p<0.05$ in model 4 and $p<0.1$ in model 6. A likelihood ratio test between model 2 and model 4 shows an improvement of fit at a level of significance $p<0.05$, while a test between model 2 and 6 shows an improvement of fit at a level of only $p<0.1$. There appears to be no significant improvement in fit between models 6 and 4, however. The interaction term only has a significant effect in one of the model specifications, and neither reach nor R&D intensity have significant effects in any of the specified models.

In fact, the only network effect on process innovations that is consistent and statistically significant is the effect of Burt's constraint on general process innovation found in table 8. Here the effect is modest, but significant at a level of 0.001 – in fact, it shows the same characteristics as the effect of Burt's constraint on general product innovation in Table 6. And like with new-to-market product innovations, the effect is nowhere to be seen when it comes to new-to-market process innovation in table 9.

Table 8: Logistic regression of the effect of network position on process innovation

	Dependent variable:					
	Process innovation					
	(1)	(2)	(3)	(4)	(5)	(6)
Strength		0.265	0.279	0.198	0.260	0.198
		(0.164)	(0.193)	(0.188)	(0.190)	(0.188)
Reach		0.081	0.080	0.136	0.082	0.136
		(0.126)	(0.126)	(0.134)	(0.126)	(0.135)
Burt's constraint		0.323^{***}	0.325^{***}	0.353^{***}	0.361^{***}	0.353^{***}
		(0.112)	(0.113)	(0.116)	(0.118)	(0.119)
R&D intensity	0.124	0.074	0.087	0.152	0.093	0.152
	(0.094)	(0.099)	(0.132)	(0.142)	(0.132)	(0.143)
Employees (log)	0.506^{***}	0.607^{***}	0.607^{***}	0.630^{***}	0.610^{***}	0.630^{***}
	(0.105)	(0.122)	(0.122)	(0.124)	(0.122)	(0.124)
SectorMarine	-0.155	-0.395	-0.392	-0.382	-0.382	-0.382
	(0.248)	(0.297)	(0.298)	(0.300)	(0.299)	(0.300)
SectorMaritime	-0.141	-0.249	-0.247	-0.242	-0.246	-0.242
	(0.281)	(0.308)	(0.308)	(0.310)	(0.309)	(0.310)
SectorOilGas	-0.220	-0.480	-0.474	-0.463	-0.475	-0.463
	(0.289)	(0.317)	(0.320)	(0.321)	(0.320)	(0.321)
Strength*R&D intensity			0.047	-0.233	-0.097	-0.233
			(0.319)	(0.350)	(0.337)	(0.357)
Reach*R&D intensity				0.358^{**}		0.358^{*}
				(0.157)		(0.183)
Burt's constraint*R&D intensity					-0.092	0.001
					(0.075)	(0.089)
Constant	0.141	0.308	0.309	0.319	0.319	0.319
	(0.210)	(0.235)	(0.235)	(0.236)	(0.236)	(0.236)
Observations	563	484	484	484	484	484
Pseudo R^2 (McFadden)	0.4800	0.5667	0.5805	0.5853	0.5821	0.5853
Log Likelihood	-376.513	-314.184	-314.173	-311.054	-313.409	-311.054
Akaike Inf. Crit.	765.026	646.367	648.345	644.109	648.817	646.109
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 9: Logistic regression of the effect of network position on new-to-market process innovation

	Dependent variable:					
	New-to-market process innovation					
	(1)	(2)	(3)	(4)	(5)	(6)
Strength		-0.071	-0.099	-0.117	-0.108	-0.115
		(0.129)	(0.141)	(0.144)	(0.145)	(0.146)
Reach		0.110	0.118	0.135	0.122	0.129
		(0.137)	(0.137)	(0.139)	(0.138)	(0.138)
Burt's constraint		0.178	0.178	0.189^{*}	0.224^{*}	0.222^{*}
		(0.113)	(0.113)	(0.113)	(0.116)	(0.116)
R&D intensity	0.298^{***}	0.289^{***}	0.231^{*}	0.257^{*}	0.242^{*}	0.252^{*}
	(0.098)	(0.102)	(0.136)	(0.139)	(0.139)	(0.141)
Employees (log)	0.400^{***}	0.449^{***}	0.446^{***}	0.454^{***}	0.444^{***}	0.448^{***}
	(0.113)	(0.126)	(0.126)	(0.127)	(0.127)	(0.127)
SectorMarine	-0.451^{*}	-0.529^{*}	-0.551^{*}	-0.546^{*}	-0.535^{*}	-0.535^{*}
	(0.270)	(0.319)	(0.322)	(0.322)	(0.323)	(0.323)
SectorMaritime	-0.551^{*}	-0.445	-0.451	-0.450	-0.451	-0.450
	(0.316)	(0.334)	(0.334)	(0.334)	(0.336)	(0.336)
SectorOilGas	-0.462	-0.389	-0.420	-0.412	-0.415	-0.412
	(0.318)	(0.338)	(0.341)	(0.341)	(0.343)	(0.342)
Strength*R&D intensity			-0.210	-0.321	-0.396	-0.415
			(0.317)	(0.328)	(0.340)	(0.341)
Reach*R&D intensity				0.152		0.064
				(0.135)		(0.153)
Burt's constraint*R&D intensity					-0.123	-0.105
					(0.077)	(0.087)
Constant	-0.852^{***}	-0.822^{***}	-0.820^{***}	-0.819^{***}	-0.813^{***}	-0.814^{***}
	(0.223)	(0.244)	(0.244)	(0.245)	(0.246)	(0.245)
Observations	563	484	484	484	484	484
Pseudo R^2 (McFadden)	0.3010	0.4176	0.4361	0.4426	0.4383	0.4426
Log Likelihood	-304.976	-268.377	-268.150	-267.481	-266.824	-266.736
Akaike Inf. Crit.	621.951	554.755	556.301	556.963	555.648	557.473
Note:				*p<0.1; **p<0.05; ***p<0.01		

4.3.4 Auxiliary regressions

As this thesis includes methodological choices that are uncommon in the innovation network literature, auxiliary regressions analyses were conducted to ensure that no unexpected biases have been introduced. The full results of these regressions can be found in appendixes 2 and 3. Appendix 2 includes the results for regressions run on variables derived from an unweighted network. In general, the effects of direct ties seem to be weaker and less significant than in the weighted model, which complies with the methodological assumption that node strength is a more accurate operationalisation of the importance of ties' in terms of knowledge exchange and resource sharing. The regression analyses presented in Appendix 3 uses the weighted network variables but includes interaction terms between reach and sector dummies. This is done in order to control for whether the size of each sectoral network has an undue effect on node reach that biases the results in one way or the other. The results in Appendix 3 show that the interaction effects between sector dummies and reach are all weak and insignificant, and the results for the other variables are largely unchanged when compared with the analyses that do not include these interaction terms.

5 Discussion

The regression results presented in chapter 4.3 offer many implications for the theories and hypotheses put forward in chapter 2. The differing results between the different dependent variables also invite further analyses. This chapter will first discuss each of the hypotheses laid out in chapter 2.4, and present the results. The discussion then moves on to explore some patterns in the results that were not explicitly predicted by the hypotheses, and suggests a few possible explanations for why these patterns appear.

5.1 Findings and theoretical implications

The results appear to confirm that R&D network effects would predominantly be found for product innovations rather than process innovations. Process innovations are, with the single exception of Burt’s constraint in table 8, pretty much unaffected by firm’s position in the research network. This should not come as a surprise, seeing as general process innovation does not appear to be significantly affected by R&D intensity at all, which can only be shown to have an effect on new-to-market process innovation. It appears that the STI-mode research network is mostly conducive to product innovation. This is in line with the findings of Parrilli and Elola (2012) and Gonzalez-Pernia et al. (2013), who both establish closer connections between STI and product innovation than STI and process innovation.

This is an interesting finding, as it brings attention to an aspect of innovation networks that is increasingly gaining attention in the literature, namely that collaboration networks will have different implications for different innovation outcomes. Vanhaverbeke et al. (2012) and Guan and Liu (2016) both show that network effects will vary depending on the type of knowledge that is being exchanged and created. While those authors look at how networks affect the development of core and non-core technologies differentially, this thesis confirms the insights from the modes of innovation literature regarding the differential effects of STI and DUI modes of innovation based on how different kinds of innovation depend on the creation and exchange of different kinds of knowledge. This brings attention to the fact that past collaboration network studies, with their focus on citations and patents, might have neglected important forms of networked knowledge exchange that are not immediately associated with R&D. As the innovation potential of the DUI mode is, at its core, based on exploiting the benefits of frequent interaction and direct contact (Jensen et al., 2007), it would be of great interest to use social network analysis to gain further insight into how networks affect innovation in more DUI-dominated contexts.

Meanwhile, as this study deals with an STI-dominated research network, network effects are primarily found for product innovation. The effects found for product innovation are therefore the focus of the discussion relating to the hypotheses put forward in chapter 2.4.

5.1.1 Direct ties and R&D intensity

The first hypothesis and the fourth hypothesis presented in this thesis, that is "H1: Node strength has a positive effect on innovation" and "H4. Network effects on innovation are strengthened by a firm's R&D intensity", are intimately interlinked in the results. Hypothesis 1 is confirmed for both general and new-to-market product innovation, but only if the firm in question has a high level of R&D intensity. The largest positive effect can be seen not from node strength or R&D intensity in isolation, but from the combined effect of the two. This appears to confirm the importance of R&D intensity to absorptive capacity when it comes to securing value from participation in a research network. This confirms the findings of Najafi-Tavani et al. (2018), who find that the level of collaboration with different partners will only affect innovation outcomes in the presence of sufficient absorptive capacity. Tsai (2001) also find a significant positive interaction effect between absorptive capacity and network position on innovation performance among business units in an intraorganisational network. What separates these studies from previous network studies that have not employed absorptive capacity as a moderating factor between network effects and innovation outcome, is that these studies both use the introduction and performance of new products as their dependent variables. A direct, unmoderated connection between network centrality and innovation performance has long been established (Ahuja, 2000, Burt, 1992, Powell et al., 1996) but it has mainly been shown using patent data as a proxy for innovation outcome. This implies that whereas the effects of collaboration network position on *invention* are relatively straightforward, there are more moderating factors at play when it comes to taking knowledge gained from research networks and translating them into actual marketable products.

Both Tsai (2001) and Najafi-Tavani et al. (2018) use complex, multidimensional conceptualisations and operationalisations of absorptive capacity. Meanwhile, for the sake of parsimony this thesis employs a simple and partial operationalisation of absorptive capacity, measuring only the effects of firms' R&D intensity as a proxy. However, the results show that for the RCN-funded research network, R&D intensity is central to firms' ability to take advantage of their network position. This can be explained by how research collaboration depends on the transfer and application of highly complex scientific knowledge. This kind of knowledge is not easily interpreted and put to use, and so the R&D human capital that a high level of R&D intensity indicates aid in the transfer and retaining of the knowledge (Jensen et al., 2007). The R&D intensity of the firm is both an indicator of the magnitude and activeness of the firm's knowledge base and the magnitude of its recombinatorial potential, as well as the resources the firm puts into actualising that potential.

The expression of the combined effect of strength and R&D intensity in a single interaction variable is particularly fitting, as it captures the idea that the two elements enhance each other. While R&D intensity aids the firm in absorbing and putting into use external knowledge, external knowledge also increases the value of internal R&D by providing the firm with points of reference by which to evaluate its R&D efforts (Dyer and Nobeoka, 2000).

The possibility does exist that the particular methodology of this study may have inflated the interaction effect between node strength and R&D intensity. The network variables were all derived from a network graph in which ties are weighted by project budgets. As pointed out in chapter 2.1.3, one assumption made in this weighting is that each tie that makes up a project containing multiple actors is equally intense, which is hardly a realistic assumption. It is plausible to assume that in a project with many collaboration partners, the ties to and from actors with a high level of R&D intensity will stronger than those to and from actors with lower levels of R&D intensity. This would inflate the interaction effect to the detriment of the effect of node strength on its own. In summary, while the combined effects of strength and R&D intensity will still have the same overall magnitude, there is a chance that less of this has to do with the way R&D intensity and strength interact than indicated by the model. Some of it could have to do with how the way model weighs tie strength is biased against highly R&D intensive firms, and so inflates the interaction effect. Of course, this inflation issue will affect unweighted graph models (such as the one estimated in Appendix 2) even more, as in these graphs all ties are taken to be equal. The weighting mitigates the inflation, but seeing as budget data is only available at project level, there is no way to weigh each dyadic relationship in projects with more than two actors.

5.1.2 Indirect ties

The second hypothesis, "node reach has a positive effect on innovation", is confirmed by the results regarding general and new-to-market product innovation. This confirms both established and recent empirical findings when it comes to the effect of indirect ties on innovation (Liang and Liu, 2018, Ahuja, 2000). The effect appears weaker than the effect of node strength, and while there are some tendencies that show an interaction effect between reach and R&D intensity, it is not statistically robust enough to claim there is a definite relationship. This could indicate that while in direct research collaboration, R&D intensity plays a role for the firm's absorptive capacity, other factors are more important for absorbing knowledge from indirect ties. This contributes to confirming Ahuja's (2000) conceptualisation of indirect ties as qualitatively different from direct ties, due to the type of knowledge and quality of information that can be exchanged.

According to Ahuja (2000), knowledge received through indirect ties will be less complex and more general, as it is more prone to noise than knowledge that is transferred through direct ties. Indirect ties do not allow for the transfer of highly complex tacit knowledge, such as the practical know-how and expertise possessed by experienced scientists or engineers. The lack of proximity and regularity of contact makes this kind of knowledge near impossible to transfer via indirect ties. The fact that the innovation effect of indirect ties seems to be less affected by R&D intensity would be in line with the conclusions drawn from the modes of innovation literature, as noise and distance precludes indirect ties to be a site of STI mode innovation.

The relative independence of the effect of indirect ties from R&D intensity might also give further credence to recent studies in the innovation network literature that examine the relationship between networks and different forms of innovation. For example, the findings of Vanhaverbeke et al. (2012) suggest that indirect ties have a positive effect mostly on the development of non-core technologies, and Guan and Liu (2016) find that indirect ties have a positive effect only on explorative innovation and not exploitative innovation. The distinctions between explorative/exploitative innovation and core/non-core technologies both relate to the extent to which certain technologies are part of the most advanced scientific and technological competencies that the firm possesses. The development of core technologies and engagement in exploitative innovation is a highly R&D-dependent process. Meanwhile, the implementation of non-core technologies and explorative innovation might have other factors that are more important to it than R&D intensity. This also suggests that while the highest innovation yields stem from the direct contact between highly R&D-intensive firms, less complex and more general knowledge diffuses through the network to the benefit of both more R&D-intensive firms and less R&D-intensive firms alike.

5.1.3 Ego-network redundancy

As for the third hypothesis about whether ego-network redundancy has a positive or negative effect on product innovation, the results are characteristically ambiguous. H3b, “Ego-network redundancy has a negative effect on innovation” is not confirmed for any of the dependent variables. H3a, on the other hand, “Ego-network redundancy has a positive effect on product innovation” does have a modest but stable and statistically significant effect on product innovation in general, but no discernible effect on new-to-market product innovation. Where there is an effect, R&D intensity does not seem to play any part in moderating it. What makes the result even more confounding is the fact that the exact same pattern can be found for process innovation as well, even though other network effects are virtually absent.

These somewhat ambiguous results are characteristic of the previous findings from the innovation network literature (Ahuja, 2000, McEvily and Zaheer, 1999, Walker et al., 1997). There is no broad consensus in the literature that either Burt’s (1992) proposed benefits of network efficiency or Coleman’s (1988) emphasis on the social benefits of closed network structures is generally the more dominant in determining the effect of network position on innovation outcomes. The results from this thesis seem to indicate that Coleman’s idea of closure, which is to say a dense network of interlocking links between actors, is positively associated with general innovation, but not significantly so when it comes to new-to-market innovations. These results are interesting to contrast with the results of Guan and Liu (2016), who find a negative effect of ego-network redundancy on exploitative innovation, while finding none on explorative innovation. If you see Burt’s network efficiency and Coleman’s closure as two effects working in the opposite direction of each other, the balance between the two will come down differently in different contexts. For example, it could be that new-to-market innovation is more dependent on exploitative innovation focused on the development of core technologies. In this context, it would make sense to see that any positive innovation effects given by ego-network closure would be nullified by the positive effect given by ego-network efficiency found by Guan and Liu (2016).

While this argument is appealing, there are many such arguments that could be formed based on inferences about possible opposing and intermediary effects of network variables. Meanwhile, the fact remains that this thesis does not have the data sources nor the research design to confirm any of these propositions with confidence. However, in the last section of this chapter I allow myself to indulge in some speculative inference regarding some of the more unexpected and ambiguous results from the analysis. The aim is to highlight how the data sources and methods used in this thesis open up new avenues for exploring the more intricate relationships between network position and innovation outcome suggested by the results.

5.2 Explorative discussion on the interpretation of effects on different dependent variables

While the effects found for node strength show the same general pattern of effect and interaction with R&D intensity for both general and new-to-market product innovations, these effects are significantly weaker for the latter. When seen in combination with the differing results that the effects of ego-network redundancy have on general innovation and new-to-market innovation, there seems to be a distinction in how networks affect the two. Below I discuss two potential explanations for this disparity: The first is that new-to-firm and new-to-market innovation are indicators of the extent to which the innovation is radical or incremental. The second is that new-to-market versus new-to-firm innovation expresses a firm’s tendency to imitate its peers, rather than deviate and create something different. Each of these will according to theory be differently affected by a firm’s position in a collaboration network.

In the empirical studies that make use of CIS data to measure innovation outcome, the distinction between general innovation and new-to-market innovation have been used as an indicator of incremental and radical innovation, respectively (Fitjar and Rodríguez-Pose, 2013). The argument goes that products or processes introduced that are not new to the market cannot by definition encompass radical technological shifts or new applications of existing technologies. Radical new developments in technology will on the other hand result in products and processes previously not seen in the market. Such radical innovations are in turn more highly associated with R&D efforts, scientific research collaborations and the STI mode in general (Fitjar and Rodríguez-Pose, 2013). For example, in their study on Norwegian firms, Fitjar and Rodríguez-Pose (2013) find that the STI is more highly associated with new-to-market innovations than with innovation in general.

In this thesis, the disparity between results for product innovation and new-to-market product innovation do show some tendency that this might be due to a difference in radical and incremental innovation. For one, R&D intensity shows a positive effect on new-to-market process innovation, while having no effect on process innovation in general. This could be a reflection of a connection between STI mode and radical innovation, wherein new-to-market process innovation is the outcome of developing new technologies and applying technologies in radically new ways. However, if new-to-market process innovations indeed are more STI-dependent, this invites the question of why node strength or reach in the research collaboration network do not have significant effects on new-to-market process innovation outcome.

What is more, the results for product innovation appear to indicate the opposite trend. While R&D intensity and reach have similar effects on general product innovation and new-to-market product innovation, node strength and its interaction with R&D intensity are actually weaker and less significant for the latter than for the former. One of the assumptions behind the hypothesis linking node strength, R&D intensity and product innovation is these constitute a nexus of the kind of complex and intensive information exchange that is crucial to STI. If anything, one would expect to see the opposite trend, where node strength and its interaction with R&D intensity would have a stronger effect on radical product innovation than incremental product innovation.

On the whole the results do not consistently fit with an explanation that sees the discrepancy between effects on general innovation and new-to-market innovation as a result of how radical and incremental innovation are affected. Instead of looking at new-to-market innovation as an indicator of more radical innovation, the results might better be explained by a framework that sees the difference between new-to-firm innovations and new-to-market innovations as the difference between imitation and deviance. From this standpoint, engaging in imitative innovation can encompass both STI-intensive processes, including implementing radical technological changes or new technological applications, as well as less STI-intensive processes, such as imitating new forms of organisation in the production process. New-to-market innovation can also include both STI-driven shifts that radically change technology, or equally incremental developments that follow the development of a firm's core competencies, be they STI-driven or not.

This idea builds upon a conceptualisation of novelty generation taken from Soda et al. (2008) and Soda and Bizzi (2012). They focus on the effect that social networks have on the creativity of actors, defining creativity as a *deviation* from what partners are doing. The question of whether a product or process is new to the market can be seen as an indicator of whether an actor deviates from the activities of their peers. This is a clear deviation from the general strand of the innovation literature, where novelty is the result of the exploitation of the recombinant potential from large and heterogeneous knowledge stocks, irrespective of whether the process involves a deviation from or imitation of the activities other actors. While in the management literature the network effects of imitation has mainly been connected to strategic and organisational behaviour (Fligstein, 1991, Haveman, 1993, Haunschild and Miner, 1997, Lieberman and Asaba, 2006), Sutton and Dobbin (1996) and Soda et al. (2008)show that network effects on imitative behaviour also can affect product imitation and differentiation.

According to Soda and Bizzi (2012), network effects can exercise both positive and negative effects on an actor's proclivity to engage in imitation. For one, the more time and resources actors devote to shared projects, the less time they have to devote to exploratory thoughts and to use new information to develop entirely new ideas (O'leary et al., 2011). In addition, network ties are themselves an important source not just of new knowledge, but also of imitative behaviour (Galaskiewicz and Burt, 1991, Greve, 1996, Soda et al., 2008). Network closure is conducive not only to efficient knowledge transfer but also to conformity (Coleman, 1988, Donaldson, 1997).

Looking at innovation outcome through the lens of imitation versus deviation, one is able to make sense of many of the differing results for new-to-market innovation compared to innovation in general. For example, the positive effect that node strength has on general product innovation might be curbed for new-to-market product innovation due to its effect on imitative behaviour. In the same vein, the positive effect that ego-network redundancy has for both general process and general product innovation could be outweighed by the effect of conformity when it comes to new-to-market innovation. In summary, it seems that while large and redundant ego-networks do affect innovation positively by providing actors with access to novel knowledge sources, they can also constrain actors' proclivity to deviate from what peers are doing.

Whether the differing network effects on general innovation and new-to-market innovation is not the main aim of this thesis, and I do not purport to show definite evidence that either the radical/incremental or the imitation/deviation dichotomies explain the divergence of network effects on different innovation outcomes. However, the discussion highlights the potential of this empirical material to explore how networks differently affect different innovation outcomes.

In summary, the discussion above shows that the thesis is successful in confirming established hypotheses around the effects of direct and indirect ties on innovation outcome using survey data. In addition to this, it has shed light on the varying importance of R&D intensity as a moderating factor for the effect of both direct and indirect ties. Lastly, the ambiguous results around network closure reflect the mixed results found in the existing innovation network literature, and the final discussion highlights how the methods and data of the thesis provides future opportunities to investigate why network position can have different effects for different types of innovation outcome.

6 Conclusion

6.1 Research aims achieved

In this thesis, I started out with a twofold mission. The first was to combine data sources in a new way to test theories on how firm network position affects innovation outcomes. The second was to make use of this new combination of data to explore how these network effects have different impacts on different measures of innovation outcome. In doing this, I have had to resolve a set of problems particular to the data used in this thesis, which has resulted in novel approaches to both the delineation and weighting of networks. In addition to testing my initial hypotheses, the results of this study have also yielded new insights into the various network dynamics that affect innovation in different ways.

The first aim achieved is to confirm the positive association between network centrality and innovation outcome posited by previous innovation network literature. This is a meaningful contribution both to the innovation literature and policymakers, as it supports the notion that collaboration networks contribute to innovation more than just the sum of their parts. Whereas patent-based studies have repeatedly shown similar relationships between research collaboration networks and *invention*, this is one of relatively few studies that estimate the effect of network position on firms' propensity actually to introduce new products and processes to the market.

In so doing, I have also brought attention to how dependent network effects are on a firm's absorptive capacity. In this thesis, I have established a strong relationship between a firm's R&D intensity and its ability to benefit from its participation in a research network. While R&D intensity is only one component of a firm's total absorptive capacity, it has here been shown to be crucial when it comes to taking advantage of knowledge flows from direct ties in a research network and use them to bring new products to market.

A finding of particular interest is the fact that while research networks have an impact on innovation outcome, they do not affect all types of innovation outcome equally. This is most clearly shown in the difference in results for product innovation and process innovation. In testing research network effects on various different innovation outcomes, I have found that the results confirm previous findings from the modes of innovation literature. That is to say, as research networks encompass the creation and exchange of highly complex scientific and technological knowledge, a firm's position in such a network mostly affects its propensity to introduce new products, while doing little to predict its level of process innovation.

These findings have implication for innovation scholars and policymakers alike, as they bring attention to the fact that there are several different forms of innovation outcome, and specific network structures will have different implications for each of them. Whereas the study's results for ego-network redundancy's effect on innovation outcome are ambiguous and context-dependent, the combined results for all four types of innovation outcome studied do shed some light on the different network dynamics at play. Both the results for node strength and ego-network redundancy indicate that network effects may be influenced by network dynamics related to how network actors tend to imitate each other. This in turn affects whether certain network positions tend to facilitate innovation that is new to the market or the imitation of products that already exist. While the thesis does not provide rigorous tests to support these claims, it does suggest that investigating the effects of imitation is a potential avenue for further research into how networks affect different forms of innovation outcome. These findings are of interest to both theorists and practitioners, as they suggest not only that the same network structures that spur innovation by facilitating knowledge exchange may also inhibit innovation by discouraging deviance and creativity, but that the balance of these effects will differ for different innovation outcomes.

Beyond its empirical findings, one of the main achievements of the thesis is the development of methodological approaches to performing network analysis on research networks. Due to the unique data source used in this thesis, new avenues have been explored by which to model innovation networks. The most important of these is the use of a network weighted by project budgets, which improves the operationalisation of the knowledge flows and resource sharing involved in research collaborations. Using a network weighted by budgets, one has a reasonable proxy to differentiate between more and less important ties that can be used for a wide variety of network measures beyond just the three employed in this study. Furthermore, delineating a network into sub-networks according to knowledge areas is one solution to the problem of determining which ties are and are not relevant to the firms participating in large and highly diverse research networks. The delineations of networks will almost inevitably introduce some arbitrary limitations or biases to network analyses, and it is therefore ever more imperative that methods be developed to mitigate these issues. While the solution applied in this thesis is an ad-hoc response to a particular dataset in a particular research context, I hope that it can inspire similar approaches for corresponding problems in the future.

6.2 Limitations and opportunities for future research

The main limitation of this study is that while it establishes a series of correlations between research network position and innovation output, there are no statistical tests to infer definite claims about the causal relationship between the two. The mechanisms for how network position affects innovation outcome have been laid out in chapter 2, though as explained in chapter 3.3, there are many possible sources of both omitted variable bias and, perhaps most importantly, endogenous processes that affect how research networks are formed. This is a significant limitation on the results, as due to the complexity of the innovation process, both theorists and policymakers could benefit greatly from statistical designs that could confirm with greater certainty the causal relationships that are proposed by the innovation network literature.

First, the data sources used in this thesis contain data on a far more diverse set of sectors than what was utilised in this study. With the experience of how well these data match the CIS data and the biases introduced, it should be possible to utilise a greater part of the data set to account for more sectors. This would open up avenues to use interaction terms to investigate how network effects vary across sectors and enable analyses of how network effects are moderated by different technological and market environments.

Second, the discontinuity between pre- and post 2014 CIS data partly prevented this study from using time-series data to control for time-invariant effects. Meanwhile, the RCN database is updated continuously, and the Norwegian CIS is conducted biannually, so the potential to use this data to investigate network effects on innovation outcome using time-series designs will only grow with time. This also opens up new avenues for using more sophisticated research designs for causal inference, such as regression discontinuities, difference-in-difference designs or Two-Stage Least Square (2SLS) regression analysis. Each of these can be used to determine causal effects in the system by investigating the effects of exogenous shocks over time, such as the introduction of policy measures or changes in external market conditions. For the Norwegian innovation system, the oil price is one example of an effect that can be seen as both highly exogenous and highly influential to the development of the research network, and carry the potential to tease out the causal processes at play in research collaboration networks.

These two approaches are just general examples among a myriad of possibilities that are are made accessible by this novel combination of data sources. This was the first time these data sources were combined and applied for research purposes, and the lessons learned in the process are highly valuable for future research. Whereas a more complex research design for causal inference has been outside the scope of this master's thesis, both the empirical findings and methodological approaches put forward in this thesis can form the basis for future research on how research networks affect innovation outcome.

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Appendix

Appendix 1: Overview of RCN project tags

Bedre helse og helsetjenester
Basal biomedisinsk forskning
LTP Bedre offentlige tjenester
LTP Et innovativt næringsliv
LTP Muliggjørende teknologier
LTP Verdensledende fagmiljøer
LTP Fagmiljøer og talenter
LTP Helse- og omsorgstjenester
LTP Næring og samfunnsutfordringer
Bioteknologi
Protomikk
Strukturbiologi
Energi
Annen miljøvennlig energi, grunnleggende og tverrgående energiforskning
LTP Miljøvennlig energi
LTP Nanoteknologi
Funksjonelle materialer
Mat
Mat - Blå sektor
Mat, helse og velvære
Annen bioteknologi
Miljøvennlig transport, hydrogen
Miljø
Bærekraftig energi
Translasjonsforskning
Globale utfordringer
Globale miljøutfordringer
LTP Hav
LTP Marint
LTP Miljø og samfunn
Marin
Fiskeri
Havbruk
Mat - Blågrønn
Reiseliv
Natur og kultur
Annen miljøvennlig energi, energisystemer
Global energisikkerhet
Global tilgang på miljøvennlig energi
Miljøteknologi
Mat - Grønn sektor
Trygg verdikjede
LTP Næringsliv i bredden
Reiselivsnæringen
Annen miljøvennlig energi, energieffektivisering bygg
IKT
IKT - Bruk og anvendelser i andre fag
Maritim
Sjøtransport
Global matsikkerhet
LTP Fornyelse i offentlig sektor
LTP Kommersialisering og nyskaping
Nanobioteknologi
Petroleum, leting og økt utvinning
LTP Petroleum
Globale klimautfordringer
Klima
Klimaeffekter og klimatilpasninger
Kulturminner og kulturmiljøer
Kultur
Kulturelle og naturlige omgivelser
Kulturmangfold
Samfunnsmedisinsk og annen helsefaglig forskning
IKT - Som fag og teknologi
Petroleum, teknologi for produksjon, prosessering og transport
Klinisk forskning
Mikro- og nanoelektronikk
Bioprospektering
Genomikk
Syntetisk biologi
Etiske, juridiske og samfunnsmessige aspekter
Annen miljøvennlig energi, energipolitikk, energimarked
Klimasystemet og klimaendringer
Offshore operasjoner
Forskning om innovasjon i og for offentlig forvaltning og tjenesteyting

Velferd, arbeidsliv og utdanning
Arbeid
Havbruks- og fiskeriteknologi
Sosioøkonomisk forskning
Global fattigdom
Global partner
Miljøvennlig transport, nye transportsystemløsninger
Annen miljøvennlig energi, energieffektivisering industri
Annen miljøvennlig energi, klimavennlig oppvarming/kjøling
Fornybar kraft, bio
Bioprosess
LTP Internasjonalisering
Rammebetingelser og virkemidler for utslippsreduksjon
LTP Forskningsinfrastruktur
Internasjonal politikk og økonomi
Fornybar kraft, vind
Samfunnets verdigrunnlag
Språk, medier og kommunikasjon
Fornybar kraft, vannkraft
Annen miljøteknologi
Petroleum, kostnadseffektiv boring og intervensjon
LTP Utdanning og læring
Undervisning og læring
Velferdssamfunnets tjenester og organisering
Utdanning i samspill med arbeids- og samfunnsliv
Demokrati og regional utvikling
Internasjonal migrasjon og innvandring
Levekår og befolkningsutvikling

Profesjonsutøvelse i velferdssektorens yrker
Ledelse, organisering og styring i utdanningssektoren
Petroleum, HMS og samfunn
Bioinformatikk
Molekylær avbildning
Sekvensieringsteknologi
Systembiologi
Vitenskap og samfunn
CCS - fangst
CCS - lagring
Helse, miljø og sikkerhet
Nanoteknologi
Lipidbiologi
Biobanker
Velferdssamfunnets kulturelle basis
LTP Avanserte produksjonsprosesser
Petroleum, energieffektiv og miljøvennlig teknologi
Fornybar kraft, sol
CCS - annet
Miljøvennlig transport, bio
Nanovitenskap
Fornybar kraft, annet
Miljøvennlig transport, el
Fornybar kraft, hav
CCS - transport
Transport og mobilitet

Appendix 2: Auxiliary regressions using unweighted network graph

	Dependent variable:					
	Product innovation					
	(1)	(2)	(3)	(4)	(5)	(6)
Degree centrality		-0.217	-0.217	1.363**	1.364**	1.719**
		(0.171)	(0.171)	(0.621)	(0.621)	(0.713)
Reach		0.486	0.486	0.526*	0.528*	0.566*
		(0.312)	(0.312)	(0.312)	(0.321)	(0.322)
Burt's constraint		0.139	0.139	0.364*	0.365*	0.412**
		(0.169)	(0.169)	(0.195)	(0.198)	(0.200)
R&D intensity	0.552***	0.451***	0.451***	1.984***	1.984***	2.177***
	(0.173)	(0.161)	(0.161)	(0.616)	(0.616)	(0.660)
Employees (log)	0.445***	0.491***	0.491***	0.504***	0.503***	0.493***
	(0.145)	(0.162)	(0.162)	(0.165)	(0.165)	(0.164)
SectorMarine	-0.180	-0.945	-0.945	-0.938	-0.942	-0.997*
	(0.293)	(0.581)	(0.581)	(0.579)	(0.602)	(0.591)
SectorMaritime	-0.072	-0.033	-0.033	-0.022	-0.022	-0.027
	(0.333)	(0.368)	(0.368)	(0.372)	(0.372)	(0.373)
SectorOilGas	-0.187	-0.268	-0.268	-0.141	-0.141	-0.097
	(0.343)	(0.375)	(0.375)	(0.381)	(0.381)	(0.383)
Strength*R&D intensity				3.254***	3.257***	4.073***
				(1.119)	(1.125)	(1.352)
Reach*R&D intensity					-0.003	
					(0.137)	
Burt's constraint*R&D intensity						0.191
						(0.164)
Constant	1.343***	1.676***	1.676***	2.306***	2.307***	2.419***
	(0.254)	(0.334)	(0.334)	(0.433)	(0.438)	(0.452)
Observations	563	490	490	490	490	490
Log Likelihood	-296.284	-251.261	-251.261	-243.644	-243.644	-242.882
Akaike Inf. Crit.	604.567	520.522	520.522	507.289	509.288	507.765
Note:						*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:					
	New-to-market product innovation					
	(1)	(2)	(3)	(4)	(5)	(6)
Degree centrality		-0.307^{*}	-0.307^{*}	1.292^{**}	1.258^{**}	1.345^{**}
		(0.163)	(0.163)	(0.552)	(0.553)	(0.601)
Reach		0.936^{***}	0.936^{***}	0.942^{***}	0.857^{***}	0.952^{***}
		(0.322)	(0.322)	(0.314)	(0.325)	(0.317)
Burt's constraint		0.093	0.093	0.307^{*}	0.272	0.314^{*}
		(0.150)	(0.150)	(0.169)	(0.172)	(0.172)
R&D intensity	0.515^{***}	0.509^{***}	0.509^{***}	2.144^{***}	2.178^{***}	2.170^{***}
	(0.135)	(0.135)	(0.135)	(0.546)	(0.548)	(0.561)
Employees (log)	0.508^{***}	0.523^{***}	0.523^{***}	0.544^{***}	0.550^{***}	0.542^{***}
	(0.128)	(0.140)	(0.140)	(0.143)	(0.143)	(0.143)
SectorMarine	-0.157	-1.605^{***}	-1.605^{***}	-1.532^{***}	-1.340^{**}	-1.546^{***}
	(0.261)	(0.578)	(0.578)	(0.567)	(0.590)	(0.571)
SectorMaritime	0.052	0.172	0.172	0.181	0.186	0.180
	(0.299)	(0.327)	(0.327)	(0.333)	(0.332)	(0.333)
SectorOilGas	-0.170	-0.117	-0.117	0.004	-0.020	0.011
	(0.306)	(0.337)	(0.337)	(0.343)	(0.343)	(0.344)
Strength*R&D intensity				3.394^{***}	3.229^{***}	3.524^{***}
				(0.987)	(1.000)	(1.143)
Reach*R&D intensity					0.179	
					(0.137)	
Burt's constraint*R&D intensity						0.030
						(0.128)
Constant	0.739^{***}	1.296^{***}	1.296^{***}	1.921^{***}	1.850^{***}	1.939^{***}
	(0.223)	(0.306)	(0.306)	(0.385)	(0.390)	(0.395)
Observations	563	490	490	490	490	490
Log Likelihood	-345.066	-292.238	-292.238	-281.658	-280.707	-281.632
Akaike Inf. Crit.	702.132	602.476	602.476	583.316	583.415	585.263
Note:				*p<0.1; **p<0.05; ***p<0.01		

	Dependent variable:					
	Process innovation					
	(1)	(2)	(3)	(4)	(5)	(6)
Degree centrality		0.357**	0.357**	0.397**	0.391**	0.391**
		(0.176)	(0.176)	(0.186)	(0.186)	(0.186)
Reach		0.078	0.078	0.066	0.015	0.056
		(0.278)	(0.278)	(0.279)	(0.288)	(0.281)
Burt's constraint		0.374***	0.374***	0.389***	0.375***	0.401***
		(0.141)	(0.141)	(0.144)	(0.144)	(0.146)
R&D intensity	0.001	-0.087	-0.087	-0.055	-0.052	-0.051
	(0.086)	(0.092)	(0.092)	(0.103)	(0.103)	(0.102)
Employees (log)	0.274***	0.288***	0.288***	0.290***	0.292***	0.293***
	(0.090)	(0.101)	(0.101)	(0.100)	(0.101)	(0.101)
SectorMarine	-0.146	-0.427	-0.427	-0.400	-0.315	-0.377
	(0.245)	(0.509)	(0.509)	(0.511)	(0.524)	(0.515)
SectorMaritime	-0.120	-0.215	-0.215	-0.209	-0.211	-0.206
	(0.277)	(0.304)	(0.304)	(0.304)	(0.304)	(0.304)
SectorOilGas	-0.147	-0.398	-0.398	-0.381	-0.394	-0.386
	(0.285)	(0.313)	(0.313)	(0.314)	(0.315)	(0.315)
Strength*R&D intensity				0.135	0.066	0.046
				(0.191)	(0.208)	(0.236)
Reach*R&D intensity					0.077	
					(0.092)	
Burt's constraint*R&D intensity						-0.053
						(0.088)
Constant	0.199	0.402	0.402	0.400	0.369	0.395
	(0.207)	(0.277)	(0.277)	(0.277)	(0.280)	(0.278)
Observations	563	490	490	490	490	490
Log Likelihood	-383.466	-325.870	-325.870	-325.614	-325.265	-325.429
Akaike Inf. Crit.	778.932	669.740	669.740	671.227	672.530	672.858
Note:						*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:					
	New-to-market process innovation					
	(1)	(2)	(3)	(4)	(5)	(6)
Degree centrality		-0.197	-0.197	-0.174	-0.175	-0.171
		(0.182)	(0.182)	(0.183)	(0.183)	(0.182)
Reach		0.359	0.359	0.341	0.353	0.331
		(0.328)	(0.328)	(0.327)	(0.334)	(0.331)
Burt's constraint		0.206	0.206	0.218	0.221	0.237
		(0.145)	(0.145)	(0.145)	(0.146)	(0.147)
R&D intensity	0.206^{**}	0.181^{*}	0.181^{*}	0.220^{**}	0.219^{**}	0.224^{**}
	(0.091)	(0.094)	(0.094)	(0.105)	(0.105)	(0.105)
Employees (log)	0.198^{**}	0.235^{***}	0.235^{***}	0.241^{***}	0.241^{***}	0.241^{***}
	(0.078)	(0.085)	(0.085)	(0.086)	(0.086)	(0.086)
SectorMarine	-0.439	-0.980^{*}	-0.980^{*}	-0.943	-0.962	-0.913
	(0.269)	(0.589)	(0.589)	(0.588)	(0.597)	(0.594)
SectorMaritime	-0.514	-0.379	-0.379	-0.375	-0.375	-0.371
	(0.314)	(0.333)	(0.333)	(0.333)	(0.333)	(0.334)
SectorOilGas	-0.395	-0.318	-0.318	-0.298	-0.297	-0.298
	(0.315)	(0.339)	(0.339)	(0.340)	(0.340)	(0.341)
Strength*R&D intensity				0.157	0.173	0.042
				(0.189)	(0.209)	(0.242)
Reach*R&D intensity					-0.018	
					(0.096)	
Burt's constraint*R&D intensity						-0.071
						(0.094)
Constant	-0.796^{***}	-0.591^{**}	-0.591^{**}	-0.599^{**}	-0.591^{**}	-0.608^{**}
	(0.221)	(0.299)	(0.299)	(0.299)	(0.301)	(0.300)
Observations	563	490	490	490	490	490
Log Likelihood	-308.178	-272.567	-272.567	-272.230	-272.213	-271.935
Akaike Inf. Crit.	628.355	563.133	563.133	564.459	566.426	565.869
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

Appendix 3: Auxiliary regressions with sector-reach interaction effect

	Dependent variable:					
	Product innovation					
	(1)	(2)	(3)	(4)	(5)	(6)
Strength		-0.356**	-0.356**	2.248***	2.060**	2.313***
		(0.140)	(0.140)	(0.842)	(0.842)	(0.887)
Reach		0.956*	0.956*	1.153*	1.302**	1.146*
		(0.569)	(0.569)	(0.615)	(0.626)	(0.616)
Burt's constraint		0.276**	0.276**	0.383**	0.400**	0.382**
		(0.139)	(0.139)	(0.155)	(0.159)	(0.154)
R&D intensity	0.552***	0.425***	0.425***	2.634***	2.722***	2.664***
	(0.173)	(0.165)	(0.165)	(0.677)	(0.674)	(0.693)
Employees (log)	0.445***	0.541***	0.541***	0.599***	0.603***	0.597***
	(0.145)	(0.168)	(0.168)	(0.178)	(0.177)	(0.178)
SectorMarine	-0.180	-0.859*	-0.859*	-0.807*	-0.828*	-0.805*
	(0.293)	(0.450)	(0.450)	(0.469)	(0.470)	(0.469)
SectorMaritime	-0.072	0.029	0.029	-0.036	-0.100	-0.031
	(0.333)	(0.579)	(0.579)	(0.604)	(0.607)	(0.605)
SectorOilGas	-0.187	-0.170	-0.170	0.344	0.278	0.363
	(0.343)	(0.623)	(0.623)	(0.694)	(0.691)	(0.700)
Strength*R&D intensity				6.206***	5.715***	6.370***
				(1.686)	(1.702)	(1.817)
Reach*R&D intensity					0.393	
					(0.307)	
Burt's constraint*R&D intensity						0.030
						(0.114)
Reach*SectorMarine		-0.476	-0.476	-0.676	-0.693	-0.668
		(0.593)	(0.593)	(0.633)	(0.632)	(0.634)
Reach*SectorMaritime		0.005	0.005	-0.319	-0.424	-0.309
		(0.798)	(0.798)	(0.853)	(0.859)	(0.855)
Reach*SectorOilGas		0.159	0.159	0.529	0.422	0.550
		(0.872)	(0.872)	(0.958)	(0.953)	(0.963)
Constant	1.343***	1.799***	1.799***	2.663***	2.702***	2.671***
	(0.254)	(0.408)	(0.408)	(0.533)	(0.532)	(0.536)
Observations	563	484	484	484	484	484
Log Likelihood	-296.284	-241.211	-241.211	-227.493	-226.496	-227.459
Akaike Inf. Crit.	604.567	506.422	506.422	480.987	480.992	482.918
Note:						*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:					
	New-to-market product innovation					
	(1)	(2)	(3)	(4)	(5)	(6)
Strength		-0.274**	-0.274**	1.177**	0.979*	0.971*
		(0.138)	(0.138)	(0.550)	(0.556)	(0.555)
Reach		0.924*	0.924*	0.981*	1.164**	1.028**
		(0.491)	(0.491)	(0.511)	(0.522)	(0.512)
Burt’s constraint		0.086	0.086	0.154	0.170	0.154
		(0.118)	(0.118)	(0.127)	(0.131)	(0.130)
R&D intensity	0.515***	0.459***	0.459***	1.746***	1.922***	1.732***
	(0.135)	(0.135)	(0.135)	(0.437)	(0.448)	(0.430)
Employees (log)	0.508***	0.535***	0.535***	0.570***	0.579***	0.581***
	(0.128)	(0.141)	(0.141)	(0.147)	(0.147)	(0.148)
SectorMarine	-0.157	-0.745*	-0.745*	-0.670*	-0.691*	-0.685*
	(0.261)	(0.380)	(0.380)	(0.392)	(0.395)	(0.393)
SectorMaritime	0.052	0.291	0.291	0.317	0.241	0.300
	(0.299)	(0.509)	(0.509)	(0.528)	(0.532)	(0.529)
SectorOilGas	-0.170	-0.151	-0.151	0.199	0.124	0.125
	(0.306)	(0.534)	(0.534)	(0.573)	(0.570)	(0.572)
Strength*R&D intensity				3.722***	3.173***	3.137***
				(1.102)	(1.130)	(1.147)
Reach*R&D intensity					0.549**	
					(0.279)	
Burt’s constraint*R&D intensity						-0.154
						(0.110)
Reach*SectorMarine		-0.528	-0.528	-0.600	-0.610	-0.648
		(0.509)	(0.509)	(0.526)	(0.527)	(0.527)
Reach*SectorMaritime		0.188	0.188	0.123	-0.004	0.073
		(0.706)	(0.706)	(0.737)	(0.742)	(0.738)
Reach*SectorOilGas		0.014	0.014	0.278	0.148	0.189
		(0.762)	(0.762)	(0.805)	(0.801)	(0.803)
Constant	0.739***	1.121***	1.121***	1.547***	1.615***	1.558***
	(0.223)	(0.338)	(0.338)	(0.396)	(0.400)	(0.394)
Observations	563	484	484	484	484	484
Log Likelihood	-345.066	-285.799	-285.799	-276.161	-273.674	-275.104
Akaike Inf. Crit.	702.132	595.597	595.597	578.322	575.348	578.208

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

	Dependent variable:					
	Process innovation					
	(1)	(2)	(3)	(4)	(5)	(6)
Strength		0.335*	0.335*	0.351*	0.274	0.331*
		(0.172)	(0.172)	(0.200)	(0.198)	(0.199)
Reach		0.073	0.073	0.069	0.163	0.119
		(0.430)	(0.430)	(0.431)	(0.435)	(0.434)
Burt's constraint		0.282**	0.282**	0.284**	0.310***	0.323***
		(0.111)	(0.111)	(0.111)	(0.114)	(0.116)
R&D intensity	0.001	-0.062	-0.062	-0.048	-0.008	-0.044
	(0.086)	(0.093)	(0.093)	(0.128)	(0.134)	(0.127)
Employees (log)	0.274***	0.290***	0.290***	0.290***	0.299***	0.297***
	(0.090)	(0.099)	(0.099)	(0.099)	(0.099)	(0.100)
SectorMarine	-0.146	-0.372	-0.372	-0.367	-0.382	-0.371
	(0.245)	(0.323)	(0.323)	(0.325)	(0.326)	(0.325)
SectorMaritime	-0.120	-0.124	-0.124	-0.119	-0.172	-0.133
	(0.277)	(0.407)	(0.407)	(0.408)	(0.410)	(0.408)
SectorOilGas	-0.147	-0.430	-0.430	-0.421	-0.456	-0.460
	(0.285)	(0.455)	(0.455)	(0.459)	(0.458)	(0.460)
Strength*R&D intensity				0.051	-0.231	-0.115
				(0.320)	(0.355)	(0.340)
Reach*R&D intensity					0.330**	
					(0.152)	
Burt's constraint*R&D intensity						-0.103
						(0.074)
Reach*SectorMarine		0.002	0.002	0.006	-0.027	-0.045
		(0.445)	(0.445)	(0.445)	(0.447)	(0.448)
Reach*SectorMaritime		0.185	0.185	0.192	0.073	0.149
		(0.594)	(0.594)	(0.596)	(0.602)	(0.599)
Reach*SectorOilGas		-0.062	-0.062	-0.056	-0.158	-0.138
		(0.673)	(0.673)	(0.675)	(0.676)	(0.678)
Constant	0.199	0.393	0.393	0.393	0.418	0.420
	(0.207)	(0.278)	(0.278)	(0.278)	(0.279)	(0.279)
Observations	563	484	484	484	484	484
Log Likelihood	-383.466	-322.519	-322.519	-322.506	-319.667	-321.516
Akaike Inf. Crit.	778.932	669.038	669.038	671.012	667.334	671.031
Note:				*p<0.1; **p<0.05; ***p<0.01		

	Dependent variable:					
	inpsnm					
	(1)	(2)	(3)	(4)	(5)	(6)
Strength		-0.023	-0.023	-0.051	-0.067	-0.058
		(0.132)	(0.132)	(0.143)	(0.146)	(0.146)
Reach		0.221	0.221	0.245	0.287	0.327
		(0.441)	(0.441)	(0.442)	(0.444)	(0.446)
Burt's constraint		0.146	0.146	0.146	0.159	0.208^{*}
		(0.115)	(0.115)	(0.115)	(0.116)	(0.119)
R&D intensity	0.206^{**}	0.189^{**}	0.189^{**}	0.128	0.151	0.135
	(0.091)	(0.096)	(0.096)	(0.132)	(0.133)	(0.134)
Employees (log)	0.198^{**}	0.196^{**}	0.196^{**}	0.193^{**}	0.199^{**}	0.201^{**}
	(0.078)	(0.085)	(0.085)	(0.085)	(0.085)	(0.085)
SectorMarine	-0.439	-0.565^{*}	-0.565^{*}	-0.594^{*}	-0.600^{*}	-0.600^{*}
	(0.269)	(0.343)	(0.343)	(0.346)	(0.346)	(0.347)
SectorMaritime	-0.514	-0.635	-0.635	-0.645	-0.671	-0.672
	(0.314)	(0.450)	(0.450)	(0.451)	(0.453)	(0.455)
SectorOilGas	-0.395	-0.330	-0.330	-0.384	-0.406	-0.442
	(0.315)	(0.468)	(0.468)	(0.475)	(0.477)	(0.480)
Strength*R&D intensity				-0.215	-0.330	-0.427
				(0.319)	(0.330)	(0.343)
Reach*R&D intensity					0.157	
					(0.132)	
Burt's constraint*R&D intensity						-0.141^{*}
						(0.078)
Reach*SectorMarine		-0.102	-0.102	-0.118	-0.144	-0.202
		(0.457)	(0.457)	(0.458)	(0.458)	(0.461)
Reach*SectorMaritime		-0.458	-0.458	-0.471	-0.529	-0.539
		(0.636)	(0.636)	(0.637)	(0.640)	(0.642)
Reach*SectorOilGas		-0.040	-0.040	-0.086	-0.153	-0.220
		(0.692)	(0.692)	(0.696)	(0.699)	(0.704)
Constant	-0.796^{***}	-0.697^{**}	-0.697^{**}	-0.690^{**}	-0.678^{**}	-0.657^{**}
	(0.221)	(0.283)	(0.283)	(0.284)	(0.284)	(0.285)
Observations	563	484	484	484	484	484
Log Likelihood	-308.178	-271.578	-271.578	-271.343	-270.607	-269.629
Akaike Inf. Crit.	628.355	567.157	567.157	568.685	569.215	567.257
Note:				*p<0.1; **p<0.05; ***p<0.01		