UiO : Centre for Entrepreneurship
University of Oslo

Drivers for Eco-innovation
A Multilevel study

MSc in Innovation and Entrepreneurship

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21.05.2018

Oppgavens tittel:	**The drivers for Eco-innovation: a multilevel study.**	**Levert dato: 22.05.18**
Forfatter:	**Faraimo Jay Vai**	
Mastergrad:	**Master of Science in Innovation and Entrepreneurship**	**Tall sider u/vedlegg: 54**
		Tall sider m/vedlegg: 64
Veileder:	**Jarle Aarstad**	
Studieobjekt:	**Investigate drivers of eco-innovation.**	
Metodevalg:	**Quantative**	

Sammendrag:

The aim of this master thesis is to investigate the drivers for eco-innovation in Norway using multilevel analysis both at the enterprise level and at the regional level. As a secondary goal of this master thesis, we also assessed whether the drivers for eco-innovation in Norway were distinct from the drivers of general innovation. Although the drivers tested in this thesis at the enterprise level, enterprise size, productivity, R&D, external collaboration, and having an international market, have been assessed before in other countries, such a study has never been carried out in Norway. In regard to the regional level, to my knowledge no other study has investigated the effect of both regional population size and regional geographic size on the propensity for eco-innovation. The findings from this study implies that enterprise size, productivity, R&D, external collaboration and having an international market are all drivers of eco-innovation. At the regional level, the findings imply that regional population size has a negative association with eco-innovation, in that a lower regional population seems to encourage eco-innovation. In addition, regional geographical size seems to have a positive association with the propensity to eco-innovate. As to the second aim of this master thesis, the findings imply that although there are differences between the drivers of some aspects of eco-innovation and some aspects general innovation, an overall conclusion that these drivers were distinctly different could not be made.

Stikkord for bibliotek: Eco-innovation. Drivers. Multilevel study. Norway. Ordinal logistics regression.

2018

The drivers for Eco-innovation

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1 *Abstract*

The aim of this master thesis is to investigate the drivers for eco-innovation in Norway using multilevel analysis both at the enterprise level and at the regional level. As a secondary goal of this master thesis, we also assessed whether the drivers for eco-innovation in Norway were distinct from the drivers of general innovation. Although the drivers tested in this thesis at the enterprise level, enterprise size, productivity, R&D, external collaboration, and having an international market, have been assessed before in other countries, such a study has never been carried out in Norway. In regard to the regional level, to my knowledge no other study has investigated the effect of both regional population size and regional geographic size on the propensity for eco-innovation. The findings from this study implies that enterprise size, productivity, R&D, external collaboration and having an international market are all drivers of eco-innovation. At the regional level, the findings imply that regional population size has a negative association with eco-innovation, in that a lower regional population seems to encourage eco-innovation. In addition, regional geographical size seems to have a positive association with the propensity to eco-innovate. As to the second aim of this master thesis, the findings imply that although there are differences between the drivers of some aspects of eco-innovation and some aspects general innovation, an overall conclusion that these drivers were distinctly different could not be made.

Norwegian Translation.

Målet med denne masteroppgaven er å undersøke drivkreftene for eco-innovasjon i Norge ved hjelp av flernivåanalyser både på foretaksnivå og på regionalt nivå. Som et sekundært mål for denne masteroppgaven, vurderte vi også om drivkreftene for eco-innovasjon i Norge var forskjellig fra drivkreftene av generell innovasjon. Selv om drivkreftene testet i denne oppgaven på foretaksnivå, bedriftenes størrelse, produktivitet, FoU, eksternt samarbeid og et internasjonalt marked har blitt vurdert tidligere i andre land, et slik studie har aldri blitt gjennomført i Norge. Med hensyn til det regionale nivået har ingen annen studie undersøkt effekten av både regional befolkningsstørrelse og regional geografisk størrelse på tilbøyelighet til økoinnovasjon. Resultatene fra dette studie innebærer at bedriftsstørrelse, produktivitet, FoU, eksternt samarbeid og et internasjonalt marked

er alle drivkrefter for eco-innovasjon. På regionalt nivå innebærer funnene at den regionale befolkningsstørrelsen har en negativ tilknytning til miljøinnovasjon, som betyr at en lavere regional befolkning ser ut til å oppmuntre til eco-innovasjon. I tillegg virker regional geografisk størrelse å ha en positiv tilknytning til tilbøyelighet til miljøinnovasjon. Når det gjelder det andre målet med denne masteroppgaven, innebærer funnene at selv om det er forskjeller mellom drivkreftene på enkelte aspekter av eco-innovasjon og noen aspekter av generell innovasjon, kunne det ikke gjøres en samlet konklusjon om at disse drivkreftene var tydeligvis forskjellige.

2 Introduction

In recent times, and especially in the last decade, there has been an increasing number of papers that have focussed on determining the drivers of eco-innovation, as distinct from the drivers of innovation in general. The reason for this is an acknowledgement that environmental innovations can lead to a so-called 'win-win' situation resulting in both economic and environmental benefits due to positive spill over as enterprises internalize negative environmental effects (Carraro, 2000).

This paper, through the use of multi-level analysis at the enterprise level and at the regional level, will add to the growing literature on the subject by approaching the analysis from a Norwegian perspective. This paper will seek to discover if some of the drivers that have already been identified at the enterprise level, namely *firm productivity, firm size, R&D, external collaboration*, and having an *International market* is also relevant in a Norwegian context. In addition, this paper will also consider drivers at the regional level such as *regional population size.* In the second part of this paper, we will test if the drivers for eco-innovation in Norway are distinct from the drivers of general innovation. The intention is by evaluating a wider range of drivers than perhaps previously in a single study, this paper will contribute a more nuanced understanding of the underlining drivers of eco-innovation.

Both Hojnik and Ruzzier (2016) and del Río et al. (2016) in carrying out comprehensive reviews of existing literature on the subject of drivers for eco-innovation identified those drivers that were most commonly reported. However, despite the numerous articles reviewed in the aforementioned articles, it still seems difficult to assume that these reported drivers are universal. In fact, the different peculiarities of each country where evidenced was gathered for each paper sometimes gave differing results. Martin et al. (2011) finds that the propensity to innovate differs significantly across countries, even after controlling for existing differences in their industry structures. Even those drivers that this paper specifically focuses on have given mixed results often with just as many papers for as there are against.

2.1 Outline of study

This paper is organized as follows: The remaining of this section will be dedicated to defining the concept of eco-innovation, and how it compares to general innovation, as well as a discussion of the theoretical approach this study will take. In section 3 a literary review and hypotheses development is carried out addressing all the independent variables that will be tested. This also includes a discussion of the secondary goal of this thesis which is to consider the differences between the drivers of eco-innovation and general innovation. In section 4 the methodology is described, which includes background information on the dataset used in the analysis. In addition, this section will also include more detailed explanation of independent, dependent, and control variables both at the enterprise and regional level. A brief description of multilevel analysis is given in section 5. In section 6 the results from regression analysis are given including how we address any possible technical issues. Furthermore, we test each hypothesis and present our conclusions. The results of the second aim of this thesis are also presented in section 6 as well as the conclusions drawn from the empirical results. In section 7 we present a summary of our general conclusions and discussions of empirical results. In section 8 we discuss limitations with this thesis, discussing such issues as odds ratio and causation, as well as possible directions for any future study. Finally, in section 9 we present a general overview of the reliability and validity of this thesis.

2.2 Definition of eco-innovation

Hojnik and Ruzzier (2016) considered the use of the term eco-innovation in literature as it is often used interchangeably with the term environmental innovation, and green innovation, and decided that despite the ambiguity of usage, they all embraced elements of fewer adverse effects on the environment and more efficient use of resources and therefore could be considered the be referring to the same thing. This paper will use the term eco-innovation.

Eco-innovation is a concept that is not easily defined and several attempts have been made in literature to clarify its definition. Hojnik and Ruzzier (2016) highlight some of the more prominent definitions put forward, such as The Eco-Innovation Observatory (2012, p. 8) which defines eco-innovation as the:

> Introduction of any new or significantly improved product (good or service), process, organizational change or marketing solution that reduces the use of natural resources (including materials, energy, water and land) and decreases the release of harmful substances across the whole life-cycle.

Another definition proposed by Kemp and Pearson (2007, p. 7) is:

> Eco-innovation is the production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organization (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives.

And yet another proposed by Horbach et al. (2012) is eco-innovations are:

> Product, process, marketing, and organizational innovations, leading to a noticeable reduction in environmental burdens. Positive environmental effects can be explicit goals or side effects of innovations. They can occur within the respective companies or through customer use of products or services.

There are other definitions, but as noted by Hojnik and Ruzzier (2016), all these various definitions seem to share two main components: "fewer adverse effects on the environment and a more efficient use of resources." Without attempting to add another definition to those that already exist, this paper chooses to follow a general definition as defined by the two main components stated above.

2.3 Eco-innovation and General Innovation.

Although it has been recognized that eco-innovations are a subset of, and have many common characteristics with innovation generally (Wagner, 2008), it has also been recognized that eco-innovations have unique, distinguishing features (Rennings, 2000) which require their own specific insights into the drivers[1] that encourage them. Hojnik and Ruzzier (2016) in reviewing Rennings (2000) outlined three distinguishing features:

1. eco-innovation can be technological, organizational, social, or institutional; developed by companies or non-profit organizations; and it can be traded or not traded on markets.
2. an interdisciplinary approach should be adopted when analysing eco-innovation because of its placement between the disciplines of innovation economics and environmental economics.
3. the "double externality problem," which emphasizes the crucial role of environmental policy instruments as drivers of eco-innovation.

This is a restatement of the 'win-win' situation referred to earlier where eco-innovation leads to positive externalities (as with general innovation) in addition to socially desirable environmental spill overs. However, it is the enterprise that bears the cost of reducing their environmental footprint which induces a higher cost for them than those experienced by their competitors leading to the importance of regulatory measures as a driver of eco-innovation, by levelling the playing field for all actors.

2.4 Theory grounds

Recognizing that general innovation theory is not the most appropriate theoretical background from which to explore the drivers of eco-innovation, researchers in this field have applied a variety of theoretical underpinnings. del Río et al. (2016) in a review of articles on the what drives eco-innovators also noted that many articles they reviewed lacked an explicit theoretical framework on which to base their evaluation.

In their review article Hojnik and Ruzzier (2016) summarized many of theories that have been adopted by researchers in studying the drivers for eco-innovation. Many, despite the

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Hojnik and Ruzzier (2016) defined drivers as a stimulus which can act as a motivation-based factor (such a regulatory pressure, competitive pressure or customer demand) or a facilitating factor (such as financial resources or technological capabilities).

inappropriateness, applied general innovation theory, other theories used include a mixture of institutional and resource-based, stake-holder theory and neo-institutional theory. Hojnik and Ruzzier (2016) concluded that a singular theoretical background may in any case be difficult to define and would depend entirely on the bundle of factors being researched and the type of eco-innovation being addressed.

In this paper we have chosen to approach this research from an enlarged general innovation theory as proposed by Horbach (2008) and termed environmental innovation theory which encompasses demand side, supply side, institutional, and political influence drivers of eco-innovation, as it captures the bundle of factors we will assess, namely characteristics of the enterprise as well as regional and geographical factors (which Horbach (2008) also assessed.).

This paper acknowledges that using this expand theory is not necessarily required given that the main inclusion by Horbach (2008) was in order to capture the policy element that this paper does not address. However, we believe that by referring to this environmental innovation theory in some way adds weight to the point made about this particular field of inquiry requiring a cohesive theory grounding.

3 *Literary review and hypotheses.*

3.1 *Literary review*

As a clear indication of just how much interest has grown in this particular area of research, Hojnik and Ruzzier (2016) in a review article identified 165 articles specifically focussed on evaluating the drivers of green innovation. del Río et al. (2016) in another review article also found no shortage of articles that addressed this subject. However, there were some issues that both articles identified as lacking in this area of research.

In conclusion Hojnik and Ruzzier (2016) stated some limitations with their literature review. Limitations associated with the literature review method lead to a methodological problem in determining the impact of drivers; each reviewed study is based on a different list of drivers or determinants, which means that other drivers are not considered. In addition, the drivers that were identified and examined in the reviewed studies are overwhelmingly proximate factors rather than distal factors or ultimate causes—such as the innovativeness of a particular sector, the distance of a country to the technology frontier, property law, systems of governance, geographic location, culture, and the international trade regime

del Río et al. (2016) in carrying out a critical review of the empirical literature based on econometric methods on what drives eco-innovators also highlighted the focus of literature on the factors of regulation, size, cooperation and environmental management systems (EMS) and the less frequent use of other internal factors to the firm, international drivers, and regional issues.

Rather than carrying out a subject wide literary review on every article related to the issue of drivers for eco-innovation generally, this paper will primarily focus on those articles that address the particular drivers we will be testing.

3.1.1 Database search for articles published after the period of 2000-2015

An attempt was made to find articles published after the inclusion period in the aforementioned review articles, to discover if any new findings had been made. However, the few articles that were found added very little to the factors mentioned by both Hojnik and Ruzzier (2016) and del Río et al. (2016).

Cai and Li (2018) using evidence gathered in China reported similar findings to those already discussed such as R&D intensity, market-based instruments, customer green demand, and environmental organizational capabilities are all contributing drivers to green innovation. Surprisingly, and perhaps further evidence that drivers for eco-innovation can be country specific, it was reported that competitive pressure provided the greatest incentive for firms to adopt eco-innovation.

Fernando and Wah (2017) in Malaysia confirmed the important role that environmental regulation plays as a driver for eco-innovation as well as confirming other drivers previously discussed such as market focus and technology.

3.2 Hypotheses

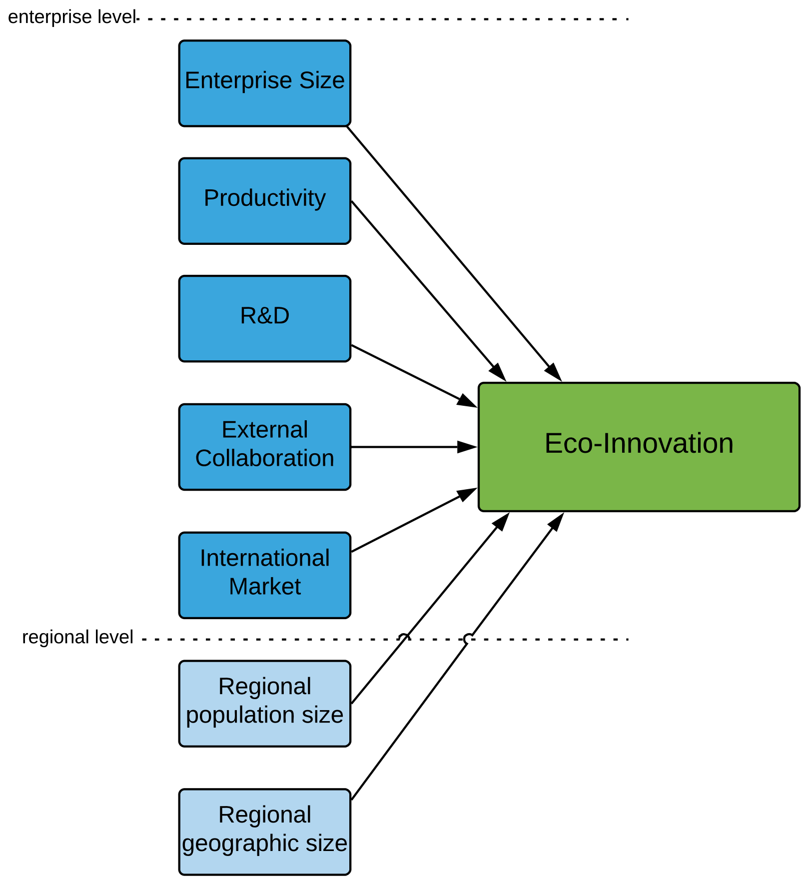

Figure 1: Conceptual model.

The above conceptual model represents the structure of the following hypotheses development and analysis.

3.2.1 Enterprise size:

Several arguments have been put forward to link firm size as a driver for innovation in general and by extension eco-innovation. One of these arguments is to approach firm size as a determinant of a firm´s competitive advantage (Schumpeter, 1942). The assumption being that large firms have vast resources that can be diverted to actions that may increase its competitive advantage including eco-innovations. Large firms are better suited to the exercise of utilizing the factors of production than smaller firms. Large firms benefit from specialization of its labor and physical resources required to promote and implement eco-innovation activities within firm boundaries (Schumpeter, 1934).

Even more related to the notion that firm size is a driver for eco-innovation, and that larger firms typically engaged in multiple eco-innovation activities is presented by both Montabon et al. (2007) and Tate et al. (2010).

Further evidence is provided by Álvarez Gil et al. (2001) in studying the hotel industry in Spain, where reasoning put forward for this positive relationship between firm size and eco-innovation include:

1. Larger firms have more impact on the environment.
2. Larger firms face considerable pressure from stakeholders because:
    a. their environment impact is more visible.
    b. it is easier to control centralized sources of pollution than disperse ones.
    c. They are considered as industry leaders and thus constitute models to imitate.
3. They have greater organizational slack.
4. Larger firms adopt a more formalized management structure which could lead to a more formalized approach to eco-innovation.
5. Economies of scale for the re-use, recycling or valuation of waste.

The findings in Álvarez Gil et al. (2001) confirmed the positive relationship between firm size and eco-innovation with the main factors being attributed to economies of scale and organizational slack. Others that support this positive association include Kammerer (2009), as well as De Marchi (2012) who found that firm size as a driver seems to be more relevant for eco-innovation than innovation in general.

Horbach (2008) offers a different approach from a theoretical perspective by stating that large monopolistic firms have less incentives to innovate as opposed to smaller firms who are forced to innovate in a competitive market in order to be better than their competitors. This viewpoint is supported somewhat by Mazzanti and Zoboli (2009) where it was found that sectors and size do not influence the adoption of innovation. Cainelli et al. (2012) also found that any benefits from such structural factors such as size on driving eco-innovation are outweighed by other factors such as firm cooperation with suppliers and universities.

However, since most of the viewpoints expressed seem to make the underlying assumption that firm size is not an element that can be defined by one element be measured but that size inherently means size in relation to other resources such as structural, financial as well as number of employees and productivity, and since we have taken the stance that productivity is a positive driver of eco-innovation in H1, it seems only logical that we also test size as a positive driver for eco-innovation.

Hypothesis 1 (H1). There is a positive association between firm size and green innovation. Larger firms will be more likely to engage in green innovation, whereas smaller firms will be less likely to do so.

3.2.2 Enterprise productivity

Given that environmental innovative activity for a firm often requires considerable financial commitment, (Tate et al., 2010), it stands to reason that it is those firms that have greater productivity - and therefore greater access to resources - that would engage in eco-innovation. This access to resources over and above what is required by an organization to maintain itself by meeting its necessary costs has been defined as organizational slack (Cyert and March, 1959, Cyret and March, 1992). Perhaps a more useful definition of organizational slack is given by L.J. Bourgeois (1981) as:

> Organizational slack is that cushion of actual or potential resources which allows an organization to adapt successfully to internal pressures for adjustment or to external pressures for change in policy, as well as to initiate changes in strategy with respect to external environment.

Taking this stance, on could infer that this organizational slack could also be diverted to general innovation activities as Aarstad et al. (2016) argues, productive enterprises will accumulate resources through productivity gains creating slack within an organization leading to an "innovation potential beyond what may be channeled into formal R&D investments." This slack can result in employees, either individually or collectively, to pursue innovation with relatively little economic restriction. Although this argument was made in regard to general innovation, it is not such a leap to assume that this slack will also lead to firms having more resources to explore the possibilities presented by eco-innovation.

Firm productivity as a driver for eco-innovation is not a new proposition, in fact several researchers have noted its role in driving eco-innovation. Mazzanti and Zoboli (2009) in studying manufacturing firms in Northern Italy made the positive connection with firms that do well financially being able to afford to spend more on environmental innovation. In a study using data from across the economic landscape of Italy, an interesting observation was made by Borghesi et al. (2012) where the relationship was expressed as a "virtuous cycle" where eco-innovation drove positive economic performance which in turn drove further eco-innovative activities. A later study by the same authors confirmed this positive relationship (Borghesi et al., 2015).

What is interesting in regard to firm productivity as a driver for eco-innovation is that other researchers have not been so positive about the relationship. Demirel and Kesidou (2011) in the United Kingdom found very little significance in productivity being a driver. Another contradictory finding is provided by Hofer et al. (2012) in studying manufacturing companies in the U.S found that companies with greater profitability is associated with lower degree of eco-innovation activity. The possible explanation offered is that comparatively profitable companies see less of a need to implement such activities in terms of gaining a competitive advantage. It should be noted that this negative result was also a surprise to the author.

Despite the findings of little significance and even a negative relationship between productivity and eco-innovation, this paper proposes to test the hypothesis from the stand point that productivity is a driver of eco-innovation. In recent times there has been an acknowledgement worldwide about the importance of eco-innovation at all levels of the economic spectrum in a country. Eco-innovation activities may require a significant financial investment where the long term payoff can be uncertain which undoubtedly affects the strategic decision to pursue them (Tate et al., 2010), given the current development in perception of business activity and how they affect the environment, making the decision not to engage in eco-innovation if a firm has the resources to do so is short-sighted. And perhaps further evidence that drivers of eco-innovation is contextual in regard to country. That productive firms will more likely engage in eco-innovation is still a reasonable assumption.

Hypothesis 2 (H2). There is a positive association between firm productivity and green innovation. Firms with high productivity will be more likely to engage in green innovation, whereas firms with low productivity will be less likely to do so.

3.2.3 R&D

R&D is generally accepted as an important element in a firms productivity and innovation activity, and this is often extended to eco-innovation (Mazzanti and Zoboli, 2009). R&D is also often mentioned as one of the areas where organizational slack is channeled (Aarstad et al., 2016). It would then stand to reason to assume that its role as a driver of eco-innovation would be a given, especially if we are to take the approach that organizational slack leads to greater resources that can be channeled into R&D – amongst other avenues – and that organizational slack is seen as a major driver of innovation both in general and environmental. Mazzanti and Zoboli (2009) indeed made this connection through empirical evidence in their study in Italy. Horbach (2008) in Germany also reported that the improvement of technological capabilities through R&D is very important for eco-innovation. Rehfeld et al. (2007) using a dummy to measure R&D also found a significant positive relationship between R&D and eco-innovation.

However, there are some dissenting voices ranging from R&D having very little significance to not having any significance at all in regard to eco-innovation. Both Horbach (2008) and Borghesi et al. (2015) found that the presence of R&D expenditure is never significant. Borghesi et al. (2015) suggested that this lack of significance is due to the fact that R&D is ultimately a proxy for general innovation-related capacity and that specific environmental R&D might be needed to capture the eco-innovation effects of R&D. Kammerer (2009) defined R&D as the share of employees in R&D which he suggests leads to this contrary result for the positive relationship between R&D and eco-innovation. Another explanation offered is that perhaps the impact of R&D activities on eco-innovation is sector specific-the focus of the study in Kammerer (2009) was the electrical manufacturing industry in Germany. Cainelli et al. (2012) found no significance of R&D on eco-innovation activities and suggests that R&D is a far too generic and weak commitment to enhance the adoption of eco-innovation.

The data we have available to us makes it possible to test R&D as a dummy variable only, i.e. whether there were R&D activities or not. This was the same approach taken by Rehfeld et al. (2007) and led to positive results, and this is the approach this paper will take. However, we acknowledge the points made by other researchers, as mentioned above, about the definition of R&D perhaps playing a role in the results. We would also like to reiterate the aforementioned point about the sector specificity of drivers - this paper takes into account all industries in Norway, although others such as Horbach et al. (2012) also used CIS data in Germany and found no significance – as well as the country context stated earlier.

Hypothesis 3 (H3). There is a positive association between R&D spending and green innovation. That is to say firms who spend on R&D are also more likely to engage in green innovation than firms who do not spend anything on R&D.

3.2.4 External Collaboration

Collaboration with external partners, whether they be suppliers, research institutions, competitors, or customers is generally accepted as advantage in terms of a firm's innovative activities. Collaboration with external partners, especially in the form of strategic alliance, was initially seen as an activity undertaken by large firms, however, the benefits of external collaboration for small to medium (SMEs) businesses, which makes up the majority of firms in Norway, have been found to be significant. In fact this external collaboration on SMEs innovative activities has the most significant impact (Zeng et al., 2010).

In reference to eco-innovation specifically, unlike some of the variables to be tested in the previous hypotheses, there seems to be more consensus about the positive effect that external collaboration has on the eco-innovation activities of firms. This positive effect has been emphasized as being of even greater importance for eco-innovation than for general innovation (Horbach et al., 2013, De Marchi, 2012, De Marchi and Grandinetti, 2013, Pereira and Vence, 2012, Yarahmadi and Higgins, 2012, Horbach, 2008). The reasoning offered for this relationship is that eco-innovation has a higher requirement for external knowledge and information than for general innovation. A further definition of this reasoning is given by Horbach (2014) in that many eco-innovations fields are relatively new, meaning there is less inherent knowledge and information within a firm which leads to firms seeking this from elsewhere.

Mazzanti and Zoboli (2009) suggested that these innovation-orientated co-operation with other firms and research institutes may partially substitute for size economies of scale when the firm environment is characterized SMEs, and may be as, if not more, important than firm structural characteristics. This is attributed to firms taking advantage of knowledge transfers within the collaborative group from spillovers. It is even suggested that firms who engage in collaborative activities will not invest directly in R&D which seems to stand to reason. Borghesi et al. (2012) also emphasized the importance of these networking or collaborative relationships in regard to environment innovation.

Given that the Norwegian firm environment is characterized by SMEs, and the literary consensus on the importance of collaboration activities for eco-innovation, one would assume that this relationship would also hold true in Norway. If eco-innovation does in fact require knowledge and competences that may not belong to the core competences that define a firm´s fundamental business, (Teece et al., 1997), then where these sources of information or collaborative partners are also a relevant issue. Horbach (2014) approaching this question from a regional context highlighted the importance of universities and other research institutions in close geographic proximity to the eco-innovating firm. However, the size of Norway as a country and the fact that from a regional perspective, Norway is characterized by many geographically large areas with low population density, one would assume that Norwegian firms would need to go beyond regional borders to gain the knowledge they required for eco-innovation. The importance of this external collaboration, at least for general innovation, for Norwegian enterprises is also pointed to by Isaksen and Karlsen (2012b)

Hypothesis 4 (H4). There is a positive association between external collaboration and green innovation.

3.2.5 Geographic market.

In general innovation theory, studies have demonstrated a strong link between firm innovation, international ownership, and export orientation (Diana A. Filipescu et al., 2013, Du and Girma, 2009, Yi et al., 2013).

del Río et al. (2016), in a review article of the drivers of eco-innovation, highlighted the neglected influences of international factors on eco-innovation. These international influences seem to have been generally assumed to be positive drivers for the adoption of eco-innovation activities. This assumption has normally been made on the basis that international customers will exert higher environmental pressures than local customers on innovating firms which will more than likely give an incentive to engage in eco-innovation (Kraatz, 1998). In addition, international trade barriers that are imposed on producers to force them to be more eco-friendly will have an effect in spurring eco-innovation in order to overcome those barriers by meeting the highest environmental standard (Rugman et al., 1999). International trade can also generate knowledge spillovers, expose domestic firms to more international competition which can lead to invest in technology for better eco-innovation (Perkins and Neumayer, 2008). This international trade can also lead to the cross-border diffusion of environmental best practice and increase the pressure on all producers to adopt more eco-friendly behavior (Vogel, 2000). However, all the above assume an international market characterized by higher levels of environmental requirement. This was in fact the case which Cainelli et al. (2012) tested as a market orientation hypothesis. In that paper the evidence indicated that this relationship was not significant, with the explanation given that a motivation to eco-innovate for an eco-innovative firm has not yet been developed as a demand from its international customers. Other have also found that there was no significant relationship between an *international market orientation* and eco-innovation (Ziegler and Rennings, 2004, Rehfeld et al., 2007)

Horbach et al. (2013) also tested for the relationship between market orientation and categorized the market as: local *(LocalMarket)*, national *(NatMarket)*, European *(EurMarket)* or other foreign countries *(OtherMarket)* and found that compared to general innovation, geographic market orientation does not seem to be a distinct characteristic of eco- innovation.

However, in this case, we propose that the peculiarities of Norway as country may provide different results. Norway is a small country in comparison to many where the impact on geographic market orientation on the engagement of domestic firms in eco-innovation. There is an argument that due to its size, markets outside of its borders are of greater importance for Norwegian firms. (60% of GDP comes from trade (The Heritage Foundation, 2018)

Hypothesis 5 (H5) There is a positive relationship between having an international market and green innovation. Enterprises that orient themselves towards an international market are more inclined to engage in green innovation than those that orient themselves towards a local market.

3.2.6 Regional population size and regional geographic size

Much of the research concerning regional innovation in Norway has been focused on the effect of regional resources normally associated with large urban areas on innovation activity (Isaksen and Karlsen, 2012a). These urban areas are characterized by a variety of industries, established universities of research institutions and a well-functioning regional innovations system, and one can also presume a large population. Knudsen et al. (2008) in the U.S for example concluded that population density is an important component of knowledge spillovers and therefore an important component of innovation.

Aarstad et al. (2016), contrary to what the above logic may suggest, found that regional population density actually had a direct negative effect on the propensity of enterprises to be innovative. The explanation given for this surprising result in based on the regional peculiarities of Norway as a country. Some regions in Norway with relatively low population density have a long history of dynamic and innovative industries such as shipping, maritime, fish farming, and oil and gas.

Another reason offered is that low population density leads to increased knowledge about complementary knowledge, resources and skills that lie within the same geographical boundaries. Low population density may even lead to increased trust which may further foster innovative activities due increased collaboration.

In regard to eco-innovation, del Río et al. (2016) expressed that regional issues have largely been a neglected issue in literature on the drivers of eco-innovation. However, there have been some exceptions, Ghisetti and Quatraro (2013) found that firms located in highly polluting regions are more likely to eco-innovate.

Another researcher who is often cited as the exception to this lack of inclusion of regional context is Horbach (2014). He explains that this lack of inclusion has mainly been because of lack of adequate data available to carry out such an analysis. In his analysis, such regional characteristics such as population density, relevance of green parties, unemployment rate are taken into account. In addition, the effect of location dummy factors such as proximity to research centres and universities, level of regional wages and trans-regional traffic infrastructure are also included. (Horbach, 2014) concluded that regional proximity to research centres and universities are more important for eco-innovations compared to other innovations. Eco-innovations seem to be more prevalent in under-developed or disadvantaged regions characterized by high rates of poverty. In addition, eco-innovations are less dependent on the typical urbanization advantages.

A possible reason as to why green innovation enterprises in sparsely populated, but large geographical regions, do not benefit from urbanization advantages is that eco-innovation requires more external cooperation as we have theorized earlier. So, this knowledge can come from anywhere, not necessarily from other enterprises in a spill over effect within more densely populated regions.

Hypothesis 6 (H6). There is a negative association between regional population size (where the firm is location) and eco-innovation.

In regard to the issue of regional geographical size and eco-innovation, there has been very no discussion in relevant literature. However, given the already cited issues discussed by Aarstad et al. (2016) concerning the peculiarities of Norway we aim to test this variable in the positive as population density mentioned was measured as population divided by regional geographic size. In addition, many of the innovative industries already mentioned are located in large geographical regions.

Hypothesis 7 (H7). There is a positive association between regional geographical size (where the firm is located) and eco-innovation.

3.3 Drivers: Eco-innovation versus General Innovation.

As to the question of whether the specific drivers for eco-innovation are different from those of general innovation, there does exists some literature on the subject, although del Río et al. (2016) in a review remarked that literature was recent and not very abundant.

Whereas there seems to be general agreement that eco-innovation and general innovation will have drivers that are common to both, of those variables that are tested in this paper, a literature search revealed that some of them have been directly compared in previous literature with mixed results.

3.3.1 Size

Horbach et al. (2013) in comparing data from Germany and France, Horbach (2008) for Germany, Rave et al. (2011) for manufacturing industry in Germany, and Cainelli et al. (2015) for Spanish manufacturing firms, amongst others all found that size plays a more prominent role as a driver for eco-innovation than general innovation. Only Horbach (2014) for Germany found no significance for size being more of a driver for eco-innovation than for innovation in general.

3.3.2 R&D

Horbach (2008) and Horbach et al. (2012) both in Germany, De Marchi (2012) in analyzing Spanish manufacturing firms, found no significance that R&D is more of a driver for eco-innovation than for general innovation, whereas Horbach et al. (2013), del Río et al. (2015) make the opposite finding.

3.3.3 External collaboration

Many researchers have found that external collaboration plays a more prominent role as a driver for eco-innovation than it does for general innovation, such as Horbach (2008) and Rave et al. (2011) for Germany and De Marchi (2012) and del Río et al. (2015) for Spain. However, there also researchers that have made the opposite observation (Horbach et al., 2013, Horbach, 2014)

3.3.4 Market

Horbach et al. (2013) for Germany was the only paper that considered where the most important market for an enterprise was located and found that market orientation did not seem to be a distinct characteristic of eco-innovation compared to other innovations.

Given the scarcity of research in comparing the drivers for these two types of innovation, this paper hopes to contribute to establishing more evidence in regard to the differences, or similarities between the drivers for eco-innovation and general innovation in a Norwegian context.

4 METHODOLOGY

4.1 Research context and data

Data used in the analysis for this paper was taken from the Community Innovation Survey (2010), which was collected by Statistics Norway in collaboration with Eurostat. Some measures were taken to ensure the data collected could be used for valid cross-country comparison given certain peculiarities of the Norwegian economic and geographic framework. This included the inclusion of small enterprises of 5-9 employees (not commonly sampled in other Eurostat member states) due to the significant presence of such enterprises in the country.

The Community Innovation Survey (2010) is a comprehensive gathering of data across the entire landscape of enterprises in a country. In Norway it is mandatory for enterprises with 50 or more employees to participate in the survey, in addition random samples were taken from 43% of enterprises with 20–49 employees, 25% of enterprises with 10–19 employees, and 19% of enterprises with 5–9 employees (with a few exceptions, see Wilhelmsen and Foyn (2012)). 6595 enterprises were captured in the survey, which included data concerning where each enterprise is located in terms of economic-geographical region. In addition, data on the population size (as of the first quarter of 2008) and geographical size in square kilometers of each of these economic-geographical regions was provided by Statistics Norway.

Norway is divided into 89 distinct economic-geographical regions, as defined by Statistics Norway. The criteria for divisions are based on trade and labor markets. Economic-geographical regions reside within counties and consist of one or more entire local municipalities. In other words, economic-geographical regions do not cross county borders, and local municipalities are not divided into economic-geographical regions. Accordingly, economic-geographical regions are at a spatial level between counties and local municipalities. The concept is analogous to the classification of local administrative units at level 2 (LAU 2) in the European Union, formerly described according to Eurostat by the nomenclature of territorial units for statistics at level 4 (NUTS 4).

The analysis of this paper focuses on the section of the survey where enterprises were asked how they rated a list of given choices concerning the goal of their innovation activities. The choices were given as:[2]

- Expand range of goods and services.
- Replace outdated products and processes.
- Enter new markets or increase market share.
- Improve quality of goods and services.
- Improve flexibility for production of goods and services.
- Reduce labor costs per produced unit.
- Reduce material and energy cost per produced unit.
- Reduce environmental effects.
- Improve health and safety for employees.

[2] Translated from Norwegian.

For the purpose of analysis, responses to the relevant section of the survey were coded in a Likert scale as:

Very important	3
Fairly important	2
Little important	1
Not relevant	0

Reduce material and energy cost per produced unit, and *Reduce environmental effects* are taken as an expression that a firm has an eco-innovation goal to its innovation activities that is distinctly different from a general innovation goal. It should be noted that on occasion, an enterprise attempting to reduce material and energy cost per produced unit may not have an eco-innovation motive, there is little doubt that such a pursuit will inevitably result in positive spillovers for the environment, and therefore falls under the definition of eco-innovation as defined in this paper.

Classification of *Improving health and safety of employees* was difficult as there was some suggestion that this could also be classified as an eco-innovation goal. However, the ambiguity in what the measures were that were taken to achieve this goal made this classification problematic. For example, a measure to improve the air quality for workers and thereby improving their health can clearly be seen as an eco-innovation measure as it will have an impact on the environment (and the definition of eco-innovation adopted by this paper does not specify that the positive effect on the environment is the primary goal of the innovation, simply that it has a positive effect on the environment). But the positive (or negative) environmental effect of, for example, improving ergonomics so that workers experience less daily physical strain, is much harder to establish. As a result: *Improving health and safety of workers* is not included as an eco-innovation goal.

4.1.1 Dependent, independent, and control variables at the enterprise level

Data from 6534 enterprises of a total sample of 6595 enterprises allow the modelling of dependent, independent, and control variables at the enterprise level of analysis.

4.1.1.1 Firm size

Firm size is an independent variable in reference to H2 and is measured in the number of employees.

We control for enterprise size when testing H1, H3, H4, H5, and H6 with the assumption that enterprise size leads to economies of scale which in turn leads to increased productivity. Enterprise size is also assumed to positively affect the previously stated concept of slack within an enterprise.

4.1.1.2 Firm productivity

Firm productivity is an independent variable with reference to H1, and is measured as sales revenue in Norwegian Kroner for 2010 divided by number of employees. (Aarstad et al., 2016) measured productivity in the same way. It should be noted that productivity does not necessarily equate to profitability (measured as net income per employee), however, they often yield similar results under human resource management practices (Huselid, 1995).

Productivity is used as a control variable with reference to H2, H3, H4, H5, and H6 given the aforementioned concept of slack where accumulated resources as a result of high productivity can lead to increased autonomy in regard to innovation activity relatively unconstrained in economic terms (Aarstad et al., 2016).

4.1.1.3 R&D spending

R&D is an independent variable with reference to H3 and the concept is measured as a dummy variable, that is to say an enterprise that allocated resources to R&D (regardless of how much) were coded 1 and those who didn´t allocate any resources to R&D were coded 0. It is a control variable when testing H1, H2, H4, H5, and H6.

4.1.1.4 External collaboration

External collaboration is an independent variable with reference to H4. The concept is measured as a dummy variable. In the survey, respondents were asked to indicate where their collaboration partner was located geographically. The choices were given as follows.

- Local/regional in Norway
- National
- Europe
- USA
- China or India
- Other countries

It is a control variable when testing for H1, H2, H3, H5, and H6.

4.1.1.5 Geographic market

Geographic market is an independent variable with reference to H5. In survey, respondents were asked to indicate where their most important market was and was coded as follows:

- Local/regional in Norway 1
- National 2
- Other EU/EFTA countries 3
- Other countries 4

An international market for the purposes of this analysis is therefore the last two options.

It is a control variable when testing for H1, H2, H3, H4, and H6.

4.1.1.6 Eco-innovation

Eco-innovation, as represented by reducing material and energy cost per produced unit, is a dependent variable for Model 1 and reducing environmental effects is a dependent variable for Model 2.

4.1.2 Independent and control variables at the regional level:

4.1.2.1 Regional population size

Population size is an independent variable with reference to H6. It is simply measured as the number of residents within the geographical boundaries of a region. It is a control variable when testing for H1, H2, H3, H4, and H5.

4.1.2.2 Regional Geographical size

Geographic size is measured in square kilometers and is tested as an independent variable with reference to H7, and as a control variable with reference to all the other hypotheses.

4.1.3 Other control variables.

The Multi-divisional variable is included to control for enterprises that are likely to have operations in subsidiaries across economic-geographical regions. As a driver for eco-innovation, its relevance is not of great interest here.

In all cases we control for random effects of enterprises operating or (being nested) in particular industries that are located (or nested) in particular regions. This takes into account the fact that some industries may invest more, in for example R&D some may be capital intensive whereas others may be labor intensive, than other industries, and that some regions may have relatively large sectors of particular industries.

5 Multilevel analysis

Multilevel analysis allows the assessment of how lower-level units, in this case enterprise characteristics, respond, behave or act in context to higher-level units, in this case regional characteristics. This allows for a much more nuanced analysis then simply looking at one particular level as most social studies normally would do. Multilevel analysis takes into account the fact that often the real causes of an event or dependent variable are not direct but a combination of different independent variables at several levels.

6 RESULTS

To test all hypotheses, a multi-level ordinal logistics regression modelling was carried out using Stata 13.1 software (StataCorp, 2013). The results for Model 1: *Reducing material and energy costs* *per unit produced is show* in Table 2 and the results for Model 2*: Reduce environmental effects* is shown in Table 3. Table 2 and 3 shows both fixed and random effects. Fixed effects represent regression estimates, whereas random effects represent estimated variance components.

For both Table 2 and Table 3, random effects shown include level two residuals which take into account enterprises nested in industries, as well as at level three residuals which take into account industries nested in regions. The Wald χ^2 is significant for both models, which confirms a robust model fit in that the variables in the models actually have an effect. The likelihood ratio χ^2 is significant for both models, because of the level two random effect of different enterprises nested in industries. We observe that level two random effects of different enterprises nested in industries is substantial (a substantial effect is usually taken as a ratio greater than 2:1). The substantial ratio of the level two random effects indicates that the industry effect within specific regions has a great effect. In other words, operating in a particular industry, in a particular region, is different in terms of eco-innovation outcomes as compared to operating in the same or in other industries in a different region.

The level-three random effect of enterprises nested in regions is zero and insignificant in both models, which indicates that industry effects within specific regions have little to say, in that after controlling for level two random effects, the variation within regions with reference to enterprise eco-innovation is not lower than the variation across the whole sample. (see Self and Liang (1987) and Andrews (1999) for a discussion of zero random effects).

Both tables include the following fixed effects regressors: Independent variables at the enterprise level of analysis, size (H1), productivity (H2), R&D (H3), external collaboration (H4), most important market (H5) and the independent variable of population size and regional size (H6) at the regional level of analysis.

6.1 Multicollinearity issues

Multicollinearity issues arise when the variables being tested correlate strongly with each other, this can lead to that the model results can become unreliable. Logistic regression requires that each data point be independent of all other data points. If observations are related to one another, then the model will tend to overweight the significance of those observations.

One method for taking account of any multicollinearity issues is by calculating and evaluating the variance inflation factor (VIF). The results of the test are shown below.

Table 1: Results for VIF.

Variable	VIF	1/VIF
Multi-division enterprise (dummy)	1.42	0.702
Size in number of employees	1.49	0.673
Productivity in turnover per employee	1.05	0.953
R&D (dummy)	1.46	0.686
Regional innovation collaboration (dummy)	1.64	0.609
National innovation collaboration (dummy)	1.78	0.562
International innovation collaboration (dummy)	2.07	0.484
Most important market (default: local)		
National	1.14	0.879
Europe	1.15	0.870
Outside Europe	1.14	0.881
Regional population size (RI)	1.19	0.844
Regional geographic size (RG)	1.22	0.818
RI*RG	1.06	0.941
Mean VIF	1.37	

Results for the test for every variable returned a highest value of 2.07 which is below the range of critical values between 4 and 10 where multicollinearity issues will cause concern. In addition, we have a large sample which increases robustness and also further decreases the probability of potential multicollinearity issues (O'brien, 2007).

Table 2: Multilevel ordinal logistics regression analysis with reducing material and energy cost per unit produced as the dependent variable.

Model 1	Coef.	Std.Err.	z	P>|z|	[95% Conf. Interval]	
FIXED EFFECTS						
Variables: Enterprise level						
Multi-division enterprise (dummy)	-.0126	.082	-0.15	0.879	-.174	.149
Size in number of employees	.052**	.026	2.02	0.043	.002	.103
Productivity in turnover per employee	.120***	.026	4.72	0.000	.070	.171
R&D (dummy)	.828***	.071	11.63	0.000	.688	.967
Regional innovation collaboration (dummy)	.254**	.107	2.38	0.018	.044	.463
National innovation collaboration (dummy)	.326**	.116	2.80	0.005	.098	.554
International innovation collaboration (dummy)	.403**	.124	3.24	0.001	.159	.647
Most important market (default: local)						
National	.137**	.062	2.19	0.028	.015	.259
Europe	.368***	.099	3.73	0.000	.175	.562
Outside Europe	.214*	.111	1.91	0.056	-.005	.434
Variables: Regional level						
Regional population size (RI)	-.106***	.029	-3.65	0.000	-.163	-.049
Regional geographic size (RG)	.102**	.035	2.92	0.004	.033	.170
RI*RG	.074**	.027	2.71	0.007	.020	.127
RANDOM EFFECTS						
Level two residuals (enterprises nested in industries)	.357					
	(.060)					
Level three residuals (industries nested in regions)	.000					
	(.000)					
Wald χ^2	546.6***					
Log likelihood	-7123.72					
LR test vs. level one tobit model: χ^2	93.67***					
N	6534					
Number of regions	89					
Number of industries nested in regions	2010					

Two-tail significance tests *p<.10, **p<.05, ***p<.001. All variables, except dummy variables are log transformed (natural logarithm).

Table 3: Multilevel ordinal logistic regression analysis with reducing environmental effects as the dependent variable.

Model 2	Coef.	Std.Err.	z	P>|z|	[95% Conf.	Interval]
FIXED EFFECTS						
Variables: Enterprise level						
Multi-division enterprise (dummy)	-.000	.079	-0.01	0.991	-.156	.154
Size in number of employees	.043*	.025	1.72	0.085	-.006	.092
Productivity in turnover per employee	.152***	.025	6.17	0.000	.103	.200
R&D (dummy)	.770***	.069	11.20	0.000	.635	.905
Regional innov. collaboration (dummy)	.370***	.104	3.56	0.000	.166	.575
National innov. collaboration (dummy)	.399***	.114	3.51	0.000	.176	.623
International innov. collaboration (dummy)	.244**	.122	2.00	0.045	.005	.483
Most important market (default: local)						
National	.103*	.060	1.71	0.087	-.150	.220
Europe	.202**	.096	2.10	0.036	.013	.391
Outside Europe	.050	.109	0.46	0.647	-.164	.264
Variables: Regional level						
Regional population size (RI)	-.090***	.026	-3.40	0.001	-.142	-.038
Regional geographic size (RG)	.091**	.031	2.90	0.004	.030	.153
RI*RG	.064**	.025	2.57	0.010	.015	.112
RANDOM EFFECTS						
Level two residuals (enterprise nested in industries)	.197					
	(.044)					
Level three residuals (industry nested in regions)	.000					
	(.000)					
Wald χ^2	525.95***					
Log likelihood	-7348.316					
LR test vs. level one tobit model: χ^2	45.37***					
N	6534					
Number of regions	89					
Number of industries nested in regions	2010					

Two-tail significance tests *p<.10, **p<.05, ***p<.001. All variables, except dummy variables are log transformed (natural logarithm).

6.2 Multilevel regression estimates and hypotheses testing

6.2.1 Hypothesis 1 (H1)

H1 suggested a positive association between eco-innovation and enterprise size. From Table 2 we find that H1 gains significant empirical support: Enterprise size is a driver for reducing material and energy costs per unit produced. From Table 3 we find that H1 also gains significant empirical support. Our conclusion is that Enterprise size is a driver for eco-innovation.

6.2.2 Hypothesis 2 (H2)

H1 suggested a positive association between eco-innovation and enterprise productivity. From both Table 2 and Table 3 we find that H2 gains very strong significant empirical support. Our conclusion is that there is a significant positive relationship between enterprise productivity and eco-innovation, therefore, it is a driver for eco-innovation.

6.2.3 Hypothesis 3 (H3)

H3 suggested a positive association between eco-innovation and R&D. From both Table 2 and Table 3 we find that H3 gains very strong significant empirical support. Our conclusion is that there is a significant positive relationship between R&D and eco-innovation. Therefore, R&D is a driver for eco-innovation.

6.2.4 Hypothesis 4 (H4)

H4 suggested a positive association between eco-innovation and external collaboration. From both Table 2 and Table 3 we find that H4 gains very strong significant empirical support, at all levels: Regional, national, as well as international. Our conclusion is that there is a significant positive relationship between external collaboration and eco-innovation. Therefore, external collaboration is a driver for eco-innovation.

6.2.5 Hypothesis 5 (H5)

H5 suggested a positive association between eco-innovation and having an international market. From Table 2 and Table 3 we find that H5 gains empirical support. But whereas for reducing material and energy cost per produced unit an international market outside Europe is also significant, this is not the case for reducing environmental effects. A possible explanation for this is that reducing material and energy cost per produced unit can be seen as indirect eco-innovation, or a goal that most enterprises would aspire to. However, reducing environmental effects can be seen as a direct goal, where Norwegian enterprises are more directly affected by the demands of environmental conformity as dictated by the European Union in form of regulation or policy. Also note that for both models, having a National market is also significant.

Our conclusion is that for some aspects of eco-innovation, having an international market is a driver, however for other aspects of eco-innovation, this international market does not extend outside the borders of Europe.

6.2.6 Hypothesis 6 (H6)

H6 suggested a negative association between a regional population size and eco-innovation. From both Table 2 and Table 3 we find that H6 gains strong significant empirical support. The negative, significant coefficient confirms this.

Our conclusion is that there is a low regional population size is a driver for eco-innovation. This in some ways adds to the conclusions drawn by Horbach (2014) who noted the lack of effect of typical urbanization advantages on eco-innovation.

6.2.7 Hypothesis 7 (H7)

H7 suggested a positive association between regional geographical size and eco-innovation. From both Table 2 and Table 3 we find that H7 gains strong significant empirical support. Our conclusion is that a large regional geographical size is a driver for eco-innovation.

6.2.8 Interactions.

A negative effect of RI means that innovation decreases as regional population increases. A positive effect of RG means that innovation increases as regional size increases. A positive effect of the interaction RI*RG means that regional size has a stronger positive effect on innovation in populous regions than in unpopulous ones. It further means that population size has a less negative effect on innovation in large regions than in small ones.

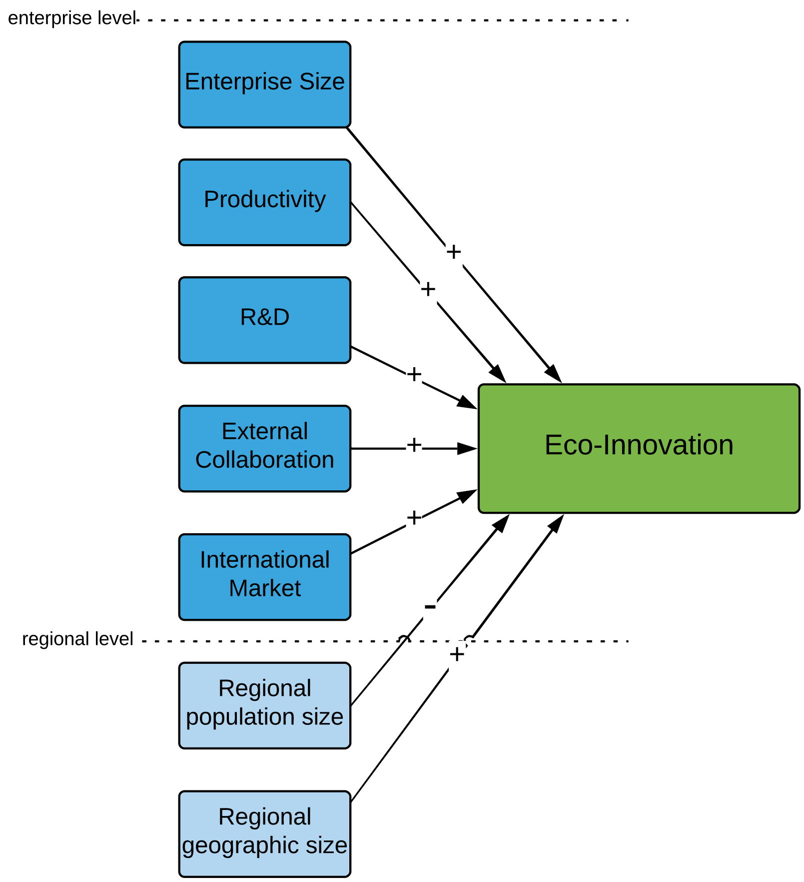

Figure 2: Empirical model of results. Drivers of eco-innovation. + sign indicates a significant positive relationship, - sign indicates a significant negative relationship.

6.3 Summary

At the enterprise level, enterprise size, productivity, R&D, External Collaboration, and an international market are all drivers for eco-innovation.

At the regional level, a low regional population and a large regional geographical size is a driver for eco-innovation.

Table 4: Multilevel ordinal logistics regression analysis with eco-innovation and general innovation as dependent variables.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
FIXED EFFECTS										
Variables: enterprise level										
Multi-division enterprise (dummy)	-.0126	-.000	-.017	.166**	.154*	.096	.059	.032	-.012	-.012
	(.082)	(.079)	(.078)	(.082)	(.079)	(.079)	(.078)	(.078)	(.078)	(.079)
Size in number of employees	.052**	.043*	.036	-.108***	-.021	-.116***	-.044*	.018	.015	.072**
	(.026)	(.025)	(.025)	(.026)	(.025)	(.025)	(.024)	(.025)	(.025)	(.025)
Productivity in turnover per employee	.120***	.152***	.090***	.021	.083***	.022	.051**	.074**	.096***	.092***
	(.026)	(.025)	(.024)	(.024)	(.024)	(.024)	(.023)	(.023)	(.024)	(.024)
R&D (dummy)	.828***	.770***	.634***	2.174***	1.618***	1.753***	1.569***	1.248***	1.128***	1.005***
	(.071)	(.069)	(.068)	(.074)	(.070)	(.070)	(.070)	(.068)	(.068)	(.068)
Regional innov. collaboration (dummy)	.254**	.370***	.234**	.497***	.405***	.487***	.473***	.413***	.370***	.404***
	(.107)	(.104)	(.103)	(.118)	(.107)	(.112)	(.111)	(.104)	(.104)	(.106)
National innov. collaboration (dummy)	.326**	.399***	.285**	.226*	.287**	.122	.361**	.232**	.213*	.207*
	(.116)	(.114)	(.114)	(.131)	(.119)	(.125)	(.123)	(.115)	(.114)	(.115)
International innov. collaboration (dummy)	.403***	.244**	.274**	.610***	.228*	.654***	.276**	.206*	.265**	.290**
	(.124)	(.122)	(.121)	(.140)	(.127)	(.134)	(.130)	(.122)	(.121)	(.123)
Most important market (default: local)										
National	.137**	.103*	.046	.346***	.307***	.292***	.209***	.176**	.152**	.150**
	(.062)	(.060)	(.059)	(.060)	(.059)	(.059)	(.058)	(.059)	(.059)	(.059)
Europe	.368***	.202**	.015	.127	.023	.346***	.104	.136	.052	.217**
	(.099)	(.096)	(.096)	(.103)	(.096)	(.099)	(.097)	(.095)	(.095)	(.096)
Outside Europe	.214*	.050	-.047	.022	-.028	.336**	.005	.062	-.040	.063
	(.111)	(.109)	(.108)	(.026)	(.109)	(.112)	(.108)	(.107)	(.107)	(.107)
Variables: regional level										
Regional population size (RI)	-.106***	-.090***	-.088***	.016	.007	.004	-.009	-.052**	-.063**	-.080**
	(.029)	(.026)	(.026)	(.027)	(.025)	(.026)	(.025)	(.026)	(.025)	(.027)
Regional geographic size (RG)	.102**	.091**	.111***	.006	.052*	.043	.054*	.087**	.117***	.094**
	(.035)	(.031)	(.030)	(.032)	(.030)	(.030)	(.029)	(.030)	(.030)	(.031)
RI*RG	.074**	.064**	.084***	.023	.035	.035	.012	.059*	.045*	.066**
	(.027)	(.025)	(.024)	(.026)	(.024)	(.024)	(.023)	(.024)	(.024)	(.025)

Table 5: Table 4 continued.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
RANDOM EFFECTS										
Level-2 residuals (enterprises nested in industries)	.357	.197	.169	.226	.132	.155	.127	.169	.143	.206
	(.060)	(.044)	(.041)	(.047)	(.036)	(.038)	(.033)	(.040)	(.036)	(.046)
Level-3 residuals (industries nested in regions)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Wald χ^2	546.6***	525.95***	335.87***	1500.8***	1102.6***	1239.9***	1019.3***	776.20***	685.14***	642.17***
Log likelihood	-7123.716	-7348.316	-7442.615	-7021.365	-7262.637	-7273.405	-7296.100	-7431.895	-7483.408	-7441.927
LR test vs. level one tobit model: χ^2	93.67***	45.37***	38.14***	62.77***	29.49***	38.17***	33.94***	43.60***	32.26***	45.29***
N	6534	6534	6534	6534	6534	6534	6534	6534	6534	6534
Number of regions	89	89	89	89	89	89	89	89	89	89
Number of industries nested in regions	2010	2010	2010	2010	2010	2010	2010	2010	2010	2010

Model 1: Reduce material and energy cost per produced unit.

Model 2: Reduce environmental effects.

Model 3: Improve health and safety for employees.

Model 4: Expand range of goods or services.

Model 5: Replace outdated products or processes.

Model 6: Enter new markets or increase market share

Model 7: Improve quality of goods or services

Model 8: Improve flexibility for production of goods or services

Model 9: Increase capacity for production of goods or services.

Model 10: Reduce labor cost per produced unit.

Two-tail significance tests *p<.10, **p<.05, ***p<.001. Standard error in parenthesis. All variables, except dummy variables are log transformed (natural logarithm).

6.4 Descriptive statistics

The results shown in Table 4 are for tests carried out where every Model represents a different eco-innovation goal or general innovation goal as a dependent variable (see Table for description of each model). Table 4 and 5 shows both fixed and random effects. Fixed effects represent regression estimates, whereas random effects represent estimated variance components.

For Table 5, random effects shown include level two residuals which take into account enterprises nested in industries, as well as at level three residuals which take into account industries nested in regions. The Wald χ^2 is significant for all models, which confirms a robust model fit in that the variables in the models actually have an effect. The likelihood ratio χ^2 is significant for all models, because of the level two random effect of different enterprises nested in industries. We observe that level two random effects of different enterprises nested in industries is substantial (a substantial effect is usually taken as a ratio greater than 2:1). The substantial ratio of the level two random effects indicates that the industry effect within specific regions has a great effect. In other words, operating in a particular industry, in a particular region, is different in terms of eco-innovation outcomes as compared to operating in the same or in other industries in a different region.

The level-three random effect of enterprises nested in regions is zero and insignificant in all models, which indicates that industry effects within specific regions have little to say, in that after controlling for level two random effects, the variation within regions with reference to enterprise eco-innovation is not lower than the variation across the whole sample. (see Self and Liang (1987) and Andrews (1999) for a discussion of zero random effects).

Table 4 includes the following fixed effects regressors: Independent variables at the enterprise level of analysis, size, productivity, R&D, external collaboration, most important market and the independent variable of population size and regional size at the regional level of analysis.

The results for possible multicollinearity issues as addressed previously in this paper are the same for the results in Table 4, in that they fall satisfactorily under the critical range and therefore should pose no issues for the results presented in the table.

6.5 Eco-innovation versus General Innovation.

Model 1 and Model 2 in Table 4 show eco-innovation goals for an enterprise, Model 3 through to Model 10 show a general innovation goal for an enterprise. Each independent variable tested will be reviewed individually below.

6.5.1 Size

In regard to enterprise size, Model 1, Model 2, Model 4, Model 6, Model 7and Model 10 show a significant positive relationship. This relationship shows no significance for the other models. The conclusion drawn is that size is not a distinct driver for eco-innovation as compared to general innovation.

6.5.2 Productivity

Table 4 shows a significant positive relationship between productivity and all models except Model 4 and Model 6. The lack of significance of productivity on Model 4 and 6, Expand range of goods or services and Enter new markets or increase market share respectively, could be interpreted as enterprises who are not productive and seeking to explore options that could lead to productivity. The conclusion is that Productivity is not a distinct driver for eco-innovation as compared to general innovation.

6.5.3 R&D

Table 4 shows a strong significant positive relationship between R&D and all models. The conclusion is that R&D is not a distinct driver for eco-innovation as compared to general innovation.

6.5.4 External Collaboration

Regional innovation collaboration is significant for all models, whereas National innovation collaboration is significant for all models except for Model 6. International innovation collaboration has a significant positive relationship with all models. The conclusion is that External Collaboration is not a distinct driver for eco-innovation as compared to general innovation

6.5.5 International market.

Having a National market has a significant positive relationship with all models except Model 3. Having Europe as the most important market has a significant positive relationship with only Model 1, 2, 6 and 10. Having a most important market outside Europe is significant only for Model 1 and 6. Given that Model 6 is innovation with the goal of entering a new market, this would seem logical. The conclusion is that this aspect, of having a market outside the region, does not seem to be a distinct driver of eco-innovation as compared to general innovation.

6.5.6 Regional population size

Regional population size has a negative significant relationship with Model 1, 2, 6, and 10. This means that for these models, a smaller regional population seems to be significant. The conclusion is that regional populations size is not a distinct driver for eco-innovation as compared to general innovation.

6.5.7 Regional geographical size

Regional geographical size has a positive significant relationship with all models except for Model 4 and Model 6. The conclusion is that regional geographical size is not a distinct driver for eco-innovation as compared to general innovation.

6.5.8 Interactions

A negative effect of RI means that innovation decreases as regional population increases (first three models and last three models). A positive effect of RG means that innovation increases as regional size increases (all models except Model 4 and Model 6). A positive effect of the interaction RI*RG means that regional size has a stronger positive effect on innovation in populous regions than in unpopulous ones. It further means that population size has a less negative effect on innovation in large regions than in small ones (positive interaction effects are found in the three first and the three models).

6.6 Summary

From our results as shown in Table 4, for the variables that were tested, it would seem that a definitive statement that the drivers for eco-innovation are distinct from the drivers of general innovation cannot be made. From our results it would seem that eco-innovation and general innovation on many occasions share the same drivers.

What is interesting to note in detail, is what aspect of eco-innovation shares which driver with which aspect of general innovation. In theory, one could for example target policy instruments or regulations to enhance a particular driver to encourage a combination of desired eco and general innovation outcomes.

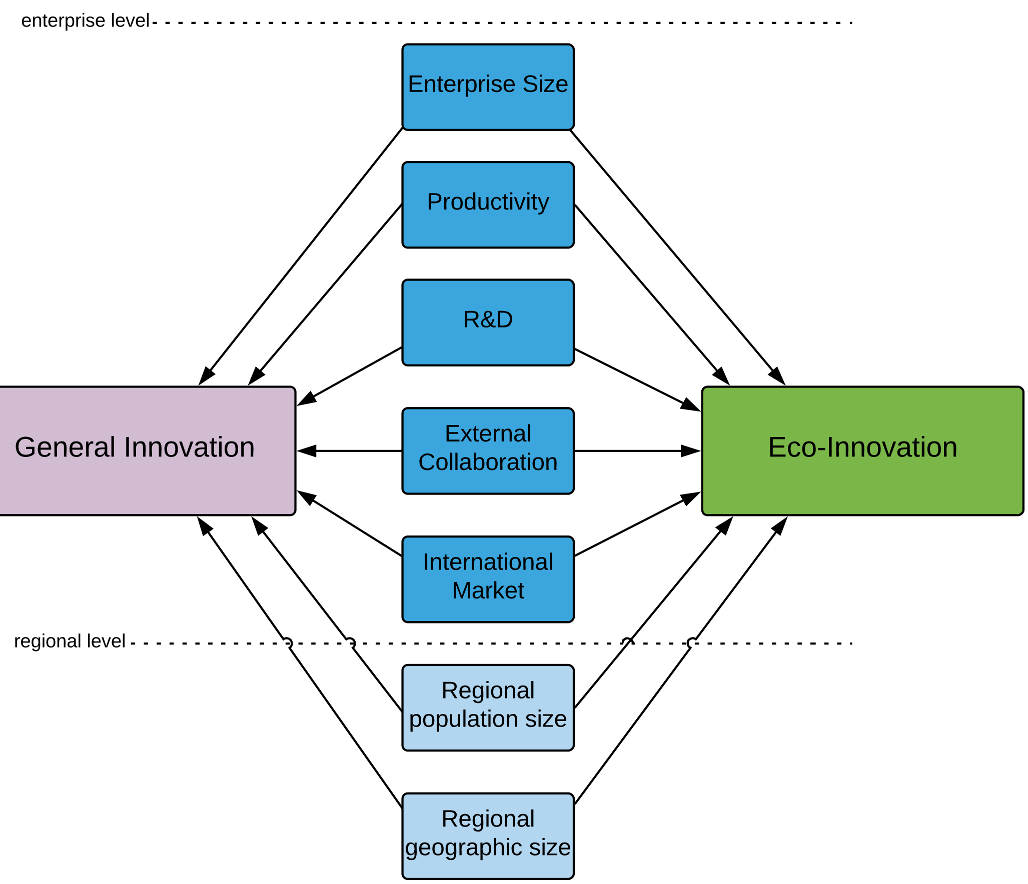

Figure 3: Empirical model of results. Drivers: Eco-innovation versus General innovation. Both types of innovations have aspects that share the same drivers.

7 CONCLUSION

7.1 Discussion of the empirical results

This paper aimed to identify the drivers of eco-innovation by analyzing data from Norway using multi-level logistics regression. As a secondary goal, this paper also sought to evaluate if the drivers for eco-innovation were distinct from those of general innovation.

7.1.1 Drivers for eco-innovation

Our empirical findings show that enterprise size has a significant positive relationship with an eco-innovation goal of reducing material and energy costs per unit produced, but not with reducing environmental effects. Enterprise productivity has a very strong significant positive relationship with eco-innovation. R&D has a very strong significant positive relationship with eco-innovation. External collaboration is very important for eco-innovation at the regional, national and international level. Having an international market does have a positive significant effect but this international market does not extend outside the borders of Europe. Regional population size has a negative relationship with eco-innovation, whereas regional geographical size has a positive relationship with eco-innovation.

7.1.2 Eco-innovation versus General innovation.

The empirical findings do not seem to support the proposition that the drivers of eco-innovation are distinct from the drivers of general innovation. However, a more detailed viewing of the results can lead one to state that this would be dependent on which aspect of eco-innovation one is comparing to which aspect of general innovation.

7.2 Implications.

With the caveat that the results in this paper can be described as a first step towards a definition of what drives eco-innovation in Norway, and that more research will be required to provide a more complete and nuanced picture, there are clear policy implications. Many drivers for general innovation, given our empirical results, will be shared by eco-innovation, therefore, policies that support general innovation will also lead to eco-innovation. However, there exists the possibility, especially given existing and generally excepted literature that eco-innovation has distinctive features that differentiate it from general innovation, and therefore may have distinct drivers. If this is the case, policy makers who intend to promote eco-innovation should take these drivers into account. It should also be noted, for policy makers, that encouraging eco-innovation, as the so called win-win situation alluded to earlier in this paper dictates, not only results in reduced environmental impact for an enterprise, but will also have a positive impact on its economic performance (Cai and Li, 2018).

8 *Limitations and future research*.

8.1 Odds ratio

This type of multi-level ordinal logistics regression modelling has some restrictions. One is that it shows a relationship, significant or otherwise, but what it actually means can be difficult to express in real terms. This has to do with the nature of probability, where the results shown in the table, although sufficiently descriptive, fails to communicate the actual effect of our independent variables on our dependent ones. A possible method to enhance the meaning of the probability results given by ordinal logistics regression is by calculating odds ratio (Rypestøl and Aarstad, 2018). The odds ratio can give more dimension to the "significant" relationship by expressing just how much more likely the independent term is connected to the dependent variable.

The multilevel ordinal logistics regression analysis in this paper shows in many instances a significant positive relationship between the independent variables tested and the dependent eco-innovation variables. However, to provide further depth in understanding just what this relationship is, the odds ratio was also calculated.

Unfortunately, when calculating the odds ratio for the *Reducing material and energy cost per produced unit* aspect of eco-innovation, despite allowing the analysis on STATA to run for an extended period of time, the model did not converge. The exact reason for this could not be established. The results presented below are the odds ratio for *Reducing environmental effects*, but it should be noted that all, but one independent variable returned very similar results in terms of significance as the multilevel ordinal logistics regression carried out earlier.

Table 6: Odds ratio.

Model 2	Odds Ratio	Std.Err.	Coef.
FIXED EFFECTS			
Variables: Enterprise level			
Multi-division enterprise (dummy)	.897	.079	-.000
Size in number of employees	1.049*	.029	.043*
Productivity in turnover per employee	1.140***	.030	.152***
R&D (dummy)	2.623***	.210	.770***
Regional innov. collaboration (dummy)	1.690***	.228	.370***
National innov. collaboration (dummy)	1.818***	.277	.399***
International innov. collaboration (dummy)	1.398**	.222	.244**
Most important market (default: local)			
National	1.116*	.073	.103*
Europe	1.164	.129	.202**
Outside Europe	.981	.123	.050
Variables: Regional level			
Regional population size (RI)	.911**	.027	-.090***
Regional geographic size (RG)	1.116**	.039	.091**
RI*RG	1.080**	.029	.064**
RANDOM EFFECTS			
Level two residuals (enterprise nested in industries)	.250		.197
	.057		(.044)
Level three residuals (industry nested in regions)	.000		.000
	(.000)		(.000)
Wald χ^2	472.42***		525.95***
Log likelihood	-4151.490		-7348.316
LR test vs. level one tobit model: χ^2	44.52***		45.37***
N	2009		6534
Number of regions	89		89
Number of industries nested in regions	2010		2010

The last column are the coefficients calculated earlier. Two-tail significance tests *p<.10, **p<.05, ***p<.001.

To generate the odds ratio, little more crude and simplified measures than the original ordinal logistics regression were used. However, the results were very similar (comparing the significance of the odds ratio and the coefficients, except for that which is highlighted where there was a substantial disparity). Still, we feel interpreting the odds ratio still adds some value to our results. For example, one could look at the odds ratio for Regional innovation collaboration (1.69) and state that the relationship is significantly positive, and that there is a 69% probability that enterprises engaged in this activity will also engage in eco-innovation.

8.2 Causation

The problem of causation is also another prominent issue. Although the models show relationship, the direction of causation can be difficult to identify and in fact no definite statement can be made about the causal relationship from the models. We have tried to control for as many variables as we have access to, but there is always the possibility that there are variables that we have not considered that can affect the results.

However, from a logical point of view there are some relationships where a causal relationship can be inferred. For example, the significant relationship between a low population size and eco-innovation, it would seem logical to infer that the causal relationship here is that a low population size leads to eco-innovation. It seems difficult to claim the reverse in that eco-innovation leads to a low population size. Even with some of the other variables where this logic analysis doesn't seem so strong this analysis can still be carried out. For example, enterprise size, the most logical direction of the causal relationship is that size leads to eco-innovation rather than the opposite. This is perhaps strengthened by the literature that show how the benefits of eco-innovation can only be realized in the long term if at all (Tate et al., 2010).

8.3 Future research

As Horbach (2008) pointed out, variables that should be included in a more complete analysis of the drivers of eco-innovation are variables such as political pressure, environmental policy instruments or the influence of pressure groups that seem, as other papers have highlighted, important especially to eco-innovation given its particular peculiarities as compared to general innovation. Given the data material we had at our disposal, these variables were not included in this paper, however, their consideration in any future research would be advisable.

The results utilized in the analysis in this paper were from CIS 2008-2010, it would be interesting to evaluate the same variables considered in this paper for the results from later years of the CIS survey in Norway for comparison. This would be especially relevant if considered alongside any new regulation, or environmental policies that are introduced during these later years in order to gauge it they have had any effect on the behaviour of Norwegian enterprises.

We would like to point out that the methodology utilized in this paper is robust, however the availability of more comprehensive, and up to date, data would be appreciated in any future studies that are carried out.

9 Reliability and Validity

9.1 Reliability

Data used for analysis in this paper was gathered by institutions such as SSB and Eurostat with use of professional procedures and internationally recognized measurements, which is assumed leads to a relatively high standard of reliability during data gathering. The CIS survey is compiled according to guidelines drawn up by Eurostat/OECD otherwise known as the Oslo Manual. The Oslo Manual is the leading international source for guidelines for innovations statistics developed specifically to achieve accurate measurements and standardization for all nations.

9.2 Validity

The testing in this paper was carried out with the assistance of a supervisor at Western Norway University of Applied Sciences. Especially in regard to the statistics modelling and results, the supervisor has extensive experience with not only the field of research generally but has also published several academic papers using the same data set as well as the modelling techniques used in this paper. His assistance with the use of the STATA analysis was invaluable in carrying out the research for this paper and we believe add an enormous amount of validity to the paper.

9.3 Internal validity

All due care was taken in carrying out testing for this paper, however, as outlined under the limitations section, there always exists the possibility that variables that were not considered, and controlled for, may affect the final results in terms of our dependent variable. Again, as outlined under the limitations section, the addition of odds ration analysis may have contributed more dimension to the internal validity by providing an extra confirmation layer to the dependent variables that were tested.

9.4 External validity

Given the size of the sample in this case, and how thoroughly it covered a cross section of all economic sectors and all regions in Norway, and that all due care was taken during this research, we believe we can claim a reasonably high level of external validity in a Norwegian context. As far as extending the relevance of the results outside the borders of Norway, we do not recommend it, especially given the evidence cited earlier as well as comparing them to our results here, which only add to the notion that the peculiarities for every country will give rise to different results.

10 References

AARSTAD, J., KVITASTEIN, O. A. & JAKOBSEN, S.-E. 2016. Related and unrelated variety as regional drivers of enterprise productivity and innovation: A multilevel study. *Research Policy,* 45**,** 844-856.

ÁLVAREZ GIL, M. J., BURGOS JIMÉNEZ, J. & CÉSPEDES LORENTE, J. J. 2001. An analysis of environmental management, organizational context and performance of Spanish hotels. *Omega,* 29**,** 457-471.

ANDREWS, D. W. K. 1999. Estimation When a Parameter is on a Boundary. *Econometrica,* 67**,** 1341-1383.

BORGHESI, S., CAINELLI, G. & MAZZANTI, M. 2012. EUROPEAN EMISSION TRADING SCHEME AND ENVIRONMENTAL INNOVATION: AN EMPIRICAL ANALYSIS USING CIS DATA FOR ITALY. *Giornale degli Economisti e Annali di Economia,* 71(Anno 125)**,** 71-97.

BORGHESI, S., CAINELLI, G. & MAZZANTI, M. 2015. Linking emission trading to environmental innovation: Evidence from the Italian manufacturing industry. *Research Policy,* 44**,** 669-683.

CAI, W. & LI, G. 2018. The drivers of eco-innovation and its impact on performance: Evidence from China. *Journal of Cleaner Production,* 176**,** 110-118.

CAINELLI, G., DE MARCHI, V. & GRANDINETTI, R. 2015. Does the development of environmental innovation require different resources? Evidence from Spanish manufacturing firms. *Journal of Cleaner Production,* 94**,** 211-220.

CAINELLI, G., MAZZANTI, M. & MONTRESOR, S. 2012. Environmental Innovations, Local Networks and Internationalization. *Industry and Innovation,* 19**,** 697-734.

CARRARO, C. Environmental Technological Innovation and Diffusion: Model Analysis. 2000 Heidelberg. Physica-Verlag HD, 269-297.

CYERT, R. & MARCH, J. 1959. *A behavioral theory of organizational objectives.,* New York (NY), Wiley.

CYRET, R. & MARCH, J. 1992. *A behavioral theory of the firm. 2nd ed.,* Cambridge (MA), Blackwell.

DE MARCHI, V. 2012. Environmental innovation and R&D cooperation: Empirical evidence from Spanish manufacturing firms. *Research Policy,* 41**,** 614-623.

DE MARCHI, V. & GRANDINETTI, R. 2013. Knowledge strategies for environmental innovations: the case of Italian manufacturing firms. *Journal of Knowledge Management,* 17**,** 569-582.

DEL RÍO, P., PEÑASCO, C. & ROMERO-JORDÁN, D. 2016. What drives eco-innovators? A critical review of the empirical literature based on econometric methods. *Journal of Cleaner Production,* 112**,** 2158-2170.

DEL RÍO, P., PEÑASCO, C. & ROMERO-JORDÁN, D. 2015. Distinctive Features of Environmental Innovators: An Econometric Analysis. *Business Strategy and the Environment,* 24**,** 361-385.

DEMIREL, P. & KESIDOU, E. 2011. Stimulating different types of eco-innovation in the UK: Government policies and firm motivations. *Ecological Economics,* 70**,** 1546-1557.

DIANA A. FILIPESCU, SHAMEEN PRASHANTHAM, ALEX RIALP & RIALP, J. 2013. Technological Innovation and Exports: Unpacking Their Reciprocal Causality. *Journal of International Marketing,* 21**,** 23-38.

DU, J. & GIRMA, S. 2009. The Effects of Foreign Acquisition on Domestic and Export Markets Dynamics in China. *The World Economy,* 32**,** 164-177.

FERNANDO, Y. & WAH, W. X. 2017. The impact of eco-innovation drivers on environmental performance: Empirical results from the green technology sector in Malaysia. *Sustainable Production and Consumption,* 12**,** 27-43.

GHISETTI, C. & QUATRARO, F. 2013. Beyond inducement in climate change: Does environmental performance spur environmental technologies? A regional analysis of cross-sectoral differences. *Ecological Economics,* 96**,** 99-113.

HOFER, C., CANTOR, D. E. & DAI, J. 2012. The competitive determinants of a firm's environmental management activities: Evidence from US manufacturing industries. *Journal of Operations Management,* 30**,** 69-84.

HOJNIK, J. & RUZZIER, M. 2016. What drives eco-innovation? A review of an emerging literature. *Environmental Innovation and Societal Transitions,* 19**,** 31-41.

HORBACH, J. 2008. Determinants of environmental innovation—New evidence from German panel data sources. *Research Policy,* 37**,** 163-173.

HORBACH, J. 2014. Do eco-innovations need specific regional characteristics? An econometric analysis for Germany. *Review of Regional Research,* 34**,** 23-38.

HORBACH, J., OLTRA, V. & BELIN, J. 2013. Determinants and Specificities of Eco-Innovations Compared to Other Innovations—An Econometric Analysis for the French and German Industry Based on the Community Innovation Survey. *Industry and Innovation,* 20**,** 523-543.

HORBACH, J., RAMMER, C. & RENNINGS, K. 2012. Determinants of eco-innovations by type of environmental impact — The role of regulatory push/pull, technology push and market pull. *Ecological Economics,* 78**,** 112-122.

HUSELID, M. A. 1995. THE IMPACT OF HUMAN RESOURCE MANAGEMENT PRACTICES ON TURNOVER, PRODUCTIVITY, AND CORPORATE FINANCIAL PERFORMANCE. *Academy of Management Journal,* 38**,** 635-672.

ISAKSEN, A. & KARLSEN, J. 2012a. Combined and Complex Mode of Innovation in Regional Cluster Development: Analysis of the Light-Weight Material Cluster in Raufoss, Norway. *In:* ASHEIM, B. T. & PARRILLI, M. D. (eds.) *Interactive Learning for Innovation: A Key Driver within Clusters and Innovation Systems.* London: Palgrave Macmillan UK.

ISAKSEN, A. & KARLSEN, J. 2012b. What Is Regional in Regional Clusters? The Case of the Globally Oriented Oil and Gas Cluster in Agder, Norway. *Industry and Innovation,* 19**,** 249-263.

KAMMERER, D. 2009. The effects of customer benefit and regulation on environmental product innovation.: Empirical evidence from appliance manufacturers in Germany. *Ecological Economics,* 68**,** 2285-2295.

KEMP, R. & PEARSON, P. 2007, p. 7. Final Report MEI Project About Measuring Eco innovation. Maastricht: 1-120.

KNUDSEN, B., FLORIDA, R., STOLARICK, K. & GATES, G. 2008. Density and Creativity in U.S. Regions. *Annals of the Association of American Geographers,* 98**,** 461-478.

KRAATZ, M. S. 1998. Learning by Association? Interorganizational Networks and Adaptation to Environmental Change. *Academy of Management Journal,* 41**,** 621-643.
L.J. BOURGEOIS, I. 1981. On the Measurement of Organizational Slack. *Academy of Management Review,* 6**,** 29-39.
MARTIN, R., MUULS, M. & WAGNER, U. 2011. Carbon Markets, Carbon Prices and Innova- tion: Evidence From Interviews With Managers. Rome (Paper presented at the EAERE conference 29 June–2 July 2011).
MAZZANTI, M. & ZOBOLI, R. 2009. Embedding environmental innovation in local production systems: SME strategies, networking and industrial relations: evidence on innovation drivers in industrial districts. *International Review of Applied Economics,* 23**,** 169-195.
MONTABON, F., SROUFE, R. & NARASIMHAN, R. 2007. An examination of corporate reporting, environmental management practices and firm performance. *Journal of Operations Management,* 25**,** 998-1014.
O'BRIEN, R. M. 2007. A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Quality & Quantity,* 41**,** 673-690.
PEREIRA, A. & VENCE, X. 2012. Key business factors for eco-innovation: an overview of recent firm-level empirical studies. *Factores empresariales dave para la eco-innovación: una revisión de estudios empíricos recientes a nivel de empresa.,* 12**,** 73-103.
PERKINS, R. & NEUMAYER, E. 2008. Fostering Environment Efficiency through Transnational Linkages? Trajectories of CO2 and SO2, 1980–2000. *Environment and Planning A: Economy and Space,* 40**,** 2970-2989.
RAVE, T., GOETZKE, F. & LARCH, M. 2011. The Determinants of Environmental Innovations and Patenting: Germany Reconsidered, Ifo Working Paper, No. 97.
REHFELD, K.-M., RENNINGS, K. & ZIEGLER, A. 2007. Integrated product policy and environmental product innovations: An empirical analysis. *Ecological Economics,* 61**,** 91-100.
RENNINGS, K. 2000. Redefining innovation — eco-innovation research and the contribution from ecological economics. *Ecological Economics,* 32**,** 319-332.
RUGMAN, A., KIRTON, J. & SOLOWAY, J. 1999. *Environmental Regulations and Corporate Strategy: A NAFTA Perspective* Oxford, Oxford University Press.
RYPESTØL, J. O. & AARSTAD, J. 2018. Entrepreneurial innovativeness and growth ambitions in thick vs. thin regional innovation systems. *Entrepreneurship & Regional Development,* 30**,** 639-661.
SCHUMPETER, J. A. 1934. *The Theory of Economic Development,* Cambridge, MA, Harvard University Press.
SCHUMPETER, J. A. 1942. *Capitalism, Socialism and Democracy. Harper, New York.*
SELF, S. G. & LIANG, K.-Y. 1987. Asymptotic Properties of Maximum Likelihood Estimators and Likelihood Ratio Tests under Nonstandard Conditions. *Journal of the American Statistical Association,* 82**,** 605-610.
STATACORP 2013. Version 13.1. StataCorp LP, College Station, TX. Version 13.1. ed.
TATE, W. L., ELRAMM, L. M. & KIRCHOFF, J. F. 2010. Corporate social responsibility reports: A thematic analysis related to supply chain management. *Journal of Supply Chain Management,* 46**,** 19-44.
TEECE, D. J., PISANO, G. & SHUEN, A. 1997. Dynamic capabilities and strategic management. *Strategic Management Journal,* 18**,** 509-533.

THE ECO-INNOVATION OBSERVATORY 2012, p. 8.
Methodological Report. Eco-Innovation Observatory. Funded by the European Commission, DG, Environment, Brussels.
THE HERITAGE FOUNDATION. 2018. *2018 Index of Economic Freedom: Norway* [Online]. Available: https://www.heritage.org/index/country/norway [Accessed].
VOGEL, D. 2000. Environmental regulation and economic integration *Journal of International Economics,* 3**,** 265-279.
WAGNER, M. 2008. Empirical influence of environmental management on innovation: Evidence from Europe. *Ecological Economics,* 66**,** 392-402.
WILHELMSEN, L. & FOYN, F. 2012. Innovasjon i norsk næringsliv 2008-2010. *Statistics Norway, Oslo***,** 35-36.
YARAHMADI, M. & HIGGINS, P. G. 2012. Motivations towards environmental innovation: A conceptual framework for multiparty cooperation. *European Journal of Innovation Management,* 15**,** 400-420.
YI, J., WANG, C. & KAFOUROS, M. 2013. The effects of innovative capabilities on exporting: Do institutional forces matter? *International Business Review,* 22**,** 392-406.
ZENG, S. X., XIE, X. M. & TAM, C. M. 2010. Relationship between cooperation networks and innovation performance of SMEs. *Technovation,* 30**,** 181-194.
ZIEGLER, A. & RENNINGS, K. 2004. Determinants of Enviromental Innovations in Germany: Do Organizational Measures Matter? *ZEW - Centre for European Economic Research Discussion Paper No. 04-030*.

11 APPENDIX.

11.1 Full results of Ordinal Logistics Regression for all models.

Appendix 1: Model 1: Reduce material and energy waste per produced unit.

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
oekreg	89	14	73.5	1,287
nace	2,009	1	3.3	212

Integration method: **mvaghermite** Integration pts. = 7

Wald chi2(13) = 546.60
Log likelihood = -7123.7156 Prob > chi2 = 0.0000

redmat	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
multidiv	-.0125662	.0822795	-0.15	0.8786	-.1738311	.1486988
nemployeeln	.0524242	.0259513	2.02	0.0434	.0015607	.1032878
productivityln	.1204604	.0255373	4.72	0.0000	.0704083	.1705125
foudummy	.8276136	.0711894	11.63	0.0000	.6880848	.9671423
reg_innov_sb	.2538381	.1067993	2.38	0.0175	.0445154	.4631609
nor_innov_sb	.3259144	.1164703	2.80	0.0051	.0976367	.5541921
int_innov_sb	.4031051	.1244695	3.24	0.0012	.1591494	.6470608
most_import_mar						
2	.1366859	.0622934	2.19	0.0282	.014593	.2587787
3	.3684483	.0986595	3.73	0.0002	.1750792	.5618174
4	.2142022	.1119425	1.91	0.0557	-.0052011	.4336054
popsizeln	-.1063954	.0291157	-3.65	0.0003	-.1634612	-.0493296
regionalsizeln	.1017059	.0348099	2.92	0.0035	.0334797	.1699321
popsizelnXregionalsizeln	.0737293	.0272165	2.71	0.0067	.020386	.1270726
/cut1	1.142976	.4976147			.1676689	2.118283
/cut2	1.799259	.4982647			.8226784	2.77584
/cut3	3.057053	.4999234			2.077221	4.036885
oekreg						
var(_cons)	6.82e-36	6.55e-20			.	.
oekreg>nace						
var(_cons)	.356655	.0600181			.2564528	.4960084

LR test vs. ologit model: chibar2(01) = 93.67 Prob >= chibar2 = 0.0000

Appendix 2: Model 2: Reduce environmental effects.

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
oekreg	89	14	73.5	1,287
nace	2,009	1	3.3	212

Integration method: **mvaghermite** Integration pts. = 7

Wald chi2(13) = 525.95

Log likelihood = -7348.3161 Prob > chi2 = 0.0000

redmilj	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
multidiv	-.0008922	.0789534	-0.01	0.9910	-.1556381	.1538536
nemployeeln	.0428901	.0249035	1.72	0.0850	-.0059199	.0917
productivityln	.1515258	.0245626	6.17	0.0000	.1033839	.1996677
foudummy	.7702402	.068762	11.20	0.0000	.6354692	.9050112
reg_innov_sb	.3704879	.1041745	3.56	0.0004	.1663096	.5746662
nor_innov_sb	.3994949	.1138524	3.51	0.0004	.1763482	.6226416
int_innov_sb	.2442536	.1219843	2.00	0.0452	.0051687	.4833384
most_import_mar						
2	.1025082	.0599509	1.71	0.0873	-.0149934	.2200097
3	.2023964	.0964225	2.10	0.0358	.0134119	.3913809
4	.049955	.1091378	0.46	0.6472	-.1639513	.2638612
popsizeln	-.0898085	.0264271	-3.40	0.0007	-.1416047	-.0380123
regionalsizeln	.0910739	.031355	2.90	0.0037	.0296193	.1525285
popsizelnXregionalsizeln	.0637638	.0247639	2.57	0.0100	.0152275	.1123
/cut1	1.350987	.4598855			.4496276	2.252346
/cut2	1.968113	.4602768			1.065987	2.870239
/cut3	3.239503	.4617022			2.334583	4.144422
oekreg						
var(_cons)	2.47e-40	3.78e-23			.	.
oekreg>nace						
var(_cons)	.1971902	.0441191			.1271858	.3057258

LR test vs. ologit model: chibar2(01) = **45.37** Prob >= chibar2 = **0.0000**

Appendix 3: Model 3: Improve health and safety of employees.

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
oekreg	89	14	73.5	1,287
nace	2,009	1	3.3	212

Integration method: **mvaghermite** Integration pts. = 7

Wald chi2(13) = 335.87

Log likelihood = **-7442.6151** Prob > chi2 = 0.0000

forbhelse	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
multidiv	-.017039	.0783536	-0.22	0.8278	-.1706091	.1365312
nemployeeln	.0360842	.0247527	1.46	0.1449	-.0124302	.0845985
productivityln	.0896175	.023736	3.78	0.0002	.0430958	.1361393
foudummy	.633754	.0681952	9.29	0.0000	.5000938	.7674142
reg_innov_sb	.2342089	.103394	2.27	0.0235	.0315605	.4368573
nor_innov_sb	.2847242	.1135228	2.51	0.0121	.0622236	.5072248
int_innov_sb	.2735978	.1208282	2.26	0.0236	.0367789	.5104167
most_import_mar						
2	.0455744	.0592048	0.77	0.4414	-.0704648	.1616136
3	.0149714	.0961058	0.16	0.8762	-.1733924	.2033353
4	-.0473335	.1082527	-0.44	0.6619	-.2595049	.1648379
popsizeln	-.0879604	.0257304	-3.42	0.0006	-.1383911	-.0375298
regionalsizeln	.1110365	.0304627	3.64	0.0003	.0513307	.1707423
popsizelnXregionalsizeln	.083534	.0240396	3.47	0.0005	.0364173	.1306508
/cut1	.9245044	.4479921			.0464559	1.802553
/cut2	1.359615	.448183			.481192	2.238037
/cut3	2.43625	.4490722			1.556084	3.316415
/cut4	9.726385	1.096161			7.577948	11.87482
oekreg						
var(_cons)	4.04e-36	6.40e-20			.	.
oekreg>nace						
var(_cons)	.1689186	.0405554			.1055149	.2704214

LR test vs. ologit model: chibar2(01) = 38.14 Prob >= chibar2 = 0.0000

Appendix 4:Model 4: Expand range of goods and services.

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
oekreg	89	14	73.5	1,287
nace	2,009	1	3.3	212

Integration method: **mvaghermite** Integration pts. = 7

Wald chi2(13) = 1500.78

Log likelihood = -7021.3651 Prob > chi2 = 0.0000

utvsp	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
multidiv	.1669917	.0815431	2.05	0.0406	.0071702	.3268131
nemployeeln	-.1079223	.0257862	-4.19	0.0000	-.1584623	-.0573823
productivityln	.0213708	.024485	0.87	0.3828	-.0266189	.0693605
foudummy	2.173812	.0744567	29.20	0.0000	2.02788	2.319744
reg_innov_sb	.4974981	.118054	4.21	0.0000	.2661165	.7288797
nor_innov_sb	.2264852	.1310537	1.73	0.0840	-.0303753	.4833456
int_innov_sb	.6102128	.1399414	4.36	0.0000	.3359327	.8844928
most_import_mar						
2	.3458003	.0603413	5.73	0.0000	.2275336	.4640671
3	.1274402	.1025698	1.24	0.2141	-.0735929	.3284732
4	.022346	.114354	0.20	0.8451	-.2017838	.2464757
popsizeln	.0158968	.0272221	0.58	0.5592	-.0374574	.0692511
regionalsizeln	.0064968	.0324094	0.20	0.8411	-.0570244	.070018
popsizelnXregionalsizeln	.0228079	.0255073	0.89	0.3712	-.0271854	.0728013
/cut1	.5935881	.4744063			-.3362311	1.523407
/cut2	1.15602	.4748414			.2253477	2.086692
/cut3	2.437119	.4760703			1.504039	3.3702
oekreg						
var(_cons)	4.73e-36	5.07e-20			.	.
oekreg>nace						
var(_cons)	.2261527	.0469367			.1505704	.3396753

LR test vs. ologit model: chibar2(01) = 62.77 Prob >= chibar2 = 0.0000

Appendix 5: Model 5: Replace outdated products or processes.

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
oekreg	89	14	73.5	1,287
nace	2,009	1	3.3	212

Integration method: **mvaghermite** Integration pts. = 7

Wald chi2(13) = 1102.61

Log likelihood = -7262.6366 Prob > chi2 = 0.0000

erstatte	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
multidiv	.1536625	.0789223	1.95	0.0515	-.0010224	.3083474
nemployeeln	-.0205809	.0247976	-0.83	0.4066	-.0691833	.0280214
productivityln	.0828579	.0238756	3.47	0.0005	.0360627	.1296531
foudummy	1.618216	.0696833	23.22	0.0000	1.481639	1.754792
reg_innov_sb	.4048338	.1071314	3.78	0.0002	.1948602	.6148074
nor_innov_sb	.2873496	.1188036	2.42	0.0156	.0544989	.5202003
int_innov_sb	.2282794	.1268533	1.80	0.0719	-.0203485	.4769072
most_import_mar						
2	.3066031	.0589314	5.20	0.0000	.1910997	.4221065
3	.022619	.0964197	0.23	0.8145	-.1663601	.2115981
4	-.0280275	.1089677	-0.26	0.7970	-.2416003	.1855452
popsizeln	.0074826	.0253236	0.30	0.7676	-.0421507	.0571159
regionalsizeln	.0520191	.0298963	1.74	0.0819	-.0065766	.1106147
popsizelnXregionalsizeln	.0350954	.0237109	1.48	0.1388	-.0113772	.0815679
/cut1	1.613326	.4485239			.7342351	2.492417
/cut2	2.241978	.4491532			1.361654	3.122302
/cut3	3.554625	.4507518			2.671168	4.438083
oekreg						
var(_cons)	2.95e-36	9.78e-20			.	.
oekreg>nace						
var(_cons)	.1316248	.0356986			.0773534	.2239732

LR test vs. ologit model: chibar2(01) = 29.49 Prob >= chibar2 = 0.0000

Appendix 6: Enter new markets or increase market share.

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
oekreg	89	14	73.5	1,287
nace	2,009	1	3.3	212

Integration method: **mvaghermite** Integration pts. = 7

Wald chi2(13) = 1239.95
Log likelihood = -7273.4053 Prob > chi2 = 0.0000

gaainn	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
multidiv	.0964738	.0792377	1.22	0.2234	-.0588293	.2517769
nemployeeln	-.1163545	.02487	-4.68	0.0000	-.1650987	-.0676102
productivityln	.0223618	.0236162	0.95	0.3437	-.0239252	.0686487
foudummy	1.753324	.0702863	24.95	0.0000	1.615566	1.891083
reg_innov_sb	.4868525	.1123764	4.33	0.0000	.2665989	.7071062
nor_innov_sb	.1215895	.1254596	0.97	0.3325	-.1243068	.3674858
int_innov_sb	.6539875	.1344235	4.87	0.0000	.3905223	.9174526
most_import_mar						
2	.2921549	.0588035	4.97	0.0000	.1769023	.4074076
3	.3461846	.0990745	3.49	0.0005	.1520022	.5403669
4	.3358627	.111608	3.01	0.0026	.1171151	.5546103
popsizeln	.0037435	.025515	0.15	0.8834	-.0462651	.053752
regionalsizeln	.0430345	.0303797	1.42	0.1566	-.0165085	.1025776
popsizelnXregionalsizeln	.035074	.0239204	1.47	0.1426	-.0118092	.0819571
/cut1	.5565336	.4497707			-.3250009	1.438068
/cut2	.9982961	.4500649			.1161851	1.880407
/cut3	2.202743	.4511296			1.318545	3.086941
oekreg						
var(_cons)	3.76e-32	2.57e-17			.	.
oekreg>nace						
var(_cons)	.1546516	.0380997			.0954232	.2506426

LR test vs. ologit model: chibar2(01) = 38.17 Prob >= chibar2 = 0.0000

Appendix 7: Model 7: Improve quality of goods or services.

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
oekreg	89	14	73.5	1,287
nace	2,009	1	3.3	212

Integration method: **mvaghermite**   Integration pts. = 7

Wald chi2(13) = 1019.33
Log likelihood = **-7296.1004**   Prob > chi2 = 0.0000

forbkval	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
multidiv	.058678	.0776031	0.76	0.4496	-.0934213	.2107772
nemployeeln	-.0444102	.0244512	-1.82	0.0693	-.0923336	.0035132
productivityln	.0513177	.0230342	2.23	0.0259	.0061716	.0964639
foudummy	1.569472	.0697851	22.49	0.0000	1.432696	1.706248
reg_innov_sb	.4728302	.1108638	4.26	0.0000	.2555412	.6901193
nor_innov_sb	.3605073	.12333	2.92	0.0035	.1187849	.6022297
int_innov_sb	.2762217	.1301936	2.12	0.0339	.021047	.5313964
most_import_mar						
2	.209031	.0579917	3.60	0.0003	.0953693	.3226927
3	.1040959	.0970476	1.07	0.2834	-.0861139	.2943057
4	.0048254	.1079364	0.04	0.9643	-.2067261	.2163769
popsizeln	-.0089668	.0247989	-0.36	0.7177	-.0575718	.0396382
regionalsizeln	.0544789	.029293	1.86	0.0629	-.0029344	.1118921
popsizelnXregionalsizeln	.0116828	.0230739	0.51	0.6126	-.0335412	.0569068
/cut1	.7643964	.43671			-.0915395	1.620332
/cut2	1.035081	.4368687			.1788345	1.891328
/cut3	2.275047	.4378743			1.416829	3.133265
oekreg						
var(_cons)	3.64e-39	1.76e-22			.	.
oekreg>nace						
var(_cons)	.1274702	.0325482			.0772793	.2102587

LR test vs. ologit model: chibar2(01) = 33.94   Prob >= chibar2 = 0.0000

Appendix 8: Model 8: Improve flexibility for production of goods and services.

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
oekreg	89	14	73.5	1,287
nace	2,009	1	3.3	212

Integration method: **mvaghermite** Integration pts. = 7

Wald chi2(13) = 776.20
Log likelihood = -7431.8952 Prob > chi2 = 0.0000

forbefleks	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
multidiv	.0316189	.0780079	0.41	0.6852	-.1212738	.1845117
nemployeeln	.0175873	.0246815	0.71	0.4761	-.0307876	.0659623
productivityln	.0742137	.0234461	3.17	0.0015	.0282602	.1201671
foudummy	1.247696	.0682703	18.28	0.0000	1.113889	1.381504
reg_innov_sb	.4129747	.104215	3.96	0.0001	.2087171	.6172324
nor_innov_sb	.2324451	.1150704	2.02	0.0434	.0069113	.4579789
int_innov_sb	.206363	.122017	1.69	0.0908	-.032786	.445512
most_import_mar						
2	.175711	.0588979	2.98	0.0029	.0602732	.2911488
3	.1360448	.0953499	1.43	0.1536	-.0508375	.3229272
4	.0617118	.1067766	0.58	0.5633	-.1475666	.2709902
popsizeln	-.0516132	.0257026	-2.01	0.0446	-.1019894	-.0012369
regionalsizeln	.0871437	.0304444	2.86	0.0042	.0274737	.1468137
popsizelnXregionalsizeln	.0585636	.0241896	2.42	0.0155	.0111529	.1059743
/cut1	1.065381	.4502			.1830051	1.947757
/cut2	1.654848	.4506479			.7715947	2.538102
/cut3	3.156664	.4523469			2.27008	4.043248
oekreg						
var(_cons)	4.98e-33	6.88e-18			.	.
oekreg>nace						
var(_cons)	.169491	.0400248			.1066935	.2692497

LR test vs. ologit model: chibar2(01) = 43.60 Prob >= chibar2 = 0.0000

Appendix 9: Increase capacity for production of goods and services.

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
oekreg	89	14	73.5	1,287
nace	2,009	1	3.3	212

Integration method: **mvaghermite** Integration pts. = 7

Wald chi2(13) = 685.14

Log likelihood = -7483.4084 Prob > chi2 = 0.0000

oekekap	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
multidiv	-.0115116	.078028	-0.15	0.8827	-.1644437	.1414205
nemployeeln	.0151263	.0245298	0.62	0.5375	-.0329512	.0632037
productivityln	.0957982	.0237363	4.04	0.0001	.049276	.1423205
foudummy	1.127556	.0675378	16.70	0.0000	.9951842	1.259928
reg_innov_sb	.3700807	.1035252	3.57	0.0004	.167175	.5729865
nor_innov_sb	.2134565	.1137731	1.88	0.0606	-.0095347	.4364477
int_innov_sb	.2646603	.1214442	2.18	0.0293	.026634	.5026866
most_import_mar						
2	.1522735	.0587808	2.59	0.0096	.0370652	.2674818
3	.0521665	.0946743	0.55	0.5816	-.1333918	.2377248
4	-.0399635	.1067839	-0.37	0.7082	-.249256	.1693291
popsizeln	-.063476	.02531	-2.51	0.0121	-.1130828	-.0138693
regionalsizeln	.1168929	.0297562	3.93	0.0001	.0585719	.175214
popsizelnXregionalsizeln	.0453142	.0236254	1.92	0.0551	-.0009907	.0916191
/cut1	1.300411	.4451167			.4279982	2.172824
/cut2	1.971647	.4458711			1.097755	2.845538
/cut3	3.328811	.4477411			2.451254	4.206368
oekreg						
var(_cons)	1.74e-34	7.82e-19			.	.
oekreg>nace						
var(_cons)	.1431931	.0375118			.0856912	.2392809

LR test vs. ologit model: chibar2(01) = 32.26 Prob >= chibar2 = 0.0000

Appendix 10: Model 10: Reduce labour cost per produced unit.

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
oekreg	89	14	73.5	1,287
nace	2,009	1	3.3	212

Integration method: **mvaghermite** Integration pts. = 7

Wald chi2(13) = 642.17
Log likelihood = **-7441.9267** Prob > chi2 = 0.0000

redarbk	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
multidiv	-.0122564	.0787867	-0.16	0.8764	-.1666754	.1421627
nemployeeln	.0717667	.0249023	2.88	0.0040	.0229591	.1205743
productivityln	.0916664	.0239401	3.83	0.0001	.0447446	.1385882
foudummy	1.004704	.0682084	14.73	0.0000	.8710179	1.13839
reg_innov_sb	.4035663	.10602	3.81	0.0001	.1957709	.6113616
nor_innov_sb	.2066502	.1151402	1.79	0.0727	-.0190205	.4323208
int_innov_sb	.2902699	.1234472	2.35	0.0187	.0483178	.5322219
most_import_mar						
2	.149953	.059403	2.52	0.0116	.0335253	.2663807
3	.2171547	.095513	2.27	0.0230	.0299526	.4043568
4	.0631785	.1073907	0.59	0.5563	-.1473034	.2736604
popsizeln	-.08017	.026517	-3.02	0.0025	-.1321425	-.0281976
regionalsizeln	.0944615	.0312253	3.03	0.0025	.033261	.155662
popsizelnXregionalsizeln	.065509	.024722	2.65	0.0081	.0170549	.1139632
/cut1	1.06214	.4606217			.1593379	1.964942
/cut2	1.529548	.4611405			.6257295	2.433367
/cut3	2.759131	.4626463			1.85236	3.665901
oekreg						
var(_cons)	**5.14e-38**	3.17e-21			.	.
oekreg>nace						
var(_cons)	.2064063	.046326			.1329471	.3204551

LR test vs. ologit model: chibar2(01) = 45.29 Prob >= chibar2 = 0.0000