Nijmegen School of Management

A cross-industry research on the effects of the degree of open innovation on a firm's adoption of sustainable process innovations

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Abstract

What is remarkable in open innovation studies is that the consideration of sustainable development in open innovation research field remains somehow on the background. Reducing manufacturing companies' energy demand is essential for sustainable development because energy usage and supply cause negative environmental effects (e.g., greenhouse gas emissions, acidification, and extensive land use). However, energy is a non-substitutable production factor. This is why reduction in energy demand is limited to a certain extent and is subject to the desired production output. Therefore, improving the ratio between energy input and the desired output of a production process—i.e., improving energy efficiency—is one of the central aspects of sustainable manufacturing. This is why the main question for this study investigated if the degree of open innovation contributes to improved sustainability (adoption of energy efficiency technologies). Using a negative binomial regression on a large scale survey sample of 149 firms across the Dutch manufacturing sector, empirical results reveal, in line with the expectations, that a higher degree of open innovation is statistically associated with a greater adoption of sustainable process innovations (H1). Contrary to expectations, no evidence was found for the moderating effect of partner type on the relationship between the degree of open innovation and the adoption of sustainable process innovations (H2).

In addition, post hoc analyses reveal that adopting sustainable process innovations results in an increase in the time to market a product, while there is a positive effect on the decrease in energy usage. Also, a distinction is made between inbound open innovation and outbound open innovation. Here, inbound open innovation is associated with a greater adoption of sustainable process innovations, while no evidence was found for an effect of outbound open innovation on the adoption of sustainable process innovations. This suggest that managers of Dutch manufacturing firms should not blindly invest in adopting sustainable process innovations to reduce energy, but also explore possible drawbacks for the firm first.

Preface and acknowledgements

Before you lies the thesis “A cross-industry research on the effects of the degree of open innovation on a firm’s adoption of sustainable process innovations”, the basis of which is a survey on the modernization of production that was conducted among the manufacturing industry in the Netherlands. It has been written to fulfill the graduation requirements of the master Innovation and Entrepreneurship at the Radboud university Nijmegen.

The research was difficult, but conducting extensive research on mostly the research analysis) has allowed me to answer the research question, which was formulated together with my supervisor, Dr. Robert A.W. Kok.

I would like to thank my supervisor for the excellent guidance and support during this process and of course my second reader, Dr. P. Vaessen, for the useful feedback. I also wish to thank all the people of the Centre for Innovation studies of the Radboud university who were responsible for collecting and digitalizing the data.

At last but not least, I would like to express my appreciation to my parents and friends, it was always helpful to discuss ideas about my research with them. They also kept me motivated if I ever lost interest.

I hope you enjoy your reading.

Freek Wellens

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1. Introduction and problem statement

On September the 6th, 2013 the Netherlands took a bold step towards a sustainable future. After an eight-month negotiation process, forty-seven organizations signed the Agreement on Energy for Sustainable Growth (SER, 2013). Energy savings in industry and agriculture need to contribute substantially to the total energy efficiency goal of 100 petajoules (PJ) by 2020. But according to the latest progress report in 2015 "*The goal of the 100 petajoules (PJ) additional energy savings and the share of renewable energy of 14 percent in 2020 are still out of reach*" (Voortgangsrapportage SER, 2015 p.58). This statement shows that organizations still struggle with adopting energy saving techniques to reach energy reduction goals.

This problem has even a greater reach than only the Netherlands. Overall, world energy use increased more than tenfold during the 20th century. In the U.S., more than two-thirds of industrial energy usage is consumed by manufacturing (EIA US, 2011). Machining is an important manufacturing process cluster. Abele et al. (2011) reported that more than 20% of the operating cost throughout the life of a machine tool stems from electrical energy consumption. Nearly 80% of the energy consumed by manufacturing is produced from fossil fuels (EIA US, 2011). As a result, a considerable amount of greenhouse gas emissions (GHG) such as CO^2 are produced. Thus, manufacturing is very energy intensive, and as a result, creates a significant environmental impact. With the drive for sustainable development, that is development "*that meets the needs of the present without compromising the ability of future generations to meet their own needs" (WCED, p. 43)*, manufacturing companies are under increasing pressure from government regulations to reduce energy consumption and related emissions. The European Community targets to reduce the primary energy consumption with 20% before the 2020. Energy savings in manufacturing can contribute for a large part in reaching these energy targets. But the sector's adoption rate of energy and material saving technologies is still modest (Palčič, et al., 2013). Accordingly, improving manufacturing processes by adopting more sustainable techniques is necessary.

Energy-efficient technologies, can be considered to be sustainable process innovations. Process innovations can be defined as, "*new elements introduced into a firm's production or service operation to produce a product or render a service (Damanpour, 2010 p.997)*" and are important for organizations to achieve greater (energy) efficiency in production (Stadler, 2011). It is assumed that a link exists between process innovation and sustainability because innovation plays a crucial role in fostering a greater level of sustainability in company activities (Perl-Vorbach et al., 2015; Hansen and Große-Dunker, 2013). In this way innovations can contribute positively to help organizations achieve their energy reduction goals. For organizations to adopt innovative techniques to reduce energy consumption, Caloghirou et al. (2004) conclude after a study that *"both internal capabilities and openness towards knowledge sharing are important for upgrading innovative performance (p.1).*" Gassmann (2006) confirmed this and pointed out that companies cannot conduct all R&D activities for technological changes by themselves, but instead have to capitalize on external knowledge. Therefore, the focus of this research will be on the approach of collaborating with (external) partners in creating/adopting innovations focused on energy saving techniques.

This phenomenon in the direction of collaborating with external partners appears in the 'open innovation model' by Chesbrough (2003). Chesbrough (2003) et al. describe open innovation as "*the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation" (Chesbrough, Vanderhavenbeke and West, 2006, p. 1).* Van de Vrande et al. (2009) described eight ways in which companies can use open innovation, so called open innovation practices, which will be used in this research. Further elaboration on these practices are given in chapter 2 of this research.

What is remarkable in open innovation studies is that the consideration of sustainable development in open innovation research field remains totally ignored (Hossain, 2013). There are only a few studies who actually research the link between open innovation and sustainability. "*In the period 2003 to 2013 only 12 publications deal specifically with the topic of generating sustainable innovations via the support of an open innovation approach"* (Perl-Vorbach et al., 2014 p.169). Even when researching this link, the literature has not addressed the impact of open innovation practices on process innovation directly, expecting that insights from studies of product innovation defined as, "*new products or services introduced to meet an external user need (Damanpour, 2010 p.997)*" can be applied to process innovation (Un and Asakawa, 2015). Therefore managers face the problem that helpful knowledge from these studies may not apply when they are targeting for sustainable innovation in their production process.

Differences among product and process innovation in their innovation mechanism clarify why findings from analyzing product innovation may not be directly used in the analysis of process innovation. The traditional distinguishing between product and process innovation is the objective being innovated. This is done by the fundamental objective that these particular innovations contribute to the firm. In product innovation novelty of the product is the key objective (Un and Asakawa, 2015). The product should provide the organization with a way to differentiate its supply from those of competitors, and ultimately have the best product in the market in terms of the price/quality ratio. In contrast, the underlying goal of process innovation is not necessarily newness, but efficiency in the way in which an organization performs operations (Ettlie and Reza, 1992; Hatch and Mowery, 1998). Secondly, the competitive impact of the innovation is different. In the case of product innovation, the classical competitive impact is a raise in the product price that the organization can charge for the differentiated product. In contrast, process innovation helps the firm to reduce the operating expenses, enlarging the margin of operations which is a set-up to better product features and quality (Clark and Fujimoto, 1991; Pisano and Shih, 2012). Another difference, which is of great importance for this research, lies in the difference of acquiring knowledge. Product innovation is seen as an organized process that utilizes existing knowledge acquired from practical experiences to develop new products that satisfy the needs of the end users and market (Tan and Nasurdin, 2011); whereas process innovation is described as an improvement to the existing process and/or a generation of new process. In other words, process innovation entails the adoption of new knowledge for product improvement (Cassiman et al., 2010).

In conclusion, given that process innovation activities are knowledge intensive, it is of great importance to clarify how the management of knowledge relates to innovation. Therefore, this research uses the knowledge based view to further explain the effectiveness of open innovation practices on the adoption of sustainable techniques. Specifically, this paper proposes that the impact of innovation collaborations on process innovation might depend on the position the partners have towards the organizations.

Most studies in the open innovation paradigm compare the performance of organizations in terms of their overall openness to external partners (Du et al., 2014). But this research extends the knowledge-based view (KBV; eg., Grant, 1996; Nonaka, 1994) to argue that the impact of open innovation is based on the type of partner because they provide the organization with different sources of knowledge. Knowledge resources are used to accommodate new technical ideas, but also ensure understanding and procedures for their development and implementation/adoption of new process technologies (Dewar and Dutton, 1986). Having R&D partners creates a combination of different perspectives/knowledge which permits a better understanding of new technical processes, encouraging their adoption. A difference can be made between science-based and market-based partners. Science-based partners are as sources of scientific-/technical knowledge and market based partners are as sources of market knowledge (Danneels, 2002). This dimension is chosen because it reflects contrasting types of external knowledge that the firm can approach, resulting in a differential value to process innovation. For the adoption of sustainable technologies - particularly when these new ideas represent major modifications in the conceptualization of a production process – a greater number of specialists are needed (Dewar and Dutton, 1986). This because these technologies need to be understood and procedures need to be developed for implementing them. This argument assumes that specialist knowledge is needed for the adoption of sustainable process innovation. Therefore it may be of influence if the organizations chooses to collaborate with market-based or science-based partners. This results in the following research question:

To what extent does the degree of open innovation relate to a firm's adoption of sustainable process innovations, and to what extent is this influenced by the type of partner?

One of the central aspects of this research is to gain a better insight in the innovation process of an organization. This is done by looking if there is an influence of organizations who execute a more open innovation process towards the adoption of sustainable process innovation. In addition, the study also takes into account that organizations can collaborate with two different types of partners. The outcome will help organizations to find out under which condition it is more likely that organizations adopt more sustainable techniques, and thereby contribute to the decision of a manager with what kind of partners they need to collaborate.

1.1 Relevance

The impact of opening up the innovation process on a firm's adoption of sustainable process innovations needs to be addressed for several reasons.

1.1.1 Managerial relevance

Bettering sustainability is an essential issue for top management because of the growing restrictive environmental regulations, consumer involvement about firms' environmental behavior, and actions of non-governmental organizations highlighting the greenhouse activities of firms (Bönte and Dienes, 2013). Energy savings can have multiple benefits. Nearly a third of the world's energy consumption and 36% of carbon dioxide (CO_2) emissions are attributable to manufacturing industries. The main benefit for organizations is a lower energy bill, although other non-energy benefits like better product quality or lower maintenance costs, might be equally important (Worrell et al. 2003). On the level of a whole country the benefits are that a country can depend less on fuel imports and a contribution to the reduction of carbon emissions. “*As there is still a large untapped potential in energy savings, there is increasing attention to implement policies to realize this potential”* (Abeelen, et al., 2015 p. 153

This study helps managers to decide on what open innovation strategy to adopt. It could be that different partners do not have an equal beneficial effect for the adoption of sustainable process innovations. The preference order of different partner types with which firms might engage with in open innovation activities is relevant for the firm because the search for external knowledge is not free (Mina et al, 2014). Helping managers to understand which partners are more appropriate for sustainable process innovation is of importance for the success of following a sustainable strategy. Being sustainable can enhance the firm’s connections with its external stakeholders, and thereby lower related costs.

1.1.2 Theoretical relevance

Some articles have described open innovation in connection with sustainability, but this is still very scarce. In the study of Perl-Vorbach et al. (2014) twelve studies were mentioned that connect open innovation to sustainability. However, this literature is inadequate because it falls short in empirical setting, being mainly qualitative or focused on product innovation. For the most part, existing literature has focused on the impact of open innovation practices on product innovation (Chesbrough, 2003; Lichtenthaler and Lichtenthaler, 2009). Analyzing these twelve papers on open innovation for sustainable innovation may be seen as an outside-in process where external knowledge is gathered to support the internal development of innovation. Hardly any research is conducted which also includes the inside-out process. Therefore this study is of quantitative nature and it also includes the inside-out open innovation practices. Two other important studies to mention are those of Un and Asakawa (2015) and Bönte and Dienes (2013), because they are one of the first who relate open innovation to sustainability.

This research extends the work of Un and Asakawa (2015) who researched how R&D collaborations - with universities, suppliers, competitors, and customers- impact process innovations in Spain. This research extends their work with incorporating all eight open innovation practices from Van de Vrande et al. (2009), instead of only four. Moreover, it conducts research on open innovation and process innovation in another country. And most importantly, by especially focusing on sustainable process innovation instead of the traditional process innovation. In their review of the body of knowledge towards innovating for sustainability, Adams et al. (2012) pointed out the difference of sustainability-oriented innovation from conventional innovation and say it is differentiated in its purpose and direction. It increasingly requires more integrated thinking, connecting a wider range of considerations than those that characterize traditional innovation. This makes the sustainability-oriented innovation process more complex and challenging. Thus, sustainable oriented innovation has significant implications for its knowledge management (particularly its ability to acquire, assimilate and exploit new knowledge).

This research extends the work of Bönte and Dienes (2013) who investigate strategies (of opening up the innovation process) for the development of new production technologies. Also, this study lacks the dimension of the in-sideout open innovation process . Their conclusion, “*Moreover, in contrast to extant literature, none of our results* *suggests that companies following a 'cooperation strategy' experience greater environmental innovation performance*" (Bönte and Dienes, 2013 p.511), is of interest. This conclusion only gives more reason to further research this area because the literature review from Perl-Vorbach et al. (2014) enables us to conclude that open innovation is suitable for fostering sustainable innovations, given the assumption that innovations result from complex and interconnected processes which depend on different actors. Bönte and Dienes' (2013) conclusion could come from the fact that their study does not include a possible moderating effect of different types of partners. It is necessary to examine if there is a possible moderating effect.

1.2 Scope

The scope of this thesis is on the manufacturing sector (defined as the transformation of materials and information into products to satisfy human needs; Palčič, et al., 2013) in the Netherlands. Since this industry is acting to meet the increasing demand for goods and consequently is one of the primary energy consumers (in 2012 approximately 24.2 percent of energy consumption in the European Union; (Eurostat, 2012)), it is important to settle sustainability in the manufacturing sector. Gahm et al. (2016) argue that reducing manufacturing companies' energy demand is essential for sustainable development because energy usage and supply cause negative environmental effects (e.g., greenhouse gas emissions, acidification, and extensive land use). However, energy is a non-substitutable production factor. This is why reduction in energy demand is limited to a certain extent and is subject to the desired production output. Therefore, improving the ratio between energy input and the desired output of a production process—i.e., improving energy efficiency—is one of the central aspects of sustainable manufacturing. Investigating if open innovation contributes to improved sustainability (adoption of energy efficiency technologies) can partially achieve the objective of this thesis. This will be accomplished by using a large-scale cross-industry database of manufacturing firms resulting from the European Manufacturing Survey.

1.3 Thesis structure

This paper has the following outline. In the first chapter the research background, objective and questions are described. Chapter 2 gives a literature review on the used theoretical concepts, with the focus on open innovation, process innovation and sustainability. This will be used to create testable hypotheses about the effect of open innovation on the adoption of sustainable process innovations. The design of the research follows in chapter 3, including measures, collection of data and data analysis. Quantitative results will be given in section 4. Finally, chapter 5 concludes and discusses these outcomes. This section will also discuss theoretical and managerial implications and possibilities for further research.

2. Literature review and conceptual model

This research draws from the Knowledge Based View (KBV) (Grant, 1996; Nonaka, 1994) to further examine how open innovation practices influences the adoption of sustainable process innovations. First of all, an understanding about how innovation is defined in this research is necessary. Next, the KBV is an appropriate theoretical lens to use because the transfer and flow of knowledge is at the core of innovative activities (Nonaka,1994). Therefore, the KBV will be further elaborated on in the second paragraph. Furthermore, an important principle of the KBV is that organizations involve themselves in practices which help them learning (Oke et al., 2013). Open innovation practices are that kind of practices that enable an organization to be exposed to innovative behaviors/knowledge of others which an organization can acquire, learn, and internalize. Therefore, the third paragraph will discuss what kind of open innovation practices an organization can execute and how open innovation practices can enhance a sustainable innovation strategy. This chapter ends with the hypotheses conducted from the theory.

2.1 Innovation

In order to discuss the adoption of sustainable innovations, it is first necessary to explain how innovation is defined in this research. Originally, Joseph Schumpeter (1934) provided the first definition of the concept of innovation:

"The introduction of new goods (…), new methods of production (…), the opening of new markets (…), the conquest of new sources of supply (…) and the carrying out of a new organization of any industry" (Schumpeter 1934, p. 66).

Schumpeter (1934) was also the first who pointed out the difference between innovation and invention. Unlike an invention, innovation always takes place according to him in an economic environment with a commercial purpose. However, an invention can occur in any context, even if the inventor has no commercial objective.

To show the multiplicity in the definitions of innovation, a couple of examples of organizational innovation definitions will follow. An early definition was given by Thompson's (1965). His definition is a quite direct one, he simply states: "*Innovation is the generation, acceptance and implementation of new ideas, processes products or services*" *Thompson's (1965, p. 2).* Another definition coming from Kimberly (1981, p. 108) defines innovation from another perspective which covers various forms of innovation: "*There are three stages of innovation: innovation as a process, innovation as a discrete item including, products, programs or services; and innovation as an attribute of organizations.*". Other researchers underline that the degree of newness in innovation is very important. For example, Van de Ven et al. (1986 p.592) argue that, "*As long as the idea is perceived as new to the people involved, it is an 'innovation' even though it may appear to others to be an 'imitation' of something that exists elsewhere*".

Other varieties appear from several varied disciplinary perspectives. For example in the knowledge management perspective, the aim is on knowledge being highly essential for innovation. As Plessis (2007, p. 21) notes: "*Innovation as the creation of new knowledge and ideas to facilitate new business outcomes, aimed at improving internal business processes and structures and to create market driven products and services. Innovation encompasses both radical and incremental innovation*." Whilst there is some overlap between various definitions of innovation, overall the number and diversity of definitions leads to a situation in which there is no clear and authoritative definition of innovation. Many different definitions of innovation exist in the literature. Baregheh, Rowley, and Sambrook (2009) reviewed different definitions regarding innovation and formulated the following multidisciplinary definition: "*Innovation is the multi-stage process whereby organizations transform ideas into new/improved products, service or processes, in order to advance, compete and differentiate themselves successfully in their marketplace*" (p. 1334).

Because this research looks at innovation with a knowledge perspective, the definition of Plessis (2007) is a suitable definition for this research to build on. This definition is aware of the characteristic that innovations can take many forms. The focus in this definition is the first part of it, "*Innovation as the creation of new knowledge and ideas to facilitate new business outcomes, aimed at improving internal business processes..*" Because process innovations are oriented toward the efficiency or effectiveness of production, which is at the center of interest in this research. Since this research looks at innovation from a knowledge perspective an elaboration on the role of knowledge will follow next.

2.2 Role of knowledge in innovation

According to the literature, one of the most important aspects to innovate is how organizations manage their knowledge (Nonaka, 1994; Galunic and Rodan, 1998; Darroch, 2005; Plessis, 2007). The KBV sees organizations as mechanisms that facilitate the integration, transfer, and creation of knowledge (Un and Montoro-Sanchez, 2010).

Knowledge is not equally allocated across individuals and organizations in society. The role of the organization is that it manages the sharing of the uneven distributed tacit (embedded inside a person) and explicit knowledge (information written in a formal language). It is namely the conversion into tacit knowledge, and its transformation into explicit knowledge, that leads to an innovation (Nonaka, 1994; Un and Asakawa, 2015). This is called knowledge management (KM). There are plenty of definitions of KM being introduced in the literature. KM is defined by Bennett and Gabriel (1999) as capturing, storing, disseminating and using the knowledge. Next, Darroch (2003) called KM a process of creating, managing, distributing and sharing knowledge within and between firms. The mention of knowledge sharing in this definition is important because sharing knowledge is considered to be the most important aspect of knowledge management (Gupta et al., 2000; Wang and Noe, 2010). Hendriks (1999) explained knowledge sharing as a communication process that includes two parts: (1) the knowledge owner externalizes the knowledge; (2) the knowledge demander internalizes the knowledge.

Generally, scholars have acknowledged knowledge sharing as a source of innovation in both intra- and interorganizational contexts (Dhanaraj and Parkhe, 2006; Dyer and Singh, 1998; Grant, 1996). External knowledge sharing is a vital requirement for a firm's innovation outcomes since innovation by character implies linking existing, often external bodies of knowledge in new ways (Chesbrough, 2003a; Huizingh, 2011). Moreover, knowledge as an asset achieves the requirements for a source of sustainable competitive advantage, which is valuable, rare, inimitable, and nonsubstitutable (VRIN; Barney, 1991). First, knowledge is valuable because it allows the organization to meet the needs of customers. In product innovations the value lies in the novelty of the product. In contrast, process innovation is valued internally by managers. Second, knowledge is rare as it is imperfectly divided throughout firms. Third, knowledge is hard to imitate as individuals know more than they can express. Competitors can undoubtedly take the product and engineers can undo its components by reversal. In contrast, process innovation can be harder to imitate by competitors because the process is an internal process to the firm, more tacit and obscure (Un and Asakawa, 2015). Fourth, knowledge is difficult to substitute as it is subject to complexity, interdependency, and causal ambiguity (Un and Asakawa, 2015). The greater complexity, causal ambiguity, and context-specific nature of process innovation makes it much harder to be replaced.

As a knowledge management paradigm, open innovation highlights the importance of acquiring and applying external knowledge (Chesbrough, 2003). Thus, the concept of open innovation provides one particular framework for aiding understanding of sustainability-related innovation which is both technologically radical and socially complex.

2.3 Open innovation

In defining open innovation, Chesbrough (2003a, p. 24) argues that “open innovation is a paradigm that assumes that firms can and should use external ideas as well as internal ideas, and internal and external paths to market, as firms look to advance their technology”. This original understanding was further clarified in 2006, when Chesbrough and colleagues stated that, ‘‘*the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively*’’(Chesbrough et al., 2006 p. 2) and ‘‘*systematically performing knowledge exploration, retention, and exploitation inside and outside an organization’s boundaries throughout the innovation process*’’ (Lichtenthaler, 2011 p.77).

Exploration refers to the acquisition of knowledge from external sources. In contrast exploitation relates to the commercialization of technological knowledge. Organizations possibly can combine these two processes. In addition, Lichtenthaler (2011) state that organizations more and more maintain knowledge externally. External knowledge retention links to the maintaining of knowledge outside the organizational boundaries of an organization over time, using cooperation as an enlargement of the internal knowledge bases. Therefore, open innovation entails the engagement of different types of partners to acquire ideas and resources from the external environment to have a lead on competitors (Chesbrough, 2003b). Under this paradigm the boundaries between a firm and its environment have become permeable because innovations can easily transfer inward or outward. By being part of a network, companies can gain access to new knowledge, resources, markets and technologies. In open innovation, the innovative ideas within an organization can be more valuable by sharing with partnering organizations, and the innovative ideas brought from outside should be shared in the organization. As claimed in any overview of the literature (Lichtenthaler, 2011), the concept of openness of the innovation process offers a variety of definitions. It can be explained in the contexts of information collection, information sharing, organizational cooperation, and organizational culture and attitudes toward change (Wu, Lin & Chen, 2013).

The open innovation concept did not come ‘out of the blue’, but it builds on earlier theories such as "lead users" (von Hippel, 1986), one-to-one marketing (Peppers & Rogers, 1993) and 'customer centric marketing (Sheth, Sisodia and Sharma, 2000). Open innovation literature gathers these ideas under an umbrella and makes it a distinct field for studies. Given that innovation activities are knowledge intensive, a key success factor of open innovation in an organization is its knowledge management capabilities (Chesbrough 2003). The process of open innovation can be implemented in multiple ways, which will be described subsequently.

2.3.1 Open innovation practices

Chesbrough and Crowther (2006) use the saying ‘’open innovation practice’’ to cite to both inbound and/or outbound activities (e.g. in-licensing and out-licensing). The other way around, inbound and outbound activities are both referred to as open innovation approaches (Lichtenthaler et al., 2011), open innovation process (Enkel et al., 2009) and open innovation practices or initiatives (Lichtenthaler, 2011). Open innovation practices can, according to van de Vrande et al. (2009), be categorized as technology exploitation practices (i.e. venturing, outward IP licensing, employee involvement) and technology exploration practices (i.e. customer involvement, external networking, external participation, outsourcing R&D inward IP licensing).

Figuur 1: Open innovation practices (van de Vrande et al. 2009)

Practice	Definition
Technology exploitation	
Venturing	Starting up new organizations drawing on internal knowledge, and possibly also with finance, human capital and other support services from your enterprise.
Outward IP licensing	Selling or offering licenses or royalty agreements to other organizations to better profit from your intellectual property, such as patents, copyrights or trade marks.
Employee involvement	Leveraging the knowledge and initiatives of employees who are not involved in R&D, for example by taking up suggestions, exempting them to implement ideas, or creating autonomous teams to realize innovations.
Technology exploration	
Customer involvement	Directly involving customers in your innovation processes, for example by active market research to check their needs, or by developing products based on customers' specifications or modifications of products similar like yours.
External networking	Drawing on or collaborating with external network partners to support innovation processes, for example for external knowledge or human capital.
External participation	Equity investments in new or established enterprises in order to gain access to their knowledge or to obtain others synergies.
Outsourcing R&D	Buying R&D services from other organizations, such as universities, public research organizations, commercial engineers or suppliers.
Inward IP licensing	Buying or using intellectual property, such as patents, copyrights or trade marks, of other organizations to benefit from external knowledge.

Other scholars define open innovation practices in different ways. Sobrero and Roberts (2002) used the expression ‘’contractual coordination mechanisms’’. Such mechanisms, according to them are defined in terms of type of collaboration, the length of it and specificity. This includes long term contracts, strategic alliance, R&D consortia, market driven transactions (e.g. licensing), intermediate form of governance structures (e.g. joint ventures and consortia). Lee et al. (2010) instead define open innovation practices as “collaboration modes”. This term includes licensing, outsourcing, R&D partnership, joint ventures and inter-firm alliance. Next, Biancie et al. (2011) call open innovation practices, ‘’open innovation organizational modes’’. With this term they refer to inbound open innovation (e.g. purchase of scientific services, in-licensing) and outbound open innovation (e.g. collaborations, supply of scientific services, out-licensing). As stated by Huizingh (2011), open innovation practices refer to the processes when deciding ‘’when, how, with whom, with what purpose, and in what way the firm should cooperate with external partners’’. In this study the focus is on the open innovation practices defined by Van de Vrande et al (2009). In addition, recent studies have highlighted that innovation is not just simply closed or open, instead it can vary in between. To account for such a continuum some researchers have introduced the concept of the 'openness degree' (Bellantuono et al., 2013; Knudsen and Mortensen, 2011). For this research this means that an organization has a high degree of openness, when it performs more innovation practices at once.

One could also say that the dimension of the degree of open innovation dimension describes the climate/culture in the organization. In open organizations (high degree of open innovation), organizations consider themselves to be open to outsiders and new employees. In contrast, closed organizations (low degree of open innovation) are typically secretive and very suspicious of outsiders as well as insiders. In this environment, only a select few may become part of the "inner circle". As the most difficult part of knowledge transfer is the transfer of tacit knowledge, the sharing of such knowledge must be done through continuous openness, trust, common language and tacit agreement (Ajmal and Koskinen, 2008). In light of this research, an open culture tends to be beneficial for knowledge transfer. In contrast, a closed system culture is distrustful of outsiders, permitting only inner circle interaction and being resistant to communication with others. Therefore, a closed system culture has a negative impact on knowledge transfer. In the next paragraphs it will become clear why an open culture is beneficial for the adoption of sustainable process innovations.

2.4 Sustainable innovations

Traditional innovation and sustainable innovation have much in common. However, by adding environmental and social considerations, sustainable innovation is differentiated from conventional innovation in its purpose and direction (Bos-Brouwers, 2010b). As sustainable innovation progresses, it increasingly requires more integrated thinking, connecting a wider range of considerations than those that characterize traditional innovation. Because sustainable innovations are at the center of attention in this research, a further elaboration desirable.

Sustainability (Elkington 1997), Sustainable Development (WCED 1987) and innovation, are all controversial concepts. As a result, to date, no standard definition of "sustainable innovation" exists. In order to provide a clear understanding of how sustainable innovation is defined in this research a review of the existing definitions is given.

For example, Little (2004 p. 3) defined 'sustainability-driven' innovation as "*the creation of new market space, products and services or processes driven by social, environmental or sustainability issues*". Charter and Clark (2007 p.) define sustainable innovations as, "*a process where sustainability considerations (environmental, social, financial) are integrated into company systems from idea generation through to research and development (R&D) and commercialization. This applies to products, services and technologies, as well as new business and organization models*". In accordance with Achterkamp and Vos (2006, p.530) the term sustainable innovation refers to state that "*the outcome of the innovation process somehow displays sustainability*" or whenever innovations helps to "*sustainable development from an economic, ecological and social point of view*" (Steiner 2008, p.596-597). An alternative, equivalent and also frequently used term is 'eco-innovation', which is defined as: "*any form of innovation aiming at significant and demonstrable progress towards the goal of sustainable development, through reducing impacts on the environment or achieving a more efficient and responsible use of natural resources, including energy*" (European Commission, 2006).

Although the two terms are often used interchangeably, eco-innovation only addresses environmental and economic dimensions while sustainable innovation embraces these as well as the broader social and ethical dimensions (Charter and Clark, 2007). According to Ilskog (2008), the social or ethical dimension is the most complex among the dimensions and is a primary value underlying sustainable development. For example, successful measures to reduce emissions at a manufacturing organizations have a positive impact on the quality of life of the wider community in the neighborhood. Therefore, in this paper the term sustainable innovations will be used.

These definitions describe sustainability as a broad concept and address the social and ethical as well as environmental and financial dimensions of sustainability. This is in line with Hart & Milstein (2003) who introduces the concept of the 'triple bottom line'. They define a sustainable enterprise as "*one that contributes ... by delivering simultaneously economic, social and environmental benefits – the so-called triple bottom line*" (p. 56).

Since this research looks at achieving sustainable development through the adaptation of new technology for processes, which lead to a reduction in consumption of raw materials used for the organization, a definition who specifically emphasizes reduction is applied. Namely, that of the OECD (2009, p. 13) who define an sustainable innovation as an innovation placing '*emphasis on a reduction of environmental impact, whether such an effect is intended or not'* (OECD, 2009, p. 13). As stated by the OECD (OECD, 2009a), eco-innovation can be environmentally motivated, but can also come along as a side-effect of other goals, such as decreasing production costs. Key characteristics of this definition are that the innovation is more environmentally kindhearted than relevant alternatives, novel to the organization developing or adopting it and it is based on effects, not on intention. Thereby the adoption of sustainable techniques will fit into this definition of innovation. If this mention of sustainability is combined to the definition of process innovation, sustainable process innovation is defined in this research as:

"*Innovation as the creation of new knowledge and ideas to facilitate new business outcomes, aimed at improving internal business processes and whose emphasis on a reduction of environmental impact, whether such an effect is intended or not"*

2.5 Open innovation and sustainable process innovations

To start with, derived from the former, sustainable innovation is definitively more challenging and complex than conventional innovation seems to be. Not only does the task itself differ, the externalities and drivers behind the introduction of the innovations also have to be considered (De Marchi, 2012). For example, De Marchi (2013) concentrates not only on process innovations but especially on the environmental type of process innovation, which is at the center of attention in this research. He states that the development of environmental process innovations is yet even harder for firms than the development of other innovations, on the grounds that such innovations are a technological frontier where firms are still inexperienced in. This frequently demands information and skills from beyond what is available internally. This feature is being driven by the intrinsic complexity of environmental innovations, which can be tackled by combining various kinds of specialist knowledge and competences that are distributed within different organizations (De Marchi and Grandinetti, 2013). Sustainable innovation very often requires new information and additional skills.

Empirical evidence reported by De Marchi (2012) seems to confirm that environmentally innovative organizations are more likely to cooperate with external partners. Also, De Marchi and Grandinetti (2013) suggest that developing environmental innovations entails a higher recourse to external knowledge strategies through the use of external sources of information, the R&D outcomes from external organizations and through cooperation. Wagner (2009) further argues that the sustainability-related innovation process tends to be socially very complex, and the knowledge to implement the innovation is widely distributed. Thus, only a very small amount of this knowledge is available in any single firm making it necessary to open up the innovation process to achieve successful sustainable innovation. Consequently sustainable innovation implies higher cooperative effort, leads to more intensive partnerships and requires higher complementarities among network partners (De Marchi 2012).

Only Bönte and Dienes conclude that, "*in contrast to extant literature, none of our results suggests that companies following a 'cooperation strategy' experience greater environmental innovation performance*" (Bönte and Dienes, 2013 p.511). The former researchers explained mainly the process of technological exploration, e.g. knowledge transported outside-in. But also the technological exploitation is of importance, e.g. knowledge transported inside-out. According to March (1991) neither exploration which ignores the application of knowledge, nor exploitation that goes by the creation of new knowledge can create sustained performance alone. This indicates that the connection between exploration and exploitation is critical. This connection works in both directions in which explored knowledge has to be exploited in order to gain from it and that experiences learned from exploitation have consequences on future exploration (because it is only profitable for organizations to explore knowledge that finally can be exploited at a certain point). Bönte and Dienes (2013) conclusion could also come from the fact that they do not include a possible moderating effect of different types of partners, which will be further elaborated on in the next paragraph.

Exploitation can also contribute in another way. Ritala et al., (p. 23, 2015) describe for instance, "*passing knowledge to external partners is an efficient way for a firm to signal to other firms, including competitors, that the firm possesses knowledge of potential value to them*". This enhances the attractiveness of an organizations as a possible partner in innovation-related inter-firm projects. So, organizations that exploit external knowledge are more likely to set-up and engage in more inter-organizational collaborations specifically targeted at improving innovation.

Prior results may indicate that a higher degree of openness enables the search and recombination of more diverse knowledge inputs and is associated with a higher adoption of sustainable process innovations. Therefore, the following hypothesis is conducted:

H1: A higher degree of open innovation is positively related with the adoption of sustainable process innovations.

2.6 Type of partner

Most studies in the open innovation paradigm compare the performance of organizations in terms of their overall openness to external partners (Du et al., 2014). Based on the literature a difference can be made between science-based and market-based partners. Former studies have highlighted that science-based partners and market-based partners allow organizations to access diverse types of knowledge (Danneels, 2002; Faems et al., 2005). Science-based partners are as sources of scientific-/technical knowledge and market based partners as sources market knowledge (Danneels, 2002). Cooperating with market-based partners like customers, suppliers or competitors can assist to better specify market requirement for processes and to spread the costs and risks of the innovation process. While early literature indicated the benefits of interaction with lead users (von Hippel, 1976; Hagedoorn, 1993), organizations might, instead, participate in collaborative arrangements with universities and research institutions in order to get access to basic knowledge. This participation can lead to exploring new avenues for innovation and growth (Bercovitz and Feldman, 2007). A broader elaboration on what the different types of partners can mean for sustainable process innovation will be described next.

2.6.1 Type of partner and the influence on sustainable process innovation

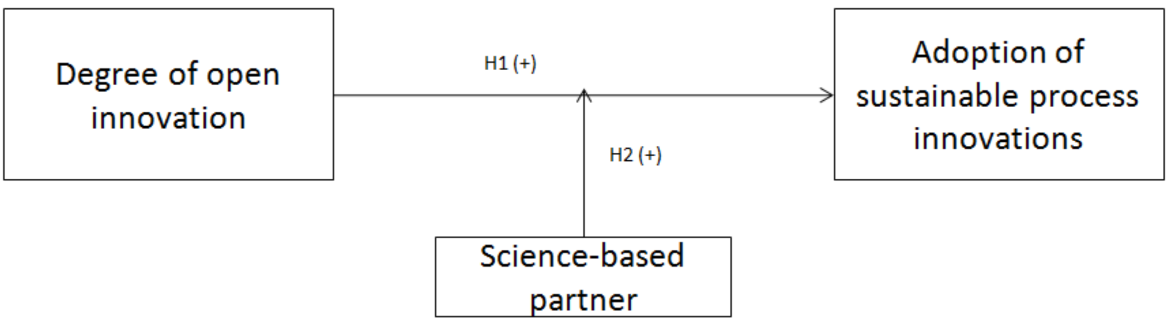
Organizations that aim for the newest technology/knowledge can team up in R&D with universities, public research institutes or with market partners (Deng, Jean and Sinkovics, 2012). A reasoning which calls especially for partnering with universities for the adoption of sustainable process innovations is that universities usually have a wide knowledge base in comparison to other types of partners (Klomp and Van Leeuwen, 2001). Scientific research executed at universities and knowledge institutes is an significant input for industrial innovation (Mansfield, 1998; Klevorick et al., 1995; Narin et al., 1997). By cooperating with science based partners, firms acquire not only access to tacit scientific knowledge but also gain access to (unpublished) codified knowledge. This enables firms to rapidly build on the most recent research findings (Fabrizio, 2009). Scientific knowledge acts as a key map for applied research (Fleming and Sorenson, 2004) by providing R&D teams with a better insights of the technological space in which they search/operate for solutions for the technical problems, in this case the sustainability issue, they are addressing. This new wave of knowledge conducted by scientific institutions is usually the consequence of basic research and is typically needed for process innovations (with a more radical nature, like sustainable process innovations).

Market partners, however, frequently have similar needs and goals in R&D, but the potential usefulness of collaborations with market partners will be limited due the fact that successful R&D cooperation frequently demands differences in knowledge rather than similarities. Market partners are more likely to have a similar knowledge base (Hyll and Pippel, 2015). Furthermore, Lhuillery and Pfister (2009) argued that market partners will have a high incentive to secure their knowledge base and so they will be restrained to team-up when it comes down to knowledge sharing in joint R&D projects. That is why the theoretical and empirical literature emphasizes that restrictions of knowledge streams is a common occurrence among market partners (Oxley and Sampson 2004). Thus, market partners as a collaboration partner holds the risk of opportunistic behavior which can damage the success of an innovation project (Un, Cuervo-Cazurra, and Asakawa 2010). Furthermore, end-users deal with the consumption side, a surrounding that is different that the competitive setting in which the organizations operates and innovates its processes (Un & Asakawa, 2015). Therefore, customers treat the products supplied by the organizations with little attention for how those products have been created, in settings that are not very related to the context of operations of the organization (Lukas, Whitwell, and Heide, 2013). The input of customers may help product innovation more than process innovation.

Next, Hyll and Pippel (2015, p. 471) conclude in their research about likeliness to cancel process innovation that, *"firms that cooperate in R&D with competitors are more likely to cancel process innovation projects than firms that do not cooperate with competitors"* and that *"firms that cooperate in R&D with public research institutes are less likely to cancel process innovation projects*". Moreover, case study analyses have implied the usefulness of innovation-oriented cooperation with governmental institutions, universities and research labs for environmental innovation processes (Bossink, 2007). Even if foreseen a relatively high influence of science-based partners in innovation activities, given the complexity to realize sustainable innovations, the small number of theoretical and empirical researches focusing on the matter do not acknowledge hypothesizing if science-based partners have a influential toward the adoption sustainable process innovations with respect to other types of innovation (De Marchi, 2012). Therefore, the more specific aim is to empirically determine if the knowledge content (i.e. science-based) of open innovation collaborations moderates the contribution of the open innovation degree to the adoption of sustainable process innovations. While sustainable process innovations tends to be technically-strong dependent projects, collaborating with universities can help the firm find those technically new methods. This helps in managing the flow of materials within the organization or introduces new concepts for better organizing material handling (Kim et al., 2006). Therefore the following hypothesis is tested.

H2: Compared to not having a partner, having a science partner has a positive effect on the relationship between the degree of open innovation and the adoption of sustainable process innovation.

2.6.2 Conceptual model



3. Methodology

This section will describe the collection of the quantitative data. In addition, an elaboration on why this approach is appropriate is given and also the research ethics are being discussed. Furthermore, type and number of respondents, reliability and validity will be described.

3.1 Research design

The research objective of this study is to examine whether there is an effect between the degree of open innovation practices on the adoption of sustainable process innovation and the effect of partner type on this relation. To reach this objective the two previously discussed hypotheses need to be tested. Hypothesis testing is the use of statistics to determine the probability that a given hypothesis is true. Based on the sample data, the test determines whether to reject the null hypothesis. Furthermore, this research applies quantitative research methods because quantitative studies are concerned with gaining information in a mathematical manner, appropriate for testing theories deductively, building in protections against biases, controlling for alternative explanations, and being able to generalize and replicate the findings (Vennix, 2011).

Quantitative research is an appropriate approach for testing objective theories by examining the relationship among variables. This allows to investigate whether there is an effect between the different constructs and to assess how strong this effect is. This will allow us to more robustly obtain a complete understanding of the causal relationships between openness strategies and the adoption of sustainable process innovations. This research also has a generalizing character because the outcomes need to be useful for a whole industry. For this characteristic the survey method is a better tool than for example an experiment or case study. It would be proper to term a case study if researching a specific case while one can make generalizations in survey method. Survey research is commonly considered as being intrinsically quantitative and is appropriate for hard prove, including factual and descriptive data (Vennix, 2011). Such data can provide for a systematical comparison amongst cases at identical characterizations (Vennix, 2011). Besides that, surveys are widely known for the structured procedure to analyze the data. The underlying logic is to match variation in one variable with variation in other variables (Vennix, 2011). These characteristics make survey data appropriate for answering the main question developed in this study.

The hypotheses stated in chapter 2 are deductively taken from findings in the literature review and will therefore be tested quantitatively by means of a regression analysis. More of the design and kind of regression is explained in paragraph 3.4.2

3.2 Sample

This research uses the 2012 version of the European Manufacturing Survey (EMS) for collecting the data necessary for answering the main question. The European Manufacturing Survey is conducted every three years and organized by a consortium of research institutes and universities from and across Europe (ISI, 2014). The EMS performs research on current technological and organizational modernization trends in the European manufacturing industry. It provides an excellent and relevant database on aspects of manufacturing firms. This survey is highly recognized by the scientific community (ISI, 2014). The 2012 survey was conducted by 12 European partners, and three non-European partners: Russia, China and Brazil. In total more than 1.600 manufacturing companies participated (ISI, 2014). The EMS aims to identify the innovativeness of the manufacturing industry in several European countries and beyond.

This research uses only the Dutch sub-sample of the EMS, gathered by the Center for Innovation studies of the Radboud University. All organizations are active within the manufacturing industry but a distinction can be made between several different industries who are all considers manufacturing industries.

To generalize findings, representativeness is very important. This means that the sample needs to be representative for the population as a whole (Vennix, 2011). For the EMS database, the representativeness has been tested on three different dimensions: sectors (types of products), firm size (in employees) and region (national provinces in a country). The Dutch sub-sample of the EMS is considered to be representative on these three dimensions for the Dutch manufacturing population (ISI, 2014). In addition to representativeness one also distinguishes reliability. Reliability is the concept of whether a particular measurement tool, repeatedly applied to the same research object, yields in the same results (Vennix, 2011). For a measurement tool being reliable means that a measurement needs to be independent from the researcher. For this study the researcher has conducted a fundamentally analysis of theory and relevant literature which increases the reliability. Another way to improve the reliability of a measurement scale is to determine to what extent mutual questions (or items) are interrelated (Vennix, 2011). If there are items in the scale that show little or no connection with the other items, it is common to remove these afterwards from the measurement construct. In this way these items do not count when determining the score of a person examined. For the EMS survey the reliability is secured trough use structured questionnaires, in this way every respondent is asked the same question in the same way. What is also an advantage for a greater reliability is that the EMS survey is executed every three years. In this way, through repetition of measurements, interrelated items can be deleted upfront. Thus a combination repetition and a measurement trying to reduce deviants as much as possible, the reliability is secured.

It is important to think about data that may occur as missing. If values are missing completely at random, the data sample is likely still representative of the population. But if the values are missing systematically, analysis may be biased (Field, 2009). A detailed elaboration of the missing data process is provided in appendix 2 and missing values per variable are shown in table 1 (appendix 2). The most important notions are that cases 24, 31 and 85 were deleted because they scored almost on every item included in the analysis a missing. Furthermore, cases 113 till 117 were also deleted because of system missing on all the open innovation practices. Due to this deletion the database consist of a final 141 cases for analyses. In summary, the missing data are due to item-nonresponse in a complete random nature (Little's MCAR test: X2 = 98,399, p = .485). The complete case approach was used as a remedy for missing data. There was also a choice of imputation of missing values but due to disadvantages these methods are disregarded.

Also the ethics in research are an important aspect to keep in mind. Ethics refer to: *'code of behavior in relation to the rights of those are subject to the research or affected by it'* (Wells, 1994: p.284). Further elaborations of this code are principles of acceptable behavior and practice. These principles are there because if these are not taken into account, the involvement of people can have possible negative consequences for the research. Attention must be given to the following: accuracy of information, confidentiality/anonymity of personal information, equal opportunities and non-discriminatory practices, fair dealing in the treatment of individuals, professional behavior: collecting and interpreting data in a careful and appropriate way, responsible privacy, no pressure to participate and clarity about the expectations and implications of participants.

The research conducted for this study is consistent with the principles for research ethics. Relationships that might be harmful for a professional behavior or ones that possibly have negative consequences on this study will be avoided. Next, the respondents who have participated in the EMS were fully aware of the purpose of the study. Also the participants had the right to withdraw from the research without any consequences. At last, the survey remains confidential to maintain the respondents' privacy, which is accomplished by maintaining restricted access to the data and the EMS database.

3.3 Construction of variables

Multiple linear regression analysis will be performed for hypotheses testing on the data obtained from the European Manufacturing Survey (2012). The following will detail the dependent, independent and control variables used for the regression analysis. A brief summary is provided in table 3.

3.3.1 Dependent variable

The dependent variable in this research is the adoption of sustainable process innovations. As shown in table 3, the adoption of sustainable process innovations is being analyses by two items. Namely, 'Energy and resources savings' and 'Technologies for generating renewable energy' are used to measure the dependent variable.

Respondents could indicate whether the firms had adopted or is planning to adopt (yes/no) a specific saving technology. To conduct the multiple linear regression analysis, one variable is constructed. The variable *adoption degree of sustainable process innovations* is constructed as a count variable, by summing the total of energy saving technologies used or planned to adopt by the organizations, ranging from 0 to 6, represent the theoretically maximum number of adapted saving/sustainable technologies.

3.3.2 Independent variable

The independent variable in this research is the open innovation practices. This is a count-variable with categories 0, 1 for one time and 2 for more than once. Because it is often hard to measure the construct of 'more than once', this is recoded into two categories. Each of the 8 practices are coded as a binary variable, 0 being no collaborating and 1 being collaboration with the given partner. Subsequently, the 8 practices are simply added up so that each firm gets a 0 when no partners are used, while the firm gets the value of 8 when all the potential collaboration partners are used.

The main issue in this research is whether the EMS measurement framework accurately measures the open innovation concept. To check if the established indicators, which are stated in table 1, are good and fully reflect the theoretical notion of open innovation, the research of De Jong (2006) on open innovation is accessed. In this study one of the main questions was how open innovation should be operationalized. The conclusion was that the following topics were important: innovation methods, networking, the role of users, the role of employees and patents. Among innovation methods, they meant different ways a business can shape its innovation function. Specifically, R&D outsourcing, setting up new businesses (venturing) and participation in new and / or existing businesses. Compared to the indicators from the EMS, all the dimensions of open innovations are included. This is a first indicator that the content validity is correct.

In practice, most researches treat ordinal variables with 5 or more categories as metric, and there is some evidence to suggest this is not likely to result in much practical impact on results (Johnson & Creech, 1983, Newsom, 2012). For the adoption of sustainable process innovations, the theoretical ranges rise-above 5 and can for that reason be analyzed as a metric variable (Johnson & Creech, 1983; Zumbo & Zimmerman, 1993).

3.3.3 Moderating variable

The moderating variables for this study is the type of partner in the collaboration. There are two possible partners for an organization, market-based or science-based partners. Because we expect that science-based partners do have an influence on the relationship of open innovation and the adoption of sustainable process innovations, the item *Cooperation in R&D with research-institutes (for example universities, TNO)* is included as the moderating item. Respondents could fill in a 0 when they do not collaborate with science partners, and a 1 when they do.

If moderator effects are found, then decisions about which partners to collaborate with depends on this information. If effects are positive at all levels of the moderator, then it does not matter with whom the organization cooperates. If effects are observed for one group and not another, it may be useful to partner with a group where a positive relation is found.

3.3.3 Control variables

This paragraph elaborates on the control variable included in the analysis.

Market based partners

This item is included for comparison reasons with the science-based partners. To check whether there is really no relationship as supposed by the literature. Market-based partners are measured by the items *Cooperation with other companies* and *Cooperation with customers and suppliers*. For this control variable a new variable will be created, market based, with a 0 when they do not score on one of the two variables of the market-based partners, and a 1 when they do score on one of the two items.

Organizational size

Organizational size is added as a control variable to control for economies of scale. In addition, given the fact that studies on environmental innovation have found that size has an impact on the sustainable innovation propensity, highlighting the difficulties of small and medium enterprises dealing with the complexity of sustainable innovations and the investments needed to change to sustainable technologies (see e.g., Hemmelskamp, 1999), the variable firm size is added. Firm size will be recoded into categories of numbers of employees. It will be recoded into the following categories: (1) firms less than 20 employees, (2) firms 20 to 49 employees, (3) firms 50 to 99 employees, (4) firms 100 to 250 employees, (5) firms 250 or more employees.

Industry
Third, we make use of a set of industry dummies to account for the fact that OI practices in SMEs and large enterprises differ across industries (Griliches, 1990). There is various evidence from other research that such an effect does exist (Keupp & Gassmann, 2006; Van de Vrande et al., 2009). The EMS measured the sector of respondents with an open question. Respondents were later assigned to one of seven categories. 1. Metals and Metal products, 2. Foods, Beverages and Tobacco, 3. Textiles, Leather, Paper and Board, 4. Construction, Furniture, 5. Chemicals (energy and non-energy), 6. Machinery, Equipment Transport and 7. Electrical and Optical equipment. Organizations not active in the manufacturing will be filtered out in further analysis. Because this was a categorical variable, seven dummy variables were created. Where 1 stood for relevant to a particular industry and 0 for not relevant for that particular industry.

Technical process innovation
Increased focus on technical process innovation most likely indicates better capabilities in this regard (Christmann, 2000). Therefore the importance of innovation activities of the firm is the second control variable. The EMS asked to rank (1 highest - 4 lowest) the importance of four organizational innovation activities for the firm: developing new services, organizational change, technical innovation in production processes and the development of new products. This data will be dichotomized because dichotomization allows distinguishing the organizations who focus on technical process innovation. This will be done as follows: a ranking of 1 or 2 indicated a high focus on technical process innovation, compared to a ranking of 3 or 4, which indicates a low focus. Dichotomization of a single variable can result in some loss of information, however, this loss should not severely affect statistical power (Cohen, 1983b).

Standards and audits
Testa et al. (2011) argue that the higher the control exerted by governmental regulatory bodies, the higher the probability of investments in technology and equipment and, consequently, the higher the probability that environmentally sustainable innovation performs satisfactorily. The ISO has developed a number of standards related to the control/management of sustainable development. Some standards could also be considered relevant in this discussion include Environmental certification according to ISO 14031 and ISO 50001 for energy management.

Environmental certification according to ISO 14031

The focus of this standard is on performance evaluation and environmental indicators. It does not address all three pillars of sustainable development. The performance evaluation standard could be used in conjunction with implementation guidelines.

Energy audit according to ISO 50001: 2011

This standard focuses especially on energy management. The standard is meant to provide technical and management guidance on the effective management of energy. The standard cannot support sustainable development on its own. However, it can be used in conjunction with other standards like the ISO 14031 (Asif & Searcy, 2014).

Overall, a number of empirical studies from the innovation literature have found that implementation of regulatory control systems has a positive impact upon sustainable innovation (Wagner, 2007). Therefore this two standards will be taken into account as a control variable in this research.

Revenue
Horbach et al. (2012) state that external factors such as environmental regulation are not the only factors driving environmentally sustainable product innovation. These authors explicitly point out technological competences and resources available as an important internal factor. In order to further capture the innovation behavior of the manufacturing firms, we additionally control for organizational revenue. This because internal financial resources may provide advantage conditions for decisions regarding adoption of sustainable process innovations, since future savings due to these innovations are often uncertain. It also may be easier for a organizations willing to invest in the adoption of sustainable innovations when there is enough money to buy such technologies. Therefore revenue will be included as a control variable. The EMS asked respondents to fill in the turnover of the organization in millions.

R&D external
Because in this research emphasis is on an open culture, it is also of interest to take a look at only cooperation in for external R&D. Halila and Rundquist (2011) found out that firms that adopt environmentally sustainable innovation practices tend to develop strong partnerships to increase the probability of solving technology-related issues. Environmental innovative solutions often stem from the original combination of knowledge and competences endowed by different organizations (Halila and Rundquist, 2011).

3.3.4 Post hoc variables
In addition, several post hoc variables are included. These are not used for hypotheses testing or as control variables. Instead, these variables are used for additional analyses that might provide more insights.

Energy consumption
It is of interest to research if adopting energy saving techniques also really leads to a reduction in the actual energy consumption. Therefore this indictor is about how the energy consumption evolved in the organization. The participant could tick which was applicable for them, energy consumption, decreased, stayed the same or increased. The variable is dummy coded, 1 for decreased and 0 for stated the same or increased.

Time to market
It is discussed that technological process innovations are new elements introduced into an organization's production system. The drivers of these innovations are, primarily, reduction in delivery time/time to market, increase in operational flexibility and decreased production costs (Boer and During, 2001). It might be interesting to analyze if sustainable process innovation also leads to a reduced time to market due to the use of new materials or changes in process features. In the EMS respondents were asked how long the development of such a new or renewed product lasted in months. This will be the indicator for time to market in this research.

In/outbound open innovation
Open innovation is described in this research as a culture, ranging from closed to open, covering varying degrees of openness to share knowledge across firm boundaries. But as earlier described there are multiple forms of open innovation. Organizations may pursue inbound open innovation but may also establish outbound open innovation (see

paragraph 2.3.1 for an explanation). In this regard, inbound open innovation has attracted substantially more attention by researches than outbound open innovation (Lichtenthaler, 2015). It is therefore of importance to also investigate inbound/outbound open innovation separately from each other. In the EMS includes five inbound practices and three outbound practices. These will also be count variables, inbound reaching from 0-5 and outbound reaching from 0-3.

Table 3: summary of variables included for data analysis.

Variables	EMS description	EMS section	Categories
Dependent variables			
Energy and resources saving			
	Dry processing / minimum lubrication	h03o1	0 no 1 yes
	Application scheduled for 2015	h03o2	0 no 1 yes
	Control system for shut down of machines in off-peak periods	h03p1	0 no 1 yes
	Application scheduled for 2015	h03p2	0 no 1 yes
	Energy recovery from kinetic and process energy	h03q1	0 no 1 yes
	Application scheduled for 2015	h03q2	0 no 1 yes
	Combined heat (Bi-and tri-generation)	h03r1	0 no 1 yes
	Application scheduled for 2015	h03r2	0 no 1 yes
Technologies for generating renewable energy			
	Technologies for generating solar or wind energy, hydropower, biomass or geothermal energy	h03s1	0 no 1 yes
	Application scheduled for 2015	h03s2	0 no 1 yes
	Technologies for heat generation through solar, biomass or geothermal energy	h03t1	0 no 1 yes
	Application scheduled for 2015	h03t2	0 no 1 yes
Count variable: Adoption of sustainable process innovation	**(h03o1+ h03o2)+ (h03p1+ h03p2)+ (h03q1+h03q2)+(h03r1+h03r2)+(h03s1+h03s2)+(h03t 1+h03t2)**		**Scale 0-6**

Independent variable			
Open innovation practices:			
Spin-offs	Starting new organizations or activities outside the company	NL_h06a	0 not 1 once 2 more than once
Outgoing intellectual property	Selling, or offering licenses / patents to other organizations	NL_h06b	0 not 1 once 2 more than once
Employee engagement	Exploiting knowledge and initiatives of non-R&D staff in achieving innovations	NL_h06c	0 not 1 once 2 more than once
Customer engagement	Directly involving customers in your innovation processes	NL_h06d	0 not 1 once 2 more than once
External networks	Collaborating with other organizations (not customers) for innovation	NL_h06e	0 not 1 once 2 more than once
External participation	Participate (with eg. capital, knowledge) in companies to access their knowledge or to create other synergies?	NL_h06f	0 not 1 once 2 more than once
Outsourcing of R&D	Outsourcing of R&D (services) to other organizations, such as universities, public research institutions, commercial engineers or suppliers?	NL_h06g	0 not 1 once 2 more than once
Incoming intellectual property	Buy or to license intellectual property from other organizations	NL_h06h	0 not 1 once 2 more than once
Count Variable Degree of open innovation	**NL_h06a+ NL_h06b+ NL_h06c+ NL_h06d+ NL_h06e+ NL_h06f+ NL_h06g+ NL_h06h**		**Scale 0-8**
Type of partner			
Science-based			
	Cooperation in R&D with research-institutes	H07a1	0 no 1 yes
Market based			
	Cooperation with other companies + Cooperation with customers	H07c1 +H07b1	0 no 1 yes
Control variables			
Firm size	Total amount of employees as in 2011 (excluding contingency personnel)	H20b1	Scale
Technical process innovation	Rank the importance of the following: providing services besides products, organizational change, technical process innovation and new product development	h12a	1. Most important 2. Considerably important 3. Somewhat important 4. Least important

Industry	Industry (e.g. Textiles, chemicals, machinery, etc.)	H01bx	Open question
Standards and audits	Environmental certification according to ISO 14031	H08p1	0. No 1. Yes
Standards and audits	Energy audit according to ISO 50001: 2011	Ho8q1	1. No 2. Yes
R&D by external partners	Does your company conducted or carried out research and development activities (R & D) by external partners?	H17a1	1. No 2. Yes
Revenue	Turnover 2011 in millions	H20a	Scale
Post hoc analyses			
Time to market	How long did it took, on average, the development of such a product? (From product concept to launch)	H11c	Scale (months)
Inbound/outbound open innovation	Outbound: NL_h06a, NL_h06b, NL_h06c Inbound: NL_h06d, NL_h06e, NL_h06f, NL_h06g, NL_h06h		Scale 0-3 Scale 0-5
Energy consumption	between 2009 and 2011,how, has the annual energy consumption (kWh) evolved in your business?	H21a	1. Decreased (1) 2. Stayed the same (0) 3. Increased (0)

3.4 Data analysis and design

This chapter will elaborate on the design of the main analysis and the post hoc analyses respectively.

3.4.1 Design of the negative binomial regression

One kind of Generalized Linear Models (GLM) is specifically appropriate when working with a count variable; the Poisson distribution (for an extensive review on this type of GLM, see appendix 3). However, when working with this distribution on is assuming that the mean of the distribution is equal to its variance. When the variance of a distribution is greater than its mean, this distribution is said to be overdispersed (Gardner, Mulvey, & Shaw, 1995). Overdispersion often occurs when there is a large number of 0's in the observed data stemming from very low frequency event. This happens to be the case in this research, see appendix 3 (Mean = .70, Std. Deviation= 1.5). An alternative strategy for dealing with this overdispersion is to use the negative binomial distribution. The negative binomial distribution has one parameter more than the Poisson regression that adjusts the variance independently from the mean (Gardner, Mulvey, & Shaw, 1995). As a matter of fact, the negative binomial distribution is a special case of the Poisson distribution. This parameter is referred to, unsurprisingly, as the dispersion parameter (Gardner, Mulvey, & Shaw, 1995). According to Gardner et al. (1995), if overdispersion is disregarded, "*the calculation of the estimates of the standard errors will be too small, test statistics for the parameter estimates will be too large, significance will be overestimated, and confidence limits will be too small* (Gardner, Mulvey, & Shaw, 1995 p.130). The purpose of the negative binomial regression is equivalent to that of the Poisson regression: to model relationships between predictors and the likelikhood of certain count outcomes. In addition, the negative binomial regression analysis has three advantages. First, it can set the relative importance of each independent or control variable for predicting the adoption of sustainable process innovation. Second, the analysis can correct for non-linear relationships when present. And third, it can research the effect of moderating relationships, as hypothesis 2 predicts. In addition, covariate values are pretended to be fixed in the Generalized Linear Model. That is, no particular distributional assumptions are made. Thus, it does not matter if they are count or not, nor if they range from 0 to 10 or, from 1 to 10000.

Other strategies to analyses data in the form of counts, are often suboptimal strategies. It can for instance be that the counts are rescaled to a set of categories (e.g., 0–2, 2–4, and more than 4). These categories and the factors that may predict them are then analyzed via a multinomial regression. It can also be that the counts are put together all the way to a dichotomy (such as "employed/unemployed"), this means that the scores can be analyzed using logistic regression or a similar technique suitable for a binary dependent variable. However, reducing counts to categories wastes information and may weaken statistical power (Gardern, Mulvey & Shaw, 1995). In addition, the results can also be affected by the choice of cut point in defining the categories.

Another questionable strategy is to analyze count data using ordinary linear regression. Regression analysis can be described in terms of two ideas: (a) a model for the mean which states how the expected value of the dependent variable relates on different predictors and (b) a model for the dispersion of the dependent variable scores around that expected value. Executing ordinary linear regression to count data is problematic on both these dimensions (Gardern, Mulvey & Shaw, 1995). According to Gardern at al.

(2009 p.127), "*On the one hand, the linear model relating the expected count to the predictors is likely to produce nonsensical, negative predicted values. On the other hand, the validity of hypothesis tests in linear regression depends on assumptions about the variance of scores that are unlikely to be met in count data*."

Another strategy possible is bootstrapping. For the following reasons analyses negative binomial regression was chosen above bootstrapping. Firstly, bootstrap sampling is sensitive to individual samples (Yu, 2003). This means that if there are any (tiny) errors, it could mess up the analysis. Secondly, Yu (2003) explained that confidence intervals obtained by simple bootstrapping are always biased though the bias decreases with sample size. If the sample comes from a normal population, the bias in the size of the confidence interval is at least $n/(n - 1)$, where n is the sample size (Yu, 2003).

The following features are important for the adaptability of the negative binomial regression.

Sample size
The complete case approach yields a sample size of N=116. Negative binomial regression requires plus ~10 cases per independent variable. In this research there are ten independent variables, so 116 cases to analyses is appropriate for this analysis.

Moderating variables
To conduct an analysis with a moderator, an interaction term will be created by multiplying the degree of open innovation with the science type of partner (Field, 2009). Moderating effects were tested for significance in a three step process (Field, 2009): (1) estimate the unmoderated equation, (2) estimate the moderated equation, and (3) assess the change in R2 . If this change is statistically significant, a moderating effect is present (Field, 2009).

Non-metric variables
Negative binomial regression can also include non-metric variables through dummy coding (Field, 2009). Each category of the nonmetric variable is represented by either 1's or 0's. A dummy variable is regarded as relevant if it is statistically different from the reference category (Field, 2009).

3.4.2 Assumptions of the negative binomial regression
Checking the assumptions of a negative binomial model involved two steps: examining whether the data violated any assumption and verifying that the observed outcomes were a reasonable fit to a negative binomial distribution. Firstly, the assumptions of the negative binomial regression are discussed.

Assumptions

- Generalized Linear Models do not assume that the dependent/independent variables are not normally distributed (Hardin & Hilbe, 2007).
- Generalized Linear Models neither assume linearity between the predictors and the dependent variables, nor homogeneity of variance for the range of the dependent variable. Homoscedasticity is no longer assumed because the variance is explicitly a function of the mean and so in general varies with the predictors (so

while the model is generally heteroscedastic, the heteroscedasticity takes a specific form) (Hardin & Hilbe, 2007).

- There must be linearity in the link function. The link function must correctly represent the relationship among dependent and independent variables. The link function for this analyses is usually a straightforward log link (rather than the logit, or log-odds, link used for binary logistic regression)—which makes the interpretation slightly easier.
- Multicollinearity is absent (Hardin & Hilbe, 2007).
- The data must be centered in order to reduce multicollinearity (Hardin & Hilbe, 2007). Unless the value 0 is intrinsically meaningful for an independent variable or moderator (e.g., in the case of a binary variable or count variable)
- The dependent data in Generalized Linear Models are continuous, ordinal, or binary (Hardin & Hilbe, 2007).
- Testing for influential observations (Hardin & Hilbe, 2007).

Although the model itself doesn't assume linearity. It can still be useful for the model to transform predictors in order to achieve linearity of the linear predictor.

Fit tests
Verifying that the observed outcomes were a reasonable fit to a negative binomial distribution

- Examine the Pearson Statistic/df. Should be close to 1
- Also, it uses Maximum Likelihood. Larger (in the closer to zero sense) log likelihoods are better.

Summary
Next is a summary of the assumptions and fit test. A detailed account is provided in appendix 4. Starting with the individual variables a natural logarithm was applied to the independent variable's *revenue* and *size* to improve upon normality (see appendix 4.1). Also metric variables were centered because that was one of the assumptions. Shifting to the assumption of the variate, there must be linearity in the link function. Therefore the Log link is used when numbers cannot be negative as when data are Poisson counts. Furthermore there were no signs of multicollinearity as can be seen in the correlation table in appendix 6, there were only expected correlations between size and revenue and between open innovation and inbound- outbound innovation, because they are a product of open innovation. Next, some cases are on the list of influential observations. After checking the database no signs of wrong entries could be found. Therefore no cases were deleted. The conclusion after assessing the model fit, is that the model fit our data (appendix 4.2). Next, a test on quadratic effects is detailed in appendix 7.2.1. The change statistics show that on the adoption of sustainable process innovation no quadratic effect were found due to insignificant changes in R2 when adding polynomials. Due to the insignificant result of the quadratic terms, no cubic effects were tested (Hair, 2009).

3.4.2 Design of post hoc analyses

For the first post hoc analyses on '*time to market*' a different analysis is conducted because this variable is not a dependent count variable. Therefore negative binomial regression would be inappropriate. Time to market is a dependent variable measured on a continuous scale. With a continuous dependent variable, multiple regression is conducted for this analysis (Field, 2009).

For the second post hoc analyses, the measurement of the variable ‘*decrease in energy’* is dichotomous (either 1 for an decrease or 0 for no decrease). Barros and Hirakata (2003) found that, “*… log-binomial regression provide correct estimates and are a better alternative for the analysis of cross-sectional studies with binary outcomes than logistic regression, since the prevalence ratio is more interpretable and easier to communicate to non-specialists than the odds ratio* (2003, p. 3:21)”. For example, if 80 out of 100 exposed persons have a specific disease and 50 out of 100 non-exposed persons have the disease, then the odds ratio is (80/20)/(50/50) = 4. However, the prevalence ratio is (80/100)/(50/100) = 1.6. The latter indicates that the exposed subjects are 1.6 times as likely to have the disease as the non-exposed subjects, this is the number in which the majority would be interested in. Therefore, the choice is also to use a GLM with a binomial regression and a log function. The following advice for choosing an appropriate log link function is excerpted from Norusis (2005, p. 84), “*The complementary log-log link may be a good model when the cumulative probabilities increase from 0 fairly slowly and then rapidly approach 1. If the opposite is true, namely that the cumulative probability for lower scores is high and the approach to 1 is slow, the negative log-log link may describe the data.”* Therefore for this analysis, a negative log-log binomial regression will be conducted because there are far more zero’s (85) then one’s (29).

For the last post hoc analyses the count of sustainable process will stay the dependent variable, only the degree of open innovation will be split in inbound and outbound open innovation. Therefore this will stay the same negative binomial regression as our main analyses.

3.4.4 Assumptions of the post hoc analyses

Because of the different analyses, the post hoc requires other assumptions than the main analyses. For the assumptions of the multiple regression on time to market a detailed account is given in appendix 5. The assumptions of the binary analysis on energy decrease are elaborated on in appendix 6. In summary, time to market was log transformed. There were no influential outliers in both cases and there were no signs of multicollinearity (only expected high correlations). Also for the post hoc a test on quadratic effects was conducted in appendix 7.2.2. The change statistics show that on time of market no quadratic effect were found due to insignificant changes in R2 when adding polynomials. Due to the insignificant result of the quadratic terms, no cubic effects were tested (Hair, 2009).

4. Results

This section elaborates on the results of the analyses. Firstly, the descriptive statistics and correlation coefficients are discussed. Secondly, the results of the negative binomial regression are presented. At last, the results of the post hoc analyses are displayed.

4.1 Descriptive statistics and correlation coefficients

Descriptive statistics and correlation coefficients are presented in the statistical output provided in appendix 7.1, an overview is provided on the next page (table 4) As expected, an open culture is positively related with the adoption of sustainable processes (.355, $p<.001$), suggesting that an increased level of openness is paired with an increased level of adoption of sustainable processes. Interestingly, science partners also show a positive relationship with the adoption of sustainable processes (.271, $p<.001$). Which means that science partners related with a higher adoption of sustainable processes. In addition, the adoption of sustainable processes is also positively correlated with the management control system ISO50001 (.308, $p<.001$) and ISO14031 (.200, $p<.05$). This means that organizations who adopted this management control system are more likely to adopt sustainable processes. What also is of interest is that both management control systems (ISO14031 and ISO50001) positively related with the degree of open innovation (respectively, .301, $p<.001$ and .194, $p<.05$). This means that organizations who are more open average, will also adopt management control systems faster. Because these control systems also related to the adoption of sustainable processes, there is more or less an indirect relationship which will enhance the adoption of sustainable processes.

Furthermore, from the post hoc variables it becomes clear that an decrease of energy positively relates with adoption of sustainable processes (.333, $p<.001$). It also becomes clear that the correlation between inbound open innovation and the adoption of sustainable processes (.366, $p<.001$) is higher compared to the correlations between outbound open innovation and the adoption of sustainable processes (.222, $p<.001$). Next, time to market positively correlates with an open innovation culture (.439, $p<.001$). In addition, the time to market correlates higher with science partners (.401, $p<.001$) than with market partners (.236, $p<.05$). Interestingly, only few manufacturing firms use environmental management systems (ISO14031, 14.9% and ISO50001, 5,7%). However, many Dutch manufacturing firms emphasize a high importance of technical process innovation (57.4%).

Variables	N	%	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Dependent variable																								
1. Sustainable process innovations	141		0,709	1,233																				
Independent variables																								
2 Open innovation	141		3,730		.355**																			
3 Science partners	140	35,5			.271**	.426**																		
4 Market partners	140	61,7			.189*	.329**	.336**																	
Control variables																								
5 Technological innovation	136	57,4			.108	-.003	-.063	-.031																
6 ISO14031	138	18,4			.200*	.301**	.183*	.155	.099															
7 ISO50001	139	5,7			.308**	.194*	.075	.068	-.046	.356**														
8 R&D External	139	27,7			.166	.436**	.379**	.353**	.020	.249**	.192													
9 Revenue	126		69,738	612,79	.257**	.474**	.301**	.298**	.105	.300**	.217*	.226**												
10 Size	139		172,21	783,30	.352**	.476**	.314**	.270**	.148	.425**	.233**	.284**	.738**											
11 Metal	140	23,4			-.078	.104	.129	.084	-.028	.099	.066	.041	.207*	.065										
12 Food	140	6,4			-.008	.105	.072	.034	-.097	.128	.066	.097	-.208*	-.021	-.146									
13 Textile	140	12,8			-.052	.063	.105	.138	-.036	-.100	-.190*	.191*	-.075	-.006	-.213*	-.101								
14 Construction	140	7,8			-.071	-.091	-.118	-.011	.033	-.036	-.156	.002	-.077	.006	-.162	-.077	-.112							
15 Chemical	140	17,7			.043	-.072	-.071	-.021	-.142	-.120	.032	-.188*	-.020	.002	-.259**	-.122	-.179*	-.136						
16 Machinery	140	20,6			.087	-.079	-.230**	-.099	.067	.023	.052	-.001	-.069	-.081	-.284**	-.134	-.169*	-.149	-.283**					
17 Electronic	140	10,6			.063	-.020	-.035	-.130	.218*	.040	.087	-.115	.027	.032	-.192*	-.091	-.133	-.101	-.162	-.177*				
18 Inbound	141		2,62	1,344	.367**	.905**	.410**	.369**	-.066	.255**	.172*	.440**	.427**	.432**	.150	.153	.080	-.067	-.100	-.079	-.128			
19 Outbound	141		1,1	0,884	.222**	.792**	.311**	.171*	.073	.277**	.149	.276**	.415**	.389**	.082	-.016	.022	-.188	.018	-.077	.102	.479**		
20 Time to market	87		14,80	16,74	.182	.439**	.401**	.236*	-.139	.205	.111	.360**	.252*	.388**	.186	.198	.141	-.076	-.078	-.295**	-.037	.428**	.279**	
21 Energy decrease	136	22,0			.333**	.160	-.001	.186*	.174*	.159	.236**	.187*	.030	.115	.056	.005	-.058	-.095	-.023	.009	.081	.142	.149	.025

Table 4: Spearman correlation coefficients. *Notes: Two tailed significance: **p<0.001, *p<0.05*

4.2 Negative binomial model results

In the negative binomial models, first, the control model for the adoption of sustainable process innovations (model 1) was estimated to determine the effect of the control variables. The second step adds the degree of open innovation (model 2) to determine their direct effect. As a point of comparison in model 3 and 4 the market partners and science partners are added. Next, the in the last model (5) the moderating effect between the degree of open innovation and science partners was added.

The negative binomial regression results[a] on the adoption of sustainable process innovation are presented in table 5 (statistical output in 7.3). The likelihood ratio test, when all the independent variables are included, shows that they collectively improve the model over the intercept-only model. Having all the independent variables in our example model we have a p-value of .000, indicating a statistically significant overall model. Hypothesis 1, that predicts a higher degree of open innovation is positively related with more adoption of sustainable process innovations, is supported. Model 2 shows a positive (Exp(B)=1.23, $p<.05$) effect of the degree of open innovation on the adoption of sustainable process innovations. Interestingly, when both partner variable are added in model 4, only the science partners show a direct effect (Exp(B)=2.25, $p<.001$) on the adoption of sustainable processes. This positive effect still remains in model 5 when the interaction is added. The market partners variable did not show a significant effect in one of the models. Hypothesis 2, which predicts that the type of partner can enforce the relationship between the degree of open innovation and the adoption of sustainable process innovation, is not supported. Model 5 shows an insignificant (Exp(B)=0.85, $p>.1$) effect of the moderating term on the adoption of sustainable processes.

In addition, in the final model, the control variable size shows a positive effect (Exp(B)=1.59, $p<.05$) on the adoption of sustainable process innovations processes, and is throughout all the models positively related as expected. This suggest that larger firms adopt more sustainable process innovations. More interestingly, revenue shows a negative significant effect (Exp(B)=0.69, $p<.05$) on the adoption of sustainable processes. This would mean that a higher revenue does not lead to a higher adoption of sustainable process innovations. Finally, the control management system ISO50001 shows a significant positive effect throughout all the models, in final model Exp(B)=3.22, $p<.05$).

[a]The raw output tables provide both the coefficient estimates (the "B" column) of the negative binomial regression and the exponentiated values of the coefficients (the "Exp(B)" column). It is usually the latter that is more informative. These exponentiated values can be interpreted, for example, the exponentiated value is 1.5. This means that the count of the dependent variable will be 1.5 times greater when the independent variable increases. another way of saying this is that there is a 50% increase. A similar interpretation can be made for the categorical variable. Therefore, the Exp(B) column is used for interpretation of the results.

Table 5: negative binomial results for the dependent count variable adoption of sustainable processes

Construct	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	Control variables	Model 1 plus degree of open innovation	Model 2 plus market partners	Model 3 plus science partners	Model 4 plus interaction	Post Hoc in/outbound open innovation
	Exp(B)	Exp(B)	Exp(B)	Exp(B)	Exp(B)	Exp(B)
Intercept	0.25 (1.95)	0.12 (1.94)	0.15 (1.94)	0.68 (1.53)	0.07 (1.53) *	0.06 (1.60)*
Independent variables						
Degree of open innovation		1.23 (0.09)**	1.29 (0.09)**	1.26 (0.07) **	1.06 (0.09)**	Inbound: 1.32 (0.13)** Outbound: 1.17 (0.22)
Market partners			1.36 (0.32)	1.15 (0.26)	1.06 (0.27)	1.16 (0.33)
Science partners				2.25 (0.26)***	4.60 (0.71) **	2.28 (0.30)
Science partners * degree of open innovation					0.85 (0.15)	
Control variables						
Industry dummies	NOT SIGN	NOT SIGN	NOT SIGN	NOT SIGN	NOT SIGN	NOT SIGN
Size[a]	1.72 (0.29)**	1.69 (0.28)*	1.73 (0.28)**	1.56 (0.19)**	1.59 (0.19)**	1.67 (0.25)**
Revenue[a]	0.78 (0.22)	0.69 (0.23)*	0.67 (0.23)*	0.66 (0.17)**	0.69 (0.17)**	0.66 (0.17)**
Technological innovation	1.22 (0.32)	1.27 (0.32)	1.28 (0.32)	1.44 (0.36)	1.42 (0.25)	1.43 (0.28)
ISO14031	0.91 (0.41)	0.80 (0.40)	0.80 (0.39)	0.70 (0.33)	0.77 (0.34)	0.75 (0.38)
ISO50001	2.67 (0.58)*	2.71 (0.56)*	2.62 (0.55)*	3.42 (0.42)**	3.22 (0.42)**	3.32 (0.36)***
External R&D	1.12 (0.37)	0.87 (0.37)	0.84 (0.37)	0.65 (0.29)	0.73 (.30)	0.68 (0.33)
Model statistics						
Deviance Value/df	1.03	1.02	1.04	1.44	1.45	1.04
Pearson Chi-Square Value /df	1.40	1.24	1.27	1.62	1.62	1.13
Log Likelihood	-136.16	-132.33	-131.97	-132.93	-132.47	-128.28
Likelihood Ratio Chi-Square/df	27.77/12**	35.42/13**	36.38/14***	48.71/15***	49.99/16***	43.52/16***
Negative binomial	0.867	0.718	0.684	0.023	0.022	0.565

Standard errors shown in brackets. [a] *natural log transformation. The "low" and "no" categories of non-metric variables are used as reference. For industry the metal category is used as reference. One-tailed significance: ***p<0.001, **p<0.05 and *p<0.1. Values are rounded to two decimal places.*

4.3 Post hoc results

In this paragraph the three post hoc analysis will be presented. First the negative binomial with open innovation split in inbound- outbound open innovation is discussed. Secondly, the regression analyses for time to market is presented. At last an elaboration of the binary analysis for the energy decrease is given.

4.3.1 Post hoc inbound and outbound open innovation

Organizations may pursue inbound open innovation but may also establish outbound open innovation. The goal of this post hoc analysis is to determine if there is a difference between outbound and inbound open innovation in the adoption of sustainable process innovation. Negative binominal results are presented in table 5, model 6 (statistical output in appendix 7.6). The model is statistically significant. The results show that there is indeed a difference, inbound open innovation turns out to be statistically significant ($Exp(B)=1.32$, $p<.05$), whereas outbound open innovation turns out to be statistically insignificant. This suggest that inbound open innovation would be more important for the adoption of sustainable process innovations then outbound open innovation.

4.3.2 Post hoc time to market

This post hoc analysis' main purpose is to analyze if sustainable process innovation also leads to a reduced time to market due to the use of new materials or changes in process features. Three models were conducted for this analysis. The first model, the control model for time to market (model 1), was estimated to determine the effect of the control variables. The second step adds the adoption of sustainable process innovation (model 2). The last step also includes the degree of open innovation to analysis if an open culture also leads to a reduction in time to market.

Regression results are presented in table 6 for time to market (statistical output in appendix 7.4). All models are statistically significant. Model 1 shows that external R&D positively correlates to time to market ($\beta=0.27$, $p<0.05$) and that the focus on technological innovation negatively correlates ($\beta= -0.22$, $p<0.1$) with the time to market. Contrary with the presumption made, model 2 show a statistically significant, positive effect of the adoption of sustainable process innovations on the time to market ($\beta= 0.28$, $p<0.05$), suggesting that adopting these innovations increases the time to market. Also model 3 shows a positive significant effect of the degree of open innovation on the time to market ($\beta= 0.26$, $p<0.1$), suggesting that an open culture would increase the time to market.

If the dependent variable is log transformed, one β unit of change for an independent variable (all other independent variables held constant) results in $(e^{\beta}-1)*100$ percentage change in the dependent variable. If both the dependent and independent variable are transformed, one percent increase for the independent variable results in $(1.01^{\beta}-1)*100$ percent change in the dependent variable. See Jing (2012).

4.3.3 Post hoc energy decrease

It is of interest to research if adopting energy saving techniques also really leads to a reduction in the actual energy consumption. To analyze this a log-binomial regression is conducted. Regression results are shown in table 7 (statistical output in appendix 7.5). All models are statistically significant. Model 2 shows that there is a different effect of partners on the decrease of energy, whereas market partners show a positive effect (Exp(B)=2.01, $p<.05$) on energy decrease, opposite science partners show the opposite, a negative effect (Exp(B)=0.48, $p<.05$) on energy decrease. Indicating that working together with science partners could be very energy consuming. Model 3 includes the most important variable for this analyses. It shows that a statistically significant effect of the adoption of sustainable processes (Exp(B)=1.27, $p<.1$) on the decrease in energy. Indicating that adapting sustainable innovations in the process of a firm really lead to an decrease in energy.

The regression results show that some of the control variables are statistical-significantly related with the decrease of energy. Most notably, external R&D is statistically significant ($p<0.05$) for all regression models, suggesting that firms who conduct more R&D externally consume less energy themselves. In addition, the ISO50001 is significantly, strongly associated an decrease in energy. So, firms that follow the regulation of the ISO5001 also enjoy a decrease in the use of energy.

Table 6: regression results for the dependent log transformed variable time to market

Construct	**Model 1** Control variables		**Model 2** Model 1 plus adoption of sustainable processes		**Model 3** Model 2 plus open innovation	
	B	β	B	β	B	β
Intercept	3.13 (1.24)**		3.58 (1.21)**		3.15 (1.20)**	
Independent variables						
Sustainable process innovations			0.16(0.07)**	0.28**	0.12 (0.07)*	0.19*
Degree of open innovation					0.13 (0.07)*	0.26*
Control variables						
Industry dummies	Machinery		Machinery		Machinery	
	-0.58 (0.31)*	-0.25*	-0.62 (0.30)**	-0.26**	-0.60 (0.29)**	-0.25**
Size ª	0.17 (0.20)	0.24	0.11 (0.20)	0.16	0.09 (0.19)	-0.14
Revenue ª	0.19 (0.16)	0.04	0.05 (0.15)	0.10	-0.02(0.15)	-0.03
Technological innovation	-0.40 (0.20)*	-0.22*	-0.48 (0.20)**	-0.26**	-.46 (0.19)**	-0.25**
ISO14031	0.11 (0.26)	0.05	0.16 (0.25)	-0.07	0.16 (0.25)	0.07
ISO50001	0.09 (0.26)	0.03	-0.10 (0.42)	-0.03	-0.07 (0.41)	-0.02
External R&D	0.55 (0.24)**	0.27**	0.56 (0.23)**	0.28**	0.52 (0.23)**	0.26**
Model statistics						
R^2	0.252		.302		0.332	
F full model (degrees of freedom)	F(12,59)=2,99***		F(13,58)=3,36***		F(14,57)=3,52***	

*Unstandardized (B) and standardized (β) regression coefficients are reported. Standard errors shown in brackets. ª natural log transformation. The "low" and "no" categories of non-metric variables are used as reference. For industry the metal category is used as reference. One-tailed significance: ***p<0.001, **p<0.05 and *p<0.1. Values are rounded to two decimal places.*

Table 7: binomial results for the dependent variable energy decrease

Construct	Model 1	Model 2	Model 3
	Control variables Exp(B)	Model 1 plus market and science partners Exp(B)	Model 2 plus sustainable process Exp(B)
Intercept	28.05 (1.81)*	25.25 (1.9)*	26.16 (1.91)*
Independent variables			
Market partners		2.01 (0.28)**	2.00 (0.30)**
Science partners		0.48 (0.34)**	0.45 (0.33)**
Adoption sustainable processes			1.27 (0.14)*
Control variables			
Industry dummies	Food: 0.24 (0.66)** Construction: 0.36 (0,56)** Machinery: 0.35 (0.42)**	Food: 0.27 (0.69)* Construction: 0.29 (0.57)** Machinery: 0.31 (0.42)**	Food: 0.24 (0.65)** Construction: 0.29 (0.54)** Machinery: 0.36 (0.45)**
Size[a]	1.24 (0.31)	1.20 (0.32)	1.68 (0.29)*
Revenue[a]	0.64 (0.22)*	0.63 (0.25)*	0.52 (0.22)**
Technological innovation	1.57 (0.27)	1.83 (0.28)**	1.68 (0.28)*
ISO14031	1.23 (0.38)	1.40 (0.36)	1.27 (0.37)
ISO50001	3.96 (0.70)**	3.42 (0.67)**	3.58 (0.79)*
External R&D	2.25 (0.32)**	2.63 (0.36)**	2.33 (0.34)**
Model statistics			
Deviance Value/df	1.04	0.99	1.01
Pearson Chi-Square Value /df	0.98	0.96	0.98
Log Likelihood	-51.12	-47.60	-48.97
Likelihood Ratio Chi-Square/df	21.46/12**	28.50/14**	31.34/15**

*Standard errors shown in brackets. [a] natural log transformation. The "low" and "no" categories of non-metric variables are used as reference. For industry the metal category is used as reference. One-tailed significance: ***p<0.001, **p<0.05 and *p<0.1. Values are rounded to two decimal places.*

5. Conclusion and discussion

Gahm et al. (2016) argue that reducing manufacturing companies' energy demand is essential for sustainable development because energy usage and supply cause negative environmental effects (e.g., greenhouse gas emissions, acidification, and extensive land use). However, energy is a non-substitutable production factor. This is why reduction in energy demand is limited to a certain extent and is subject to the desired production output. Therefore, improving the ratio between energy input and the desired output of a production process—i.e., improving energy efficiency—is one of the central aspects of sustainable manufacturing. Therefore, the main question for this study is, *to what extent does the degree of open innovation relate to a firm's adoption of sustainable process innovations, and is this influenced by the type of partner?.* This study investigated if the degree of open innovation contributes to improved sustainability (adoption of energy efficiency technologies). Using a negative binomial regression on a sample (EMS) across the Dutch manufacturing sector, empirical results reveal, in line with the expectations, that a higher degree of open innovation is statistically associated with a greater adoption of sustainable process innovations (H1). Contrary to expectations, no evidence was found for the moderating effect of partner type on the relationship between the degree of open innovation and the adoption of sustainable process innovations (H2).

Interestingly, the effect of adopting sustainable process innovations is also tested on the time to market and the decrease in energy. Here, adopting sustainable process innovations results in an increase in the time to market a product, while there is a positive effect on the decrease in energy usage. Also, a distinction is made between inbound open innovation and outbound open innovation. Here, inbound open innovation is associated with a greater adoption of sustainable process innovations, while no evidence was found for an effect of outbound open innovation on the adoption of sustainable process innovations.

The following discussion attempts to clarify possible reasons for these empirical findings. Contrary to expectations from case study analyses who have implied the usefulness of innovation-oriented cooperation with governmental institutions, universities and research labs for environmental innovation processes for sustainable innovations (Bossink, 2007), no moderating effect was found in this study. One possible explanation for this insignificant effect is the type of sustainable process innovations included in the EMS. This innovations are mostly incremental or incorporated in existing machinery and technology, therefor it may require a lower R&D effort, whereas the contrary is true for innovations who are completely new. Interestingly, the results show a direct effect of science partners. Which suggest that science partners do positively influence the adoption of sustainable process innovations. An possible explanation for that could also be the type of innovations asked in the EMS as stated above, which mostly are ready to buy applications. So, it could be that if a firm has an open culture, it would come up against these innovations anyhow, and does not necessarily need a science partner for adopting. The direct effect could imply that if an organization is not open, a firm could better work together with a research institution. It would than adopt more sustainable processes then with market partners. The variable indicating the presence of collaboration with market partners was not significant, suggesting that their relevance does not influence a greater adoption. This outcome is not surprising: environmental features are frequently hard to detected by end users and may require highly advanced technical knowledge to be tackled (De Marchi, 2012).

The positive effect of scientific partners might suggest that firms involved in innovation activities related to sustainable process innovations may not rely solely on the outcomes of applied research. In addition, basic research conducted in universities and public research institutions is also of importance. This is why governments can stimulate sustainable innovations by investing in fundamental research at universities and other research institutions.

Next, this study also investigated whether the adoption of sustainable process innovations affect the time to market. Contrary with the presumption made, results suggest that adopting these innovations increases the time to market. Suggesting that these innovations may be more energy-efficient but may slower the time in which a product can be made. As discussed above, this effect could be different with more radical sustainable process innovations as most of the innovations included in the EMS do not need a major change in production process. Also the effect of the degree of open innovation on the time to market suggests that an open culture would increase the time to market. This may be explained through the suggestion of that too much open innovation may lead to negative side effects, including a lengthened search process (Tidd, 2013).

Furthermore, the post hoc analysis shows an insignificant effect of outbound open innovation on the adoption of sustainable processes. This insignificant effect could be due to the characteristics of outbound open innovation. Firms can outbound their ideas to make more profit from them, for example companies can out-license their intellectual property to earn more value from it. However, time-effects might make it hard to investigated this. Because an investment in outbound open innovation could possibly lead to a greater adoption of sustainable processes on the long-run. Licensing especially is focused on learning (Lichtenthalter & Lichtenthalter, 2010), and learning just happens to be quite time consuming.

Indeed, the control variables also show some interesting effects. Most notably in the main analysis is revenue, which was expected to be positively correlated, but results showed an opposite effect. Again, this can also be explained due to the incremental type of innovations which therefor may require a lower R&D effort. In addition, while European firms are pressured to become more environmentally aware (European

Commission, 2014), only a small amount of firms has adopted an environmental management system. Using such systems do significantly affect the adoption of sustainable process innovation and also show a highly significant correlation with energy decrease. It is therefore of interest for the government to promote the implementation of management control systems.

5.1 Limitations and future research

Like any other research, this research has also its limitations. First, as already discussed, based on our findings, this study encourages future research to provide further insight into radical sustainable process innovations. Future research could possibly investigate such type of radical innovations to determine their impact on some unexpected empirical results.

Second, in this study the focus is on a sample of Dutch manufacturing industry. This limited geographical coverage limits the generalizability outside this context. However, doing so has provided us with the possibility to reduce uncontrolled noise in our sample, and future studies could benefit from building on our findings and testing the stated hypothesis in samples from multiple countries.

Next, theoretically, the success of new implemented technologies is dependent several different factors including, cultural (Tidd & Bessant, 2011), firm specific (Lankoski, 2000) and technical factors (Christmann, 2000). The current study only assessed the effect of cultural factors, which suggest that firms with a more open culture have more potential to adopt sustainable processes. However, the remaining factors could also prove to be more important. A large number of different partners will not ensure that a company will take advantage of this cooperation in the context of the new knowledge acquisition, particularly the firm's ability to leverage and benefit from transferred knowledge (Pilav-Velić, & Marjanovic, 2016). These factors were beyond the scope of this study and not controlled for. Future research might research this factors on the relationship between open innovation and the adoption of sustainable process innovations.

Several other limitations of our study can also be gaps for future research. Since our empirical analysis is based on cross-sectional data in the manufacturing industry, the results should not be generalized to nonprofit and government institutions. Future studies could benefit from building on our findings and testing the stated hypothesis in samples from multiple industries.

It is also of interest for future studies to include various web-portal technologies (specially designed Web site that brings information together) and their role in enabling collaborative innovation relationships. In addition, various low-cost social networking platforms such as cloud-based innovation management and collaboration tools should be addressed in further research and their effect on the adoption of sustainable innovations because it could be a potentially useful practical implications for firms struggling with very limited resources.

At last, qualitative data can be used for the interpretation of the unexpected quantitative results (Field, 2009) by providing a deeper understanding about situational contingencies that might affect the hypothesized relationships, a more comprehensive overview of the phenomenon is provided (Field, 2009).

5.2 Theoretical implications

This research contributes in multiple ways to the existing literature. For the most part, existing literature has focused on the impact of open innovation practices on product innovation (Chesbrough, 2003; Lichtenthaler and Lichtenthaler, 2009). This research focuses on process innovations, to be specific on sustainable process innovations. These findings contribute to the literature on process innovation by being among the first articles to focus on analyzing how open innovation affect the adoption of sustainable process innovation (Perl-Vorbach et al., 2014). Empirical result from this study confirmed that firms that intensively source knowledge and technology from external sources are more likely to adopt sustainable process innovations. This focus reinforces/parallels results of previous studies, which point to the relevance of cooperation with external partners for a greater adoption of sustainable process innovations (Perl-Vorbach et al., 2014). The findings also offers a reply to the results raised by Bönte and Dienes (2013) in their work on cooperation strategy and process innovations, that an 'cooperation strategy' does not influence the adoption of sustainable process innovations. Additional evidence, on the hardly included outbound open innovation practices, suggest that on the short term outbound practices are less important for the adoption of sustainable processes than inbound open innovation practices.

5.3 Managerial implications

This paper also has important managerial implications. This research encourages cooperating with other firms because it helps organizations achieve a greater adoption of sustainable process innovation because these collaborations provide access to different knowledge bases. However, not all collaborations may have the same influence on sustainable process innovation. While general openness of the innovation process of the firm will be successful in assisting the firm innovate, managers may like to select those cooperation's that have a better change to facilitate sustainable process innovation. Due to a direct effect of science partners, it can be suggested that, besides that it is good to be open innovative, at the same time it is also great to collaborate with science partners. The reason for this is that organizations and science partners often work together on new products (Du, Leten, & Vanhaverbeke, 2014), this could enhance the technological advanced knowledge absorption, which in turn could help with the adoption of sustainable process innovations.

Furthermore, from a cost-reducing perspective, adopting sustainable process innovation significantly reduces the energy consumption. This can be important for managers because this effect may also improve a firm’s competitive advantage (Hart & Ahuja, 1996; Frondel et al., 2007). In addition, unfortunately it also slower the time to market a product. Thus, managers should realize that using these technologies might have other possible negative effects for the firm. Therefore, managers should explore their firm in depth to discover potential, but also possible drawbacks before spending capital to adopt sustainable process innovations.

However, due to the scope of the study, researchers should be aware that these results might not be generalizable to other sectors or countries.

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Appendix 1: EMS

Only items which are included in the research

Dependent variables:

			Energie en grondstoffenbesparing						
h03o2	0/1	←0	Droge bewerking/minimum smering	h03o1	1→	19/20	h03o3	h03o4	h03o5
h03p2	0/1	←0	Controlesystemen die machines stilleggen bij onderbenutting	h03p1	1→	19/20	h03p3	h03p4	h03p5
h03q2	0/1	←0	Terugwinning van kinetische en procesenergie (terugwinnen afvalwarmte)	h03q1	1→	19/20	h03q3	h03q4	h03q5
h03r2	0/1	←0	Warmtekrachtkoppeling (Bi-/Trigeneratie)	h03r1	1→	19/20	h03r3	h03r4	h03r5
			Technologieën voor het opwekken van duurzame energie						
h03s2	0/1	←0	Technologieën voor het opwekken van zonne- of wind-, waterkracht, biomassa of geothermische energie	h03s1	1→	19/20	h03s3	h03s4	h03s5
h03t2	0/1	←0	Technologieën voor warmte-opwekking door middel van zonne-energie, biomassa of geothermische energie	h03t1	1→	19/20	h03t3	h03t4	h03t5

Independent variables:

6 **Hoe vaak heeft uw organisatie vanaf 2009 de volgende activiteiten verricht?** (0=niet; 1=1 keer; 2=vaker)

Spin-offs	Opstarten van nieuwe organisaties of activiteiten buiten de onderneming	h44a_nl (0) (1) (2)
Uitgaand intellectueel eigendom	Verkopen, of aanbieden van licenties/patenten aan andere organisaties	h44b_nl
Werknemer-betrokkenheid	Benutten van kennis en initiatieven van niet-R&D medewerkers bij het realiseren van innovaties	h44c_nl
Klantbetrokkenheid	Direct betrekken van klanten in uw innovatieprocessen	h44d_nl
Extern netwerken	Het samenwerken met andere organisaties (niet klanten) voor innovatie	h44e_nl
Externe participatie	Deelnemen (met bijv. vermogen, kennis) in ondernemingen om toegang te krijgen tot hun kennis of om andere synergieën te creëren?	h44f_nl
Uitbesteden van R&D	Uitbesteden van R&D (diensten) aan andere organisaties, zoals universiteiten, publieke onderzoeksinstellingen, commerciële ingenieurs of leveranciers?	h44g_nl
Inkomend intellectueel eigendom	Kopen of in licentie nemen van intellectueel eigendom van andere organisaties	h44h_nl

Moderating variable:

7 **Werkt uw bedrijfsvestiging samen met andere bedrijven op de volgende terreinen? Welke zijn uw belangrijkste motieven voor samenwerking op deze terreinen?** (samenwerking = vrijwillige samenwerking die verder gaat dan eenmalige transacties tussen bedrijven)

Nee			Ja	Locatie van de partners: regionaal (< 50 km)	nationaal (> 50 km)	Buitenland		Belangrijkste motieven voor samenwerking: nieuwe kennis	toegang tot human resources	toegang tot nieuwe markten	kostenbeheersing
0	Samenwerking in onderzoek & ontwikkeling (O&O) met onderzoeksinstituten (bijv. universiteiten, TNO)	h07a1	1→	1	2 (h07a2)	3 h07a3	0/1	h07a4	h07a5	h07a6
0	Samenwerking in O&O met afnemers of leveranciers	h07b1	1→	1	h07b2	3 h07b3	0/1	h07b4	h07b5	h07b6
0	Samenwerking in O&O met andere bedrijven (afnemers en leveranciers uitgesloten)	h07c1	1→	1	h07c2	3 h07c3	0/1	h07c4	h07c5	h07c6
0	Samenwerking in inkoop	h07d1	1→	1	h07d2	3 h07d3	0/1	h07d4	h07d5	h07d6
0	Samenwerking in de productie (voor gezamenlijke systeemleveringen of capaciteitsuitbreiding)	h07e1	1→	1	h07e2	3 h07e3	0/1	h07e4	h07e5	h07e6
0	Samenwerking in distributie/verkoop	h07f1	1→	1	h07f2	3 h07f3	0/1	h07f4	h07f5	h07f6
0	Samenwerking in service	h07g1	1→	1	h07g2	3 h07g3	0/1	h07g4	h07g5	h07g6

Control variables:

Firm size & revenue

20 **Hier worden enkele gegevens over uw bedrijfsvestiging gevraagd:**

Jaaromzet	2011	h20a1	miljoen €	2009	h20a2	miljoen €
Aantal werknemers (excl. uitzendwerkers)	2011	h20b1	aantal	2009	h20b2	aantal

Technical process innovation

12 **In de voorgaande vragen heeft u informatie gegeven over technologie, organisatie, productgerelateerde diensten en productvernieuwing. Rangorden deze activiteiten naar mate van belangrijkheid voor uw bedrijfsvestiging.**
Geef met een score van 1 tot 4 de volgorde van belangrijkheid aan met 1 als het belangrijkst; gebruik elke score slechts één keer.

h12a

1	2	3	4
Toevoegen van diensten aan uw producten	Organisatie-vernieuwing	Technologische vernieuwing in het productieproces	Ontwikkeling van nieuwe producten
h12a1 1 - 4	h12a2 1 - 4	h12a3 1 - 4	h12a4 1 - 4

Industry

1.2 Bedrijfstak (bijv. textiel, chemische industrie, machinebouw, enz.): h01bx

hoofdproductgroep h01cx

aandeel van hoofd-product (groep) in omzet ca. h01d %

Standards and audits

h08p2 0/1	0	Milieucertificering volgens ISO 14031	h08p1	1	19__ / 20__ h08p3	h08p4
h08q2 0/1	0	Energie-audit volgens ISO 50001:2011	h08q1	1	19__ / 20__ h08q3	h08q4

R&D external

17.1 **Heeft uw bedrijfsvestiging onderzoek en ontwikkelingsactiviteiten (O&O) uitgevoerd of laten uitvoeren door externe partners?**

0 nee 1 ja h17a1 → O&O-uitgaven in procenten van de omzet in 2011 ca. h17a2 %

17.2 **Heeft uw bedrijfsvestiging van 2008 tot en met 2010 O&O uitgevoerd of laten uitvoeren door externe partners?**
(meerdere antwoorden mogelijk)

h17b_nl 0/1 h17b nee — 0/1 h17c1 ja, O&O in 2008 — 0/1 h17c2 ja, O&O in 2009 — 0/1 h17c3 ja, O&O in 2010

Post hoc variables

Time to market

11.1 **Heeft uw bedrijf sinds 2009 nieuwe producten geïntroduceerd of producten die ingrijpend zijn vernieuwd (kleine verbeteringen buiten beschouwing laten a.u.b.)?** (Bijv. door nieuwe grondstoffen of materialen te gebruiken, veranderingen in productfuncties e.d.)

0 nee 1 ja h11a → Hoe groot was het aandeel van deze producten in de omzet van het jaar 2011? ca. h11b %

→ Hoe lang duurde gemiddeld genomen de ontwikkeling van zo'n product? (van productidee tot lancering) ca. h11c maanden

Energy consumption

21 **Tussen 2009 en 2011, hoe heeft het jaarlijkse energieverbruik (kWh)in uw bedrijfsvestiging zich ontwikkeld?**

h21a

	1 gedaald	2 gelijk gebleven	3 gestegen
Energieverbruik sinds 2009	h21a1 0/1	h21a2 0/1	h21a3 0/1
Energieverbruik is...	gedaald met ca. h21b %		gestegen met ca. h21c %

Hartelijk dank voor uw bijdrage aan dit onderzoek.

Appendix 2: Missing data analysis

Missing data can influence the generalizability of results, therefore it is a concern to analyze patterns and relationships underlying the missing data process. The following will detail a four-step process to investigate the missing data.

1 **The type of missing data**
Analysis of the raw data suggests that in some cases the nonresponse/system missing of the respondent on various items is very high, either due to refusal to respond or when the respondent has insufficient knowledge to answer the question (Hair, 2009). This type of data is non ignorable and warrants action (Hair, 2009). Because in this cases the missing where on multiple items, list wise deletion was conducted to increase the comparability across analyses cases. Therefore, cases 24,31 and 85 were deleted because they scored almost on every variable a missing. Furthermore, cases 113 till 117 were also deleted because of system missing on all the open innovation practices. Due to this deletion the database consist of a final 141 cases for analyses.

2 **Determine the extent of missing data**
Table 1 contains the missing data statistics for all variables. Missing data is present on both metric and non-metric variables and ranges from 0% to 38,3%. Before proceeding, this missing data requires an analysis of randomness (Field,2009).

3 **Diagnosing the randomness of the missing data process**
Two levels of randomness exists, missing at random (MAR; missing data is generated due to an underlying pattern) or missing completely at random (MCAR; truly random, with no underlying process that biases results; Hair, 2009). The data was MCAR as indicated by a non-significant Little's MCAR test (X^2 = 398,399, DF =398, sig=0,485).

4 **Remedies for missing data**
As the missing data process is truly random, techniques exists to replace missing values. The options for dealing with missing data are (Field, 2009).
1. analyzing only the data available (i.e. ignoring the missing data);
2. imputing the missing data with replacement values, and treating these as if they were observed (e.g. last observation carried forward, imputing an assumed outcome such as assuming all were poor outcomes, imputing the mean, imputing based on predicted values from a regression analysis) (Field, 2009). The mean disadvantages with imputation is that it can lead to an overestimated model fit and correlation estimated and also weakens the variance. Due to these disadvantages of imputation option 1 is chosen. This is appropriate when data can be assumed to be missing at random.

Table 1 : missing data per variable

Variable	Category	Number of valid cases	*Missing data* Number of cases	Percent
Dependent variable				
1. Adoption of sustainable process innovations	Dry processing / minimum lubrication	140	1	0,7
	Control system for shut down of machines in off-peak periods	140	1	0,7
	Energy recovery from kinetic and process energy	141	0	0
	Combined heat (Bi-and tri-generation)	141	0	0
	Technologies for generating solar or wind energy, hydropower, biomass or geothermal energy	140	1	0,7
	Technologies for heat generation through solar, biomass or geothermal energy	139	2	1,4
Independent variables				
2. Open innovation practices	Spin-offs	141	0	0
	Outgoing intellectual property	141	0	0
	Employee engagement	141	0	0
	Customer engagement	141	0	0
	External networks	141	0	0
	External participation	141	0	0
	Outsourcing of R&D	141	0	0
	Incoming intellectual property	141	0	0
3. Partners	Science Based	140	1	0,7
	Market Based 1	141	0	0
	Market Based 2	137	4	2,8
Control variables				
4. Firm size	Categorical	139	2	1,4
5. Technical process	Dichotomous	136	5	3,5

	innovation				
6.	Industry	Categorical	141	1	0,7
7.	Standards and audits	Environmental certification according to ISO 14031	138	3	2,1
		Energy audit according to ISO 50001: 2011	139	2	1,4
8.	R&D by external partners	Does your company conducted or carried out research and development activities (R & D) by external partners?	139	2	1,4
9.	Revenue	Scale	126	15	10,6
Post hoc variables					
10.	Energy decrease	Dichotomous	136	5	3,5
11.	Time to market	Scale	87	54	38,3
12.	Inbound/outbound open innovation	See open innovation practices			

Appendix 3: Design of the negative binomial regression analysis

This appendix details the choice for the negative binomial regression.

There are many dependent variables that no matter how many transformations you try, you cannot get to be normally distributed, which is also the case in this study. The most common causer of this are count variables. In this research the dependent variable consists of count data. Count data is different to the data measured in other well-known types of regression. In contrast, count variables require integer data that must be zero or greater. Also, since count data must be "positive" (i.e., consist of "nonnegative" integer values), it cannot consist of "minus" values. With ordinary least squares (OLS) regression, count outcome variables are often log-transformed. With this approach problematic issues arise, including loss of data due to undefined values generated by taking the log of zero (which is undefined) and biased estimates (Gardner, Mulvey, & Shaw, 1995). Count variables need to be modeled differently than either continuous or dichotomous variables (Cameron & Trivedi, 1998). Therefore this research makes use of a slightly different approach than the OLS regression, reasons why will be explained next.

As a background for understanding the choices made, we provide a quick review. The three major assumptions regarding the errors for OLS regression are (a) conditional normality, (b) homoscedasticity (or constant variance), and (c) independence. Count variables can trespassing the first two assumptions of OLS regression in more than one way (Gardner, Mulvey, & Shaw, 1995). Count variables often violate the assumption of constant variance by showing larger conditional variance with increases in the value of the predictor (Gardner, Mulvey, & Shaw, 1995). This is also called heteroscedasticity. The problem with this is that it will lead to biased standard errors and biased tests of significance when OLS regression is applied. Testing homoscedasticity for this research it is indeed true that the data is heteroscedastic, see next page (Levene's Test of Equality of Error Variances: F = 3,572, p=.001). Second, the distributions of count variables also have a tendency to be positively skewed and kurtotic. This is due to the many low-count observations and no observations below zero (see test of normality on the next page). When looking at the data in this research this is idem, see appendix 3. Due the fact that the data heteroscedastic and non-normal distributed, the statistical significance tests will be biased and inefficient for count outcomes (Gardner et al., 1995; Long, 1997). In addition, the actual Type 1 error rate in this way may not match the stated Type 1 error rate (typically, $\alpha = .05$) and that the statistical power to discover true effects may be influenced (Gardner, Mulvey, & Shaw, 1995). For this type of data the Generalized Linear Models are designed.

The Genaralized Linear Models (GLM) performs two large modifications to the OLS framework. First, it permits transformations of the predicted outcome, which can linearize a potentially nonlinear relationship between the dependent variable and the predictors (Gardner, Mulvey, & Shaw, 1995). Second, the GLM is flexible in error structure. The OLS regression presume a conditional normal error structure, whereas GLM allows for a variety of other error structures (Gardner, Mulvey, & Shaw, 1995).

Test of Homoscedasticity

Count variables often violate the assumption of constant variance by displaying increasing conditional variance with increases in the value of the predictor. This is known as heteroscedasticity; it leads to biased standard errors and biased tests of significance when OLS regression is applied. When testing homoscedasticity for this research it is indeed true that the data is heteroscedastic (Levene's Test of Equality of Error Variances: F = 3,572, p=.001)

Levene's Test of Equality of Error Variances[a]

Dependent Variable: count sustainable process

F	df1	df2	Sig.
3,572	8	132	,001

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + Count_open

Test of Normality

The distributions of count variables tend to be positively skewed and kurtotic with many low-count observations and no observations below zero. From the Kolmogorov-Smirnov test it becomes already clear, due to a significant result that the data is not normal distributed.

Taking a closer look at the data it indeed tells us that the data is skewed and kurtotic. This is also confirmed through the histogram and the normality plots, with dots that diverge from the normality line. Another important assumption for negative binominal regression is that different then the Poisson regression the main and variance don't need to equal 1. Which in this case is true (mean=0,7, variance=1,5). This means that there is overdispersion. There are certain types of models proposed for accommodating overdispersion in statistical analysis but negative-binomial regression models are perhaps the most convenient to deal with (Lawless, 1987).

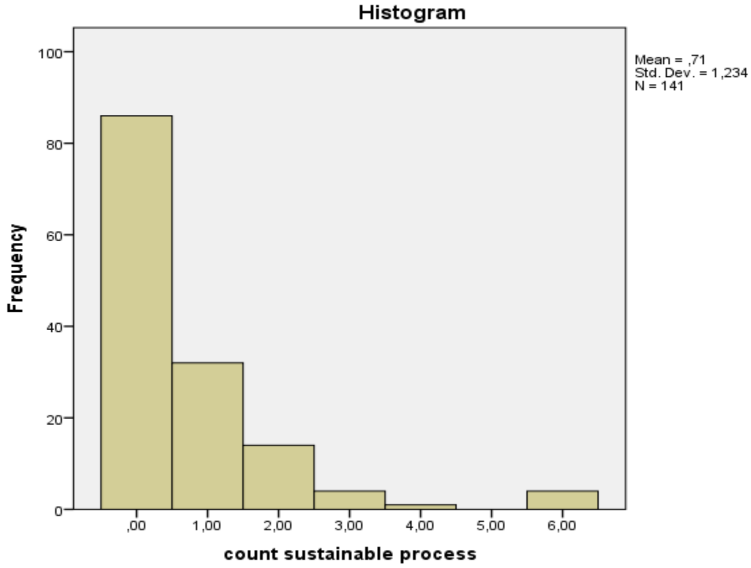
Tests of Normality

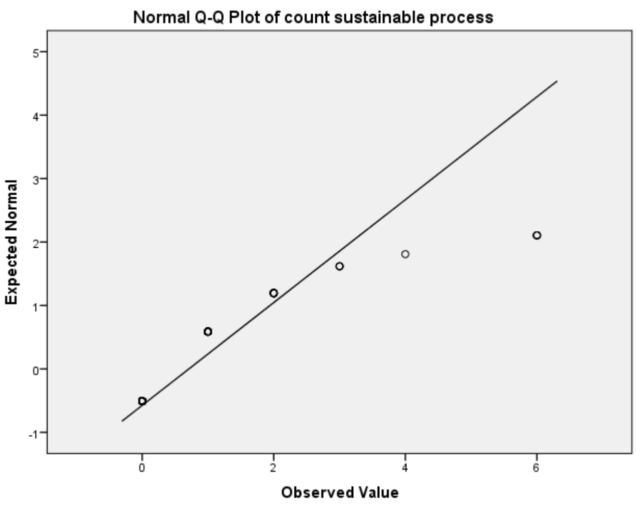
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
count sustainable process	,327	141	,000	,615	141	,000

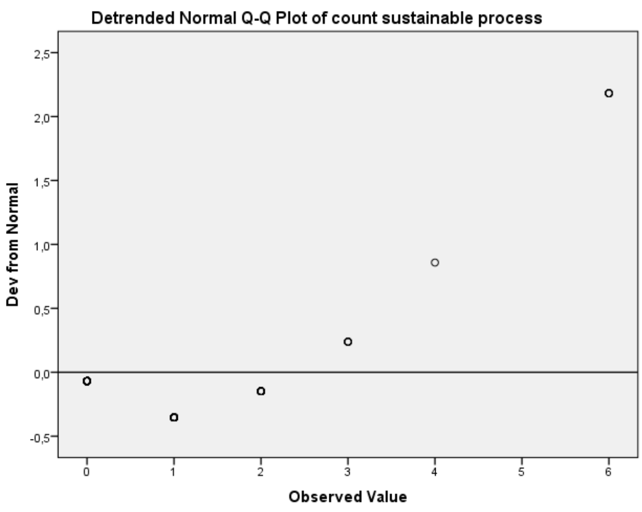
a. Lilliefors Significance Correction

Descriptives

			Statistic	Std. Error
count sustainable process	Mean		,7092	,10390
	95% Confidence Interval for Mean	Lower Bound	,5038	
		Upper Bound	,9146	
	5% Trimmed Mean		,5189	
	Median		,0000	
	Variance		1,522	
	Std. Deviation		1,23369	
	Minimum		,00	
	Maximum		6,00	
	Range		6,00	
	Interquartile Range		1,00	
	Skewness		2,610	,204
	Kurtosis		7,950	,406







Appendix 4: Assumptions for the negative binomial regression

This appendix details the assumptions for negative binomial regression at both the individual variable (section 4.1) and the variate (section 4.2) level.

4.1 Individual variables

In paragraph 3.4.2 the assumptions where discussed and it was stated that although the model itself doesn't assume linearity. It can still be useful for the model to transform predictors in order to achieve linearity of the linear predictor. To achieve this normality of the variables will be checked in the following section.

Normality

Normality refers to the data distribution for a metric independent or control variable. It is desirable that it correspondence to the normal distribution. The following will assess normality for the metric independent and control variables.

Significant deviations from normality are observed for all independent and control variables as shown in the histograms on next page and Kolmogorov-Smirnov results. As can been seen in the tables of the normality test all the variables where significant, meaning none of the variables are normally distributed. Visual inspection of the histograms shows indeed a skew distribution on 'revenue' and 'size'. But when looking at the count of sustainable processes we see that the normal curve is somewhat equal to a normal distribution, which are considered to be acceptable (Field, 2009). Because count data are hard to transform (log transformation did not work, see histogram), this variable will not be transformed. For the positively skewed control variables, a natural log transformation was applied to increase normality (Field, 2009). After transforming normality tests showed no more significant effect. Meaning that the variable is normally distributed. The normality line in the histogram also shows a normal distribution, see next page.

Test of normality: untransformed variables

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
count open innovation	,112	124	,001	,959	124	,001
Revenue	,447	124	,000	,130	124	,000
Size	,422	124	,000	,151	124	,000

a. Lilliefors Significance Correction

Test of normality: *Log transformed variables*

Tests of Normality

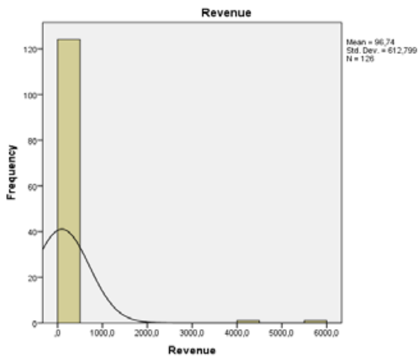
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
LN_size	,071	124	,200*	,916	124	,000
LN_Revenue	,069	124	,200*	,936	124	,000

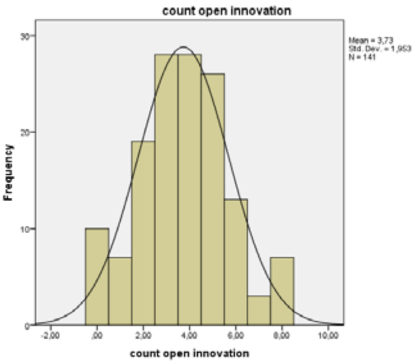
*. This is a lower bound of the true significance.

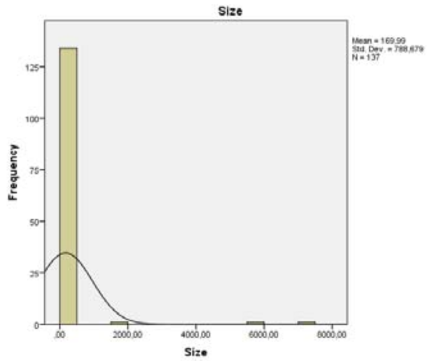
a. Lilliefors Significance Correction

Histograms to assess normality for metric independent variables

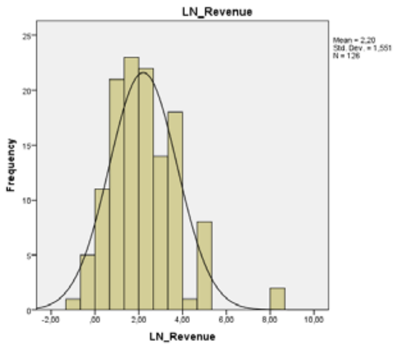
Before transformation

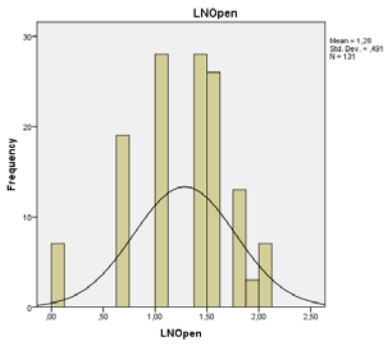


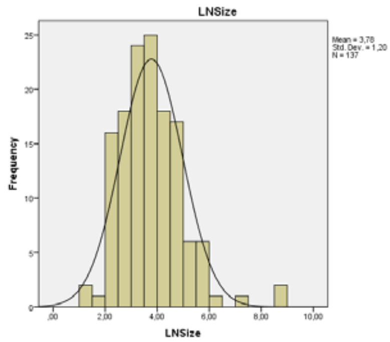




After transformation







4.2 Assumptions for the variate

In paragraph 3.4.3 assumptions for the variate were discussed. The first one is that multicollinearity is absent (Hardin & Hilbe, 2007). The second one is checking for influenctial observations. These will be discussed next.

Multicollinearity

Multicollinearity indicates the correlation among independent variables, which should be low in order for these variables to reliably predict the dependent variable. If there is a multicollinearity between any two predictor variables, then the correlation coefficient between these two variables will be near to unity. Checking multicollinearity of independent variables includes checking if the absolute value of Pearson correlation is greater than 0.8. Then collinearity is very likely to exist. If the absolute value of Pearson correlation is close to 0.8 (such as 0.7±0.1), collinearity is likely to exist. Inspecting Pearson's correlations in appendix 6, a high correlation between size and revenue exist. However it is very common in economic data that two (or more) independent variables are strongly, but not exactly, related. Common sense tell us these variables will be strongly related, so we shouldn't be surprised to find that they are. Futhermore, Allison (2012) state the following about multicollinearity, "*it's only a problem for the variables that are collinear. It increases the standard errors of their coefficients, and it may make those coefficients unstable in several ways. But so long as the collinear variables are only used as control variables, and they are not collinear with your variables of interest, there's no problem*" (Allison ,2012 p.1). Because size and revenue are both control variables and common sense tells us that these two variables are related to each other, the only thing done to reduce the multicollinearity is that the variables are mean-centered (Field, 2009).

Influential observations

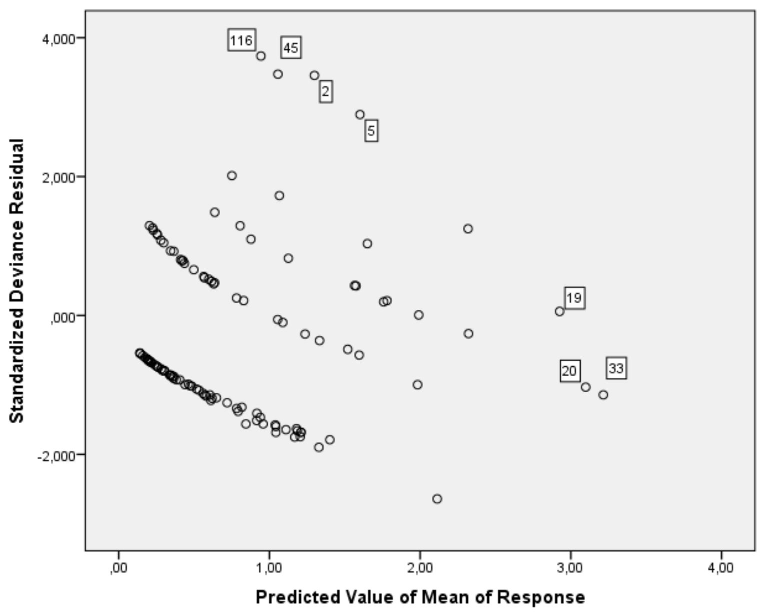
In fitting a regression model, all observations do not have an equal influence on the parameter estimates in the fitted model. Those with unusual values of the independent variables tend to have more influence than the others. The Influential Points pane displays any observations that have high influence on the fitted model:

Leverage_2	CASE
,604	33,00
,579	20,00
,451	19,00
,408	52,00
,393	131,00

Figuur 2: Avarage leverage 0.137

The table displays all points with high leverage. Leverage is a statistic that measures how distant an observation is from the mean of all N observations in the space of the independent variables. The higher the leverage, the greater the impact of the point on the fitted values. Points are placed on the list if their leverage is more than 3 times that of an average data point, for this data three times 0,137 = 0,413. Therefore, case 33, 20, 19 should be on the list of influential observations.

Another way to test for outliers of the variate is to make a residual plot from the predicted mean against the residuals. If the model is correct then the overwhelming majority of these residuals should fall between ± 2,5. A residual plot provides evidence of poor model fit if substantially more than 5% of the residuals have an absolute value greater than 2,5. Inspecting the plot show several cases who score higher than 2.5 on the standardized residuals. Influential observations should never be deleted in order to maintain a representative sample, except in the case for incorrect data entries (Hair, 2009). In this case all the respondents have a high score on the adoption of sustainable processes, because this is in important indicator and there were no signs of incorrect data entries these cases are therefore included in the analyses. Further inspection also shows cases that score higher that 2.5 on the predicted mean. This cases scored high on size and/or revenue, but there were no signs of incorrect entries. Running the analyses with and without these cases did not impact regression results, and it is therefore suggested to include the influential observation into the regression models (Hair, 2009).



Fit tests

The output begins with the Goodness of Fit table. This lists various statistics indicating model fit. To assess the fit of the model, the goodness-of-fit chi-squared test is provided in the first line of this table. We evaluate the deviance (146.952) as Chi-square distributed with the model degrees of freedom (99). This is not a test of the model coefficients (which we saw in the header information), but a test of the model form: Does the negative binomial model form fit our data? We conclude that the model fits reasonably well because the goodness-of-fit chi-squared test is not statistically significant (with 99 degrees of freedom, $p = 0.2231$. The result is not significant at $p < 0.05$.). If the test had been statistically significant, it would indicate that the data do not fit the model well.

Next is the Omnibus Test. This is a test that all of the estimated coefficients are equal to zero- a test of the model as a whole. From the p-value it can be seen that the model is statistically significant.

Goodness of Fit[a]

	Value	df	Value/df
Deviance	146,952	99	1,484
Scaled Deviance	146,952	99	
Pearson Chi-Square	163,901	99	1,656
Scaled Pearson Chi-Square	163,901	99	
Log Likelihood[b]	-133,090		
Akaike's Information Criterion (AIC)	300,179		
Finite Sample Corrected AIC (AICC)	306,424		
Bayesian Information Criterion (BIC)	346,990		
Consistent AIC (CAIC)	363,990		

Dependent Variable: count sustainable process

Model: (Intercept), vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Science, Market_based, Tech_Innov, ISO14031, ISO50001, RD_external, count open innovation, Science * count open innovation

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
50,885	16	,000

Dependent Variable: count sustainable process

Model: (Intercept), vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Science, Market_based, Tech_Innov, ISO14031, ISO50001, RD_external, count open innovation, Science * count open innovation

a. Compares the fitted model against the intercept-only model

Appendix 5: Assumptions for the post hoc analysis 'Time to Market'

This appendix details the assumptions for multiple linear regression for the post hoc variable 'Time to market' at both the individual variable (section 5.1) and the variate (section 5.2) level. Preliminary analyses showed violations of the assumptions for the dependent variable, thus, firstly the focus was shifted to the individual variable.

5.1 Individual level

Normality

Normality refers to the shape of the data distribution for a metric independent or control variable and its correspondence to the normal distribution. Because normality was also assessed in our main analysis, the only new variable is the dependent metric variable 'time to market'. Therefore, the following will assess normality for the metric dependent variable. Assumptions are checked with the Kolmogorov-Smirnov statistics and histograms, which are presented below. Kolmogorov-Smirnov statistics show significant deviations from normality. To increase normality a logarithm transformation was applied (Field, 2009). After the transformation the variable show a non-significant deviation from normality which means that the variable after transformation now normally is distributed.

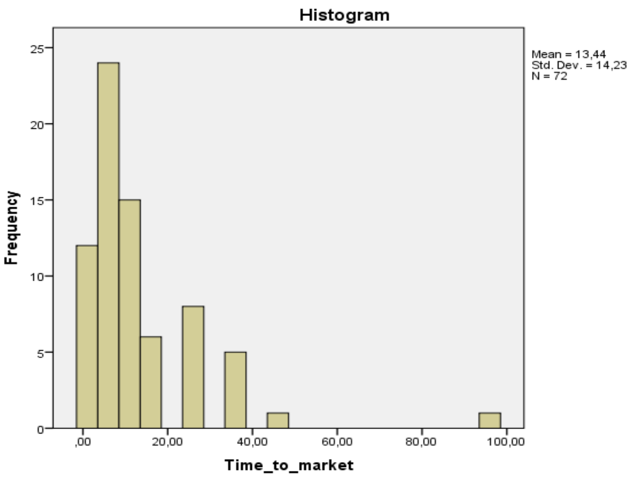
Before transformation 'Time to market':

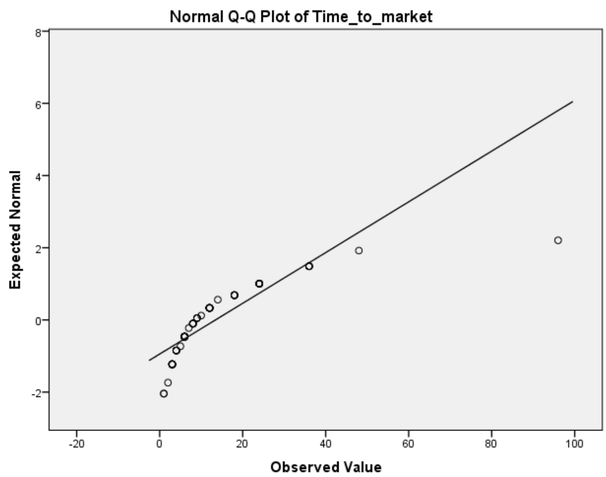
Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Time_to_market	,249	72	,000	,686	72	,000

a. Lilliefors Significance Correction

Normality plots





After transformation ‘Time to market’:

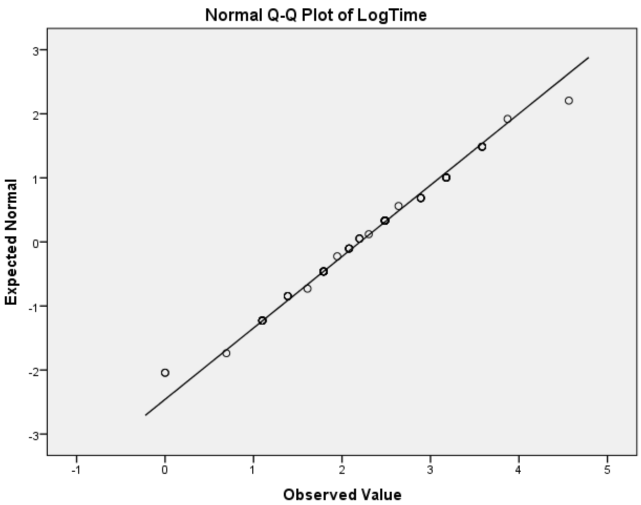
Tests of Normality

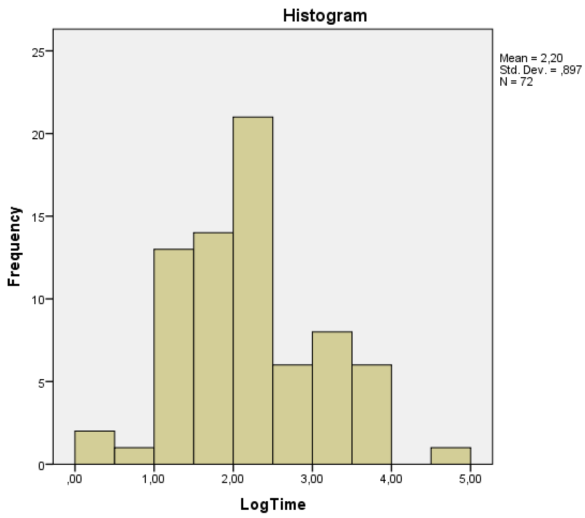
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
LogTime	,086	72	,200*	,980	72	,292

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Normality plots:





Next, the variable ‘*sustainable process innovation’* is now an independent variable instead of a dependent. This variable shows a non-normal distribution, see test of normality below. Because it is a count-variable and count data as discussed earlier are concentrated on a few small discrete values and are severely positively skewed (due to a high frequency of 0s). In the main analysis it has also been tried to increase the level of normality, which fail due the characteristics of a count- variable. While deviations from normality should be avoided when possible, detrimental effects of non-normality are reduced at large sample sizes. The current sample sizes do diminish the effects of non-normality to a great degree, as long as there is homogeneity of variance (Field, 2009).

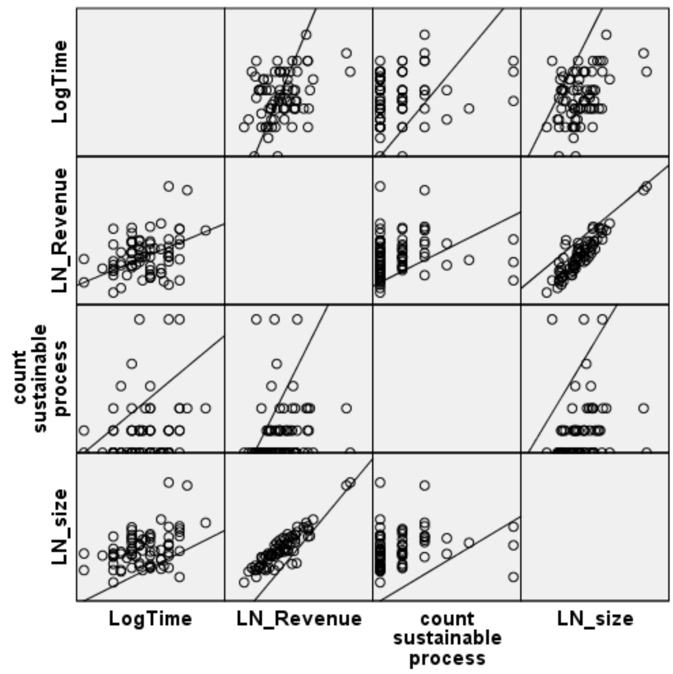
Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
count sustainable process	,303	114	,000	,627	114	,000

a. Lilliefors Significance Correction

Homogeneity of variance

To inspect for homogeneity of variance, the relationship between two metric variables can best be inspected graphically through scatter plots (Field, 2009). The dependent variable time to market is homoscedastic across the metric independent variables (see scatter plot below).



Linearity

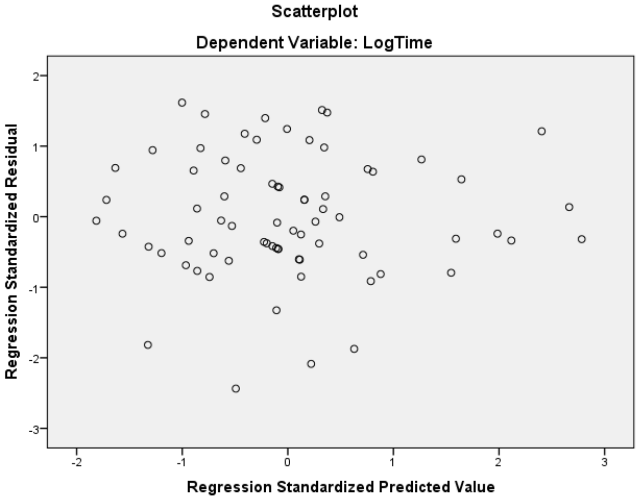
Next another assumption is linearity, which assesses whether correlations between variables represent linear relationships (Field, 2009). Also linearity can be inspected through scatter plots between the metric variables. Looking at the scatter plot above no indications of a non-linear relationship are present.

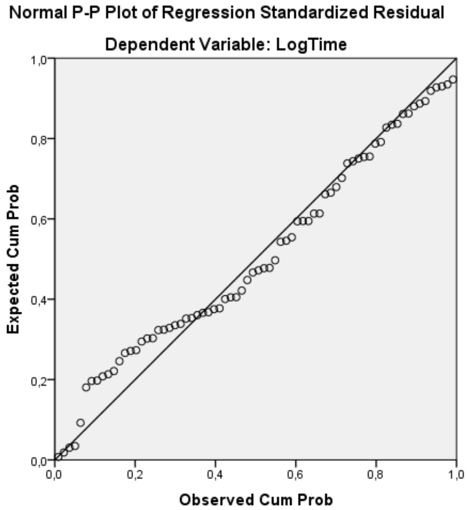
5.2 Assumptions for the variate

Now that the assumptions for individual variables have been met, multiple regression analysis also requires assumptions for the variate (Field, 2009). This is done after the regression is conducted.

Linearity, normality and homoscedasticity of the variate

The first relationship we want to test for is if there is a linear relationship between the dependent variable and the independent variables. To check for this the probability plot can be assessed. It can been seen in the plot below that there are some deviations from the linear line, especially in the beginning. But in general the dots follow the linear line, and therefore we assume that there is a linear relationship. The residual plot below shows that no dots fall outside ±3. Furthermore, the scatter plot shows a random distribution of residuals. Therefore, it can be assumed that the regression model does not violate any of the linearity, normality and homoscedasticity of the residuals assumption.





Influential observations

For assessing if there are any influential observations Cook's distance can be checked. If there are observations greater than one, it can be that an observation needs to be deleted. But as can been seen in the table below, the maximum Cook's distance is .159 and therefore there are no influential observations.

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,1436	3,8337	2,2049	,58522	72
Std. Predicted Value	-1,814	2,783	,000	1,000	72
Standard Error of Predicted Value	,271	,593	,399	,062	72
Adjusted Predicted Value	1,1529	3,9427	2,2106	,63151	72
Residual	-1,91650	1,27177	,00000	,67953	72
Std. Residual	-2,437	1,617	,000	,864	72
Stud. Residual	-2,639	1,795	-,003	,997	72
Deleted Residual	-2,29091	1,68949	-,00568	,90983	72
Stud. Deleted Residual	-2,804	1,835	-,006	1,017	72
Mahal. Distance	7,462	39,357	17,750	5,904	72
Cook's Distance	,000	,159	,018	,027	72
Centered Leverage Value	,105	,554	,250	,083	72

a. Dependent Variable: LogTime

Multicollinearity

Next, we want to check for multicollinearity. Two measures are used. First, tolerance levels (amount of variability of an independent variable not explained by other independent variables) should exceed 0.10, indicating low correlation (Field, 2009). Second, variance inflation levels should not exceed 10 (Field, 2009). In the collinearity statistics table it can been seen that all tolerance and VIF values are ≥0.1 and <10. Therefore, there is no case of multicollinearity. Size and revenue have high VIF values but this issues is no problem as explained in section 4.2.

Tolerance	VIF
,114	8,790
,598	1,673
,786	1,272
,798	1,253
,726	1,378
,691	1,447
,650	1,538
,113	8,831
,770	1,299
,543	1,840
,657	1,523
,629	1,591
,584	1,713
,565	1,771
,623	1,606

Appendix 6: Assumptions for the post hoc analysis ‘Energy decrease’

For this post hoc analyses a binary analysis is conducted for the dichotomous dependent variable ‘energy decrease’. This implies that there are other assumptions than with an analysis were the dependent variable is of a metric scale. Firstly, it does not need a linear relationship between the dependent and independent variables. Secondly, the independent variables do not need to be multivariate normal – although multivariate normality yields a more stable solution. Next, homoscedasticity is not needed. What is of importance is that the model should have little or no multicollinearity and testing the influence of outliers.

Next, the binary regression with log link assumes linearity of independent variables. Whilst it does not require the dependent and independent variables to be related linearly, it requires that the independent variables are linearly. Otherwise the test underestimates the strength of the relationship and rejects the relationship too easily, that is being not significant (not rejecting the null hypothesis) where it should be significant.

6.1 Individual level

Normality and Linearity

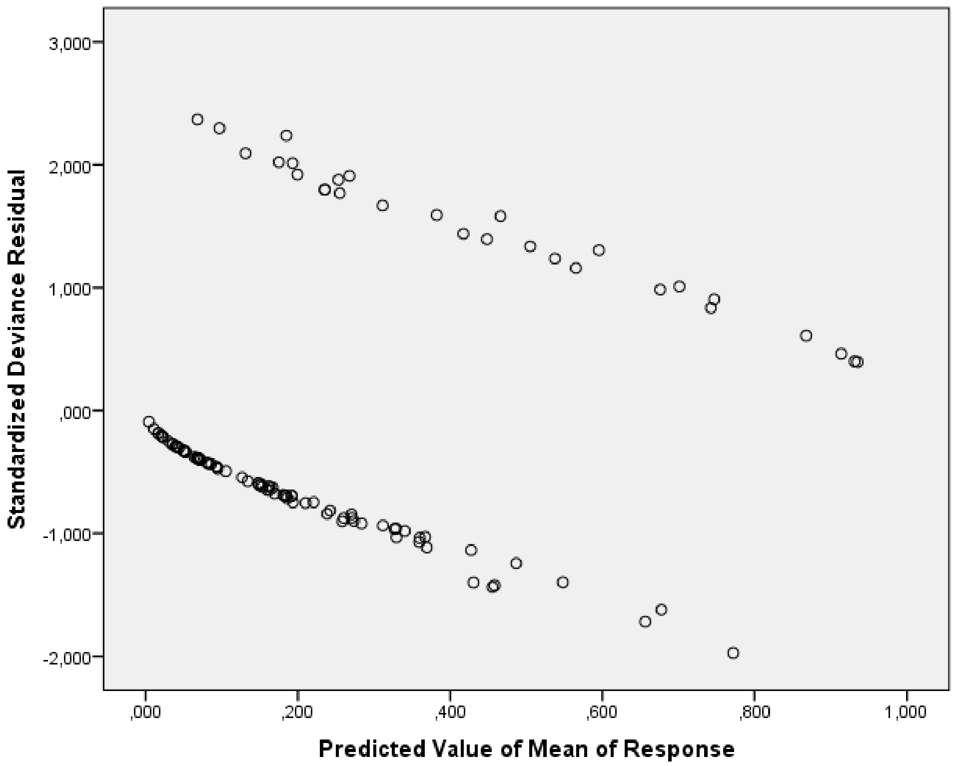
There are three metric independent variables in this analysis. Namely, ‘sustainable processes’, ‘revenue’ and ‘size’. All three of them where already assessed in previous analyses. The conclusion about sustainable processes was that the count variable cannot be improved upon normality and linearity, but the current sample sizes do diminish the effects of non-normality to a great degree (Field, 2009). The other variables, revenue and size, were log-transformed to improve normality and linearity. This will also be the case in this analyses.

6.2 Assumptions for the variate

Now that the assumptions for individual variables have been met, binary regression analysis also requires assumptions for the variate.

Influential cases

Observation from the scatter plot below shows that no case exceeds the ± 2.5 standard scores of standardized residuals. This results that no case was deleted from the analyses.



Multicollinearity

If the absolute value of Pearson correlation is close to 0.8 (such as 0.7±0.1), collinearity is likely to exist. Inspecting Pearson's correlations in appendix 7, none of the correlations shows a 0.7 or higher.

Appendix 7: Statistical output

7.1 Correlations

Correlations

			count sustainable process	count open innovation	Science	Market_based	Tech_Innov	ISO14031	ISO50001
Spearman's rho	count sustainable process	Correlation Coefficient	1,000	,355**	,271**	,189*	,108	,200*	,308**
		Sig. (2-tailed)	.	,000	,001	,025	,209	,018	,000
		N	141	141	140	140	136	138	139
	count open innovation	Correlation Coefficient	,355**	1,000	,426**	,329**	-,003	,301**	,194*
		Sig. (2-tailed)	,000	.	,000	,000	,970	,000	,022
		N	141	141	140	140	136	138	139
	Science	Correlation Coefficient	,271**	,426**	1,000	,336**	-,063	,183*	,075
		Sig. (2-tailed)	,001	,000	.	,000	,471	,033	,381
		N	140	140	140	140	135	137	138
	Market_based	Correlation Coefficient	,189*	,329**	,336**	1,000	-,031	,155	,068
		Sig. (2-tailed)	,025	,000	,000	.	,718	,070	,426
		N	140	140	140	140	135	137	138
	Tech_Innov	Correlation Coefficient	,108	-,003	-,063	-,031	1,000	,099	-,046
		Sig. (2-tailed)	,209	,970	,471	,718	.	,258	,599
		N	136	136	135	135	136	133	134

ISO14031	Correlation Coefficient	,200*	,301**	,183*	,155	,099	1,000	,356**
	Sig. (2-tailed)	,018	,000	,033	,070	,258	.	,000
	N	138	138	137	137	133	138	138
ISO50001	Correlation Coefficient	,308**	,194*	,075	,068	-,046	,356**	1,000
	Sig. (2-tailed)	,000	,022	,381	,426	,599	,000	.
	N	139	139	138	138	134	138	139
RD_external	Correlation Coefficient	,166	,436**	,379**	,353**	,020	,249**	,129
	Sig. (2-tailed)	,051	,000	,000	,000	,818	,003	,133
	N	139	139	138	138	135	136	137
Revenue	Correlation Coefficient	,257**	,474**	,301**	,298**	,105	,300**	,217*
	Sig. (2-tailed)	,004	,000	,001	,001	,250	,001	,015
	N	126	126	125	125	121	124	125
Size	Correlation Coefficient	,352**	,476**	,314**	,270**	,148	,425**	,233**
	Sig. (2-tailed)	,000	,000	,000	,001	,088	,000	,006
	N	139	139	138	138	134	136	137
vMetal	Correlation Coefficient	-,078	,104	,129	,084	-,028	,099	,066
	Sig. (2-tailed)	,362	,223	,131	,325	,743	,252	,439
	N	140	140	139	139	135	137	138
vFood	Correlation Coefficient	-,008	,105	,072	,034	-,097	,128	,066
	Sig. (2-tailed)	,927	,218	,401	,689	,263	,135	,445

	N	140	140	139	139	135	137	138
vTextile	Correlation Coefficient	-,052	,063	,105	,138	-,036	-,100	-,190*
	Sig. (2-tailed)	,544	,461	,218	,104	,675	,244	,026
	N	140	140	139	139	135	137	138
vConstruction	Correlation Coefficient	-,071	-,091	-,118	-,011	,033	-,063	-,156
	Sig. (2-tailed)	,404	,282	,165	,901	,703	,468	,068
	N	140	140	139	139	135	137	138
vChemical	Correlation Coefficient	,043	-,072	,071	-,021	-,142	-,120	,032
	Sig. (2-tailed)	,614	,395	,406	,810	,100	,163	,709
	N	140	140	139	139	135	137	138
vMachinery	Correlation Coefficient	,087	-,079	-,230**	-,099	,067	,023	,052
	Sig. (2-tailed)	,307	,353	,006	,247	,439	,790	,546
	N	140	140	139	139	135	137	138
vElectronic	Correlation Coefficient	,063	-,020	-,035	-,130	,218*	,040	,087
	Sig. (2-tailed)	,456	,812	,686	,128	,011	,639	,312
	N	140	140	139	139	135	137	138
Inbound	Correlation Coefficient	,367**	,905**	,410**	,369**	-,066	,255**	,174*
	Sig. (2-tailed)	,000	,000	,000	,000	,442	,003	,040
	N	141	141	140	140	136	138	139
Outbound	Correlation Coefficient	,222**	,792**	,311**	,171*	,073	,277**	,149

		Sig. (2-tailed)	,008	,000	,000	,044	,397	,001	,080
		N	141	141	140	140	136	138	139
	Time_to_market	Correlation Coefficient	,182	,439**	,401**	,236*	-,139	,205	,111
		Sig. (2-tailed)	,091	,000	,000	,028	,199	,060	,309
		N	87	87	87	87	87	85	86
	Energycon_org1	Correlation Coefficient	,333**	,160	-,001	,186*	,174*	,159	,236**
		Sig. (2-tailed)	,000	,063	,992	,030	,046	,066	,006
		N	136	136	135	135	131	134	135

Correlations

			RD_external	Revenue	Size	vMetal	vFood	vTextile	vConstruction	vChemical
Spearman's rho	count sustainable process	Correlation Coefficient	,166	,257**	,352**	-,078	-,008	-,052	-,071	,043
		Sig. (2-tailed)	,051	,004	,000	,362	,927	,544	,404	,614
		N	139	126	139	140	140	140	140	140
	count open innovation	Correlation Coefficient	,436**	,474**	,476**	,104	,105	,063	-,091	-,072
		Sig. (2-tailed)	,000	,000	,000	,223	,218	,461	,282	,395
		N	139	126	139	140	140	140	140	140
	Science	Correlation Coefficient	,379**	,301**	,314**	,129	,072	,105	-,118	,071
		Sig. (2-tailed)	,000	,001	,000	,131	,401	,218	,165	,406
		N	138	125	138	139	139	139	139	139
	Market_based	Correlation Coefficient	,353**	,298**	,270**	,084	,034	,138	-,011	-,021

	Sig. (2-tailed)	,000	,001	,001	,325	,689	,104	,901	,810
	N	138	125	138	139	139	139	139	139
Tech_Innov	Correlation Coefficient	,020	,105	,148	-,028	-,097	-,036	,033	-,142
	Sig. (2-tailed)	,818	,250	,088	,743	,263	,675	,703	,100
	N	135	121	134	135	135	135	135	135
ISO14031	Correlation Coefficient	,249**	,300**	,425**	,099	,128	-,100	-,063	-,120
	Sig. (2-tailed)	,003	,001	,000	,252	,135	,244	,468	,163
	N	136	124	136	137	137	137	137	137
ISO50001	Correlation Coefficient	,129	,217*	,233**	,066	,066	-,190*	-,156	,032
	Sig. (2-tailed)	,133	,015	,006	,439	,445	,026	,068	,709
	N	137	125	137	138	138	138	138	138
RD_external	Correlation Coefficient	1,000	,226*	,284**	,041	,097	,191*	,002	-,188*
	Sig. (2-tailed)	.	,011	,001	,630	,257	,025	,984	,027
	N	139	124	137	138	138	138	138	138
Revenue	Correlation Coefficient	,226*	1,000	,838**	,207*	-,208*	,075	-,077	-,020
	Sig. (2-tailed)	,011	.	,000	,020	,020	,407	,391	,822
	N	124	126	126	125	125	125	125	125
Size	Correlation Coefficient	,284**	,838**	1,000	,065	-,021	-,006	,006	,002
	Sig. (2-tailed)	,001	,000	.	,451	,810	,942	,948	,980
	N	137	126	139	138	138	138	138	138

vMetal	Correlation Coefficient	,041	,207*	,065	1,000	-,146	-,213*	-,162	-,259**
	Sig. (2-tailed)	,630	,020	,451	.	,086	,011	,056	,002
	N	138	125	138	140	140	140	140	140
vFood	Correlation Coefficient	,097	-,208*	-,021	-,146	1,000	-,101	-,077	-,122
	Sig. (2-tailed)	,257	,020	,810	,086	.	,237	,369	,150
	N	138	125	138	140	140	140	140	140
vTextile	Correlation Coefficient	,191*	,075	-,006	-,213*	-,101	1,000	-,112	-,179*
	Sig. (2-tailed)	,025	,407	,942	,011	,237	.	,187	,034
	N	138	125	138	140	140	140	140	140
vConstruction	Correlation Coefficient	,002	-,077	,006	-,162	-,077	-,112	1,000	-,136
	Sig. (2-tailed)	,984	,391	,948	,056	,369	,187	.	,109
	N	138	125	138	140	140	140	140	140
vChemical	Correlation Coefficient	-,188*	-,020	,002	-,259**	-,122	-,179*	-,136	1,000
	Sig. (2-tailed)	,027	,822	,980	,002	,150	,034	,109	.
	N	138	125	138	140	140	140	140	140
vMachinery	Correlation Coefficient	-,001	-,069	-,081	-,284**	-,134	-,196*	-,149	-,238**
	Sig. (2-tailed)	,995	,443	,345	,001	,115	,020	,078	,005
	N	138	125	138	140	140	140	140	140
vElectronic	Correlation Coefficient	-,115	-,027	,032	-,192*	-,091	-,133	-,101	-,162
	Sig. (2-tailed)	,178	,769	,711	,023	,286	,117	,234	,057

	N	138	125	138	140	140	140	140	140
Inbound	Correlation Coefficient	,440**	,427**	,432**	,150	,153	,080	-,067	-,100
	Sig. (2-tailed)	,000	,000	,000	,076	,072	,349	,433	,239
	N	139	126	139	140	140	140	140	140
Outbound	Correlation Coefficient	,276**	,415**	,389**	,082	-,016	,022	-,118	-,018
	Sig. (2-tailed)	,001	,000	,000	,335	,851	,801	,164	,837
	N	139	126	139	140	140	140	140	140
Time_to_market	Correlation Coefficient	,360**	,252*	,388**	,186	,198	,141	-,076	-,078
	Sig. (2-tailed)	,001	,027	,000	,087	,068	,196	,488	,475
	N	86	77	87	86	86	86	86	86
Energycon_org1	Correlation Coefficient	,187*	,030	,115	,056	,005	-,058	-,095	-,023
	Sig. (2-tailed)	,031	,740	,187	,520	,957	,503	,274	,795
	N	134	123	134	135	135	135	135	135

Correlations

			vMachinery	vElectronic	Inbound	Outbound	Time_to_market	Energycon_org1
Spearman's rho	count sustainable process	Correlation Coefficient	,087	,063	,367**	,222**	,182	,333**
		Sig. (2-tailed)	,307	,456	,000	,008	,091	,000
		N	140	140	141	141	87	136
	count open innovation	Correlation Coefficient	-,079	-,020	,905**	,792**	,439**	,160
		Sig. (2-tailed)	,353	,812	,000	,000	,000	,063

	N	140	140	141	141	87	136
Science	Correlation Coefficient	-,230**	-,035	,410**	,311**	,401**	-,001
	Sig. (2-tailed)	,006	,686	,000	,000	,000	,992
	N	139	139	140	140	87	135
Market_based	Correlation Coefficient	-,099	-,130	,369**	,171*	,236*	,186*
	Sig. (2-tailed)	,247	,128	,000	,044	,028	,030
	N	139	139	140	140	87	135
Tech_Innov	Correlation Coefficient	,067	,218*	-,066	,073	-,139	,174*
	Sig. (2-tailed)	,439	,011	,442	,397	,199	,046
	N	135	135	136	136	87	131
ISO14031	Correlation Coefficient	,023	,040	,255**	,277**	,205	,159
	Sig. (2-tailed)	,790	,639	,003	,001	,060	,066
	N	137	137	138	138	85	134
ISO50001	Correlation Coefficient	,052	,087	,174*	,149	,111	,236**
	Sig. (2-tailed)	,546	,312	,040	,080	,309	,006
	N	138	138	139	139	86	135
RD_external	Correlation Coefficient	-,001	-,115	,440**	,276**	,360**	,187*
	Sig. (2-tailed)	,995	,178	,000	,001	,001	,031
	N	138	138	139	139	86	134
Revenue	Correlation Coefficient	-,069	-,027	,427**	,415**	,252*	,030

	Sig. (2-tailed)	,443	,769	,000	,000	,027	,740
	N	125	125	126	126	77	123
Size	Correlation Coefficient	-,081	,032	,432**	,389**	,388**	,115
	Sig. (2-tailed)	,345	,711	,000	,000	,000	,187
	N	138	138	139	139	87	134
vMetal	Correlation Coefficient	-,284**	-,192*	,150	,082	,186	,056
	Sig. (2-tailed)	,001	,023	,076	,335	,087	,520
	N	140	140	140	140	86	135
vFood	Correlation Coefficient	-,134	-,091	,153	-,016	,198	,005
	Sig. (2-tailed)	,115	,286	,072	,851	,068	,957
	N	140	140	140	140	86	135
vTextile	Correlation Coefficient	-,196*	-,133	,080	,022	,141	-,058
	Sig. (2-tailed)	,020	,117	,349	,801	,196	,503
	N	140	140	140	140	86	135
vConstruction	Correlation Coefficient	-,149	-,101	-,067	-,118	-,076	-,095
	Sig. (2-tailed)	,078	,234	,433	,164	,488	,274
	N	140	140	140	140	86	135
vChemical	Correlation Coefficient	-,238**	-,162	-,100	-,018	-,078	-,023
	Sig. (2-tailed)	,005	,057	,239	,837	,475	,795
	N	140	140	140	140	86	135

	vMachinery	Correlation Coefficient	1,000	-,177*	-,079	-,077	-,295**	,009
		Sig. (2-tailed)	.	,036	,353	,367	,006	,919
		N	140	140	140	140	86	135
	vElectronic	Correlation Coefficient	-,177*	1,000	-,128	,102	-,037	,081
		Sig. (2-tailed)	,036	.	,131	,229	,732	,351
		N	140	140	140	140	86	135
	Inbound	Correlation Coefficient	-,079	-,128	1,000	,479**	,428**	,142
		Sig. (2-tailed)	,353	,131	.	,000	,000	,099
		N	140	140	141	141	87	136
	Outbound	Correlation Coefficient	-,077	,102	,479**	1,000	,279**	,149
		Sig. (2-tailed)	,367	,229	,000	.	,009	,084
		N	140	140	141	141	87	136
	Time_to_market	Correlation Coefficient	-,295**	-,037	,428**	,279**	1,000	,025
		Sig. (2-tailed)	,006	,732	,000	,009	.	,821
		N	86	86	87	87	87	84
	Energycon_org1	Correlation Coefficient	,009	,081	,142	,149	,025	1,000
		Sig. (2-tailed)	,919	,351	,099	,084	,821	.
		N	135	135	136	136	84	136

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

7.2 Quadradic effects

This appendix test for potential quadradic effects. The change statistics show that both on sustainable processes innovation and on time of market no quadratic effect were found due to insignificant changes in R2 when adding polynomials. Due to the insignificant result of the quadratic terms, no cubic effects were tested (Hair, 2009).

7.2.1 Quadradic effects on the adoption of sustainable processes

Open innovation on sustainable processes

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,450[a]	,202	,193	,84384	,202	21,553	1	85	,000
2	,451[b]	,203	,184	,84834	,001	,101	1	84	,752

a. Predictors: (Constant), count open innovation

b. Predictors: (Constant), count open innovation, Qopen

Revenue on sustainable processes

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,322[a]	,104	,092	,86378	,104	8,668	1	75	,004
2	,328[b]	,107	,083	,86774	,004	,317	1	74	,575

a. Predictors: (Constant), LN_Revenue

b. Predictors: (Constant), LN_Revenue, Qrev

Size on sustainable process

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,461[a]	,212	,203	,83855	,212	22,903	1	85	,000
2	,470[b]	,221	,202	,83893	,009	,923	1	84	,340

a. Predictors: (Constant), LN_size

b. Predictors: (Constant), LN_size, Qsize

7.2.2 Quadradic effects on time to market

Count of sustainable process on time to market

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,202[a]	,041	,030	,92527	,041	3,624	1	85	,060
2	,212[b]	,045	,022	,92890	,004	,338	1	84	,563

a. Predictors: (Constant), count sustainable process

b. Predictors: (Constant), count sustainable process, Qsus

Count of open innovation on time to market

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,450[a]	,202	,193	,84384	,202	21,553	1	85	,000
2	,451[b]	,203	,184	,84834	,001	,101	1	84	,752

a. Predictors: (Constant), count open innovation

b. Predictors: (Constant), count open innovation, Qopen

Size on time to market

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,461[a]	,212	,203	,83855	,212	22,903	1	85	,000
2	,470[b]	,221	,202	,83893	,009	,923	1	84	,340

a. Predictors: (Constant), LN_size

b. Predictors: (Constant), LN_size, Qsize

Revenue on time to market

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,322[a]	,104	,092	,86378	,104	8,668	1	75	,004
2	,328[b]	,107	,083	,86774	,004	,317	1	74	,575

a. Predictors: (Constant), LN_Revenue

b. Predictors: (Constant), LN_Revenue, Qrev

7.3 Negative binomial regression

Model Information

Dependent Variable	count sustainable process
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	116	82,3%
Excluded	25	17,7%
Total	141	100,0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	count sustainable process	116	,00	6,00	,8017	1,31361
Covariate	count open innovation	116	,00	8,00	3,7672	1,95763
	Science	116	,0	1,0	,388	,4894
	Market_based	116	,00	1,00	,6034	,49130
	vMetal	116	,0	1,0	,741	,4398
	vFood	116	,00	1,00	,9224	,26868
	vTextile	116	,00	1,00	,8621	,34632
	vConstruction	116	,000	1,000	,93103	,254495
	vChemical	116	,00	1,00	,8276	,37938
	vMachinery	116	,00	1,00	,8103	,39373
	vElectronic	116	,00	1,00	,9052	,29425
	Centsize	116	-2,42	5,08	,0024	1,19039
	CentRevenue	116	-3,12	6,44	,0651	1,57703
	Tech_Innov	116	,0	1,0	,621	,4873
	ISO14031	116	,0	1,0	,198	,4004
	ISO50001	116	,0	1,0	,060	,2392
	RD_external	116	,0	1,0	,259	,4398

Goodness of Fit[a]

	Value	df	Value/df
Deviance	143,653	99	1,451
Scaled Deviance	143,653	99	
Pearson Chi-Square	160,453	99	1,621
Scaled Pearson Chi-Square	160,453	99	
Log Likelihood[b]	-132,436		
Akaike's Information Criterion (AIC)	298,871		
Finite Sample Corrected AIC (AICC)	305,116		
Bayesian Information Criterion (BIC)	345,682		
Consistent AIC (CAIC)	362,682		

Dependent Variable: count sustainable process
Model: (Intercept), vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Tech_Innov, ISO14031, ISO50001, RD_external, count open innovation, Market_based, Science, count open innovation * Science
a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
49,986	16	,000

Dependent Variable: count sustainable process
Model: (Intercept), vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Tech_Innov, ISO14031, ISO50001, RD_external, count open innovation, Market_based, Science, count open innovation * Science a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	3,078	1	,079
vFood	,129	1	,719
vTextile	,332	1	,565
vConstruction	,284	1	,594
vChemical	,115	1	,734
vMachinery	,001	1	,977
vElectronic	,491	1	,484
Centsize	5,519	1	,019
CentRevenue	4,776	1	,029
Tech_Innov	1,856	1	,173
ISO14031	,542	1	,462
ISO50001	7,736	1	,005
RD_external	1,062	1	,303
count open innovation	9,331	1	,002
Market_based	,044	1	,834
Science	4,589	1	,032
count open innovation * Science	1,169	1	,280

Dependent Variable: count sustainable process
Model: (Intercept), vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Tech_Innov, ISO14031, ISO50001, RD_external, count open innovation, Market_based, Science, count open innovation * Science

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	-,176	2,4825	-5,042	4,690	,005	1	,943	,838	,006	108,800
count open innovation	,231	,0795	,076	,387	8,466	1	,004	1,260	1,078	1,473
Science	,810	,2637	,294	1,327	9,448	1	,002	2,249	1,341	3,771
Market_based	,138	,2649	-,381	,657	,270	1	,603	1,148	,683	1,929
vMetal	-,420	,5002	-1,400	,561	,704	1	,402	,657	,247	1,752
vFood	-,636	,6741	-1,957	,685	,891	1	,345	,529	,141	1,984
vTextile	-,179	,5931	-1,341	,984	,091	1	,763	,836	,262	2,675
vConstruction	-,087	,5980	-1,259	1,086	,021	1	,885	,917	,284	2,961
vChemical	-,282	,5470	-1,354	,790	,266	1	,606	,754	,258	2,203
vMachinery	-,392	,4851	-1,343	,559	,653	1	,419	,676	,261	1,749
vElectronic	0[a]	.	.	.	.	.	.	1	.	.
Centsize	,469	,1978	,081	,857	5,626	1	,018	1,599	1,085	2,356
CentRevenue	-,410	,1692	-,742	-,078	5,875	1	,015	,664	,476	,925
Tech_Innov	,363	,2577	-,142	,868	1,981	1	,159	1,437	,867	2,382
ISO14031	-,357	,3320	-1,008	,294	1,155	1	,283	,700	,365	1,342
ISO50001	1,229	,4237	,399	2,060	8,416	1	,004	3,418	1,490	7,842
RD_external	-,419	,2960	-,999	,161	2,003	1	,157	,658	,368	1,175
(Scale)	1[b]									
(Negative binomial)	,023[b]									

Dependent Variable: count sustainable process

Model: (Intercept), count open innovation, Science, Market_based, vMetal, vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Tech_Innov, ISO14031, ISO50001, RD_external

a. Set to zero because this parameter is redundant.

b. Fixed at the displayed value.

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	-2,676	1,5254	-5,666	,314	3,078	1	,079	,069	,003	1,368
vFood	-,212	,5885	-1,365	,942	,129	1	,719	,809	,255	2,565
vTextile	,226	,3931	-,544	,997	,332	1	,565	1,254	,580	2,710
vConstruction	,255	,4785	-,683	1,193	,284	1	,594	1,290	,505	3,296
vChemical	,128	,3779	-,612	,869	,115	1	,734	1,137	,542	2,384
vMachinery	-,010	,3496	-,695	,675	,001	1	,977	,990	,499	1,964
vElectronic	,352	,5026	-,633	1,337	,491	1	,484	1,422	,531	3,808
Centsize	,462	,1968	,077	,848	5,519	1	,019	1,588	1,080	2,335
CentRevenue	-,374	,1711	-,709	-,039	4,776	1	,029	,688	,492	,962
Tech_Innov	,348	,2554	-,153	,849	1,856	1	,173	1,416	,858	2,336
ISO14031	-,251	,3406	-,918	,417	,542	1	,462	,778	,399	1,517
ISO50001	1,167	,4195	,345	1,989	7,736	1	,005	3,212	1,411	7,309
RD_external	-,318	,3089	-,924	,287	1,062	1	,303	,727	,397	1,333
count open innovation	,282	,0922	,101	,462	9,331	1	,002	1,325	1,106	1,588
Market_based	,058	,2760	-,483	,599	,044	1	,834	1,059	,617	1,820
Science	1,526	,7124	,130	2,922	4,589	1	,032	4,601	1,139	18,587
count open innovation * Science	-,167	,1542	-,469	,135	1,169	1	,280	,846	,626	1,145
(Scale)	1[a]									
(Negative binomial)	,022[a]									

Dependent Variable: count sustainable process

Model: (Intercept), vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Tech_Innov, ISO14031, ISO50001, RD_external, count open innovation, Market_based, Science, count open innovation * Science

a. Fixed at the displayed value.

7.4 Post hoc analyses ‘time to market’

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	vElectronic, ISO14031, vConstruction, count sustainable process, vTextile, Market_based, Tech_Innov, vFood, vChemical, RD_external, ISO50001, CentRevenue, Science, vMachinery, LN_size[b]	.	Enter

a. Dependent Variable: LogTime

b. Tolerance = ,000 limit reached.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,656[a]	,430	,278	,77337	,430	2,819	15	56	,003	1,956

a. Predictors: (Constant), vElectronic, ISO14031, vConstruction, count sustainable process, vTextile, Market_based, Tech_Innov, vFood, vChemical, RD_external, ISO50001, CentRevenue, Science, vMachinery, LN_size

b. Dependent Variable: LogTime

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25,292	15	1,686	2,819	,003[b]
	Residual	33,494	56	,598		
	Total	58,786	71			

a. Dependent Variable: LogTime

b. Predictors: (Constant), vElectronic, ISO14031, vConstruction, count sustainable process, vTextile, Market_based, Tech_Innov, vFood, vChemical, RD_external, ISO50001, CentRevenue, Science, vMachinery, LN_size

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	3,145	1,208		2,604	,012	,726	5,564		
	vFood	-,229	,392	-,080	-,585	,561	-1,014	,556	,506	1,977
	vTextile	-,161	,349	-,056	-,461	,647	-,861	,538	,637	1,569
	vConstruction	-,434	,381	-,133	-1,139	,259	-1,196	,329	,694	1,441
	vChemical	-,430	,308	-,177	-1,396	,168	-1,046	,187	,584	1,714
	vMachinery	-,596	,295	-,254	-2,019	,048	-1,186	-,005	,596	1,676
	vElectronic	-,317	,330	-,116	-,959	,341	-,978	,345	,644	1,554
	LN_size	,098	,196	,144	,503	,617	-,293	,490	,114	8,758
	LN_Revenue	-,015	,153	-,029	-,099	,921	-,321	,290	,108	9,242
	Tech_Innov	-,458	,198	-,252	-2,315	,024	-,854	-,062	,796	1,256
	ISO14031	,157	,246	,072	,636	,527	-,336	,649	,735	1,361
	ISO50001	-,072	,411	-,020	-,176	,861	-,896	,751	,702	1,424
	RD_external	,519	,230	,257	2,260	,028	,059	,979	,726	1,377
	count sustainable process	,124	,072	,190	1,735	,088	-,019	,267	,780	1,281
	count open innovation	,136	,072	,256	1,904	,062	-,007	,279	,520	1,923

a. Dependent Variable: LogTime

7.5 Post hoc analyses 'energy decrease'

Model Information

Dependent Variable	Energycon_org1[a]
Probability Distribution	Binomial
Link Function	Negative log-log

a. The procedure models decreased as the response, treating ,0 as the reference category.

Case Processing Summary

	N	Percent
Included	114	80,9%
Excluded	27	19,1%
Total	141	100,0%

Categorical Variable Information

			N	Percent
Dependent Variable	Energycon_org1	,0	85	74,6%
		decreased	29	25,4%
		Total	114	100,0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Covariate	vMetal	114	,0	1,0	,746	,4374
	vFood	114	,00	1,00	,9211	,27085
	vTextile	114	,00	1,00	,8596	,34888
	vConstruction	114	,000	1,000	,92982	,256570
	vChemical	114	,00	1,00	,8246	,38202
	vMachinery	114	,00	1,00	,8158	,38937
	vElectronic	114	,00	1,00	,9035	,29657
	Centsize	114	-2,42	5,08	,0169	1,19323
	CentRevenue	114	-3,12	6,44	,0602	1,58937
	Tech_Innov	114	,0	1,0	,623	,4868
	ISO14031	114	,0	1,0	,202	,4031
	ISO50001	114	,0	1,0	,061	,2411
	RD_external	114	,0	1,0	,263	,4423

Market_based	114	,00	1,00	,5965	,49277
Science	114	,0	1,0	,386	,4890
count sustainable process	114	,00	6,00	,8070	1,32289
count open innovation	114	,00	8,00	3,7632	1,97463

Goodness of Fit[a]

	Value	df	Value/df
Deviance	97,958	97	1,010
Scaled Deviance	97,958	97	
Pearson Chi-Square	95,320	97	,983
Scaled Pearson Chi-Square	95,320	97	
Log Likelihood[b]	-48,979		
Akaike's Information Criterion (AIC)	129,958		
Finite Sample Corrected AIC (AICC)	135,566		
Bayesian Information Criterion (BIC)	173,737		
Consistent AIC (CAIC)	189,737		

Dependent Variable: Energycon_org1

Model: (Intercept), vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Tech_Innov, ISO14031, ISO50001, RD_external, Market_based, Science, count sustainable process[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
31,342	15	,008

Dependent Variable: Energycon_org1

Model: (Intercept), vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Tech_Innov, ISO14031, ISO50001, RD_external, Market_based, Science, count sustainable process[a] a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	2,901	1	,089
vFood	4,645	1	,031
vTextile	1,338	1	,247
vConstruction	4,881	1	,027
vChemical	1,662	1	,197
vMachinery	4,929	1	,026
vElectronic	,850	1	,357
Centsize	3,303	1	,069
CentRevenue	8,336	1	,004
Tech_Innov	3,372	1	,066
ISO14031	,432	1	,511
ISO50001	2,601	1	,107
RD_external	6,196	1	,013
Market_based	5,170	1	,023
Science	5,529	1	,019
count sustainable process	2,848	1	,091

Dependent Variable: Energycon_org1

Model: (Intercept), vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Tech_Innov, ISO14031, ISO50001, RD_external, Market_based, Science, count sustainable process

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	3,264	1,9165	-,492	7,020	2,901	1	,089	26,160	,611	1119,339
vFood	-1,420	,6589	-2,711	-,129	4,645	1	,031	,242	,066	,879
vTextile	-,525	,4540	-1,415	,365	1,338	1	,247	,592	,243	1,440
vConstruction	-1,215	,5499	-2,293	-,137	4,881	1	,027	,297	,101	,872
vChemical	-,572	,4434	-1,441	,297	1,662	1	,197	,565	,237	1,346
vMachinery	-1,015	,4571	-1,911	-,119	4,929	1	,026	,362	,148	,888
vElectronic	-,505	,5478	-1,579	,569	,850	1	,357	,603	,206	1,766
Centsize	,527	,2902	-,041	1,096	3,303	1	,069	1,694	,959	2,993
CentRevenue	-,648	,2245	-1,088	-,208	8,336	1	,004	,523	,337	,812
Tech_Innov	,519	,2824	-,035	1,072	3,372	1	,066	1,680	,966	2,922
ISO14031	,243	,3700	-,482	,968	,432	1	,511	1,275	,617	2,634
ISO50001	1,275	,7905	-,275	2,824	2,601	1	,107	3,578	,760	16,844
RD_external	,847	,3405	,180	1,515	6,196	1	,013	2,334	1,197	4,549
Market_based	,694	,3050	,096	1,291	5,170	1	,023	2,001	1,100	3,638
Science	-,791	,3364	-1,450	-,132	5,529	1	,019	,453	,235	,877
count sustainable process	,244	,1445	-,039	,527	2,848	1	,091	1,276	,961	1,694
(Scale)	1[a]									

Dependent Variable: Energycon_org1

Model: (Intercept), vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Tech_Innov, ISO14031, ISO50001, RD_external, Market_based, Science, count sustainable process

a. Fixed at the displayed value.

7.6 Post hoc analyses 'inbound and outbound open innovation'

Model Information

Dependent Variable	count sustainable process
Probability Distribution	Negative binomial (MLE)
Link Function	Log

Case Processing Summary

	N	Percent
Included	116	82,3%
Excluded	25	17,7%
Total	141	100,0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	count sustainable process	116	,00	6,00	,8017	1,31361
Covariate	vMetal	116	,0	1,0	,741	,4398
	vFood	116	,00	1,00	,9224	,26868
	vTextile	116	,00	1,00	,8621	,34632
	vConstruction	116	,000	1,000	,93103	,254495
	vChemical	116	,00	1,00	,8276	,37938
	vMachinery	116	,00	1,00	,8103	,39373
	vElectronic	116	,00	1,00	,9052	,29425
	Centsize	116	-2,42	5,08	,0024	1,19039
	CentRevenue	116	-3,12	6,44	,0651	1,57703
	Science	116	,0	1,0	,388	,4894
	Market_based	116	,00	1,00	,6034	,49130
	Tech_Innov	116	,0	1,0	,621	,4873
	ISO14031	116	,0	1,0	,198	,4004
	ISO50001	116	,0	1,0	,060	,2392
	RD_external	116	,0	1,0	,259	,4398
	Inbound	116	,00	5,00	2,6207	1,33615
	Outbound	116	,00	3,00	1,1466	,89690

Goodness of Fit[a]

	Value	df	Value/df
Deviance	102,055	98	1,041
Scaled Deviance	102,055	98	
Pearson Chi-Square	111,174	98	1,134
Scaled Pearson Chi-Square	111,174	98	
Log Likelihood[b]	-128,285		
Akaike's Information Criterion (AIC)	292,570		
Finite Sample Corrected AIC (AICC)	299,621		
Bayesian Information Criterion (BIC)	342,134		
Consistent AIC (CAIC)	360,134		

Dependent Variable: count sustainable process
Model: (Intercept), vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Science, Market_based, Tech_Innov, ISO14031, ISO50001, RD_external, Inbound, Outbound
a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
43,521	16	,000

Dependent Variable: count sustainable process
Model: (Intercept), vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Science, Market_based, Tech_Innov, ISO14031, ISO50001, RD_external, Inbound, Outbound
a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	3,052	1	,081
vFood	,333	1	,564
vTextile	,601	1	,438
vConstruction	,370	1	,543
vChemical	,337	1	,562
vMachinery	,004	1	,949
vElectronic	,813	1	,367
Centsize	4,175	1	,041
CentRevenue	5,783	1	,016
Science	7,511	1	,006
Market_based	,199	1	,655
Tech_Innov	1,644	1	,200
ISO14031	,504	1	,478
ISO50001	11,067	1	,001
RD_external	1,306	1	,253
Inbound	4,395	1	,036
Outbound	,500	1	,480

Dependent Variable: count sustainable process
Model: (Intercept), vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Science, Market_based, Tech_Innov, ISO14031, ISO50001, RD_external, Inbound, Outbound

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	-2,800	1,6029	-5,942	,341	3,052	1	,081	,061	,003	1,407
vFood	-,293	,5070	-1,287	,701	,333	1	,564	,746	,276	2,016
vTextile	,290	,3736	-,443	1,022	,601	1	,438	1,336	,642	2,779
vConstruction	,289	,4749	-,642	1,220	,370	1	,543	1,335	,526	3,387
vChemical	,265	,4566	-,630	1,160	,337	1	,562	1,303	,533	3,190
vMachinery	-,027	,4276	-,865	,811	,004	1	,949	,973	,421	2,250
vElectronic	,454	,5039	-,533	1,442	,813	1	,367	1,575	,587	4,228
Centsize	,513	,2510	,021	1,005	4,175	1	,041	1,670	1,021	2,732
CentRevenue	-,422	,1754	-,766	-,078	5,783	1	,016	,656	,465	,925
Science	,826	,3016	,235	1,417	7,511	1	,006	2,285	1,265	4,127
Market_based	,149	,3330	-,504	,801	,199	1	,655	1,160	,604	2,229
Tech_Innov	,357	,2787	-,189	,904	1,644	1	,200	1,430	,828	2,469
ISO14031	-,275	,3877	-1,035	,485	,504	1	,478	,759	,355	1,624
ISO50001	1,201	,3609	,493	1,908	11,067	1	,001	3,323	1,638	6,741
RD_external	-,384	,3361	-1,043	,275	1,306	1	,253	,681	,352	1,316
Inbound	,276	,1315	,018	,533	4,395	1	,036	1,317	1,018	1,704
Outbound	,159	,2255	-,283	,601	,500	1	,480	1,173	,754	1,825
(Scale)	1[a]									
(Negative binomial)	,565	,2564	,233	1,375						

Dependent Variable: count sustainable process

Model: (Intercept), vFood, vTextile, vConstruction, vChemical, vMachinery, vElectronic, Centsize, CentRevenue, Science, Market_based, Tech_Innov, ISO14031, ISO50001, RD_external, Inbound, Outbound

a. Fixed at the displayed value.