Ambidexterity Trends in Dutch Manufacturing Firms

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ABSTRACT,
Research on ambidexterity focused mainly on finding optimal approaches to deal with tensions & difficulties between exploration & exploitation activities. Ignoring that there may be interdependent variables that cause specific ambidextrous behavior and resulting exploration/exploitation patterns. This research is a first step to identify key variables that may cause or at least correlate with specific ambidextrous patterns. Identifying such variables can help firms and researchers to better understand decision making and biases that influence the innovative activities a firm pursues. A sample of respectively 106 and 91 companies has been used for the variables industry section and firm size. This sample has been created by combining machine learning to classify innovation projects in the period of 2010-2014 with metadata from the financial database Orbis, in order to research whether the interdependent variables size and industry section correlate with specific trends in exploration/exploitation balances. The structure and quality of the data and the lack of metadata made it difficult to reach definite results, but some indication has been found that firm size influences the ambidextrous behavior of a firm.

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Keywords
Ambidexterity, exploration, exploitation, innovation, innovation portfolio, firm size, industry sector, trends

1. INTRODUCTION

Innovation, an abstract concept that has been defined dissimilar by scholars. A general definition of innovation can be defined as: 'The successful exploitation of new ideas' (Irani et al., 2004). Elaborating on this definition Schilling provides a more detailed description of innovation: 'Innovation is the implementation of creative ideas into some new device or process. Requires combining creativity with resources and expertise' (Schilling 2013). As a result of the comprehensive nature of innovation as illustrated by these definitions different types of innovation have been defined, to support understanding innovation and its related behavior.

Companies invest in innovation projects to gain a competitive advantage. This investment would hypothetically lead to a larger innovation capacity resulting in supreme organizational performance. (Hult et al., 2003). This competitive advantage can be sustained for example by innovating to produce more efficiently, thus being able to offer products at a lower price point than competitors. Or creating a product that has superior characteristics over those of competitors. Furthermore, being too conservative and clamping on to existing business models or processes could lead to the demise of the firm. An excellent example are firms active in the music industry at the time music streaming made its appearance. There were five large companies that dominated the industry: Universal/Polygram, Sony Music Entertainment, EMI, Warner Music Group and the Bertelsmann Group (BMG), at their peak controlling approximately 80 percent of the market. When streaming appeared, they reacted by allocating resources to innovation activity that aimed at defending the physical cd business model. Trying to exploit their current business, instead of exploring new business models. This failed, resulting in a decimation of organizational performance (Dolata, 2011).

When firms pursuit innovation they will face an uncertain and rapid changing environment. Resulting in high risks, the making of missteps could have serious consequences. (Brown and Eisenhardt, 1997; Drucker, 1999). In addition to the complexity that the environment adds research showed that different types of innovation are interdependent. This means that they are influencing each other and the overall company performance. (Fritsch & Meschede, 2001; (Damanpour & Evan, 1984; Kotabe & Murray, 1990). Most studies focus however on a single innovation type when researching the innovation-performance relationship. Mostly disregarding the interdependency between innovations (Damanpour, 2009). Exploring this interdependency further shows that undertaking innovative activities confronts firms with demands that are often cross with one another, demanding flexibility and experimentation or commitment and focus (Van Looy & Visscher, 2011). Firms are juggling between sustaining current business (exploiting) and creating new opportunities by innovating (exploring). This balancing act is defined in literature as the ambidexterity concept. This concept focusses on the interdependency of innovation types and how to overcome the problems that arise, by examining the tensions between exploration and exploitation activities. Ambidexterity describes the firm's ability to simultaneously exploit and explore (Luger et al., 2018).

Further exploring the complexity of innovation, it can be broken down into for example product, process, explorative or exploitative innovation. By categorizing the innovation, in order to help grasp this comprehensive concept, innovation portfolios can be created. The managing of these include dividing scarce resources over the different innovation projects in order to realize competitive advantage. As explained before this is difficult due to the uncertainty and risks involved, wrong choices could decimate or bankrupt companies as occurred in the music industry. There are thus multiple variables that need tuning for success, an example is the number of resources to put in exploitation vs. exploration activities. Making the 'right' decision does to not come down to a binary: innovate/not innovate decision but is more complex.

To fill the research gap that exists on the interdependency of innovative activities previous research has been done on the effect of the innovation portfolio mix of explorative and exploitative innovation on financial performance (Wiegard, 2018). This research aimed to identify if such a mix exist and did not differentiate between firms.

Companies however are not identical, so it would seem unlikely to have a one size fits all innovation portfolio. As for example small firms have different resources than large firms that help them to overcome barriers that prove a greater challenge for larger firms. (Dean et al., 1998) Also there are significant differences in innovation patterns of industry sectors. (Tether, 2010) It is thus plausible that in different sized firms or industry sectors different patterns emerge when using the ambidexterity concept for analysis. Innovation choices that are made can be influenced by such interdependent variables, providing fertile ground for biased decision making. However, to recognize this and understand decision making, the variables that correlate with certain ambidextrous behavior need to be identified. This paper will explore the patterns of exploration and exploitation in the innovation portfolio of companies by incorporating the variables size and industry sector. This will be executed by first analyzing the theory in section 2, then the dataset of 4689 Dutch manufacturing SME's innovation cases which have been classified using machine learning techniques and the dependent and independent variables will be introduced in section 3. Concluding with the results of analysis and discussion in section 4 and 5.

2. THEORY

2.1 Definitions

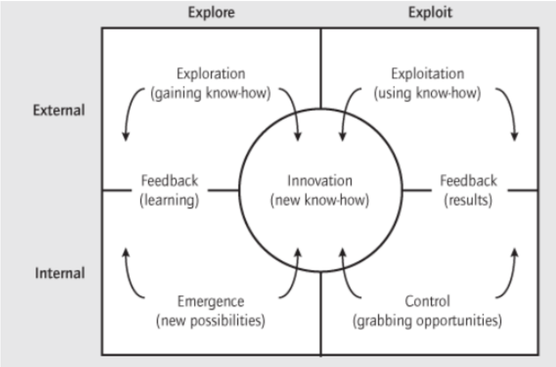
Firstly, before going into analysis it is important to establish consensus about the definition of innovation as used in this paper. The term innovation as explained is broad and has been broken down into different types for easier comprehension and analysis. The overarching definition: 'The successful exploitation of new ideas' (Irani et al., 2004), already provides some ambiguities: When can something be defined as new? Does the idea need to take a physical (product) form or can it be a process? Although a bit ambiguous it describes the core of innovation, only having an idea is not considered innovating, it should be put into practice. The second description found in the book of Schilling (Schilling, 2013) is more specific:' Innovation is the implementation of creative ideas into some new device or process. Requires combining creativity with resources and expertise.' As it states some prerequisites: creativity and resources and describes two forms of innovation: process and product innovation. This study concerns something to be an innovation when it is new to the organization. As stated, earlier researchers have come up with various typologies to classify innovation in order to create some grip on the concept. A widely known typology is the radical/incremental innovation typology. Incremental innovations are for example increasing the features or lowering the costs of products or services and are relatively predictable and safe. Radical innovation entails more than that: entering new markets and facing high risk of losing major amounts of capital. It requires doing something not on the foundations of already existing business or technologies (Doyle, 2001).

Another typology adopted by the OECD can be characterized as the classical four types: product innovation, process innovation, organizational innovation and marketing innovation (Mortensen & Bloch, 2005). Summarizing the definitions of the OECD each type can be described for as:

- Product: A significantly improved good or service, improved in its characteristics or intended uses.
- Process: innovating the process or delivery method.
- Marketing: significant changes in the marketing method, such as product design, packaging, placement, promotion or pricing.
- Organizational: execution of a new organizational method. Changing firm's business practices, external relations or workplace organization.

Innovation opportunities can also be classified based on the characteristics of the opportunity that drives them. Either demand pull, or technology push (Dorf & Byers, 2004, p. 28). The demand-pull means that one starts with a market need that needs to be filled. This demand may be filled by several different products. In the technology push case one start with a new capability (often a new technology or a new application of existing technology). Combining this capability with others leads to a new cohesive product, a new capability can even be applied to multiple products. Which can be applied to different markets and customer needs. Central in this typology is matching important needs with a good solution.

A fourth way and the typology that will be used in this paper is the separation in exploration and exploitation. This typology was introduced by March (March, 1991). He defined exploitation activities being: ‘'such things as refinement, choice, production, efficiency, selection, implementation, execution'’ explorative activities as: ‘'things captured by terms such as search, variation, risk-taking, experimentation, play, flexibility, discovery, innovation'’. The concept as he defined it is visually represented in figure 1. Chou et al. provide a less abstract description by stating exploration activities as: ‘'the development of qualitatively new products and exploitation activities as: the refinement and improvement of existing products'’ (Chou et al., 2017). When in this research is spoken about the ambidexterity distribution, the distribution between exploration and exploitation activities is meant. This typology is used for two reasons: firstly the database this study uses classified the innovation projects this way. As it consists out of just 2 types and with clear keywords known in literature, making it easier to classify. Furthermore, the exploitation/exploration typology is used in the research on ambidextrous innovation, this literature provides an excellent basis for this research, the choice for this typology and the previous research performed on this typology will be further explained in the following part 2.2 previous research.



Source. James G. March (1991) Exploration and Exploitation in Organizational Learning. *Organization Science* 2(1): 71–87

Figure 1. Overview of exploration and exploitation (March, 1991)

2.2 Previous Research

Now the typology to use when analyzing has been selected. In the paper of de Visser et al. (de Visser et al., 2015) it is stated that different studies firm level studies on innovation (e.g., Gibson and Birkinshaw, 2004; Raisch and Birkinshaw, 2008; O'Reilly and Tushman, 2004; Tushman and Anderson, 1986; Tushman and O'Reilly, 1996; Van Looy et al., 2005; Jansen et al., 2006) put forward for consideration that if a company wants to shine in both developing new products and improving current products the company should enroll in different kind of innovation activities. It continues by describing that: ‘'exploitative activities such as optimization, standardization, and refinement are linked to derivative innovation performance, whereas explorative activities such as fundamental research, experimentation, and search are connected to breakthrough innovation performance'’. Shining in new product development and improving existing products means that the outcome is successful.

Engaging in innovation however is not a guarantee for success, it requires taking risk and committing resources and capital into developments that can turn out to flop. Resulting in a loss of capital and resources. Although the risk of failure exists and commitments (capital/resources) exist most firm still pursue innovativeness. This is understandable and supported by literature. As for example in the work of Walker where 30 empirical studies on organizational performance were reviewed (Walker, 2004) only 5% of time a negative relationship was discovered between innovativeness and firm performance, in contrast 60% of the time a positive relationship was discovered, the remaining 35% did not produce significant results. Furthermore, if hypothesizing that a company would not undertake any innovative actions, this would soon lead to the company being out of business. As competitors start to do or produce things more efficient, better and faster. The bottom line here is that the focus should not be on if a firm should pursue innovative activity, but how it should pursue innovative activity.

Initially scholars advocated to focus on either exploration or exploitation activities (Porter, 1985; Barney 1991), in order to avoid becoming undistinguished at both (March, 1991). This recommendation can be understood when taking into account the tension between exploitation and explorative activities, this tension is there because of the radically different organizational routines and mindsets they require (Gupta et al., 2006). In the paper of de Visser et al. a supplement to this claim is made: ‘'exploitative and explorative activities compete for scarce resources within firms, more focus on exploitation (exploration) is likely to imply less attention to exploration (exploitation).'' (de Visser et al., 2015). Thus, it is crucial to manage these in order to achieve successful innovative activities in both the area of exploration and exploitation. In order for the whole firm to flourish. To achieve this, studies have proposed either of two approaches: sequential ambidexterity or simultaneous ambidexterity as a tool to manage these tensions (Chou et al., 2017). Simultaneous ambidexterity implies that an organization undertakes both exploitation activities and exploration activities at the same time. On the contrary sequential ambidexterity means that firms should cycle through periods of exploration or exploitation, avoiding the for mentioned tension between the two activities. Chen argues in his work that firms need to adopt dynamic ambidexterity instead, which entails that firms should adopt structural ambidexterity on the corporate level, contextual ambidexterity on the business unit level and sequential ambidexterity on the project level (Chen, 2017). He thus expands on the typology of ambidexterity by using the concepts structural and contextual ambidexterity. Contextual ambidexterity implies that employees can choose to exploit or explore, supported by an organizational context that makes this possible (Birkinshaw & Gibson, 2004; Gibson & Birkinshaw, 2004). An example as cited in the work of Chen is Alphabet, who let employees free to choose what to do 20% of their working time, resulting in side projects that turn out to become successful ventures. Thus creating opportunities for emerging innovation. Structural ambidexterity divides exploration and exploitation into different and separated business units, which are coordinated by top managers (O'Reilly & Tushman, 2004, 2016; Tushman & O'Reilly, 1996). Having as a main advantage that different business units can adopt varying strategies, processes and structures suitable to their innovative activity. In the work of Luger et al. the approach is again different, as they conceptualize ambidexterity as the dynamic process of balancing the emerging outcomes of capability building processes (to balance exploration/exploitation) with capability shifting processes (to adapt the exploration/exploitation balance) (Luger et al., 2018).

In summary there are numerous views on how to manage ambidexterity. Whether it may be by adopting varying approaches on different business level units, adopting sequential or simultaneous ambidexterity or introducing adaptation into the ambidexterity concept.

2.3 Hypothesis Development

As previously explored in the theory there are different conceptualizations and varying views about how firms should manage and structure innovation based on the ambidexterity concept. This study is not per se focused on determining on finding the best approach, but on empirically examining which trends appear and if they differ from sector to sector or between different sized firms. As there is debate about what the optimal approach may be, however there is little empirical research on which ambidexterity patterns companies actually display in practice.

Firstly, the manufacturing firms operate in different industry sectors. Different sectors require different innovation solutions. 'Several scholars have suggested that the characteristics of an industrial sector have an influence on innovation development' (Forsman, 2011). Furthermore, when firms operate in different sectors this means that the competitive environment they operate in differs. The study of Chang et al. also showed the that the relationship between environmental forces and company performance is partially mediated by a balancing of innovation ambidexterity (Chang et al., 2011). In addition, Jansen et al. claim that companies that are in sectors that are more competitive require exploitative innovation to survive, while companies active in dynamic sectors require explorative activity to prepare for uncertain future states of the sector (Jansen et al., 2006). This difference in dynamic and goods & services lead to stable business sectors to become more incremental innovation focused (Brem & Voigt, 2009). Furthermore, competition intensity (Ganter & Hecker, 2013) and industry wide R&D intensity (Uotila et al., 2009) have been identified as anteceding and moderating factors between innovation and firm performance. Customer orientation has been identified as being one of the causes of exploration-exploitation tensions (Andriopoulos & Lewis, 2009). Sectors in which most economic activity is in a business to business model have customers with different demands than sectors in which most activity for example is business to consumer. All in all, sectors differ significantly from each other and it would be expected that their innovation patterns differ to match their respective challenges (i.e. environmental, customer or technological challenges). Meaning thus that the search for an exploration/exploitation trend in the dataset consisting out of mainly manufacturing firms can be classified by using as independent variable the sectors in which these manufacturing firms operate. This possible relationship is interesting to research as the ambidexterity literature does not contain numerous contributions yet that provide insights into the dynamic between industry sectors and the trend in ambidexterity of the firms that operate in them.

H1*: In various industry sectors emerge different distributions between exploration and exploitation.*

Another important variable factor is the firm size. Firms can be categorized as either small (<50 employees), medium (50-249 employees) or large (>249 employees) sized (OECD, 2019). Firm size is significantly associated with both the new and incremental R&D. Moreover, firm size is found to be significantly associated with other types of R&D compositions such as the share of R&D devoted to incremental innovation and multidimensional combinations of product, process, new and incremental R&D (Choi, 2018). Boiling this down to more concrete arguments it can be argued first that small enterprises cannot actively realize the same benefits of organizational learning, as they do not have the same slack in resources as large companies (Cegarra-Navarro & Dewhurst, 2007). Secondly the organizational learning processes differs as there is an absence of institutionalized or formal routines along with mechanisms for distribution and gathering of new knowledge (Jones & Macpherson, 2006). Thirdly large firms have more complex bureaucracies, in contrast to the SME in which senior managers have direct and extensive involvement in strategic and tactical decision making (Lubatkin et al., 2006). The work of Benner and Tushman moreover, argues that firms should departmentalize explorative activities into R&D departments, to avoid the difficulties of having to deal with the contradictory demands of exploitation and exploration throughout the whole firm (Benner & Tushman, 2003). However smaller companies mostly are not able to found departmentalized R&D departments. Lastly firm size has been identified as anteceding and moderating variable between innovation and firm performance (Needy & Hii, 1998; Hadjimanolis, 2000; Lavie et al., 2010). Together these arguments make it likely that firm size impacts the inclination of a firm, making it plausible that different sized firms have different distributions in portfolios regarding to the exploitation and exploration classifications used in this paper.

H2: *Different distributions between exploration and exploitation emerge when classifying firms based on size.*

Researching the above-mentioned hypothesis is interesting as there is not much research on what ambidexterity patterns emerge in practice and what the causes are for different patterns. Researching these hypotheses provides an interesting side effect. The data used in this research is gathered by machine learning techniques as will be explained in section 3.1. By researching these hypothesizes, data is structured and prepared for analysis such that one can identify individual innovation patterns of firms, which can be coupled back to firms to check how accurate the machine learning was and if the data corresponds with their real-life experience.

3. METHODOLOGY

3.1 Data and sample

For this research a dataset consisting out of 4689 projects that have been started in the period of 2008 till the end of 2014. This dataset has been aggregated from client data of a European consultancy firm and then classified by Roelofs last year using machine learning techniques. Roelofs found out that using the naïve Bayes (nB) classifier provided the highest accuracy when classifying the projects based on exploration/exploitation traits. The accuracy of this automatic classifying was 82%. The nB worked well mainly due to the small sample size over which the classifying was performed, as there were just 300 labelled cases. Other classifiers therefore did not perform well in the project of Roelofs, nB however has a high tolerance to noise and needs little data in order to be accurate. Rather short or ambiguous project descriptions made it more difficult to accurately classify the projects, however for exploration/exploitation it outperformed manual classification (Roelofs, 2018).

To understand better how the classifying has been performed and to be transparent about the quality of the data a detailed explanation will be given based on the work of Roelofs. He started with a raw database, consisting out of 5901 project descriptions from 440 manufacturing firms between 2008-2016. Each project description was written for a grant application and approximately 500 words long. Thus, not all projects of a firm in the period may be present, as they may not have applied for grants for every project they started. From this raw data, cases were merged that were part of long-lasting projects that were resubmitted every year. Process innovation cases were removed to ease classifying as he used different typologies not all suited for process innovation (this project will only focus on the classifying based on the exploration/exploitation typology). This resulted in 1649 remaining descriptions. Of these descriptions 300 were semi-random selected, not completely random to ensure that there were no firms overrepresented. For the exploration/exploitation the distinction was made based on whether the projects aimed for new knowledge (exploration) or build on existing knowledge (exploitation). With the sample selected 2 raters labelled the cases, each familiar with the typologies used. After labelling approximately one third of the cases they compared labels and discovered inter-rater agreement was low. They then agreed on clearer typology definitions. Resulting eventually in an agreement of 51% in the case of exploration/exploitation.

Now the part of automatic classifying using machine learning makes its appearance. The approach used was using machine learning based on Natural Language Processing (NLP). There are two prominent approaches to NLP: traditional text classification and deep learning. For the classification of this dataset traditional text classification has been used. Firstly, the data needed pre-processing. Meaning that capitals, punctuation, non-alphabetic tokens and stop words were removed, in addition all words were reduced to their word stem. The remaining word list did still contain words that are not useful for modelling, to improve classification performance and reduce training time feature selection can be used (Guyon & Elisseeff, 2003). Based on the work of de Visser et al. (2017) that feature selection on basis of information gain (Perkins, 2014) provides the best input data this was the selected method. The pre-processed data was stored in a bag-of-words depiction (set of separate words, not using word order or grammar).

Now the algorithm can be trained, in the work of Roelofs there are different algorithms tested, as previously stated the naïve Bayes proved to give the best results and there will be zoomed in on this algorithm here. The Bernoulli naïve Bayes variant was used, as this is most commonly used (McCallum & Nigam, 1998). A set of simple logistic classifiers form the naïve Bayes classifiers. The logistic classifiers try to model the distribution of data between the cases and their matching class, based on this Bayes theorem is used to calculate the probability that a set of features is part of a certain class, making it a generative model. The main assumption, over simplifying, made is that all features are statistically independent.

After training the naïve Bayes algorithm using the manually classified cases it was ran on the complete dataset consisting out of 4689 projects. Resulting in a nB classifier that classified each individual project as either explorative or exploitative. Enabling the analysis of trends within the projects. For more in-depth knowledge and background it is advised to read the work of Roelofs (2018).

To enable more detailed analysis each company in the dataset must be classified based on the NACE Rev. 2 system of the European union. This method differentiates between 21 industry sections marked by a letter see figure 2. Note that in this research the terms sector and section are used interchangeable. To enable analysis based on firm size out of the Orbis database the company size is extracted, out of the same database the NACE Rev. 2 classification is drawn.

NACE Rev. 2	
Section	**Description**
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning supply
E	Water supply, sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
I	Accommodation and food service activities
H	Transportation and storage
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U	Activities of extraterritorial organisations and bodies

Figure 2. NACE Rev. 2 section classification source: https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF

A problem occurred when searching for the data in Orbis, as for most of the companies in the database there was no data available on size or industry sector. The cause was twofold, firstly as there are a lot of firms in the database that do not produce public financial reports, secondly the firms were nicknamed in the database. This nickname was only coupled to a short name for the company that was often a generic abbreviation such as for example ABC B.V. or a very generic name as for example John Doe B.V.. This made it difficult to match those names to the correct data from a database such as Orbis. After manually checking results, it resulted eventually in 91 companies that could be classified based on their most recent company size and 106 companies that could be classified based on industry section into a total of 6 sections: C – Manufacturing, F-Construction, G- Wholesale, retail and trade, K-Financial and insurance activities, M-Professional scientific and technical activities & N-Administrative and support service activities.

Out of the 21 sections there were more than 6 that contained companies when preparing the data for analysis, however there were only 1 or 2 companies in some of those remaining sectors, therefore they were excluded from analysis, resulting in the 106 companies that could be classified in either of the six sections. As there was not enough data on the years 2008 and 2009 these were excluded from analysis, leaving the interval 2010-2014.

3.2 Variables

As previously mentioned, the two independent variables are size and industry section. In table 1 the frequency (amount of companies) per industry section and the number of projects that are undertaken in the period between 2010-2014 is displayed.

SECTION	FREQUENCY	#PROJECTS
C	36	512
F	8	65
G	13	265
K	35	373
M	8	213
N	6	97

Table 1. Frequency & total number of projects per industry section

In total there were 106 companies and 1525 projects available for analysis.

In table 2 the number of firms per size classification is displayed. With exactly the same indicators as in the previous table.

SIZE	FREQUENCY	# OF PROJECT
SMALL (<50)	14	206
MEDIUM (49<250)	41	503
LARGE (249<)	36	605

Table 2. Frequency & total number of projects per firm size

For the variable size there were 91 companies and a total of 1314 projects available for analysis.

The dependent variable will be the percentage of exploration project hours over the total project hours. So, if there is a total of 2 project hours, of which 1.5 is in exploration the dependent variable will have a score of 1.5/2= 0,75 = 75%.

3.3 Research Design

Analysis will be executed by plotting graphs that show the percentage of exploration activity expressed in man hours invested in projects relative to total innovation activity per year in between 2010 and 2014. So, if for example in 2010 the percentage is 60%, it means that 60% of total hours invested in innovation was in exploration related projects and the remaining 40% in exploitation projects. This will be done for the sample differentiated for the independent variable industry sector and for the sample differentiated based on the independent variable company size. For the total amount of projects in the database the same plot will be created as a mean division between exploration and exploitation per year. The plotting of these graphs enables visual analyses of the trend that occur for each independent variable. As the sample is too small to use statistics reliably this visual method still enables the user to spot possible trends. In addition to this analysis tables will be created that indicate the quality of the sample by showing the number of projects, hours & companies. Furthermore, the table shows the standard deviation for both the number of projects and hours per company & the mean projects and hours per company.

4. RESULTS

4.1 Results for Industry Sections

Firstly, the results of structuring the data revealed that there is a big difference between companies regarding the total hours companies and the number of projects companies contribute when analyzing hypothesis 1: *H1: In various industry sectors emerge different distributions between exploration and exploitation.* As for the number of projects the standard deviation is either almost equal to or larger than the mean projects per company (table 3). Indicating that there are some companies that contribute almost no projects and some companies dominate the sample. When looking at individual contributions this is indeed the case, as can be seen in appendix 1.

	C	F	G	K	M	N
#projects	499	43	248	362	212	86
#hours	1417580	17340	256205	415285	220833	80145
#companies	36	8	13	35	8	6
Mean projects/company	13,86	5,38	19,08	10,34	26,50	14,33
Mean hours/company	39377	2168	19708	11865	27604	13358
STD #projects	17,13	10,08	14,72	12,53	14,18	17,45
STD #hours	111410	4256	32561	25222	20920	21838

Table 3. Characteristics of each section

When then looking at the results it is clear that the trendline in figure 3 for each year is all over the place, especially compared to the total sample that is steadily around 60% exploration. The detailed table showing exact numbers and total hours of exploitation and exploration can be found in appendix 2.

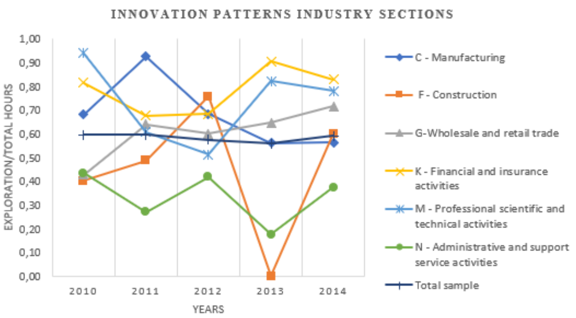


Figure 3. Exploration trendline for industry sections

The data can be made a bit more reliable by checking how many projects were classified in each year as seen in table 4. The threshold value for the year to be incorporated in the analysis was set on 20 projects. This led to exclusion of section F completely, year 2010 for section M and year 2013 and 2014 for section N.

	C	F	G	K	M	N
2010	43	18	23	29	11	15
2011	45	13	39	48	24	26
2012	112	6	67	85	58	31
2013	133	4	61	100	55	6
2014	166	2	58	100	64	8

Table 4. Number of projects per year for each section

This resulted in figure 4. That is a bit less all over the place but does not provide a clue for a clear trend for each industry section.

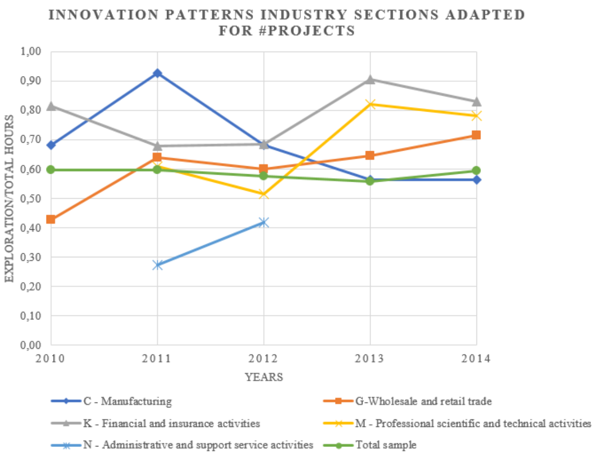


Figure 4. Cleaned exploration trendline for industry sections

Based on the dominating presence of a few firms and the absence of a clear trend H1 must be rejected. There is little evidence that there is a trend within each section.

4.2 Results for Firm Size

For H2: *Different distributions between exploration and exploitation emerge when classifying firms based on size.* The sample looked more promising as each category contains relative to the industry sections categories more firms and have more large contributors within each sample (appendix 3). Resulting in a more representative image of each category instead of images of individual firms. Still as seen in table 5 the standard deviations for both the number of projects and the number of hours is high compared to their respective means. So, it is not possible to state that the sample is representative for the total population for each respective size. The detailed table showing exact numbers and total hours of exploitation and exploration can be found in appendix 4.

	Small	Medium	Large
#projects	190	484	548
#hours	140374	429234	1600368
#companies	14	41	36
Mean projects/company	13,57	11,80	15,22
Mean hours/company	10027	10469	44455
STD #projects	15,48	14,39	17,24
STD #hours	14043	18105	112113

Table 5. Characteristics of each firm size

Plotting the graph shows however an interesting image, the trendline for each firm size seems rather constant and does not show large outliers (figure 5). Except the 2010 plot for small firms, however this is the year with the least projects and does not make the previous set threshold of at least 20 projects per year (table 6). Excluding this datapoint leaves a trendline in which medium firms score relatively high on exploration activity, large firms show a peak in 2011 and a downward trend as years progress further towards the total sample line. Small firms show equal exploration activity to that of the total sample, with an upwards outlier in 2013.

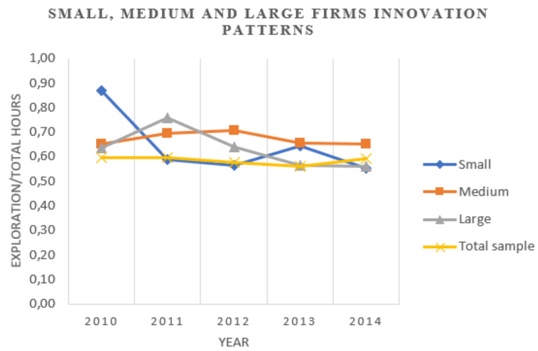


Figure 5. Exploration trendline for firm sizes

	Small	Medium	Large
2010	18	55	65
2011	28	74	75
2012	59	86	136
2013	44	118	126
2014	41	151	146

Table 6. Number of projects per year for each firm size

Although this data seems more reliable it is difficult to extract hard conclusions out of it to conclude whether the hypothesis proves to be true. However, the line that illustrates exploration activity seems to follow a clear trend. The data for especially the period 2012-2014 of medium and large firms is rather extensive. These datapoints show that medium sized firms on average show 10%. more exploration activity than large firms. Not enough to confirm H2, but interesting non the less.

5. DISCUSSION AND CONCLUSION

5.1 Implications of Results

Overall the dataset did not contain enough data and data of good enough quality to accurately make claims that truly state something about the different sized firms or industry sections. Therefore, the results should not be considered as scientifically true or representative, but as exploratory research that presents an indication about what trends are possibly present.

With that in mind looking at the results it is clear that testing H1: *In various industry sectors emerge different distributions* *between exploration and exploitation*, no evident trend per industry section can be identified. Not one of the lines representing the amount of exploration for an industry section is progressing around a clear mean. Therefore, based on this research there is no indication that industry section is a determining variable that results in specific innovation portfolio distributions to emerge.

For H2: *Different distributions between exploration and exploitation emerge when classifying firms based on size*, there is a bit more of a constant trend emerging, with small firms and large firms showing exploration activity of around 60% and medium firms around 70% (exact data is in appendix 4). Especially the results for the 2013 and 2014 that contain relatively large amounts of data for medium and large firms indicate a 10%. difference. These categories show that except for 2011 the medium sized firms score significantly higher on exploration than large firms. Small firms score around 10%. lower than the medium firms except for an outlier in the graph in 2013. So, all in all there is some indication that indeed firms of different sizes possess different exploration/exploitation distributions resulting in different innovation patterns. However, the evidence is not very convincing.

The field of ambidextrous studies however was predominantly focused on identifying optimal exploration/exploitation balances or optimal sequencing of these activities. No major contributions were made to identify why companies innovate as they do. Is for example their strategy, competitive environment, geographical location or as in this research used their firm size and industry section an interdependent variable that correlates with certain innovation patterns. This research was a first step in identifying variables that may correlate or even be the cause of ambidextrous innovation patterns. If key variables can be identified that significantly correlate with various ambidextrous approaches to innovation it can help scholars understand why firms may not be making the optimal choice and provide more understanding about why firms pursue the innovation projects that they started. Their choice may be subject to bias caused by an interdependent variable(s). If these can be identified it enables firms to overcome biases when making innovation decisions that work contra productive.

The results in this research imply that there is no indication that the industry section in which a firm is classified is a key variable that determines which ambidextrous distribution emerges. Considering firm size there is some indication that it is a variable that affects the composition of innovation portfolios, however research with higher quality and more data is needed to find out if this is true.

Analysis also incorporated the trendline of the whole dataset, interestingly enough this trendline was constant at around 60% exploration activity, indicating that in the whole sample there is a preference for performing 60% exploration activities and 40% exploitation activities. Providing some evidence that the search for trends is possible and that key determinants can be identified.

5.2 Comparing Results with Previous Research

Although previous research on ambidexterity was conducted to find out companies could optimally manage the tensions between exploration and exploitation activities, there was little research on emerging structures and distributions of exploration and exploitation. Research such as that from Jansen et al. claim that competitive sectors require more exploitative innovation and dynamic sectors require more exploitative research (Jansen et al., 2006), Chang et al. stated that the relationship between environmental forces and company performance is partially mediated by the balancing of innovation ambidexterity and numerous scholars showed that there are differences between large and small firms in innovation behavior (Choi et al., 2018; Cegarra-Navarro & Dewhurst, 2007; Jones & Macpherson, 2006; Lubatkin et al, 2006). However, although they showed differences between firms active in various sectors or from different sizes the identification of key determinants of actual emerging ambidexterity distributions in practice was not yet present. In addition, there work was survey based instead of using a database.

This research therefore can be considered as one of the first to empirically examine emerging real-world trends and the key determinants that seem to cause certain distributions.

5.3 Limitations and Further Research

There were quite some limitations to this research. Firstly, the gathering of data was difficult due to the database consisting out of short ambiguous company names or abbreviations that are difficult to match with the correct company in databases such as Orbis. Even though this was done carefully and checked manually the connection of industry sectors and firm sizes to the companies in the dataset could have contained mistakes, leading to potential biases in the research, especially if a mistake was made for a company that contributed a lot of projects to the database. In the data there were probably also numerous companies that do not publish financial statements, so even if a researcher could be sure which exact company to look for, it would be nearly impossible to gather data efficiently for the 440 companies in the dataset. A recommendation for the future construction of these databases with machine learning is to not only collect data about projects, but also gather relevant data about the firm immediately. When characteristics such as industry sector or size as used in this research, but also other variables such as turnover are known, it enables more accurate and overall better analyses. For now, this database was a good practice for machine learning techniques but did not provide a solid basis for in depth analysis of the ambidexterity concept. This lack of data made proper regression analysis difficult and resulted in unreliable results that cannot be classified as representative for the whole population.

Next the construction of the database itself cannot be considered to be a process that is 100% accurate. As the classification was first performed manually for 300 projects. This was done by 2 students separately and afterwards the inconsistencies were discussed. However, it remained a subjective process, as some projects showed both explorative and exploitative traits, projects descriptions were short or did not indicate whether the company already performed something similar. The machine learning classifier was then trained on basis of this manual process. Different classifications for the cases that were inconsistent would lead to different outcomes throughout the whole sample. The classifier itself also did not attain a 100% accuracy in classifying. Furthermore, the descriptions of projects were used for fund applications, possibly exaggerating newness of an innovation in order to gain attention for funding. Also, projects of the companies for which they did not apply for funding are not in the dataset, when companies mainly apply for funding for for example exploration projects it results in a dataset that does not provide an accurate overall overview of actual firm innovation portfolios. The classification is also binary, leaving little room for nuance, as some projects that are actually in between still get classified as either explorative or exploitative. All in all, it is questionable how reliable the project classifications can be considered.

Thirdly the sample that was used for analysis was for both industry sector and firm size dominated by some companies. To exaggerate a bit, you could say the Pareto principle held and 20% of the companies were responsible for 80% of the projects. This was not exactly the case, the point however is that this decreased representativeness. As the amount of companies was already rather limited it resulted in a comparison between individual companies instead of a comparison between representative samples for size and sectors. The sample furthermore contained only Dutch firms, making it not representative for the whole world, therefore a more balanced sample that contains data of international and firms of different origin would be required.

Fourthly the analysis assumed a direct relationship between the dependent and independent variable, excluding third variables that may have an influence. For example: centralization, company age, ownership structures, economic circumstances etc. could possibly influence innovation patterns and ambidextrous behaviors of firms. Therefore, the results may show correlation, but it is not certain whether it is actually causation between the two variables.

Fifthly the NAVE Rev 2. classification is rather broad. The sections are not a perfect classifier to determine in which industry sector a firm is active as the 21 sections are further divided into 88 divisions, 272 groups and 615 classes, implying that there are still large differences between firms in the same section. However, due to the limited data available it was not favorable to further divide the firms into divisions or even further.

For further research it is advisable to use the knowledge and experience about machine learning to create a new database. If the goal is to not only learn about machine learning but also use the data for research it is important to not only gather data about projects, but to connect as much interesting parameters to the companies as possible, making sure that the projects are clearly linked to companies. If such a database is created a researcher can do interesting research to possibly identify innovation patterns/trends and if these are emerging search for causes that create different trends. Providing more insight in ambidextrous behavior and capacities. This research provided some indication that different sized firms indeed display alternating ambidexterity patterns, which can be validated by using a larger database containing more parameters, that enables the researcher to use proper statistical techniques. Considering the machine learning part of this project the results of the data structuring in this research can be used to verify the outcomes of the machine learning classifier. By creating innovation patterns for individual firms and checking with them if it represents reality, enabling assessment of how accurate machine learning is and where it can be improved.

Further research can optimally be conducted by combining an extensive international database with metadata with either the statistical method known as ANOVA or ANCOVA if your sample size is large enough and complies to the assumptions of each test. These tests are suitable for comparing differences between groups (different sized firms for example). ANOVA can be used if the researcher does not expect the dependent variable to be influenced by covariates, which are variables that influence the dependent variable next to the interdependent variable. If the researcher expects that covariates are present an ANCOVA can be used, that takes these covariates into account. In the database a dependent variable that represents the ratio between exploration and exploitation needs to be created, as for example done in this research by expressing total explorative activity as explorative activity/total innovative activity. This can be done per year or in total. After doing so the ANOVA or ANCOVA test enables a researcher to determine whether there is a significant difference between the different exploration and exploitation balances of firms categorized based on an interdependent variable such as size. By supplementary making a trend analysis over the years as done in this research, preferably using a larger interval such as for example 2000-2020, to enable visual inspection to determine whether a clear trend or recurring patterns are actually there, a reliable result can be created to determine what variables influence differences in ambidextrous behavior.

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APPENDIX 1: TOTAL HOURS AND NUMBER OF PROJECTS PER COMPANY FOR SECTION ANALYSIS

C		
Nickname	*#Projects*	*#hours*
C182 B.V.	6	1150
C14 B.V.	6	57600
C17 B.V.	9	2080
C192 B.V.	2	1250
C137 B.V.	3	325
C434 B.V.	36	23750
C169 B.V.	4	87000
C223 B.V.	57	296171
C428 B.V.	3	256
C104 N.V.	69	624506
C49 B.V.	33	13550
C275 B.V.	2	3788
C272 B.V.	3	800
C388 B.V.	17	15600
C191 B.V.	14	10437
C137 B.V.	3	325
C262 B.V.	4	5600
C65 B.V.	13	25456
C321 B.V.	13	4194
C11 B.V.	21	60545
C117 B.V.	39	14674
C311 B.V.	3	1608
C51 B.V.	1	750
C273 BV	12	55223
C35 B.V.	8	11718
C238 B.V.	3	1170
C236 B.V.	2	370
C300 B.V.	2	1566
C421 B.V.	2	1325
C46 B.V.	4	2788
C435 B.V.	6	2000
C276 B.V.	46	71000
C315 B.V.	27	19890
C386 B.V.	2	340
C408 B.V.	1	500
C142 B.V.	36	2075

F		
Nickname	*#Projects*	*#hours*
C36 B.V.	27	12900
C364 B.V.	2	690
C444 B.V.	24	8075
C364 B.V.	2	690
C402 B.V.	2	1175
C364 B.V.	2	690
C441 B.V.	4	2200
C385 B.V.	2	1300

G		
Nickname	*#Projects*	*#hours*
C331 B.V.	27	5500
C184 B.V.	30	21040
C137 B.V.	3	325
C177 B.V.	38	8875
C49 B.V.	33	13550
C226 B.V.	11	1086
C274 B.V.	8	7875
C12 B.V.	33	128394
C147 B.V.	9	11630
C263 B.V.	5	7300
C63 B.V.	49	32480
C144 B.V.	16	20480
C33 B.V.	3	570

M		
Nickname	*#Projects*	*#hours*
C68 B.V.	36	53025
C273 BV	12	55223
C214 B.V.	10	1450
C308 B.V.	50	24710
C57 B.V.	21	7425
C281 B.V.	45	52200
C229 B.V.	22	12000
C388 B.V.	17	15600

K		
Nickname	*#Projects*	*#hours*
C273 BV	12	55223
C364 B.V.	2	690
C29 B.V.	17	1666
C262 B.V.	4	5600
C258 B.V.	1	500
C7 B.V.	2	1320
C41 B.V.	5	130
C216 N.V.	49	19314
C118 B.V.	12	11400
C117 B.V.	39	14674
C94 B.V.	7	1613
C35 B.V.	8	11718
C421 B.V.	2	1325
C93 B.V.	2	450
C16 B.V.	1	700
C247 B.V.	5	570
C38 B.V.	9	3200
C12 B.V.	33	128394
C93 B.V.	2	450
C385 B.V.	2	1300
C98 B.V.	35	60300
C225 B.V.	4	5800
C271 B.V.	1	300
C310 B.V.	21	8404
C32 B.V.	9	2120
C68 B.V.	36	53025
C17 B.V.	9	2080
C338 B.V.	2	900
C73 B.V.	2	840
C388 B.V.	17	15600
C83 B.V.	3	6800
C408 B.V.	1	500
C182 B.V.	6	1150
C145 B.V.	10	755
C131 B.V.	3	974

N		
Nickname	*#Projects*	*#hours*
C115 B.V.	3	1920
C323 B.V.	2	2860
C302 B.V.	6	510
C159 B.V.	45	41100
C41 B.V.	5	130

APPENDIX 2: OVERVIEW OF SECTION ANALYSIS

C - Manufacturing				n=	36	
Year	Exploration	Exploitation	Total	% exploration	Standard I	#project
2010	47545	22264	69809	0,68		43
2011	85584	6830	92414	0,93		45
2012	224057	104200	328257	0,68		112
2013	249094	194302	443396	0,56		133
2014	272356	211348	483704	0,56		166
Total	878636	538944	1417580	0,62	17,13	499

K - Financial and insurance activities				n=	35	
Year	Exploration	Exploitation	Total	% exploration	Standard	#project
2010	9900	2255	12155	0,81		29
2011	50593	24070	74663	0,68		48
2012	73416	34103	107519	0,68		85
2013	92013	9520	101533	0,91		100
2014	98987	20428	119415	0,83		100
Total	324909	90376	415285	0,78	12,53	362

F - Construction				n=	8	
Year	Exploration	Exploitation	Total	% exploration	Standard I	#project
2010	2650	3925	6575	0,40		18
2011	2100	2200	4300	0,49		13
2012	2500	800	3300	0,76		6
2013	0	1865	1865	0,00		4
2014	780	520	1300	0,60		2
Total	8030	9310	17340	0,46	10,08	43

M - Professional scientific and technical activit				n=	8	
Year	Exploration	Exploitation	Total	% exploration	Standard	#project
2010	17200	1100	18300	0,94		11
2011	19850	12800	32650	0,61		24
2012	26650	25275	51925	0,51		58
2013	47978	10430	58408	0,82		55
2014	46485	13065	59550	0,78		64
Total	158163	62670	220833	0,72	14,18	212

G-Wholesale and retail trade				n=	13	
Year	Exploration	Exploitation	Total	% exploration	Standard I	#project
2010	5350	7160	12510	0,43		23
2011	32683	18420	51103	0,64		39
2012	48864	32649	81513	0,60		67
2013	40132	21975	62107	0,65		61
2014	35012	13960	48972	0,71		58
Total	162041	94164	256205	0,63	14,72	248

N - Administrative and support service activiti				n=	6	
Year	Exploration	Exploitation	Total	% exploration	Standard	#project
2010	4050	5280	9330	0,43		15
2011	5510	14800	20310	0,27		26
2012	15800	22075	37875	0,42		31
2013	870	4100	4970	0,18		6
2014	2860	4800	7660	0,37		8
Total	29090	51055	80145	0,36	17,45	86

APPENDIX 3: TOTAL HOURS AND NUMBER OF PROJECTS PER COMPANY FOR SIZE ANALYSIS

Small Firms			Medium Firms			Large Firms		
Nickname	*#projects*	*#hours*	*Nickname*	*#projects*	*#hours*	*Nickname*	*#projects*	*#hours*
C258 B.V.	1	500	C364 B.V.	2	690	C182 B.V.	6	1150
C7 B.V.	2	1320	C216 N.V.	49	19314	C14 B.V.	6	57600
C177 B.V.	38	8875	C94 B.V.	7	1613	C17 B.V.	9	2080
C226 B.V.	11	1086	C137 B.V.	3	325	C192 B.V.	2	1250
C274 B.V.	8	7875	C262 B.V.	4	5600	C36 B.V.	19	9150
C35 B.V.	8	11718	C444 B.V.	24	8075	C434 B.V.	36	23750
C412 B.V.	6	430	C364 B.V.	2	690	C169 B.V.	4	87000
C147 B.V.	9	11630	C402 B.V.	2	1175	C414 B.V.	27	109900
C308 B.V.	50	24710	C11 B.V.	21	60545	C115 B.V.	3	1920
C93 B.V.	2	450	C16 B.V.	1	700	C223 B.V.	57	296171
C435 B.V.	6	2000	C214 B.V.	10	1450	C364 B.V.	2	690
C68 B.V.	36	53025	C117 B.V.	39	14674	C68 B.V.	36	53025
C315 B.V.	27	19890	C49 B.V.	33	13550	C387 B.V.	4	1121
C386 B.V.	2	340	C311 B.V.	3	1608	C137 B.V.	3	325
			C51 B.V.	1	750	C104 NV	69	624506
			C238 B.V.	3	1170	C49 B.V.	33	13550
			C236 B.V.	2	370	C29 B.V.	17	1666
			C247 B.V.	5	570	C275 B.V.	2	3788
			C159 B.V.	40	28100	C262 B.V.	4	5600
			C38 B.V.	9	3200	C41 B.V.	5	130
			C441 B.V.	4	2200	C272 B.V.	3	800
			C300 B.V.	2	1566	C273 BV	12	55223
			C421 B.V.	2	1325	C68 B.V.	36	53025
			C46 B.V.	4	2788	C388 B.V.	17	15600
			C281 B.V.	45	52200	C118 B.V.	12	11400
			C385 B.V.	2	1300	C117 B.V.	39	14674
			C98 B.V.	35	60300	C191 B.V.	14	10437
			C276 B.V.	46	71000	C35 B.V.	8	11718
			C431 B.V.	2	350	C421 B.V.	2	1325
			C32 B.V.	9	2120	C93 B.V.	2	450
			C144 B.V.	16	20480	C65 B.V.	13	25456
			C229 B.V.	22	12000	C321 B.V.	13	4194
			C307 B.V.	3	6000	C323 B.V.	2	2860
			C73 B.V.	2	840	C302 B.V.	6	510
			C33 B.V.	3	570	C12 B.V.	33	128394
			C65 B.V.	13	25456	C63 B.V.	49	32480
			C408 B.V.	1	500			
			C145 B.V.	10	755			
			C311 B.V.	3	1608			
			C145 B.V.	10	755			
			C147 B.V.	9	11630			

APPENDIX 4: OVERVIEW OF FIRM SIZE ANALYSIS

Small firms				n=	14	
Year	**Exploration**	**Exploitation**	**Total**	**% exploration**	**Standard D**	**#projects**
2010	6400	960	7360	0,87		18
2011	15460	10750	26210	0,59		28
2012	28856	22225	51081	0,56		59
2013	17988	10035	28023	0,64		44
2014	15270	12430	27700	0,55		41
Total	83974	56400	140374	0,60	15,48	190

Medium firms				n=	41	
Year	**Exploration**	**Exploitation**	**Total**	**% exploration**	**Standard D**	**#projects**
2010	23325	12525	35850	0,65		55
2011	53650	23750	77400	0,69		74
2012	65124	27055	92179	0,71		86
2013	69043	36376	105419	0,65		118
2014	77168	41218	118386	0,65		151
Total	288310	140924	429234	0,67	14,39	484

Large firms				n=	36	
Year	**Exploration**	**Exploitation**	**Total**	**% exploration**	**Standard D**	**#projects**
2010	51145	32294	83439	0,61		65
2011	99877	48180	148057	0,67		75
2012	247195	152924	400119	0,62		136
2013	259083	211789	470872	0,55		126
2014	284458	213423	497881	0,57		146
Total	941758	658610	1600368	0,59	17,24	548