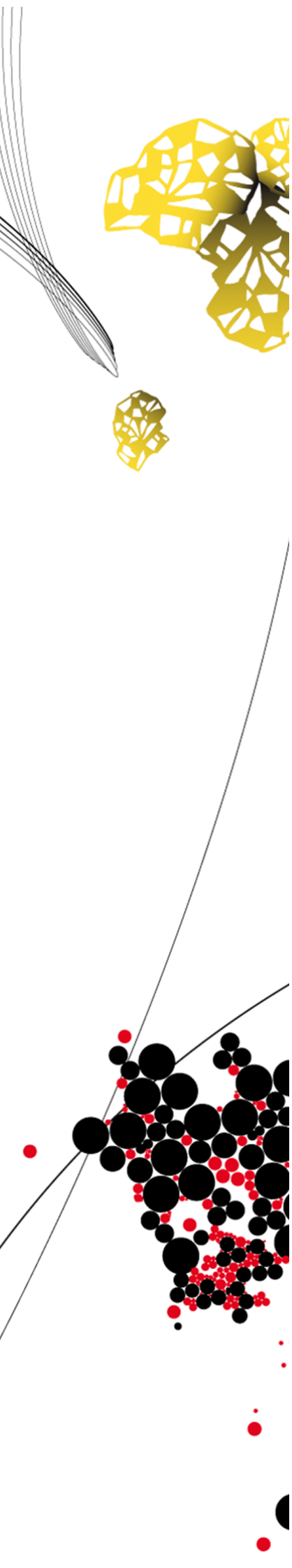

UNIVERSITY OF TWENTE.

Faculty of Behavioural, Management and Social Sciences

Dynamic ambidexterity: implications of balancing exploration and exploitation over time

Steffan Winkelhorst

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Study:
Master Business Administration,
Digital business

Supervisors:
Dr. M. de Visser
Dr. M.L. Ehrenhard

University of Twente
P.O. Box 217
7500 AE Enschede
The Netherlands

Abstract

This thesis investigates how SME firms allocate resources into exploration and exploitation and what effect this has on firm performance. Research showed how this can be achieved in a structural or a sequential way, whereas recently attention has shifted towards the idea that firms should dynamically balance exploration and exploitation over time. However, it remains unclear how firms should dynamically achieve a balance between exploration and exploitation. Furthermore, longitudinal research on this topic among small-medium enterprises (SME) is underrepresented. This thesis extends on current ambidexterity literature and proposes the idea that dynamically balancing exploration and exploitation is a combination of structural and sequential ambidexterity. Time-series regression analysis on a panel dataset consisting of 47 SME firms from several industries supports the idea that dynamic ambidexterity is a combination of structural and sequential ambidexterity factors. Dynamic ambidexterity describes the process of balancing exploration and exploitation innovation, whereas in contrast to other research, structural or sequential ambidexterity does not. This thesis contributes to the literature regarding ambidexterity and bridges the gap between several theories about balancing exploration and exploitation. It helps to clarify that the process of balancing exploration and exploitation consists of both structural as well as time-dependent variables and that both should be taken into account to enhance firm performance.

Contents

Chapter 1

Introduction

Organisations need to balance their exploration and exploitation innovation for short term profitability and long term survival (March, 1991). Many scholars identified this ambidextrous way of innovation as an important aspect for innovating companies, in which ambidexterity is the way companies pursue both exploration and exploitation (Benner & Tushman, 2003; A. K. Gupta et al., 2006; O'Reilly & Tushman, 2013). Others showed empirically that this ambidextrous strategy enhances firm performance (J. J. Jansen et al., 2006; Luger et al., 2018; Uotila et al., 2009; Walrave et al., 2017). Nevertheless, the question of whether companies should strive for ambidexterity in a static or dynamic way has brought some new perspectives in recent years (Luger et al., 2018; Mavroudi et al., 2020; Walrave et al., 2017). How dynamic ambidexterity should be achieved is still unclear, but research suggests that for maximum long-term performance, firms should embrace a combination of structural ambidexterity and dynamically adapt their ambidexterity balance to changing environmental conditions (Luger et al., 2018). Also, most researchers showed the interaction within the research based on large companies, whereas small-medium enterprises (SME's) are underexposed within this field. Therefore, this thesis investigates how SME firms should balance exploration and exploitation in order to enhance firm performance.

The exploration and exploitation literature was introduced by March (1991) and since then a lot of research has been published about this topic. The topic describes the tension between exploration and exploitation and the mutual learning process due to this tension. According to March (1991, p. 85): "the essence of exploitation is the refinement and extension of existing competences, technologies, and paradigms. Its returns are positive, proximate, and predictable. Whereas the essence of exploration is experimentation with new alternatives. Its returns are uncertain, distant, and often negative. The time and uncertainty it takes for exploration to realise a return is generally larger compared to exploitation." Researchers accepted this fundamental meaning of exploration and exploitation A. K. Gupta et al. (2006).

But how can businesses be successful and stay profitable? Firms should be ambidextrous (Tushman & O'Reilly, 1996). They need to build organisations which can

deal with current customer demand and new future customer demands. Exploitation innovation enhances short-term profitability but simultaneously dampens exploration (Benner & Tushman, 2003). Ambidextrous firms have the internal structures to be able to both explore and exploit within a single organisation.

The last two decades showed a wide variety of research on the topic of exploration and exploitation and ambidexterity. The research divides up into three main categories (O. V. Bernal & Toro-Jaramilo, 2019). First, research focusing on the cultural aspects of companies and on how companies address the issues related to these tensions. Secondly, research that aims at the structural aspects of ambidexterity in a company. In what way companies design their internal structures to facilitate both exploration and exploitation. Thirdly, research that focuses on the strategic choices concerning exploration and exploitation. This thesis will fall into this last category. Furthermore, people look at the ambidexterity perspective in an environmental context (Vrontis et al., 2017), organisational context (O'Reilly & Tushman, 2013) and at the individual context (Mom et al., 2009). Consequently, the topic of ambidexterity is complex.

While most studies showed that ambidexterity enhances firm performance, the ongoing debate whether this should be achieved statically or dynamically is not yet fully developed. A. K. Gupta et al. (2006) already identified several dilemma's in the ambidexterity theory in which the punctuated equilibrium versus static ambidexterity is one of them. Most researchers investigated the static ambidexterity theory where firms need to balance exploration and exploitation continuously (Belderbos et al., 2010; He & Wong, 2004; McDermott & Prajogo, 2012; Uotila et al., 2009). The punctuated equilibrium theory, or also referred to as vacillation (Boumgarden et al., 2012) or sequential ambidexterity (Venkatraman et al., 2007), is underdeveloped in comparison to the static ambidexterity theory. Punctuated equilibrium describes the process of balancing exploration and exploitation over time (Boumgarden et al., 2012; Venkatraman et al., 2007). Periods of exploration follow periods of exploitation and vice versa and if firms should alternate exploration and exploitation via a discontinuous jump or gradually (Kang & Kim, 2019). Boumgarden et al. (2012) compared vacillation and static ambidexterity and found both to be a viable option for long term performance.

These two theories come together in the dynamic ambidexterity theory. Recently researchers showed the dynamic process of ambidexterity (Chen & Ibhagui, 2019; Luger et al., 2018; Walrave et al., 2017) and the effect on firm performance. The environmental context changes the optimal balance of ambidexterity. They showed that ambidexterity is affected by environmental conditions and that the optimal diversification changes over time. Furthermore, they argued that dynamic ambidexterity is a combination of structural capabilities as well as shifting capabilities (Luger et al., 2018). Thus, research shows that balancing exploration and exploitation is a dynamic process

rather than a static one and that this is probably a combination of static ambidexterity and vacillation. However empirical evidence of continuous dynamic ambidexterity is not found.

The reason why the static versus dynamic ambidexterity theory is not fully developed is the differences in research design. A lot of researchers showed the ambidexterity theory via questionnaires. These questionnaires were designed to measure how important it is for firms to carry out innovation projects on developing products for new markets domains or to improve existing product market efficiency (He & Wong, 2004). Also questions regarding the process in developing current products and services as well as to what extend and how firms approach new products and services are part of these questionnaires (J. J. Jansen et al., 2006). Longitudinal studies are rare and the first innovative study design came from Uotila et al. (2009). However, time is an important factor to measure dynamic ambidexterity in relation to firm performance. Gathering data from a large group of companies over a period can be difficult. Also collecting data about innovation portfolios of companies can be a difficult process. The method designed by Uotila et al. (2009) is one of the only standardized approaches to collect exploration and exploitation innovation data of companies (Walrave et al., 2017). This might be one of the reasons why vacillation is not researched as often.

Furthermore, researchers suggest extending the ambidexterity research to SME companies (Uotila et al., 2009; Walrave et al., 2017). Those companies represent a small portion of the research, whereas most of those are investigated with a survey study (Lubatkin et al., 2006; McDermott & Prajogo, 2012). Although the scientific value of those studies is backed up, no hard financial data is used. Empirical evidence among SME companies in which studies use accounting measures is not found.

This thesis tries to give more insight into the ambidexterity theory within SME companies and elaborates on the ongoing debate regarding dynamic, static and sequential ambidexterity. Therefore, I would like to know if the structural and sequential (vacillation) ambidexterity theory also applies to SME companies. I will come up with a measurement model for measuring both structural as well as sequential ambidexterity and combine these into a model which measures dynamic ambidexterity.

The findings of this thesis will contribute to the ambidexterity literature and tries to bridge the gap between the theory regarding structural, sequential and dynamic ambidexterity. Researchers saw structural and sequential ambidexterity as two different modes of balancing exploration and exploitation (A. K. Gupta et al., 2006). However, researchers doubted this separation and suggested that the best mode is a combination of structural and sequential factors which is dynamic ambidexterity (Luger et al., 2018; Walrave et al., 2017). This thesis contributes to the dynamic ambidexterity theory and empirically shows that the optimal balance of exploration and exploitation is indeed a

combination of both structural and sequential ambidexterity. This was not done before and therefore this thesis links the three different modes of ambidexterity together and favours dynamic ambidexterity as the most optimal one.

Furthermore, this thesis can give practical guidelines to managers. It shows the complexity and contradictions they encounter when making decisions about what innovation type to follow. What the effect of a more structural focus versus a more sequential focus is. Therefore, this thesis can help managers in making better decisions in allocating resources to the different projects firms execute.

In the next section, a theoretical background on the topic is shown. The development of the hypothesis is followed, which is about the combination of structural and sequential ambidexterity as a way to pursue dynamic ambidexterity. A description of the methodology and the sample is showed, followed by the results of the time series regression analysis. In the last part, a discussion of the results is presented including the limitations and possible future research directions and summed up by the conclusion.

Chapter 2

Theoretical background

The exploration and exploitation literature was introduced by March (1991) and since then a lot of research has been published about this topic. The topic describes the tension between exploration and exploitation and the mutual learning process due to this tension. According to March (1991, p. 85): "the essence of exploitation is the refinement and extension of existing competences, technologies, and paradigms. Its returns are positive, proximate, and predictable. Whereas the essence of exploration is experimentation with new alternative. Its returns are uncertain, distant, and often negative. The time and uncertainty it takes for exploration to realise a return is generally larger compared to exploitation."

To achieve short term profitability and maintain long term sustainability companies need to balance exploration and exploitation innovation. Too much exploitation leads to the so-called 'success trap', when firms have a profitable short term period, but lack new technology to stay profitable in the long run (A. K. Gupta et al., 2006; Junni et al., 2013). On the other hand, when firms only explore, they can fall into the 'failure trap' (A. K. Gupta et al., 2006). This happens when the exploration innovation cannot generate enough profit to keep the company alive in the short run. The distant returns of the exploration innovation showed not enough return to keep the company alive (Junni et al., 2013). Hence firms should balance their exploration and exploitation innovation.

The process of balancing exploration and exploitation is also called ambidexterity. Tushman and O'Reilly (1996) introduced the concept concerning the innovation theory. Ambidextrous firms are able to both explore and exploit simultaneously (O'Reilly & Tushman, 2013). They need to build organisations that can deal with the current customer demand and new future customer demand. Researchers described the process of ambidexterity also in relation to the absorptive capacity theory (J. J. P. Jansen et al., 2005), the dynamic capabilities theory (P. Bernal et al., 2019; O'Reilly & Tushman, 2008, 2013) and the organizational learning theory (O'Reilly & Tushman, 2013). In the context of the dynamic capabilities theory, "organizational ambidexterity is reflected in a complex set of decisions and routines that enable the organization to sense and seize new opportunities through the reallocation of organizational assets (O'Reilly &

Tushman, 2013, p. 11)." The hard part with ambidexterity is that exploitation innovation enhances short term profitability, but simultaneously dampen exploration. Therefore, successful ambidextrous firms have the internal structures to be able to both explore and exploit within a single organisation (Benner & Tushman, 2003).

Empirical research showed that this theory indeed leads to better firm performance. It is positively associated with sales growth (He & Wong, 2004; Venkatraman et al., 2007), market valuation (Uotila et al., 2009), new product development (Wei et al., 2014), firm survival and longevity (A. Gupta, 2019; Kim & Huh, 2013). These relationships are found at the individual level, project level, business unit level and the organisational level (Birkinshaw & Gupta, 2013). However, some researchers found no evidence for the positive effect ambidexterity has on performance (Vrontis et al., 2017). Only when firms accumulated external sources of knowledge, ambidexterity indirectly enhanced firm performance. Furthermore, researchers also found that specialisation on either exploration or exploitation showed a stronger performance effect than ambidexterity (Mathias, 2014). Solís-Molina et al. (2018) extended this view and stated that ambidexterity works the best with high levels of absorptive capacity and where specialization works the best at low levels of absorptive capacity. Thus, research showed that ambidexterity has a positive effect on firm performance, but there is no one best mode found yet.

From the beginning on, different modes of ambidexterity were identified. All of them pursuing the same goal, balancing exploration and exploitation within a firm. March (1991) already stated that balancing exploration and exploitation innovation is about the mutual learning effect. Researchers identified sequential ambidexterity, structural ambidexterity and contextual ambidexterity as three modes to achieve a balance between exploration and exploitation (Gibson & Birkinshaw, 2004; A. K. Gupta et al., 2006; O'Reilly & Tushman, 2013). Here, sequential ambidexterity is the process of cycling between temporally periods of exploration and exploitation over time (Venkatraman et al., 2007). Other researchers also called this process punctuated equilibrium or vacillation (Boumgarden et al., 2012; A. K. Gupta et al., 2006). Early on researchers mentioned sequential ambidexterity as another approach referring to the long term transitions firms made (Boumgarden et al., 2012; O'Reilly & Tushman, 2013). However, researchers doubted if this is really sequential ambidexterity. Following this logic, sequential ambidexterity was researched more often into a shorter time span. In today's world, it is not reasonable to use the long term cycling as sequential ambidexterity, but rather the short term periods. This is especially the case in fast-moving industries (Mudambi & Swift, 2011). Structural ambidexterity is the process in which exploration and exploitation are always balanced through time. It is the firms' ability to simultaneously

explore and exploit (Raisch et al., 2009). Others also called this process simultaneous ambidexterity (O'Reilly & Tushman, 2008). Contextual ambidexterity, on the other hand, is the balancing process at the individual level (Gibson & Birkinshaw, 2004). This is subtly different from structural and sequential ambidexterity. These two concepts focus more on structurally balancing exploration and exploitation within the organization, whereas contextual ambidexterity is within the context of individuals in an organization (O'Reilly & Tushman, 2013). However, research suggests that firms adopt ambidexterity mostly on the corporate and business unit level of analysis (O'Reilly & Tushman, 2008). Still, contextual ambidexterity can coexist within a structural or sequential ambidextrous environment. Therefore, Kauppila (2010) argued that firms are more likely to create ambidexterity through a combination of structural and contextual ambidexterity. Hence structural, sequential and contextual ambidexterity formed the basis for the majority of the research in the direction of ambidexterity.

These theoretical foundations are strong but tend to describe only a limited part of the process of ambidexterity. Kim and Huh (2013) mentioned firms typically pursue a static balance as well as a dynamic balance between exploration and exploitation. This idea is further backed up empirically by Walrave et al. (2017) and Luger et al. (2018), where the ideal balance of exploration and exploitation depends on environmental conditions and changes over time. Alos-Simo et al. (2020) suggest that firms should adapt their ambidexterity balance after markets permit them to change products. In the internal context, eco-innovative firms perform better when they maintain a balance of exploration and exploitation, but at the same time also tend towards dynamic movements. Those firms explore new products and modify their routines. Then they give themselves time to adjust to those new routines through exploiting until they introduce a new product again (Alos-Simo et al., 2020). The slow transition from a more exploration dominant to exploitation dominant and vice versa showed to be better in comparison to a radical shift from one mode to the other (Kang & Kim, 2019). This means that there is a balance between exploration and exploitation continuously, but this balance shifts in a sequential fashion. Therefore Luger et al. (2018, p. 466) redefined ambidexterity as "the ability to dynamically balance exploration and exploitation." It is the combination of capability-building processes and capability-shifting processes (Luger et al., 2018). According to Chen (2017) dynamic ambidexterity is achieved by structural ambidexterity at the corporate level, contextual ambidexterity at the business-unit level, and sequential ambidexterity at the project level. However, it is unclear what the effect will be on firms as a whole.

For the rest of this thesis, I use the description of Luger et al. (2018) as dynamic ambidexterity. I look at the dynamic capabilities theory and therefore this definition fits the best. It describes the way companies should dynamically align their resources to

enhance firm performance.

Research showed how ambidexterity is seen and that there exist different modes of ambidexterity. However, the dynamic ambidexterity theory is still underdeveloped. There exist evidence that both sequential and structural ambidexterity enhance firm performance and that the optimal balance of structural ambidexterity depends on the context and environmental conditions of the firm (Walrave et al., 2017). Dynamic ambidexterity can bridge the gap between sequential and structural ambidexterity. In the next section, I will develop hypothesis combining structural and sequential ambidexterity as a way to pursue dynamic ambidexterity. In this way, I will try to bridge the gap between the sequential and structural ambidexterity theories and explain how firms could manage innovation in a dynamic ambidextrous way.

2.1 Hypothesis

2.1.1 Structural and sequential ambidexterity

When firms develop the structures in a firm to explore new opportunities while at the same time exploit existing opportunities they are ambidextrous. This idea embraces the view of March (1991) when he developed the theory. It is important for firm to allocate resources efficiently. Following the dynamic capabilities theory firms who allocate resources more effectively perform better.

The empirical theory related to structural ambidexterity is not changed in recent periods. Several researchers found an inverted U-shape relationship between the balance of exploration and exploitation and firm performance (Peng et al., 2019; Uotila et al., 2009). A balance of exploration and exploitation enhanced firm performance more than either exploration or exploitation. This finding of Uotila et al. (2009) was backed up by Walrave et al. (2017). The balance between exploration and exploitation is determined as the amount of exploration divided by the total amount of exploration and exploitation. Furthermore, structural ambidexterity is not influenced by time and the optimal amount of structural ambidexterity stays constant over time as shown in figure 2.1a.

On the other hand, sequential ambidexterity shows somewhat different views in the literature. Boumgarden et al. (2012) stated that it is the temporally and sequentially altering between organisational structures that either promote exploration or exploitation. This altering frequency is illustrated in figure 2.1b. The period in which this happens was six years in his research. This long time frame could explain why the theory regarding sequential ambidexterity is small. Often researchers looked into either specialization or static ambidexterity and found mixed results. Perhaps this specialization could also be part of a longer-term sequential ambidexterity process.

The speed or duration of the cycling between exploration and exploitation is key in understanding the process of sequential ambidexterity. Research showed empirically that this matters. Mavroudi et al. (2020) showed that the speed of temporal cycling affects firm performance. High-speed temporal cycling decreased firm performance in general, but this changed to a positive effect in R&D intensive industries. This is in line with the findings of Mudambi and Swift (2011), where firms in fast-moving industries perform better when sequential ambidexterity was high and firms in slow-moving industries performed worse. Furthermore, high tech firms are more likely to govern the process of sequential ambidexterity (Evers & Andersson, 2019). Projects first go through the exploration phase followed by the exploitation phase where the product is commercialized. Besides, the speed of change also has an optimal middle just like in the structural ambidexterity theory. The speed has an inverted U-shape relationship between the speed of change and firm performance (Kang et al., 2017).

2.1.2 Dynamic ambidexterity

In recent years the discussion among researchers in the ambidexterity literature leaned more towards a dynamic perspective on the theory. Structural and sequential ambidexterity are rather two contradictory theories which both seem viable options for firms to balance exploration and exploitation (Uotila, 2018). It seems therefore viable that the best solution of ambidexterity lies within a combination of structural ambidexterity and sequential ambidexterity (Luger et al., 2018). Furthermore, it looks like structural ambidexterity enhances firm performance in a broader set of firms and therefore this could form the basis of dynamic ambidexterity.

The relationship between structural, sequential and dynamic ambidexterity can also be seen in a different context. The situation when these coexist alongside each other. In stable slow-moving environments where the likelihood of radical change is low, structural ambidexterity should be suitable. With a moderate probability of radical transformation, sequential ambidexterity might be the best solution and in environments where the likelihood of radical transformation is high, dynamic ambidexterity could be the best solution (Uotila, 2018). In slow-moving environments, the structural strategy will be sufficient for firms to align their innovation. However, as speed and change increases, firms need to realign their ambidextrous focus (Posen & Levinthal, 2012; Stieglitz et al., 2016). Therefore, in an increasing dynamic environment, structural ambidexterity negatively influences firm performance (Luger et al., 2018). In environmental change existing knowledge devaluates. However, this does not mean that the value diminishes. In a later stage, the knowledge gained in the past could still be valuable and therefore a

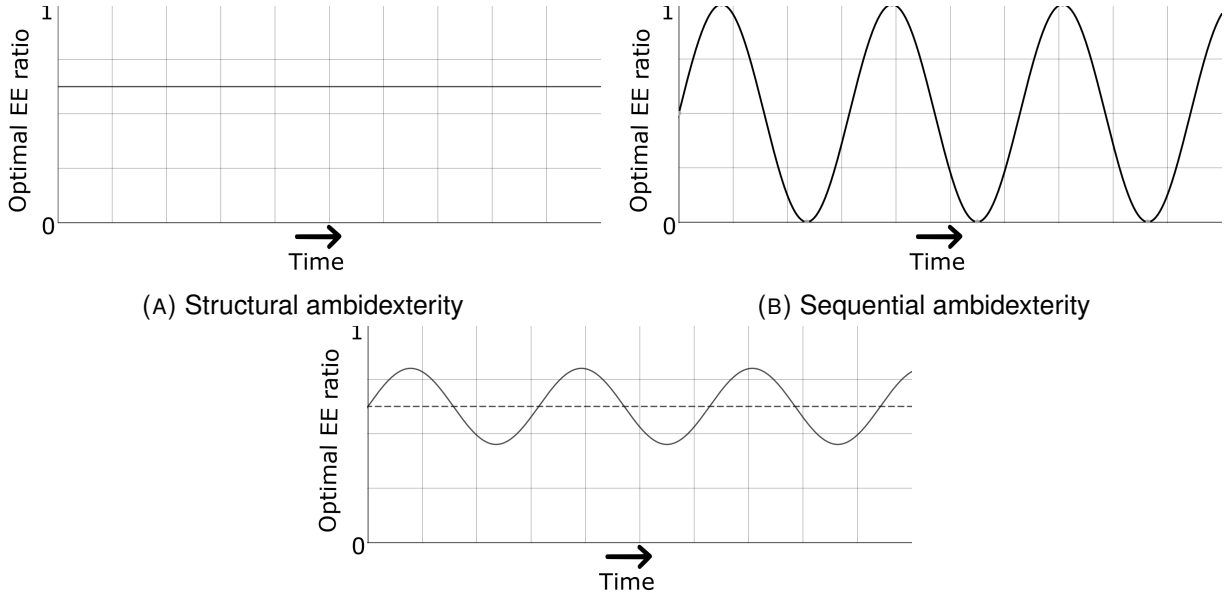
complete shift in focus might not be the best solution either (Posen & Levinthal, 2012). Hence, a dynamic ambidextrous strategy could also be a viable option.

The environmental context can be seen in relation to the speed in which they change. In slow-moving industries varying R&D investments negatively influences firm performance (Mudambi & Swift, 2011). In line with static ambidexterity theory, these firms should follow a static ambidexterity theory. When environmental conditions change drastically, the ideal balance of static ambidexterity changes. In that case, when firms do not adapt their ambidexterity balance, they perform worse than firms who adapt (Luger et al., 2018). In times of a recession, firm in fast-moving industries should lean more towards exploration and more towards exploitation in the recovery phase (Walrave et al., 2017). Therefore the industry in which firms operate matter.

The dynamic balance of ambidexterity, therefore, depends on the timing of exploration and exploitation innovation. Research suggests that firms should adapt only after the market permits them to change (Alos-Simo et al., 2020). The simulation of Fu et al. (2019) demonstrates that firms who quickly adapt to unexpected financial performance perform better over the long run. Especially in environments where firms prefer exploratory innovation. In fast-moving industries in that sense. On the other hand, radically shifting from one mode to the other has shown to negatively influence firm performance. A gradual shift towards one of the modes enhances firm performance on the other hand. This is especially the case when firms have limited resources (Kang & Kim, 2019). Therefore firms should adapt their balance accordingly.

But how exploration and exploitation enhance each others effect on firm performance could determine the dynamic ambidexterity process. Exploitation could be the leading mode of innovation and exploration moderates the effect of exploitation on firm performance (Bustinza et al., 2019). This process can also be the other way around (Chao et al., 2017; Evers & Andersson, 2019). Either way, a shift in focus could enhance firm performance (Alos-Simo et al., 2020). What is important in this case is that both exploration and exploitation have a high level of alignment in order to enhance firm performance the most (Cembrero & Sáenz, 2018). It seems therefore logical that this order of focus goes hand in hand with adapting firms ambidexterity balance.

Luger et al. (2018) showed that static ambidextrous firms are less likely to change their exploration-exploitation ratio. Furthermore, this was also the case when firms performed better. Besides, ambidextrous firms performed better in incremental environments, but when they face discontinues change in their environment, ambidexterity is no longer positively related to firm performance. Luger et al. (2018) also showed that firms who maintain high levels of ambidexterity in dynamic environments actually perform worse. So again, in dynamic environments maintaining static ambidexterity lowers firm performance. Besides this, firms who perform better and are ambidextrous change



(A) Structural ambidexterity

(B) Sequential ambidexterity

(C) Dynamic ambidexterity

FIGURE 2.1: Illustration of the three different modes of ambidexterity

their relative exploration and exploitation less. These two findings show the contradictory between structural ambidexterity and sequential ambidexterity. While both modes have a positive influence on firm performance measured separately, they show opposing forces in dynamic environments.

These opposing forces suggest that there exist an optimum in achieving structural ambidexterity and at the same time, sequential ambidexterity. Therefore dynamic ambidexterity describes the process of balancing structural and sequential ambidexterity simultaneously. I illustrated this behaviour in figure 2.1c where the dotted line represents the structural basis and the solid line shows the alternating optimum around this structural ambidexterity mean. Therefore, I hypothesize that:

Hypothesis 1. *Firms who balance their exploration and exploitation ratio like dynamic ambidexterity achieve better financial performance compared to firms who only perform sequential or structural ambidexterity.*

Chapter 3

Methodology

3.1 Sample

The main objective of this thesis is to establish a relationship between a firm's exploration and exploitation portfolio and its financial performance. Furthermore, researchers often address the lack of generalizability and the lack of research regarding SME (Luger et al., 2018; Uotila et al., 2009; Walrave et al., 2017). These two limitations in previous research is addressed with the sample selection for this thesis.

A sample originated from a non-public dataset made available for this thesis. The dataset contains hundreds of firms based in The Netherlands ranging from a lot of micro and small firms to medium-large firms and some large firms. All the firms act in a variety of industries. This enables me to further extend the research to a broader spectrum of industries in comparison to most previous research. A disadvantage of this dataset is that all firms are privately owned. Small and micro-sized firms do not have the obligation to publish an income statement in The Netherlands. These fall in this category when they meet at least two of the three criteria. Namely, if their total amount of assets is less than 6 million Euro, their net revenue is below 12 million Euro, and their total amount of employees is below 50 ("Waaruit bestaat de jaarrekening?", n.d.). Therefore those firms are excluded from the dataset as there is no accounting measure available to measure firm financial performance. This limited access to data is a disadvantage, but this is inherent with SME research. Still, measures can be constructed for these type of firms.

The sample included descriptions ranging from 2009 until 2017. Not all firms are represented in the whole time range and therefore this is seen as an unbalanced panel dataset. For every company, the total hours per exploration and exploitation type per year were derived. Furthermore, only SME companies were selected according to the standards defined by the European Commission (Bureau voor publicaties van de Europese Unie, 2015). These include companies who's number of employees is less than 250 and their total assets are less than € 43 M. This resulted in a total of 88 firms and

229 firm-year observations usable for the static ambidexterity measurements. The number of observations reduced furthermore as firms had to be present in the dataset for at least three consecutive years to measure sequential and dynamic ambidexterity. As a result, the dynamic ambidexterity measurements consisted of 64 usable observations spread over 47 firms.

3.2 Measures

3.2.1 Dependent variable

Firm performance

Researchers used several measures to determine firm performance in ambidexterity studies. Researchers often used Tobin's Q as a variable for testing firm performance as this indicates both short term and long term profitability (Uotila et al., 2009). However, this measure is only available for publicly traded firms. In my case, firms are privately owned and therefore no market valuation is available. Other researchers also used accounting measures as a dependent variable for firm performance (Chen & Ibhagui, 2019; Luger et al., 2018; Walrave et al., 2017). These are available and therefore accounting-based measures are used to determine the firm financial performance.

To determine how firms perform based on accounting measures, previous research showed several options. I use the measure of return on assets (ROA). It is similar to the measure of Walrave et al. (2017), but I measure ROA as the total assets divided by the profit/loss before tax. Normally ROA is measured using net income in the denominator, but taxes do not say anything about the firm-specific performance. Also, net income can be used as a dependent variable to test for consistency. This measure is comparable with other research and therefore I can give concluding remarks in line with other research. Others also followed this direction and used ROA as a variable as well (Chen & Ibhagui, 2019). Sales and sales growth are also measures often used (He & Wong, 2004; Mavroudi et al., 2020; Venkatraman et al., 2007), but medium-large firms publish a simplified version of their income statement and balance which do not include revenue and sales. Therefore this measure is not usable. On the other hand, ROA and net income are measures which show the firm performance and therefore these measures will enable me to determine the effect of ambidexterity on firm performance.

3.2.2 Independent variables

Exploration and Exploitation

The independent variables for this thesis are combinations of exploration and exploitation. These form the basis of either structural, sequential or dynamic ambidexterity.

Researchers used various methods to collect information about firms exploratory and exploitatory innovations. Either they determine exploration and exploitation activity based on questionnaires (He & Wong, 2004; J. J. Jansen et al., 2006; Randall et al., 2017; Shirokova et al., 2013), patents (Kang & Kim, 2019), and news articles (Luger et al., 2018; Uotila et al., 2009; Walrave et al., 2017). The news article method probably gives not enough insight into small and medium innovation activities. These firms are not actively followed by news media in comparison to large listed firms. Patents give also a limited view of the innovation activities of SME firms. Filing for patents is costly and takes a long time and the advantages do not weigh over the disadvantages. Therefore this method also gives not enough insight. Questionnairres are difficult to determine long term patterns and especially in this thesis as time is limited. To determine long term trends requires historical data which makes questionnaires unfeasible. Therefore all of these methods are not suitable.

Another method to determine exploration and exploitation among SME firms was developed previously which I use in this thesis. This method uses descriptions of innovation projects from firms to determine the amount of exploration and exploitation a firm executed in a given time frame. Furthermore, those descriptions include the amount of hours people work on those projects. This gives a rather detailed view of the number of man-hours firms put into the exploration and exploitation innovation separately. In comparison to the textual analysis of news articles, this dataset can give weight to the different innovation projects as it also includes the number of hours worked on those projects. The project descriptions are textual descriptions of those projects and are classified with a machine learning algorithm (Roelofs, n.d.). Per project, a classification of either exploration or exploitation is assigned. To determine a yearly measure, all the projects per category per company for a given year are added up. This method gives a yearly measure for exploration and exploitation per company per year.

Structural ambidexterity

Structural ambidexterity is the ability the balance of exploration and exploitation. There is no common agreement on the way they operationalise structural ambidexterity. Researchers use three different measures (Birkinshaw & Gupta, 2013). Either $(A * B)$,

$A+B$ or $|A-B|$. Where A and B represent the ratio of relative exploration and exploitation respectively. Another method is to keep exploration and exploitation as two separate measures (Birkinshaw & Gupta, 2013). In the context of the dynamic capabilities theory, I assumed that firms deliberately allocate resources. In line with the assumption of Walrave et al. (2017) I assume that the allocation of resources to either exploration or exploitation are two ends of the same continuum. Therefore I operationalise structural ambidexterity as the hours of exploration divided by the sum of exploration and exploitation hours (see table 3.1 for the calculations of the key variables). Furthermore, to measure the long term performance effect of both exploration and exploitation on firm performance, a three year moving average of the EE ratio is taken. This three year period is a standard period for measuring organizational learning and should capture the effect of both exploration and exploitation (Haunschild & Bilian, 2002; Luger et al., 2018).

Sequential ambidexterity

In contrast to structural ambidexterity, sequential ambidexterity is rather underdeveloped. There is no unified method to measure sequential ambidexterity. One measure is to determine a firms focus on either relatively more focus on exploration or exploitation (Kang et al., 2017; Kang & Kim, 2019; Mavroudi et al., 2020). Meaning when structural ambidexterity at a given time point is either higher or lower than 0.5 EE, the focus is on either exploration or exploitation respectively. The sequential ambidexterity frequency is given by the number of changes in focus and the sequential ambidexterity scale is the magnitude of change at a given time frame ($|EE_t - EE_{t-1}|$). On the other hand, researchers associate R&D expenditure volatility with sequential ambidexterity and showed that a higher volatility is associated with higher firm growth (Mudambi & Swift, 2011). So this is more related to the overall spending of firms into R&D rather than the diversification. Furthermore, Luger et al. (2018) used the change in relative exploration as a measure related to firm performance. This is in line with the measures previously discussed.

Sequential ambidexterity is seen as an alternating process and therefore this measure can only be determined during a longer time frame. Also, the two components of sequential ambidexterity should be seen as two measures. For the same reason as in the above section, a three-year moving average is taken to capture the long term performance of both frequency as well as scale (Luger et al., 2018).

Dynamic ambidexterity

As I mentioned in the hypothesis, dynamic ambidexterity is a combination of structural and sequential ambidexterity. This means that for the measurement model both are included into the equation. As I mentioned in the hypothesis, structural ambidexterity forms the basis of the dynamic ambidexterity hypothesis. In addition, the sequential dynamics form around the arithmetic mean for every firm. So this gives two options which I will include to test the hypothesis. I define sequential ambidexterity as I did before, where the frequency measure is measured as the change in focus around 0.5 EE. However, this rules out changes in focus for firms who on average tend to lean more towards exploration or exploitation respectively. Therefore a better measure, in this case, would be to define sequential ambidexterity frequency as a change in focus in comparison to the firms three-year average arithmetic mean. In this way there is no measurement bias due to the arbitrary number of ambidexterity I picked. Furthermore, research already identified that an optimal mean is not necessary at 0.5 (Uotila et al., 2009). Therefore I account sequential frequency as the number of changes around the mean of the firm. So dynamic ambidexterity will add up the mean static ambidexterity and the frequency around that mean plus the magnitude of change.

3.2.3 Control variables

To reduce possible confounding effects control variables are included in the analysis. Several firm characteristics are used to control for firm variability across the sample.

Firm size

First of all, firm size. In line with other researchers firm size is measured as the natural logarithm of total assets (Chen & Ibhagui, 2019; Walrave et al., 2017) and the natural logarithm of the number of employees (Uotila et al., 2009; Walrave et al., 2017). Firm age is also used and is the number of years since the date of incorporation in the register of the chamber of commerce (He & Wong, 2004; Walrave et al., 2017). Firm age and size are measures which influence the effect of exploration and exploitation on firm performance.

Unabsorbed slack

Others also show how the financial position of a firm has an effect on firm performance. Unabsorbed slack influences the ability of firms to leverage exploration and exploitation to enhance firm performance (X. Liu & Xie, 2014). Unabsorbed slack refers to assets which are ready-to-deploy (Lavie et al., 2010). I almost use the same definition

of unabsorbed slack as Luger et al. (2018) which is the ratio of cash and short-term investments divided by their-short term debt. However as SME firms do not mention short-term investments on their balance sheet and therefore I use the current assets instead. The ratio I use instead is therefore the current ratio, which is cash and current assets, divided by current liabilities. This measure is used to measure the liquidity of a firm and a higher ratio, therefore, indicates the amount of ready-to-deploy assets a company has.

Environmental dynamism

Environmental dynamism is a measure which determines the industry dynamics. Environmental dynamism is measured the same way Luger et al. (2018) used. This method uses a standardized measure of the volatility of the industry sales growth (Boyd, 1995). The variable is measured per industry according to the European industry classification system (NACE) industry classification system. The time frame measure for this variable is from 2008 to 2017. The first year of the dataset is the smallest and therefore a more reasonable period to include this measure is for this period. The environmental dynamism variables then aggregated to the firms using the letter variable of their firm classification according to NACE.

Firm R&D intensity

Lastly, the firms R&D intensity is an important measure to control for. Other researchers already stated the importance of the firms R&D intensity in the context of ambidexterity (Mudambi & Swift, 2011; Uotila et al., 2009; Walrave et al., 2017). Often R&D intensity is measured as the R&D expenditure divided by the sales. But again sales are reported in most SME companies. Also, R&D divided by the total assets is used (Mudambi & Swift, 2011). I operationalize R&D expenditure as the total amount of hours worked per year on both exploration and exploitation. Here I assume that all the R&D investments are included in these projects and that the number of hours worked on those projects is proportional to the total investments those companies make. Therefore R&D intensity is measured as the natural logarithm of the total project hours divided by the total assets.

3.2.4 Analysis

In short panel data analysis, the system Generalized Method of Moments (GMM) is a popular analysis method (Roodman, 2009a). This method is in line with other researchers in the field of ambidexterity (Uotila et al., 2009; Walrave et al., 2017). The GMM method estimates a system of equations in both first-differences and levels,

Measure	abbreviation	Definition	Calculation
Exploration exploitation ratio	EE	Total hours of exploration divided by the total amount of exploration and exploitation	$\frac{\text{Exploration}}{\text{Exploration + Exploitation}}$
Moving average of EE	MA EE	Three year moving average of EE	$\frac{1}{3}\sum_{t=0}^{2} EE_{-t}$
Scale of change	Scale	Three year moving average period to period change in EE ratio	$\frac{1}{3}\sum_{t=0}^{2} \lvert EE_{-t} - EE_{-t-1}\rvert$
Frequency of change	Freq	Number of changes from exploration to exploitation and vice versa around the firms three year moving average EE ratio	# of shift in focus from exploration to exploitation in last three years
Frequency around 0.5 EE	Freq Half	Frequency of change from from more explorative to exploitative and vice versa	# of shifts in focus from EE > 0.5 to EE < 0.5 and vice versa in the last three years
Return on assets	ROA	Firms earnings before interest and taxes divided by the total assets	$\frac{\text{EBIT}_t}{\text{Total Assets}_t}$
R&D Intensity	R&DIntensity	Total hours of exploration and exploitation divided by firm size	$\frac{\text{Total hours of EE}_t}{\text{Total assets}_t}$
Unabsorbed slack	CurrentRatio	Current Ratio - Liquidity ratio of a firm	Current assets divided by current liabilities
Environmental dynamism	EnvDyn	Volatility of industry sales growth	Standard error of regression slope coefficient divided by the mean value (Boyd, 1995)

TABLE 3.1: Key variables

where the instruments used in the levels equations are lagged first-differences of the series (Bond et al., 2001). The parameters are then estimated minimizing the norm of the sample averages and moment conditions. The system GMM is suitable for panel data with a small time frame and a relatively large cross-section. Furthermore it is possible to control for endogeneity and unobserved heterogeneity (Roodman, 2009a; Uotila et al., 2009). This model allows for lack of good external instruments, fixed effects and autoregression Blundell and Bond (1998), Roodman (2009a). Especially the lack of external instruments is useful as there are factors which influence the success of ambidexterity within firms, but which I am unable to include in this study.

The independent variables are measures from a three-year moving average and therefore I treat them as predetermined. This means that the moving average of the last three years from time t is compared with the dependent variable at time t as well. Note that the firms' financials of a given year are measured at the end of that year and the projects are from the three years before. The control variables are also taken at time t whereas only the industry dummies were treated as exogenous. In that sense, I measure what the effect of previous periods exploration and exploitation choices were on the financial performance at the end of that period. Roodman (2009a) recommends putting all explanatory variables into the instrument matrix. The only exception I did not put in was the environmental dynamism variable as this one did not change over time.

This introduces a lot of variables and a standard method to test for over-identification is to use the Sargan/Hansen test (Bun & Sarafidis, 2015; Roodman, 2009a). To test for the need for auto-correlation I use the Arellano-Bond test which is valid for GMM regression models (Arellano & Bond, 1991; Roodman, 2009a). These two test are the only ones used in system GMM models. These test will validate if the key independent variables are consistent in terms of their sign, effect size and significance level (Walrave et al., 2017).

Chapter 4

Results

4.1 Descriptive statistics

Table 4.1 shows the descriptive statistics of the analysis. What is interesting is that all independent variables of interest show a negative correlation with the return on assets. These include EE, frequency and scale and their quadratic measures. Furthermore significant correlations exist in comparison to the previous year's return on assets. This suggests that firms do adapt their innovation portfolio according to past performance.

4.2 Regression results

Table 4.2 shows the results of the system GMM regression analysis. The EE ratio, the frequency and the scale measures are all three-year moving averages including the year of measurement. This means that at measurement time t the moving average ranges from time t until time $t-2$. In this way, the ambidextrous strategy of a company from the past three years is compared to the performance at the end of those three years. The frequency and is measured from a firms moving average EE ratio and the scale is the average in EE ratio from period to period.

The three models analysed were the static one which measures structural ambidexterity, sequential which measures sequential ambidexterity and the dynamic model according to the developed hypothesis. The static model describes the structural ambidexterity theory and test if there an inverted U shape exist between ambidexterity and firm performance. The sequential model describes the theory of sequential ambidexterity and tests for a inverted U shape in both frequency as well as in scale. Third, the dynamic model test hypothesis 1 which measures the combination of structural and sequential ambidexterity. As illustrated in figure 2.1c, the moving average EE ratio is the baseline EE ratio shown with the dotted line and around this baseline fluctuates the real EE ratio with a magnitude and frequency. That is why the dynamic model is a

TABLE 4.1: Descriptive statistics

Variable	Mean	Sd	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.
1. ROA	0.09	0.20																
2. ROA_{t-1}	0.11	0.19	0.71^{***}															
3. EE	0.65	0.38	-0.17	-0.37^{*}														
4. EE^2	0.56	0.42	-0.09	-0.29^{*}	0.97^{***}													
5. MA EE	0.65	0.36	-0.23^{*}	-0.40^{**}	0.92^{***}	0.89^{***}												
6. MA EE^2	0.57	0.38	-0.15	-0.30^{*}	0.90^{***}	0.91^{***}	0.98^{***}											
7. Freq	1.17	1.18	-0.12	-0.24	-0.12	-0.26^{*}	-0.12	-0.27^{**}										
8. $Freq^2$	2.75	3.93	-0.03	-0.16	-0.03	-0.15	-0.03	-0.15	0.94^{***}									
9. Freq Half	0.44	0.81	-0.31^{**}	-0.46^{**}	-0.14	-0.22^{*}	-0.10	-0.20	0.40^{***}	0.27^{**}								
10. Freq $Half^2$	0.84	1.93	-0.29^{**}	-0.39^{**}	-0.11	-0.18	-0.09	-0.18	0.38^{***}	0.29^{**}	0.95^{***}							
11. Scale	0.10	0.12	-0.23^{*}	-0.34^{*}	-0.23^{*}	-0.33^{**}	-0.16	-0.28^{**}	0.64^{***}	0.50^{***}	0.74^{***}	0.66^{***}						
12. $Scale^2$	0.02	0.05	-0.20	-0.33^{*}	-0.22^{*}	-0.26^{*}	-0.08	-0.14	0.38^{***}	0.30^{**}	0.62^{***}	0.59^{***}	0.89^{***}					
13. R&D Intensity	1.12	2.88	0.21^{*}	0.33^{*}	-0.23^{*}	-0.26^{*}	-0.31^{**}	-0.31^{**}	0.22^{*}	0.21^{*}	-0.11	-0.08	0.13	0.05				
14. Current Ratio	1.12	2.88	0.27^{**}	0.26	0.16	0.19	0.16	0.20	-0.18	-0.11	-0.12	-0.09	-0.18	-0.10	-0.08			
15. Num of employees	81.56	48.83	0.01	0.15	0.01	-0.06	0.05	0.00	0.18	0.15	-0.06	-0.09	0.08	0.02	0.04	-0.13		
16 Total Assets	14252	12278	-0.01	-0.02	0.15	0.08	0.17	0.12	0.08	0.03	-0.01	-0.04	-0.02	-0.08	-0.22^{*}	0.21^{*}	0.28^{**}	
17. EnvDyn	0.01	0.004	0.47^{***}	0.54^{***}	-0.42^{***}	-0.34^{***}	-0.43^{***}	-0.35^{***}	-0.16	-0.10	-0.13	-0.11	-0.11	-0.01	0.07	0.03	0.03	-0.08

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

combination of the moving average of EE plus both the frequency and the scale. The dynamic model tests for an inverted U shape relationship in all three variables.

These models show some interesting results. First of all, the explanatory variables of the static model as well as in the sequential model showed no significant effect on the firm performance. The dynamic model shows a significant U shape relationships between the moving average EE ratio and firm performance ($p < 0.01$) and shows a significant relationship between the frequency and firm performance ($p < 0.05$). This analysis therefore shows that firm performance depends both on the EE ratio as well as the frequency of change. The optimal EE ratio depends on their average EE ratio as well as the amount of changes of focus from either more exploration to more exploitation. Figure 4.1 shows how the EE ratio and frequency both describe the return on assets for the firms in the sample according to the fixed effects in table 4.2. Although not significant, the square root of frequency was also taken into account in this figure as the $p < 0.08$ and probably would not change the sign of the variable.

What is interesting about the relationship between the moving average EE ratio and the frequency is that the most optimal solution is actually impossible to achieve. Mathematically the most optimal solution for ambidexterity would be to have a fully focused strategy on exploitation, but also change focus from relatively more exploration to exploitation orientated and vice versa a few times over the course of three years. This is impossible as when the frequency is above 0, the EE ratio cannot be 0 or 1. There should always be some kind of exploration as well as exploitation in order to achieve a frequency above 0. This suggests that there is a range of optimal frequency and EE ratio in which firms perform at best.

Hypothesis 1 stated that firms who dynamically balance their exploration and exploitation ratio achieve better performance compared to firms who only perform sequential or structural ambidexterity. The tests I ran showed that static ambidexterity alone has no significant contribution to better financial performance. The second question is whether sequential or dynamic ambidexterity describes the process better. To answer this question I also tested the frequency measured as the number of changes from more exploitative ($EE < 0.5$) to more exploitative ($EE > 0.5$) and vice versa. This test relates more to the traditional theory about sequential ambidexterity. These test (see table 4.3) show that in the sequential ambidexterity model, scale is now significant and that frequency is not. In the dynamic model, only scale was significant. The model shown in table 4.2 is the actual dynamic model from hypothesis 1 and additionally, I show that the frequency around 0.5 does not matter. Therefore, I conclude that a dynamic approach (which is a combination of structural and sequential ambidexterity factors) to balance exploration and exploitation indeed shows better financial performance than either structural or sequential ambidexterity alone.

TABLE 4.2: Regression results (Dependent variable: ROA

	Static	Sequential	Dynamic (H1)
MA EE_t	$-0.12\ (0.49)$		$-1.67\ (0.62)^{**}$
MA EE^2_t	$0.04\ (0.44)$		$1.50\ (0.57)^{**}$
$Freq_t$		$-0.01\ (0.07)$	$0.21\ (0.09)^{*}$
$Freq^2_t$		$0.00\ (0.02)$	$-0.03\ (0.02)$
$Scale_t$		$0.90\ (0.49)$	$-0.22\ (0.68)$
$Scale^2_t$		$-2.67\ (1.64)$	$0.87\ (1.82)$
ROA_{t-1}	$0.41\ (0.25)$	$0.51\ (0.12)^{***}$	$0.35\ (0.20)$
R&D $Intensity_t$	$-0.00\ (0.02)$	$-0.00\ (0.02)$	$-0.02\ (0.02)$
Current $ratio_t$	$0.02\ (0.01)$	$0.02\ (0.01)$	$0.02\ (0.01)$
log Num of $employees_t$	$0.03\ (0.06)$	$0.00\ (0.04)$	$0.10\ (0.07)$
log Total $assets_t$	$-0.02\ (0.04)$	$-0.03\ (0.05)$	$-0.01\ (0.06)$
Env dyn_t	$8.02\ (4.12)$	$9.18\ (3.12)^{**}$	$5.58\ (3.13)$
Num of firms	47	47	47
Num. obs. used	64	64	64
Sargan-Hansen Test: p (df)	$0.62\ (24)$	$0.99\ (42)$	$0.99\ (44)$
Wald χ^2 (df)	$417.37\ (8)$	$506.30\ (10)$	$343.50\ (12)$

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; One step system GMM; Time dummies used in the model

TABLE 4.3: Regression results with freq half measure (Dependent variable: ROA)

	Static	Sequential Half	Dynamic Half
MA EE_t	$-0.12\ (0.49)$		$-0.76\ (0.56)$
MA EE^2_t	$0.04\ (0.44)$		$0.64\ (0.49)$
Freq $Half_t$		$-0.17\ (0.12)$	$-0.09\ (0.11)$
Freq $Half^2_t$		$0.08\ (0.04)$	$0.03\ (0.04)$
$Scale_t$		$2.60\ (1.07)^{*}$	$1.41\ (0.70)^{*}$
$Scale^2_t$		$-8.60\ (3.81)^{*}$	$-3.34\ (2.55)$
ROA_{t-1}	$0.41\ (0.25)$	$0.42\ (0.21)$	$0.33\ (0.29)$
R&D $Intensity_t$	$-0.00\ (0.02)$	$-0.02\ (0.02)$	$-0.01\ (0.02)$
Current $ratio_t$	$0.02\ (0.01)$	$0.03\ (0.02)^{*}$	$0.02\ (0.01)$
log Num of $employees_t$	$0.03\ (0.06)$	$0.01\ (0.04)$	$0.05\ (0.07)$
log Total $assets_t$	$-0.02\ (0.04)$	$-0.06\ (0.05)$	$0.00\ (0.05)$
Env dyn_t	$8.02\ (4.12)$	$12.91\ (5.23)^{*}$	$7.84\ (3.50)^{*}$
Num of firms	47	47	47
Num. obs. used	64	64	64
Sargan-Hansen Test: p (df)	$0.62\ (24)$	$0.95\ (34)$	$0.99\ (44)$
Wald χ^2 (df)	$417.37\ (8)$	$307.02\ (10)$	$900.86\ (12)$

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; One step system GMM; Time dummies used in the model

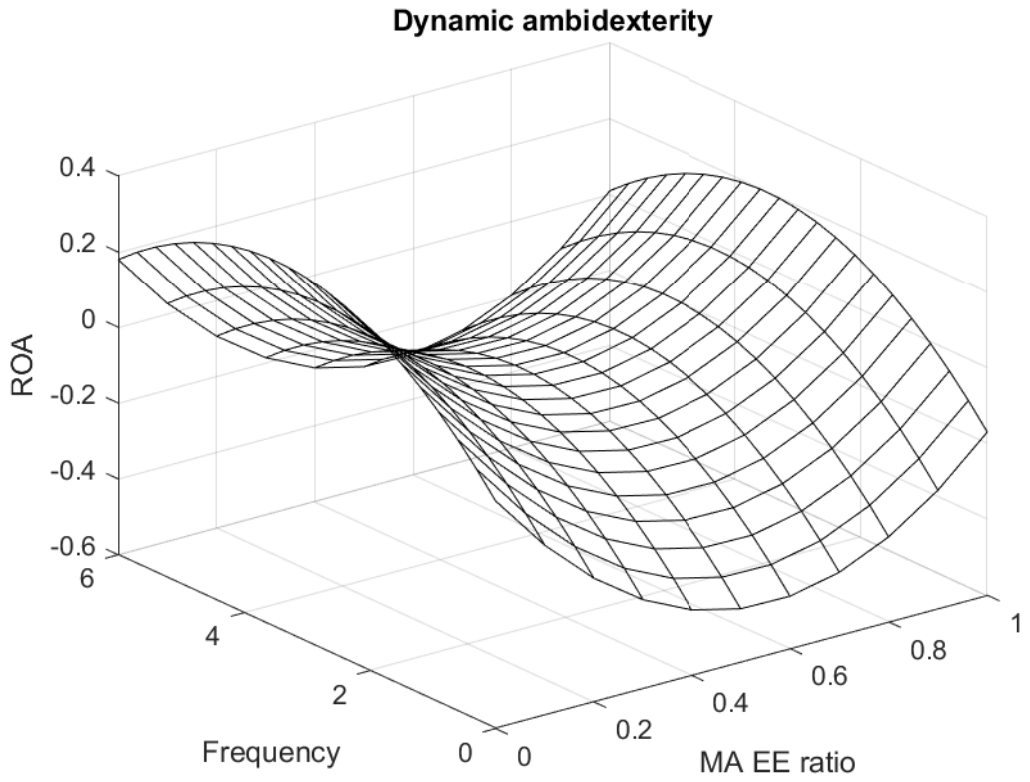


FIGURE 4.1: Dynamic ambidexterity

4.3 Robustness checks

The system GMM method is a dynamic panel data model which works best for small T and large N samples. One of the most important test regarding the robustness of the model is the Sargan Hansen test over overidentification. Too many instruments can bias the results from the GMM and therefore it is important to test for overidentification (Roodman, 2009a, 2009b). Roodman (2009a) advises to put every regressor into the instrument matrix but this lead to an overidentification problem in my measurement. With 260 instrument variables, this was much more than the number of firms (47) which resulted in a Sargan Hansen test probability of 1. A Hansen statistic of 1.000 is a telltale sign that the instrument count is too high as 1.000 is an implausible value (Roodman, 2009a, 2009b). As a robustness check, instrument variables should be reduced, which lead to p-values below 1.000. The number of instrument variables maxed to 44 in the dynamic model where I used one year lagged variables of ROA, and the linear variables of moving average EE, frequency and scale. Reducing the number of instrument variables even further reduced the Sargan Hansen p-value below 0.25, which should be seen as a concern (Roodman, 2009b). The number of instrument variables is at least smaller than the sample size, but it remains unclear to what extend my measurements

are biased. There is no practical limit what is an acceptable limit, but from theory, it is shown that for very small samples the bias rises with more instrument variables (Roodman, 2009b). Therefore some bias might be persistent within my model.

Secondly, for the same reason, I used a one-step system GMM as opposed to a two-step GMM. The number of instruments rises quadratic in a two-step GMM (Roodman, 2009b). Furthermore, the measurement design, which consisted of a three-year moving average, limited the sample size as firms needed to be present at least three consecutive years within the sample. Due to this limitation the sample size reduced to 64 observations with 47 firms. In relatively small samples the one-step System GMM is a more reliable estimator in terms of power and error type-1 (Soto, 2010) and often a one-step system GMM performs as well as a two-step GMM (Kiviet et al., 2017). Therefore a one-step system GMM model was chosen.

Chapter 5

Discussion and conclusion

5.1 Theoretical contribution

This thesis further elaborates on the perspective of dynamically balancing exploration and exploitation. It tries to extend the view that ambidexterity is 'the ability to dynamically balance exploration and exploitation (Luger et al., 2018, p. 466). Since March (1991) developed his theory about balancing exploration and exploitation research developed into two streams of balancing those two. The question whether exploration and exploitation should be balanced in a structural way (structural ambidexterity) or in a sequential way (sequential ambidexterity) was identified early on (A. K. Gupta et al., 2006). Most of the research focused on structural ambidexterity, whereas sequential ambidexterity lacked a bit in terms of attention. Uotila et al. (2009) empirically showed the validity of structural ambidexterity theory on a large sample but for sequential ambidexterity, this large sample study only came in 2017 by Kang et al. (2017). In combination with the two papers of Walrave et al. (2017) and Luger et al. (2018), I got more into the idea of a valid theory regarding dynamic ambidexterity. As a combination of both structural as well as sequential ambidexterity. Besides, empirical evidence regarding SME's only showed evidence with the use of survey analysis. Empirical longitudinal tests for SME companies could broaden the view in regards to the ambidexterity literature (Uotila et al., 2009). These two ideas formed the design and sample of this thesis.

In line with previous research I used two models measuring structural and sequential ambidexterity (Kang et al., 2017; Uotila et al., 2009) and combined these as hypothesis into a dynamic ambidexterity model. I found no significant effect on firm performance in both structural as well as the sequential ambidexterity model alone. Combining the two models into a dynamic ambidexterity model showed that both structural factors as well as sequential factors were important for explaining the firm performance. Therefore as Walrave et al. (2017) already suggested, I provide evidence that dynamic ambidexterity is a combination of structural and sequential ambidexterity.

The EE ratio and the frequency of change create a hyperbolic paraboloid shape (see figure 4.1) explaining ROA. This shape shows the counteracting forces firms need to deal with. On one hand firms need to allocate resources to projects and maintain a balance between their portfolio of projects in exploration and exploitation. On the other hand, firms need to adjust their allocation of resources according to changing market circumstances, project potential and firms financial resources. This shows the complexity of resource allocation in companies.

The dynamic model shows results that the sequential and structural ambidexterity theory are both present in the dynamic ambidexterity model. The frequency of change is important to improve financial performance. In line with the sequential ambidexterity theory, firms who do not adjust their relative focus (i.e. in comparison to a firms mean EE ratio) perform worse than firms who shift their focus sometimes (Kang et al., 2017). The structural theory on the other hand, describes that an inverted U shape exists between relative EE and firm performance (Uotila et al., 2009; Walrave et al., 2017). I found an U shape instead, but Uotila et al. (2009) mentioned that low R&D intensive firms have a U-shape curve and Walrave et al. (2017) also showed this shape when the economy is in their recovery phase. In my dataset most data points were from 2014 to 2017, which is after the European debt crisis which ended in 2013. This means that I measured the years after the recession when firms were in the recovery phase and the economy was growing. I am not sure if this is a justifying argument due to the long timeframe of the dataset, but this might explain the U-shape.

However dynamic ambidexterity is not about these two separate, but how they behave together. Structural and sequential ambidexterity are radically different mechanisms (A. K. Gupta et al., 2006), but still they show relatively similar effects on firm performance in theory. Some have argued that sequential ambidexterity enhances firm performance more than structural ambidexterity (Boumgarden et al., 2012; Venkatraman et al., 2007) and especially in high tech new ventures (Evers & Andersson, 2019). I did not find evidence for that. In all cases, my thesis suggests that the worst strategy is to be static ambidextrous and have a relative exploration and exploitation ratio around 0.5. This finding is in line with the results of Luger et al. (2018). My results show that also for SME companies staying indecisively whether to perform more exploration or exploitation focused innovation is negatively impacting firm performance.

But what is new is that this thesis shows the relatively focused strategy works the best while also shifting their focus regularly. Most of the firms who shifted their EE ratio once a year or more had their relative EE ratio lying around 0.8 and had an average change between 0.1 and 0.25. On the other hand a lot of well-performing firms only showed one single mode of innovation without any shifts in EE ratio. Overall the model suggest that a dynamic way of ambidexterity with a tendency for either exploration or

exploitation innovation with some shifts in relative focus works the best. On the other hand I cannot rule out the fact that some firms with a specialization strategy performed really good as well. This was the case for both the larger firms as well as the smaller firms and also firms with a higher R&D intensity and those with a lower R&D intensity. This shows the complexity of the topic which makes it hard to generalize the results.

To further elaborate on this finding, I did not expect that a specialization strategy could be an option to improve firm performance from a theoretical perspective. One explanation could be that these firms approach a sequential ambidexterity approach with a longer timeframe than the three years I examined in my thesis. For example, HP vacillated about every four to six years (Boumgarden et al., 2012). However, I find this explanation unlikely given the fact in the study of Kang et al. (2017) which was conducted over a much larger sample, the average shift was on average every two years. On the other hand, in 50% of the time companies with a focused strategy put resources into more than one project at the time. Voss and Voss (2013) showed how product and market innovation from the same category have complementary interaction effects on revenue in SME companies. Therefore complementary effects within the same type of innovation were possible. Moreover, Solís-Molina et al. (2018) compared a specialization strategy and an ambidexterity strategy and concluded that the role of absorptive capacity plays an important role in the performance outcomes. Where firms with low absorptive capacity perform better with a specialization strategy and firms with high levels of absorptive capacity are better off with an ambidexterity strategy. The theory regarding absorptive capacity might explain why different resource allocation strategies showed to be profitable in my thesis.

Also it is known that SME companies struggle to be ambidextrous and that attempts of firms to be ambidextrous are compromised. Internal factors including salespeople's opportunism as well as external customer attraction effect ambidextrous attempts negatively (Randall et al., 2017). But maybe this process is not as bad as originally thought and aligning innovation resources in line with internal and external parties benefits the companies.

To sum up, I think that the findings from my model should guide research more into the direction of firms' interaction between their exploration and exploitation activities and how this interaction affects successful commercialization. My results suggest that a more dominant exploitation focused mode with some variance in that EE ratio generates better financial performance. The paper of Bustinza et al. (2019) addresses the importance of the order of innovation to enhance firm performance. Exploitation followed by exploration lead to the best financial performance in their study. However, other researchers suggest the other way around (Evers & Andersson, 2019). Either way, dynamic ambidexterity shows a good way for firms to drive profitability.

5.2 Managerial implications

My thesis shows that dynamic ambidexterity (which is a combination of structural and sequential ambidexterity) significantly explains SME firm profitability. In literature, static ambidexterity has been the way to go, but research has also addressed the existence of sequential ambidexterity. This made it complicated for managers as no obvious mode existed.

Recently the ambidexterity theory shifted towards a dynamic perspective and my thesis confirms the existence of this dynamic ambidextrous view. Furthermore it can give a bit more practical guidance towards managers in contrast to other research such as Luger et al. (2018). The main takeaway for managers is that in order to be successful resources should be allocated mainly towards either exploration or exploitation and this should be kept constant over time. In addition managers should adapt their EE ratio frequently, but not too much. So over time, it is important to stay focused towards one side, but also vary a bit in EE ratio.

I can imagine that this means that projects add value to the profitability of companies, but that resource demand for projects changes over time. So shifting resources from one project to the other, or adding resources to certain projects do not harm the financials of the company. In contrast, it actually improves profitability according to my findings. Therefore investing in different types of innovation shows to be profitable, but one type of innovation should be dominant. The other type should be supportive, but managers should drive resources towards the other type of innovation when necessary. And my research furthermore showed that it does not matter if there is a large shift of resources or a small shift. As long as the average ratio is relatively focused to either exploration or exploitation.

5.3 Limitations and future research

The biggest limitation of this study comes from the data. A text classification algorithm is used to classify the projects accordingly. The long time frame could introduce some limitation regarding the quality of the algorithm. In earlier years a manual check for the algorithm was done, but the most recent years are not manually checked. Furthermore, these documents are written by people and over the course of the years, they might have adapted their writing behaviour. Furthermore, it could be possible that certain project types were included in earlier years, but were not included in later years. As these descriptions are written for a specific purpose and the rules have changed over the years. This might include some bias in the project classification and therefore can give an unreliable view of a companies project portfolio.

Another problem was the lack of available financial data. This showed to be problematic for the system GMM model. This model works better when there are a lot of firms over a small time period. Due to the limited sample size model bias could have been introduced as the number of instrument variables was close to the number of firms I investigated. I checked for this problem, but as there does not exist a general rule for this overfitting problem (Roodman, 2009b). The number of firms was larger than the maximum number of instrument variables and the results from the Sargan Hansen test showed a p-value below 1.000. Therefore I assume that my results are trustworthy.

What is inherent to the ambidexterity theory is that there exist numerous variables which influence ambidexterity and firm performance. I only looked at financial data and external variables as control variables, but researchers also showed that internal variables describe the effect of ambidexterity on firm performance. For example leadership style (L. Liu et al., 2019), strategic orientation (Barbosa Ferreira et al., 2019; Su et al., 2017) and also external knowledge sourcing (Vrontis et al., 2017). Also as I mentioned earlier, researchers could include the absorptive capacity theory into the dynamic ambidexterity theory. Both internal, as well as external measures, could generalize the theory even more, giving managers more practical guidance in developing an ambidexterity strategy. This might also explain why I found successful companies achieving a dynamic ambidexterity strategy but also companies with a specialization strategy performing just as well.

Another thing I want to point out was the significant correlation between the previous years ROA and the EE ratio. Although not investigated it could suggest that firms in my sample allocate resources as a result of last years performance. Future research could investigate how firms allocate resources according to their performance expectations. Fu et al. (2019) simulated that firms who adapt quicker in allocating resources to changing financial performance perform better over the long run. This will give an additional view of the dynamic behaviour firms carry out. This is also what is missing in literature and will transit to the dynamic ambidexterity literature.

5.4 Conclusion

Research showed that firms should adapt their exploration and exploitation ratio over time. The environment in which they act forces them to adapt this ratio which made researchers suggest that a dynamic ambidexterity approach works better for firms. On the other side, researchers also addressed sequential ambidexterity as a viable approach besides structural ambidexterity. In addition, no longitudinal evidence was provided which shows the effect of this theory on SME companies.

My thesis shows that dynamic ambidexterity can be seen as a combination of structural as well as sequential ambidexterity factors. Together they form the dynamic ambidexterity strategy, which significantly explains firm performance in SME companies. A relatively focused ambidexterity strategy with some flexibility in exploration and exploitation resource allocation showed to enhance SME firm performance over a static ambidexterity strategy. This thesis, therefore, shows the dynamic ambidexterity existence in SME companies and that strategic and sequential ambidexterity theories could be linked together. Future researchers, as well as managers, can use this thesis to bridge the gap between the conflicting ambidexterity theories and expand this idea including other factors which influence exploration and exploitation and firm performance.

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