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Can innovation be bought? – An empirical analysis of innovation acquisition effects on corporate performance

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Abbreviations

2SLS	=	Two stage least squares (estimation)
BLUE	=	Best linear unbiased estimator
CapEx	=	Capital expenditures
COVID-19	=	Coronavirus disease 2019
CV	=	Control variable
DV	=	Dependent variable
EBIT	=	Earnings before interest and taxes
FE	=	Fixed-effects (model)
FGLS	=	Feasible generalized least squares (estimation)
GEE	=	Generalized estimating equation (estimation)
GVKEY	=	Global company key
i.i.d.	=	Identically and independently distributed
IV	=	Independent variable
KPI	=	Key performance indicator
LSDV	=	Least squares dummy variables (estimation)
M&A	=	Mergers and acquisitions
OECD	=	Organization for Economic Cooperation and Development
OLS	=	Ordinary least squares (estimation)
OpEx	=	Operational expenditures
POLS	=	Pooled ordinary least square
R&D	=	Research and development
RE	=	Random-effects (model)
ROA	=	Return on assets
ROCE	=	Return on capital employed
ROS	=	Return on sales
ROE	=	Return on equity
ROI	=	Return on investment
S&P 500	=	Standard and Poor’s 500 (index)
SIC	=	Standard industry classification (code)
SUR	=	Seemingly unrelated regressions
TotEx	=	Total expenditures
UNESCO	=	United Nations Educational, Scientific and Cultural Organization
VHB	=	Verband der Hochschullehrer für Betriebswirtschaft e.V. (engl.: Association of university lecturers for business administration)
WRDS	=	Wharton Research Data Services

Abstract

Corporate innovations have long been at the center of discussions about business opportunities, investment management, and corporate as well as economic growth. Similarly, has corporate performance always been amongst the most important and frequent considerations of entrepreneurs and managers who target not only the survival but the competitiveness of their companies. However, these two aspects are rarely discussed in combination and with simultaneous regard to substantial conditions. The underlying thesis attends to this exact issue. Two overall forms of innovation are distinguished. Internal innovation refers to efforts directed towards the research and development of innovations within the company by using the company's own resources. External innovation concerns corporate activities and participation in acquisitions of other corporations. The two kinds are found to both significantly affect firms' performance and hence function as a valuable business means to improve a company's competitiveness and resistance towards unwanted and unexpected disruptions. Nonetheless, these significances and impacts of various extent are not unconditioned and unrestricted. For specific industries and under specific externally given circumstances innovation effects on corporate performance can dramatically change.

1. Introduction and relevance

1.1 Relevance of the research focus

Entrepreneurs and managers are continuously confronted with fundamental decisions about how to increase their companies' process efficiency, which markets to enter, or which products to offer. Under the term of the rationally thinking *homo economicus* the economic and business science has dedicated its efforts and thinking to the problem of efficiently using scarce resources in an entrepreneurial decision-making process for decades. A corresponding existential question of entrepreneurs and managers is often: How much money or resources should be invested in which opportunities?

This question includes the examination of how to be more *innovative* in the light of increasing competition and whether investments in that direction pay off in the sense of a *performance* increase.

Recent studies (cf. Soumitra Dutta et al., 2019, p. 4) demonstrate how countries have continuously increased *research and development* (R&D) expenditures over the past decades. Between 1996 and 2017 the gross domestic expenditure in R&D has almost doubled for high-income nations (up to 1.08bn USD in 2017)[1] and increased by a factor greater than seven (up to 598bn USD in 2017) [2] for middle- and low-income states, if including China (ibid.). China ranks amongst the countries which make up for the majority of global R&D spending. Only the United States has invested more money (543.2bn USD) than China (496.0bn USD) in 2019 (UNESCO, 2019, p. 3). Also, China and the United States account for the most valuable brands and successful companies by market cap (cf. BrandZ, 2020, p. 32; PWC, 2019, p. 19). Is R&D expenditure linked to success?

These studies are underlined by various opinions of scientists who accentuate the relevance of being an innovative company from different perspectives. Consequently, Walcher & Wöhrl (2018, p. 71) refer to innovation as "[…] one of the most important strategic and operational levers for gaining competitive advantage and generating organic growth in an unstable economic environment". Accordingly, Kaschny & Nolden (2018, p. 1) agree that innovation is first and foremost a means to make a company more **competitive**. Other authors agree to competition being one of the most important and most powerful advantages

[1] Based on a 2005 purchasing power parity
[2] Based on a 2005 purchasing power parity

of innovations (cf. Camillus, Bidanda & Mohan, 2017, p. 58; Zajac, Golden & Shortell, 1991). Howitt (2009, p. 20) even speaks of innovation as support to "[…] escape competition […]". He also emphasizes an interrelationship of competition and innovation as both would affect each other. Moreover, Walcher & Wöhrl (2018, p. 71) bring forward that there are multiple advantages which go hand in hand with successful innovation, such as an increase (and preservation) of **growth** for the company (see also Camillus, Bidanda & Mohan, 2017, p. 33) and an increase in **profitability** (see also Kaschny & Nolden, 2018, p. 2). While these represent more corporate benefits of innovation Kaschny & Nolden (2018, p. 1) combine both a corporate and a national perspective as they assign a certain national **economic significance** to innovation. They argue that it would play a significant role for countries because they depended on the competitiveness of their enterprises. Hence, innovation seems to possess an intermediary position. On top of competition and growth, there are more factors that justify the effort for further investigation, e.g. an increase in the quality of life, a higher probability of realizing a first-mover advantage, and the fact that innovation is essential to a company's future (cf. Kaschny & Nolden, 2018, p. 2; 4; 28). Kaschny & Nolden (2018, p. 57) even consider innovation as a "royal road" to achieve the above-mentioned benefits.

Additionally, it seems that *mergers & acquisitions* (**M&A) activities** play an increasing role in the business environment. "Since 2000, more than 790'000 transactions have been announced worldwide with a known value of over 57 trillion USD. In 2018, the number of deals has decreased by 8% to about 49'000 transactions, while their value has increased by 4% to 3.8 trillion USD" (imaa, 2020). Apparently, innovation and corporate acquisitions both share common goals and effects. Acquisition activity is perceived as a means for company growth as well. It is also considered a method to add **value** to the company (cf. Ransbotham & Mitra, 2010, p. 2078) and to **expand** the current product and service portfolio or to expand market-wise (cf. Renneboog & Vansteenkiste, 2019, p. 650). In alignment with these statistics, surveys demonstrate that "[…] 91.4 % of all publicly listed firms in the US engaged in at least one merger or acquisition in the 1990s and 2000s […]" (cf. Renneboog & Vansteenkiste, 2019, p. 651; Netter, Stegemoller & Wintoki, 2011).

Amongst all these studies, perceptions, and opinions, even more questions, which need to be and will be answered throughout this thesis, come up: How is innovation defined? Why do companies buy other companies? Does innovation effort and acquisition activity (significantly) affect corporate performance? How is performance defined? What implications would a possible effect of innovation effort and innovation acquisition on corporate performance have regarding a company's strategic management?

1.2 Research methodology

All these questions play an important role and lead to the overall and most important question – the research question of this thesis:

Can innovation be bought?

The way it is presented in this thesis' title, one could argue that there is already enough evidence to answer this question with a clear "yes" given the experience from numerous past M&A deals where companies bought other companies and where innovation and technology played an important role. Because of this, the thesis focus question is more to be understood in the sense of "**Should** innovation be bought?" Nonetheless, the question as it is provokes deeper thinking about the topic and therefore has been chosen as the thesis' issue.

The headline demands an investigation of whether an acquisition of another company leads to a measurable performance increase. The terms *innovation* and *performance* are intentionally left unexplained at this point and thereby the focus question is intentionally left an open question here in order to emphasize the fact that there are multiple ways and arguments to answer it and to also emphasize that this issue is often discussed on many different levels. We will find that performance is a commonly used term for describing *innovation performance, acquisition performance, financial performance,* and other such types. Although, the question still remains rather shady and needs a clear differentiation of these aspects: "Thus despite decades of research, what impacts the financial performance of firms engaging in M&A activity remains largely unexplained" (King et al., 2004, p. 198; cf. Mcnamara, Haleblian & Dykes, 2008, p. 114).

In the process of answering the focus question, we will come to a convention about necessary definitions of central concepts, derive implications from various models in the management and M&A literature. The question will eventually be narrowed down to a more precise and measurable study focus which is the interplay between innovation effort and acquisition respectively and corporate financial performance. In that, the question is sharpened to:

Is there evidence that innovation efforts and acquisitions directly or indirectly affect corporate financial performance for the better and that innovation efforts and acquisitions should be considered important tools to improve a company's competitive position?

Inspired by the work of Ransbotham & Mitra (2010) who have researched on an interplay of performance in the form of the market value of the buyer, acquisition measures such as target age, and innovation in the shape of expenditures for e.g. research and development and driven by the statistics and documentations about past acquisition waves (of which some have been recently presented) which indicate a time-invariant relevance of firm acquisitions, the author of this thesis has decided to further investigate significances and effects between the areas of performance and innovation. He has also decided to examine whether such significances and effects depend on additional environmental factors, like the competitive and industrial environment of a firm. The sections of the thesis are structured as follows:

After having revealed the relevance of the thesis' research focus in the first chapter, Chapter 2 ("Terminology") guides through central terms and establishes a **shared understanding of definitions**. These definitions are built around the three central research areas: corporate performance, corporate internal innovation effort, and corporate external innovation acquisition. This chapter's findings are based on a comprehensive screening of relevant journals[3] and other sources that are selected after a systematic search of the relevant terms. The information gathered in this chapter allows the reader to not only understand the resulting implications made at the end of this thesis but also to engage in a discussion about them.

Chapter 3 ("Innovation management theory") starts with an introduction into the theory of growth and links its historical scientific development to innovation in general, both from an economic and a business perspective. The main models of growth are followed by an introduction of strategic innovation management which deepens the view about innovation and provides more detailed insights from the business perspective. Furthermore, it provides a review, overview, and **comparison of the key perspectives, opinions, and hypotheses** from science regarding innovation management strategies in the context of a firm's performance increase. In this chapter, the study's focus is refined and own central hypotheses which build the basis for the later processed regressions and analyses are elaborated based on the before conducted literature review.

Chapter 4 ("Data & empirical methodology") begins with the introduction and review of the **data sources**. Two central databanks will be used and described in detail. As the following step, relevant measures will be worked out, i.e. allocated and calculated based on existing

[3] The main focus lies on journals with a rating of A+ according to VHB (2020) but is not solely restricted to them.

measurement history and experiences from state-of-the-art science. Next, a common ground **about econometric methods** will be developed by reviewing fundamental assumptions for the later econometric validation of our regression models. *Gauss-Markov assumptions* will be the basis for that. In doing so, the fundamentals of *cross-sectional data models, time series data models*, and *panel data models* will be presented. In alignment with these assumptions and requirements, **regression models** will be developed starting with our ***controls-only model***. These models will be based on information about US American companies that have been listed in the S&P 500 index between 2003 and 2018. To cope with Gaussian assumptions, *generalized estimating equations* (GEE), which solve multiple problems that other model types do not, are used.

Chapter 5 ("Results & discussion") presents the chosen composition and, with this included, the choice of our **final measures/variables**[4] of the regression models which will be explained in detail. Also presented are the **regression results** with the focus being the significance and effects of innovation effort and innovation acquisition variables on corporate financial performance. These include linear and non-linear relationships and interaction terms to connect these variables to other influences such as the firms' underlying industry or the observed time period. The objective of this chapter is the **alignment** of our findings with the before-presented **scientific theories and foundations**. The additional value is created with the linking of identified effects of a firm's innovation effort and acquisition activity on corporate financial performance to certain **conditions** (e.g. the mentioned relatedness to a specific industry). On top of that, a data-based discussion about the theory of innovation management and corresponding business opportunities which are substantial for the decision-making process is provided. The fifth chapter also contains an explanation of the models' restrictions and a derivation of implications which mostly originate in the nature of the processed data and unobservable influences within the business environment.

Chapter 6 ("Conclusion & outlook") summarizes the presented theories, elaborated hypotheses, discussed results and implications for managerial decision-making. It also aligns this empirical study to the current situation, **future problems**, and **research obligations** for the strategic innovation management science. This chapter proposes follow-up questions and suggests an outlook about the future development of this research area in the business context.

[4] Both terms are used interchangeably throughout the thesis.

2. Terminology

As the present thesis intends to investigate the three central research fields – innovation, acquisition, and performance – it is indispensable to come to an agreement about their meaning and definitions of related issues. With the focus of this thesis being the empirical analysis of evidential effects between these three central concepts, and in compliance with the self-set standard to provide a more fundamental and practical understanding of the concepts, the core features of these are introduced and discussed with reference to opinions from science and literature. Thereby, this thesis does not purport to provide all perspectives and characteristics of either concept but the necessary ones to enable the reader to both understand and comply with the later presented methodology and results to be able to answer this study's research question.

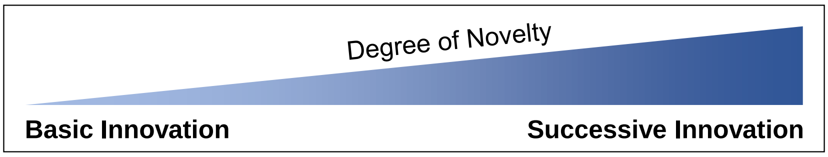
On top of that, it is the author's intention to initiate a discussion about the research topic. In order to lead such a discussion, it is indispensable to establish a common ground about fundamental definitions. The following section aims to live up to this necessity.

2.1 Definition of innovation and related concepts

Innovation

To establish a shared understanding, we begin by differentiating ***innovation*** from other terms such as *innovativeness*, *invention*, *technology*, and *knowledge*. The concept of innovation exhibits specific properties that distinguish it from other concepts. Kaschny & Nolden (2018, p. 5) present six fundamental categories of innovation. As one of those categories, they mention the "**degree of novelty**" which demonstrates a pairwise comparison of both the new and a previous, old condition (see Figure 1). From this, one could derive two kinds of innovation, the "*basic innovation*" and the "*successive innovation*" (Kaschny & Nolden, 2018, p. 8). In accordance with this distinction, White & Bruton (2011, p. 20) present four different groups resulting from the differentiation between new and old products/processes and usage/problems. It seems that newness is a central and repeatedly mentioned factor when talking about innovation. In the following, this assumption is evaluated and various comments are presented. Although, we will mostly stick to the six categories of Kaschny & Nolden (2018, p. 5).

Figure 1: Basic and successive innovation

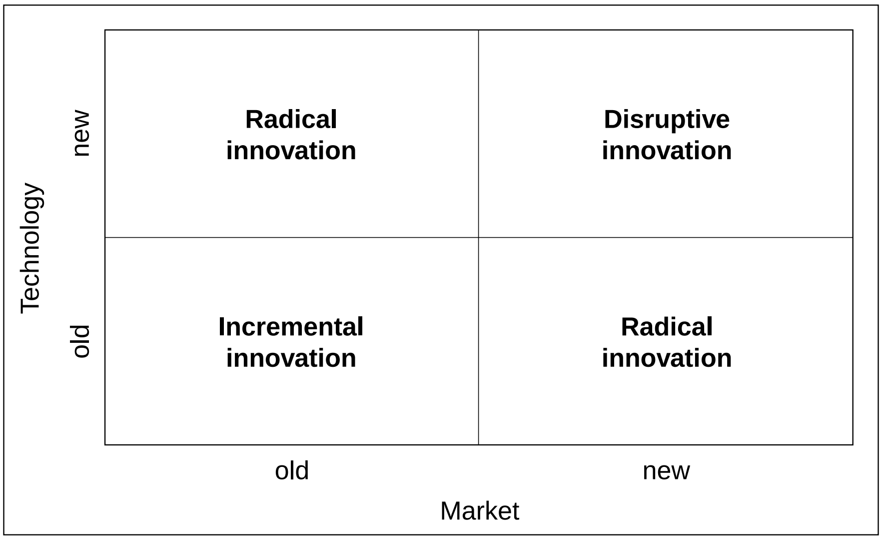


(Source: own representation)

A slightly different characteristic is described with the "**scope of change**" which, according to Kaschny & Nolden (2018, p. 9), led to other types: *incremental*, *radical*, and *disruptive innovation*. Figure 2 shows these innovation types. Swann (2019, p. 99) mentions that both incremental and radical innovation could be differentiated in that incremental innovation encouraged innovators to think "inside the box" and radical innovation to think "outside the box". This becomes clearer when looking at exemplary definitions of the two. Incremental innovation is described as an almost continuous innovation which, in comparison to the radical form, would not deliver fundamental, groundbreaking changes to the existing product or service. Instead, it provides customers with rather slight changes and the company with a continuing cash flow to finance its ongoing business as well as its expenditures to come up with new products or services which themselves represent grand changes. Radical innovations, on the other hand, could be considered "[…] an innovation with a large degree of invention […]" (Kaschny & Nolden, 2018, p. 10).

Alongside, disruptive innovations are explained as such that would cause new markets to be created. As an example to reveal the difference between radical and disruptive innovations, Kaschny & Nolden (2018, p. 10) mention Apple's iTunes, which was "itself" not a disruptive but a radical innovation. Correspondingly, Apple's iPhone can be considered a disruptive innovation because it has dramatically changed the existing cell phone market which had not solely focused on touchscreen functionality, internet connection, and an app-based user interface before. Camillus, Bidanda & Mohan (2017, p. 34; cf. C. M. Christensen, 1997, p. 10) come up with a slightly different breakdown of innovation. Thereafter, "*sustaining innovation*" was an innovation type which enhanced the existing business model and responded to the needs of existing markets. "Disruptive innovation" would not do that. Instead, disruptive innovation would create new business models and new markets.

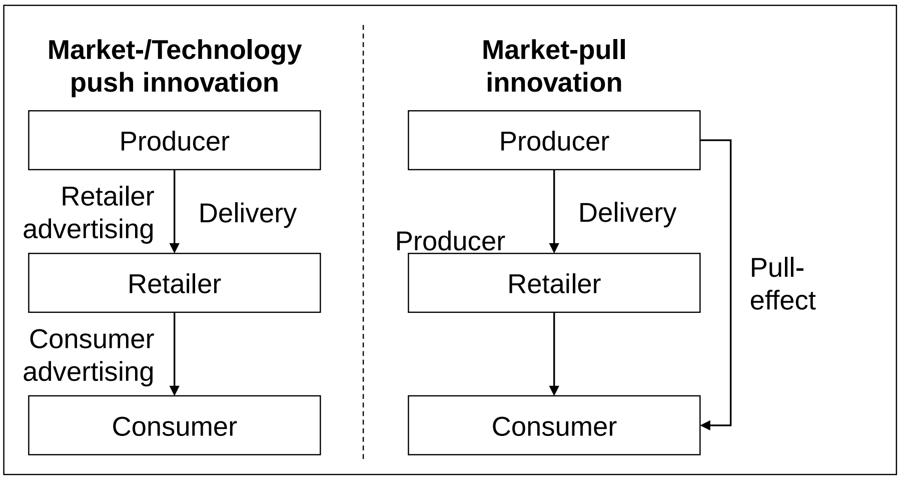
Figure 2: Incremental, radical and disruptive innovation



(Source: Kaschny & Nolden, 2018, p. 10)

The third category under which Kaschny & Nolden (2018, p. 11) highlight the extent of the concept of innovation are the so-called "**triggers**" by which they emphasize the two possible drivers of innovation – the *market push* and the *market pull*. According to them, the latter would describe the situation, when the demands of customers were so strong that the industry would see itself in need of finding satisfactory solutions fast. This drive is often enhanced when customer demands become so obvious that there is a quasi-contest developing amongst companies which aim to solve the customers' problem first and in the best possible way. An example of this is Figure 3. Often this comes along with a certain market structure, i.e. buyers' markets, where the buyers or customers with a greater bargaining power tend to create a stronger pulling force than in sellers' markets where the customers' bargaining power is limited and the markets are led by sellers due to a scarcity of demanded products or services. In the latter, the general demand predominates the supply of a certain product or service. The market-push innovation (often referred to as the *technology push*), on the other hand, is much more driven by innovations and new technologies that have been created and are pushed onto the market. These innovations would mainly originate from R&D and be derived from preliminary strategic objectives of companies than from the customer side.

Figure 3: Market-/Technology-push and market-pull innovation

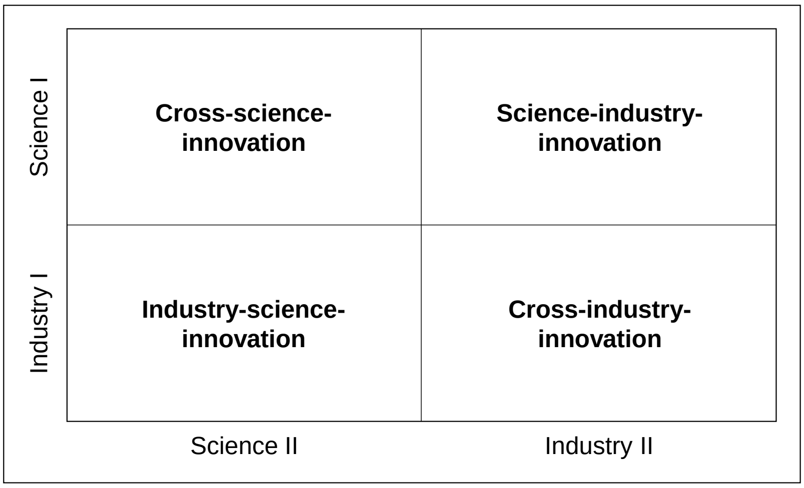


(Source: based on Martin, 1994, p. 44)

At this point, it is anticipated, that in the process of finding empirical evidence to study's focus question and other hypotheses, developed in Section 3.3, it will predominantly be referred to innovation as the kind of market push innovation. This is since market push innovations can be directly connected to financial measures and other corporate actions and can be easier measured.

Other characteristics would include the differentiation of innovation by the **source of the underlying idea**, where innovations are classified as *industrial* and *scientific innovations* (cf. Kaschny & Nolden, 2018, p. 12) (Figure 4) and by "**technical classification**" (Kaschny & Nolden, 2018, p. 13), where it is differentiated between *technical innovation*, *social innovation*, *organizational innovation* and *legal innovation*.

Figure 4: Industrial and scientific innovation



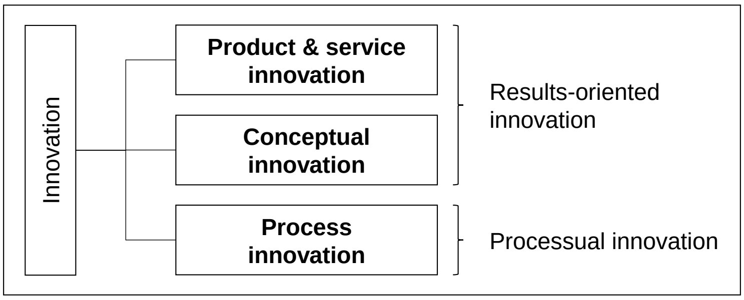
(Source: Kaschny & Nolden, 2018, p. 13)

According to Kaschny & Nolden (2018, p. 13) these innovation types are all directed onto a specific subject area. They also offer various examples such as the "[…] invention of the light bulb by Edison in 1879 […]" (ibid.) for technical innovation. However, this and other examples illustrate the mentioned types but neither do they set clear boundaries, nor do they create exhaustive definitions. Especially, the technical innovation seems to strongly overlap with *technological innovation* by which one understands the transformation of a new idea into a product or process which would, then, be used for internal or commercial purposes (cf. Kleis et al., 2012, p. 43). Shantanu Dutta & Weiss (1997, p. 344) even include the term "*innovativeness*" translating technological innovation as "[…] the extent to which a firm creates technologies which are technologically significant as the firm's level of technological innovativeness."

Regarding organizational innovation, Gault (2015, p. 9) presents a more sharpened thought by citing the OECD's definition from the 2005 Oslo Manual: "An organizational innovation is the implementation of a new organizational method in the firm's business practices, workplace organization or external relations". With this, the OECD builds upon previous understandings of the matter, such as Damanpour (1996, p. 694), Daft (1978), and Damanpour & Evan (1984, p. 393) who see organizational innovation as new ideas allocated by an organization. Also, they present an explanation of Bloch & Bugge (2013, p. 143), who bring forth that organizational innovation would be the "[…] implementation of new methods for organizing or managing work […]".

The most seen distinction of innovation types in science as well as in the business context is the one referring to so-called "**subject areas**" (Kaschny & Nolden, 2018, p. 6). Correspondingly, innovation could be divided up into *product & service innovation*, *conceptual innovation*, and *process innovation* (see Figure 5). The literature screening regarding the differentiation of the relevant terms has shown that product innovation is amongst the most discussed shapes of it. Kaschny & Nolden (2018, p. 5) refer to it as a "market-ready product". They understand innovation as a new idea introduced to the market regardless of its success (cf. Kleis et al., 2012, p. 43). The OECD (2005, p. 46) goes a step further, linking innovation to a product introduced on the market which is a new and "significantly improved" version of the old. Gault (2015, p. 12) specifies this by linking such significant improvement to the corresponding product's characteristics and intended usage. In contrast, Bloch & Bugge (2013, p. 143) only see it as a new or improved product which is introduced.

Figure 5: Product & service, conceptual and process innovation

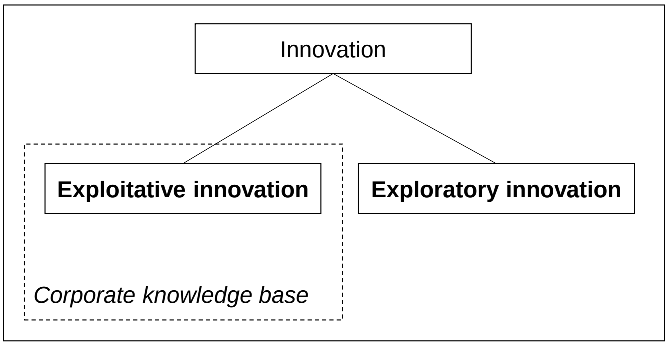


(Source: Kaschny & Nolden, 2018, p. 6)

More general definitions tend to describe innovation as the implementation of a new idea which would need to be market-ready (cf. Kaschny & Nolden, 2018, p. 5). Adams, Bessant & Phelps (2006, p. 22) emphasize that even success played an important part. According to them, innovation is the “successful exploitation of new ideas”. The question is, what is meant with “successful”. Other citations show different approaches, e.g. the one of Damanpour (1996, p. 694) who characterizes innovation as “[…] a means of changing an organization […]”. What “changing” in this context means is left unanswered as well. As Gault (2015, p. 12) points out, that all these definitions do not solve the problem of generating a clear understanding. What does introduction of innovation mean? How is significant improvement defined? These questions are left open and will be further accommodated later in this thesis.

Another possible distinction of innovation is the one between exploratory and exploitative innovation. This distinction is frequently discussed in various scientific papers. Katila & Chen (2008, p. 595) describe it as firms either introducing new products based on their existing knowledge base (exploitative innovation) or by exploring new fields apart from their existing knowledge (exploratory innovation) as shown in the following figure:

Figure 6: Exploitative and exploratory innovation



(Source: own representation)

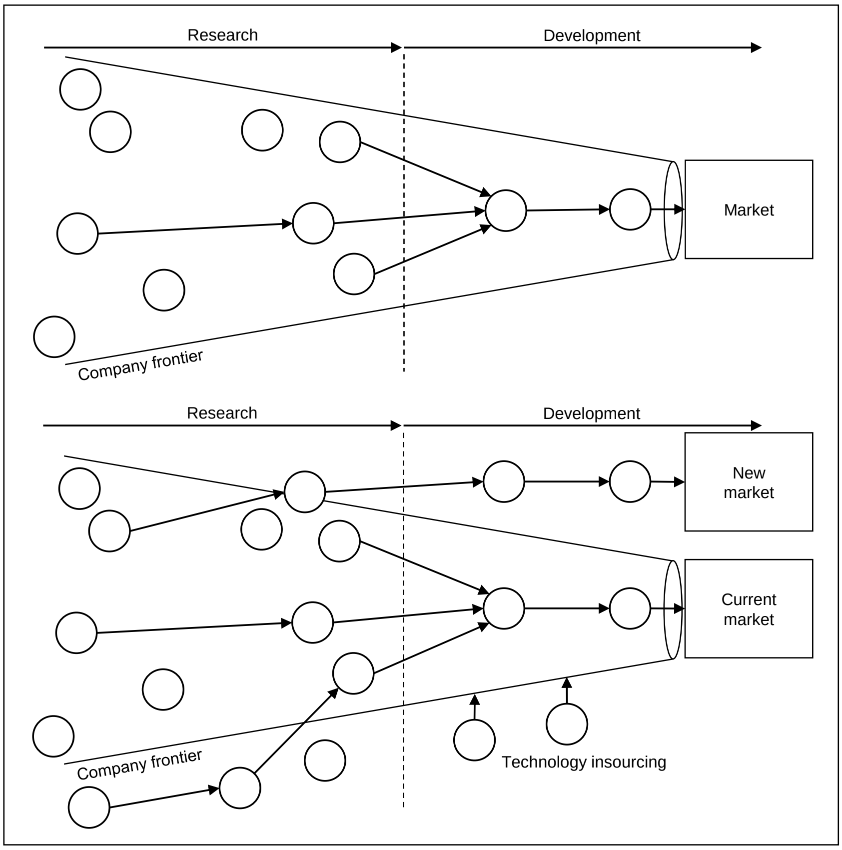
In addition to the six presented categories of innovation characteristics of Kaschny & Nolden (2011, p. 5) and to the four innovation categories after White & Bruton (2011, p. 20), Pilat et al. (2009, 92) finally present two last types: *closed* and *open innovation*. Thereafter, open innovation was not to be mixed-up with free access to knowledge or technology. Instead, open innovation is to be understood as a package of collaborative methods. In contrast, closed innovation can be considered a form lacking these exact collaborative components.

The difference between closed and open innovation is well-described by the concept of the "*closed innovation paradigm*" and "*open innovation paradigm*" by Chesbrough (2003, p. 31; 44). As can be seen in Figure 7, Chesbrough finds that open innovation is based on internal R&D efforts. His model also shows that R&D includes a sequence of the two steps, research and development, rather than working on both simultaneously. The open innovation paradigm, on the other hand, demonstrates that technologies can be sourced from outside the company frontier both in the research and in the development phase. Obviously, Chesbrough understands external technology acquisition as a source of corporate R&D support. To anticipate, closed and open innovation will be referred to as internal and external innovation throughout this thesis.

After all these views and explanations have been introduced, it becomes clear that there is a lack of common definition, understanding, and even perception of the concept innovation (cf. Edison, bin Ali & Torkar, 2013, p. 1391). This is not to be understood as a critique in general but highlights the fact that the term innovation invites to frequent use, whenever there is something new or improved to be described. But when one digs deeper into its terminology and relatedness to other concepts, one could be overwhelmed by the number of subtypes intended to combine the mentioned "newness" with something relevant to the individual examined matter. Consequently, it becomes obvious that without such fundamental understanding, the answering of the thesis' focus question becomes not only very difficult but opens doors for critique from an equally large number of perspectives.

Thus, it becomes more and more clear that multiple layers of definitions are needed, including one, which sees innovation as a general concept, on the one hand, and another which allows a deeper, more specific differentiation of innovation types, on the other hand. In the opinion of the editor, an easy-to-understand approach is to develop a top-down logic of innovation definitions where at the top there is an explanation of the general concept and its core properties shared across all sub-types and where there are very specific innovation types explained at the bottom. Figure 8 provides such logic. It also shows which of the innovation types are targeted in this study.

Figure 7: Closed and open innovation



(Source: based on Chesbrough, 2003, p. 31; 44)

All the here presented shapes have in common that there are, in fact, a few characteristics which are mentioned up throughout most literature sources, e.g. the newness and improvement to an older version or substitute, as well as its introduction to the corresponding market(s). Not only is it the objective of this thesis to present different and relevant findings on innovation management and corporate performance from scientific literature, but also to match them to the own approach and work. We define innovation (level 1 in the framework) as follows:

Definition 1: Innovation

Innovation describes all corporate activities which aim to transform ideas and information into a market-ready solution with new and improved components, functionality, and features to meet customer needs.

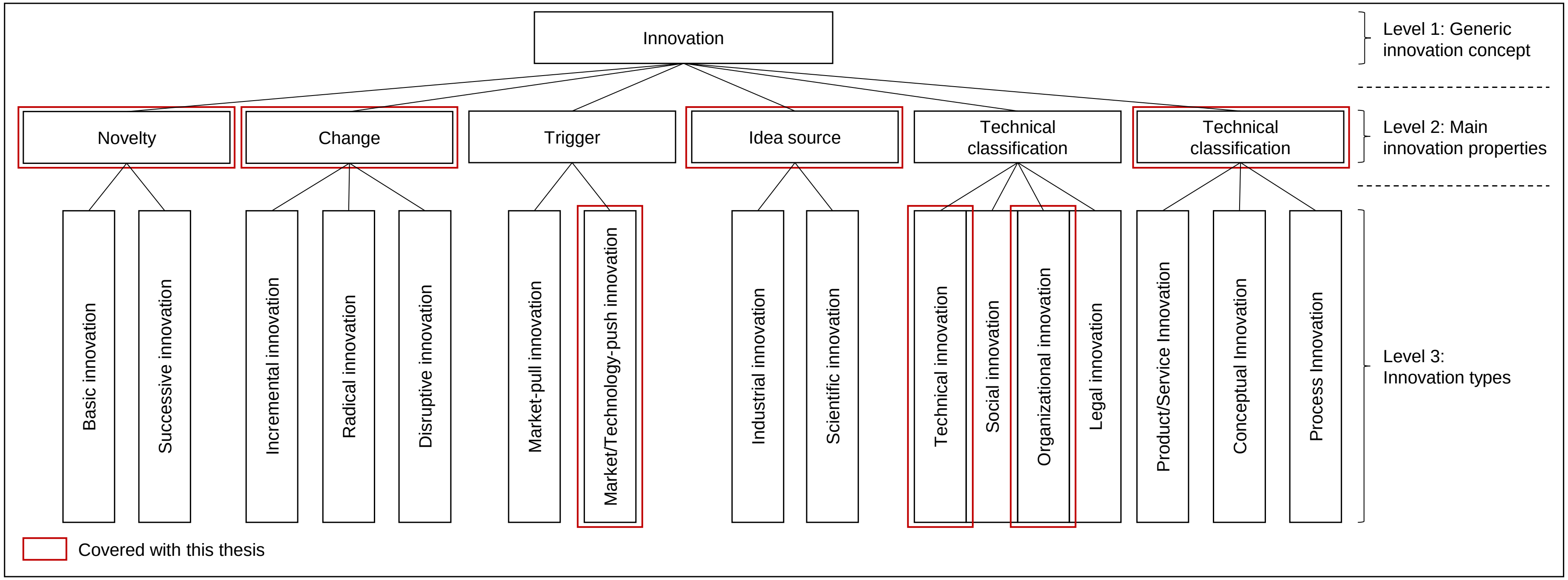
Definition 1.1: Internal innovation

Internal innovation describes all corporate activities of innovation which originate from inside a company's borders. (Internal innovation effort is used synonymously.)

Definition 1.2: External innovation

External innovation describes all corporate activities of innovation which originate from outside a company's borders. (External innovation acquisition is used synonymously.)

Figure 8: Innovation definition framework



(Source: own representation)

Innovativeness

In the process of allocating various perspectives and definitions of innovation, it has been worked out that there are multiple terms which repeatedly come up, cause mix-ups and obscure the definition of innovation. One here addressed aspect is **innovativeness**. Fang (2011, p. 159) refers to it and to *new product innovativeness* respectively, as the degree of dissimilarity between a new product and corresponding substitutes. He adds that such dissimilarity should have a certain significance to the customer. The aforementioned definition of technological innovativeness by Shantanu Dutta & Weiss (1997, p. 344) is similar to the product innovativeness as it describes an extent of something or a magnitude. This is an important factor as it closes the gap between innovation, which equals a list of certain characteristics and describes a certain condition and innovativeness which describes a continuum of a more or less satisfied feature and, with that, allows for comparison amongst peers of companies, innovations, technologies and other related aspects.

In the sense of innovativeness being the extent of dissimilarity, Gielnik et al. (2014, p. 353) value innovativeness as an important and to be pursued objective. According to them, a high degree of innovativeness led to an increased likelihood of being able to offer unique benefits to customers and of being more competitive in niche markets (see also his past references: Fiet, 2002; Gaglio & Katz, 2001; Shepherd & DeTienne, 2005, p. 92). In scientific practice, innovativeness is often perceived as efforts made towards innovation (cf. Rubera & Kirca, 2012, p. 137)

It becomes unmistakable that innovation represents an unscalable term, which can itself not be measured. Instead, it is the subject that causes certain effects. These innovation effects are what will ultimately be measured and analyzed in the upcoming regressions. However, we define innovativeness as follows:

Definition 2: Innovativeness

Innovativeness is the extent to which an innovation distinguishes from existing solutions regarding its components, functionality, and features.

Meanwhile, *innovation frequency* is a form of innovation effect and part of what will be measured in the upcoming regressions amongst other variables (compare Section 5.1.3). Illuminating the subject area of innovation from a perspective of strategic management, we are interested as to what extent managers and entrepreneurs can pilot their companies' performance by changing their efforts to be more innovating and innovative.

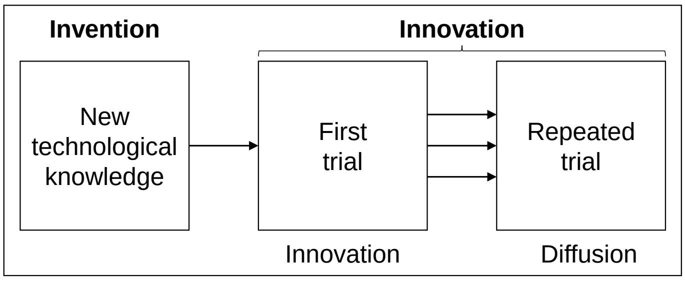
Invention and technology

Another related and frequently discussed aspect is **invention**. We remember that Kaschny & Nolden (2018, p. 10) mentioned radical innovation as having a higher degree of invention. This lets one assume that invention was a part of innovation. In fact, this is not the case. Demonstrated by the structure based on Godin (2006, p. 655) (Figure 9), invention is the preceding state of innovation. Thus, invention is the development of a new idea (concept, product, service etc.), whereas innovation describes the first use and testing of the idea on the market. Afterwards, the innovation diffuses with every repeated trial on the market. That implies that an invention has a maximum degree of novelty. We define invention accordingly:

Definition 3: Invention

Invention is the initial creation of a solution based on entirely new knowledge. It is the preceding state of innovation and the proceeding state of discovery.

Figure 9: Invention and innovation



(Source: based on Godin, 2006, p. 655)

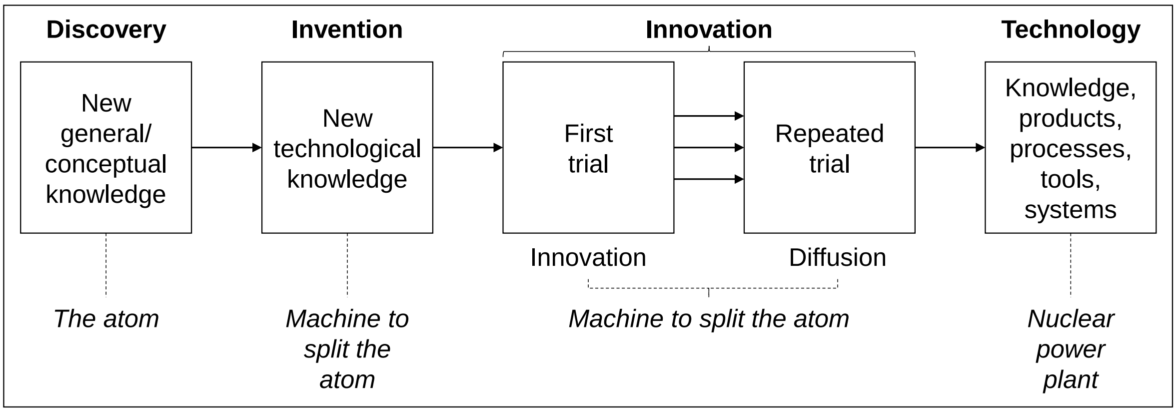
A third important term related to innovation besides innovativeness and invention is **technology**. Zhao (2009, p. 1172) draws attention to the importance of technological innovation and the effect of firm acquisitions on it. White & Bruton (2011, p. 14) emphasize the importance of technology due to its impact on the worldwide economy. This is in accordance with irregularly occurring technology shocks mentioned by Schilling (2015, p. 9–10). Such shocks would foster innovation. On the other hand, Bailetti (2012, p. 5) highlights the importance of technology in the context of entrepreneurship. Thus, "technology entrepreneurship" (ibid.) had an important role in the context of corporate growth, political-economic development and other discussions. It would be a "vehicle" that supported and strengthened the prosperity of the corresponding object, e.g. individuals, companies and countries (cf. ibid.). In the same manner Burns (2009, p. 170) refers to "technological progress" as improvements for producing, marketing and delivering products. Thereby, it was "[…] at the heart of human progress and development." Nonetheless, the question about the translation of the word technology and a generic definition remains without reply.

In the early 1990s Franklin (1990, p. 78) has described technology as the "way things are done". This is a very practical understanding of the term. As will be discussed in the context of growth theory (Section 3.1), technology is often measured by the positive growth of the efficiency factor. Arthur (2009, p. 10), instead, steers the focus in the direction of a goal-oriented definition describing technology as the "means to fulfill human purposes". As Figure 10 shows, technology ranges as the next step of the solution development process after innovation itself (compare to Figure 9). The figure shows the exemplary development from the discovery of the atom to nuclear power plants as the resulting technology. Following White & Bruton (2011, p. 15) we define technology as follow:

Definition 4: Technology

Technology is the package of knowledge, products, processes, tools, and systems that companies and individuals use to create solutions, in order to preserve or improve their competitive position and to fulfill a specific purpose as efficiently as possible.

Figure 10: Solution development process



(Source: based on White & Bruton, 2011, p. 14)

2.2 Definition of performance

At the beginning of this thesis is has been discussed that entrepreneurs and managers are constantly facing the challenge of making decisions, which in the end should lead to a **performance** increase. But what is meant by performance? Before defining the concept for the here-presented purposes, it is made clear at this point, that throughout this study, performance is always understood and referred to as some form of corporate performance. Consequently, that rules out all other forms of individual or national-economic performance.

Literature provides various perspectives that seemingly depend on which argument or view is presented. As is the case with the term innovation, the screened literature lacks a clear and generic definition of the term performance as well. From reviewing various sources and in the context of this thesis, it becomes clear that performance is associated with three basic terms: *innovation performance* (cf. X. Liu, 2010; J. Liu, 2011), *acquisition performance* (cf. Mcnamara, Haleblian & Dykes, 2008), and *financial performance* (cf. King et al., 2004). The latter is the most common performance association and represents the most shared view amongst researched papers. This is because a firm's main objective lies within the pursued improvement of its financial metrics and *key performance indicators* (KPIs) as these describe and determine the ability to pay employees, make necessary investments and thereby increase market shares. Eventually, this accounts for becoming more and more competitive. At this point, it is anticipated that corporate financial performance will be the performance type which is set as the dependent variable in this thesis. For the purpose of getting a clear discussion baseline, performance, i.e. corporate financial performance is defined as follows:

Definition 5: Corporate financial performance (Firm performance)
Corporate financial performance is the deviation of the actual financial achievement from the planned financial target. It is measured by every financial indicator which reflects a company's success, whereas success is determined by the company's individual strategic objectives. For the present thesis, corporate financial performance is synonymous with profitability.

The OECD (2005, p. 35) connects innovation to performance. Thereafter innovation would aim to improve the performance of a firm "[…] by gaining a competitive advantage" (ibid.). This will have to be confirmed with upcoming tests in this thesis.

However, the further above-mentioned term innovation performance describes a concept different from the OECD's understanding. The screened literature understands innovation performance as the financial improvement which is caused by the firm's innovations (cf. Arnold, Fang & Palmatier, 2011, p. 238). Thus, under this perception innovation performance is a specific sub-type of corporate financial performance.

The same applies to the term acquisition performance. It describes the financial performance improvement or worsening respectively which is induced by the engagement in an acquisition deal. Mcnamara, Haleblian & Dykes (2008, p. 114) see financial performance as a result of acquisition performance. In other words, the good performance of an executed firm acquisition would affect the financial situation of the firm accordingly.

By examining the three above-mentioned performance terms, it becomes clear that the performance of companies, if set as a corporate goal, should always be directed towards an improvement of the firm’s financial situation. By no means is innovation performance, for instance, meant as the performance of innovation itself but as the improvement of a firm’s financial KPIs (revenues, returns etc.) induced by innovation. Likewise, acquisition performance is to be understood as the measurable improvement of the firm’s financials induced by acquisition activities.

3. Theory of innovation management

Before we can derive the central hypotheses corresponding with our research focus and before both the empirical methodology and its later results and implications can be discussed, a closer look at the theoretical foundations of innovation management must be taken. The following pages give an overview of the topic’s origins, developments, and today’s status quo of managing innovation in the business environment.

3.1 Foundations of economic growth theory

Assuming that the purpose of innovation is to generate either a wealth increase or a competitive advantage relative to other actors, i.e. entire economies, corporations or organizations, one finds himself in the midst of numerous explanations which are frequently referred to in scientific literature and intend to describe how economies and businesses grow – the **growth theory**. These theories and perceptions have undergone dramatic changes and have been modified respectively over the past centuries. In the following, a closer look is taken at these theories before the most important and recent findings in the field of innovation management are highlighted.

Around the 18th century, the fundamental conviction was that economies remain in a stationary state. This time period is often referred to as **mercantilism** and describes a time span when states began to interfere with economic processes, interests, and practices. In this era countries also started to aim for the growth of their domestic productions, an increase in their sales and an improvement in their foreign economic affairs. It was the first time in Europe (despite ancient history) that economic policies were introduced, currencies were unitized, and internal markets began to grow. The underlying idea of mercantilism is to achieve a positive balance of trade in order to gain more money than is spent. (Cf. Screpanti & Zamagni, 2009, p. 34; Encyclopaedia Britannica, 2020a)

Physiocrats were mainly present in France around the 18th century and differed from mercantilists in that they did not see wealth from the perspective that only a few powerful individuals would benefit from economic strength but the entire society. Therewith, physiocrats imply that economic 'growth' was not the growth of a few wallets, but growth from which everyone would benefit. (Cf. Encyclopaedia Britannica, 2020b)

The **classical growth theory** builds upon these developments and can be distinguished from mercantilism and physiocrats in that it not only questions how the economic development of countries can be steered, but it is a systematic analysis of that question. It is often considered the genesis of growth theories as it insinuates a non-stationary economy. Based on Adam Smith in 1776 it is assumed that work would be the key driver of economic growth and wealth (cf. Smith & Campbell, 2009). Consequently, the exchange and trade of goods which are the result of work would be the basis of every economy, while prices would be the central factor for the distribution of income. His fundamental hypothesis is that prices are flexible. In that, he distinguishes market prices from natural prices, where the earlier would be formed through demand and supply and the latter would mainly depend on business profits. In addition to that, Smith (cf. Smith & Campbell, 2009, p. 49) highlights that work should be apportioned amongst parties which each should focus on their specific tasks. That way, efficiency and productivity could be increased. According to his work, growth could be achieved by three central aspects: a productivity increase, an expansion of internal and foreign markets and most importantly business investments (cf. Smith & Campbell, 2009, p. 32). Thereby, Adam Smith represents an entirely contradictory opinion to mercantilists and physiocrats, convinced that free trade for all actors, not only nations themselves, would lead to profits and economic growth, meaning that everyone, while being focused on his/her own advantages would therewith contribute to the overall economy's wealth.

The "*invisible hand*" is an often-used term and has been introduced by Smith to explain how market equilibrium is achieved through the market itself, although no market actor would himself be interested in increasing the overall economy's wealth. With this term Smith has introduced what has been recognized as the core of classical growth theory: a self-regulating economy (cf. Smith & Campbell, 2009, p. 18). Smith has also been the first to include technological progress in his work. However, he considers technology an external factor (cf. Smith & Campbell, 2009, p. 31). On top of that, by accentuating business investments (which represent a pre-step of innovations) as growth drivers, Adam Smith's hypotheses set the basis for the theory that innovations are an instrument to initiate growth. However, he has done so unconsciously and without even referring to innovation itself. (Cf. Smith & Campbell, 2009, p. 49)

The **neoclassical growth theory** suggests that growth is obtained and maintained through labor, capital and technology. The shift from classical to neoclassical theory is known as the *marginal revolution* which, basically, has been a slow process of including new insights to scientific discussions during and after the last quarter of the 19th century. The neoclassic adapts the understanding of an “invisible hand” which steers the economy. Furthermore, neoclassical theorists put resource allocation at the center of their investigations, while the classical growth theory focuses more on the overall economy’s growth. Nonetheless, the term marginal revolution becomes clearer when looking at the origins of neoclassic. (Cf. Screpanti & Zamagni, 2009, p. 165)

Initiated by William Stanley (1871), Carl Menger (1871), and Léon Walras 1874–1877) discussions about growth have included *utility* as a new considerable component for the first time. In addition to that, they were the first scientists who applied the *marginal principle* to the concept of utility. Marginal utility describes the phenomenon that at a certain point an additional entity of an observed product or service leads to a less utility increase than any before added entity, i.e. the utility (u) of a product/service (x) converges against zero ($\lim_{x \to \infty} u = 0$). This implies understanding utility maximization of individuals and households respectively and customer satisfaction as well as profit maximization as the central goals (cf. Weintraub, 2007; Weintraub, 1974, p. 20). Individuals with these objectives are covered with the term homo economicus (cf. Persky, 1995) which was mentioned at the very beginning of this thesis. Thereby, the neoclassic assumes a rationally thinking of each economic individual who would aim to make use of scarce resources in the most efficient way. Moreover, the neoclassic investigates how these goals affect market forces, i.e. supply and demand. Given the objectives of customer satisfaction and business profit maximization, the neoclassic imposes the power over the market forces on households and firms. (Cf. Screpanti & Zamagni, 2009, p. 163–192))

At the beginning of the 20th century, the *Schumpeterian theory* by Joseph Alois Schumpeter (1911) dominated scientific discussions about economic growth. In his early work, Schumpeter has shown how important innovations are for the development of economies and which impact they have on societies. The term “development” already highlights the novelty in his theory relative to classical opinions. Schumpeter is the first scientist to assume that economies are not continuously circumcised by the same environment. Instead of assuming a single constant market equilibrium, Schumpeter suggests an ongoing structural change: "[…] development in our sense is a distinct phenomenon, entirely foreign to what may be observed in the circular flow or in the tendency towards equilibrium. It is spontaneous and discontinuous change in the channels of the flow, disturbance of equilibrium, which forever alters and displaces the equilibrium state previously existing" (Schumpeter 1911, p. 64 cited as per Croitoru, 2012). Also, the beforementioned difference between an invention which is the first trial of gained new knowledge and innovation being a repeated trial of such knowledge and its diffusion over time originates in Schumpeter's theory (cf. Godin, 2006, p. 655).

Howitt (2009, p. 16) differentiates the Schumpeterian growth theory from others, especially the so-called neoclassical theories in that it would treat technological progress "[…] as an economic phenomenon." He also points out that Schumpeter's theory would assume technological progress being mainly driven by industrial innovations which was "[…] the same source that is central to the competitive process of any market economy". Moreover, the success of technological strategies would depend on country-specific characteristics such as the geography itself, educational levels, and environmental conditions. Aghion & Howitt (2006, p. 269) state that less innovative countries would rather adopt innovations of relatively more innovative countries while the latter would come up with innovations themselves. Aghion & Howitt (2006) call that the "appropriate growth policy".

Frank Plumpton Ramsey (1928) has extended the work of classicists by introducing a growth model which claims to be the "(model of optimal growth; translation of the editor)" (Heinemann, 2015, p. 57). The model is considered the foundational model of dynamic macroeconomics, although it has become popular, decades after its establishment. The model's core is the investigation of the growth rate of consumption and the question of how large a nation's rate of saving should be: "The rate of saving multiplied by the marginal utility of money should always be equal to the amount by which the total net rate of enjoyment of utility falls short of the maximum possible rate of enjoyment" (Ramsey, 1928, p. 543). Understanding innovations as an investment, one could surely conclude that savings represent the opposite of investments and hence, innovations. Therewith, Ramsey indirectly projects macroeconomic rules for the restriction of innovations and implies that investments may account for utility growth. However, this growth is marginally decreasing with every additional investment. That raises the question: Is there a maximum amount of money spent on innovative technologies and the like above which these investments become unprofitable?

Such questions will be targeted with our hypotheses in Section 3.3. According to Ramsey's model, long-term growth normalized by population is possible in an equilibrium state with a given exogenous technological progress. (Cf. Heinemann, 2015, p. 57)

The neoclassical understanding experienced broader attention during and after the *Great Depression* in the '30s of the 20th century when people wondered about the causes of such financial crises. John Maynard Keynes has been recognized amongst the most popular scientists during this time. The core of his investigations is *aggregate demand*. Such demand was "[…] influenced by a host of economic decisions – both public and private […]" (Blinder, 2019). **Keynesian theory** investigates both short- and long-term economic developments. Keynes provides some initial answers to the above-asked question regarding investment maxima. He states that, although an increase in savings would not lead to an equal increase in investments, its maximum volume would be determined by investments. Hence, investments would depend on savings (cf. Keynes, 1936, p. 67). This causal relationship becomes more comprehensible if imagining that one can only save as much capital as is not invested but surely can invest more than is saved when running into debts. Nonetheless, Keynes also includes income in his hypotheses and suggests that it would be equal to the "effective demand" (Keynes, 1936, p. 59). Despite investments and savings, also the supply of money would drive income according to Keynes (cf. Keynes, 1936, p. 155–163).

Probably, the most important insight of Keynes is that in a market-driven economy, investment decisions are also determined by an entrepreneur's perception and feeling. He calls that the animal spirit and introduces the entrepreneur's point of view for the first time (cf. Keynes, 1936, p. 148; Blinder, 1987, p. 130). This view is still actual in today's scientific discussions (cf. Miller & Le Breton-Miller, 2011).

On the one hand, Keynes' work is as often considered neoclassical, on the other hand, it is also frequently referred to as a stand-alone perspective which exhibits various differing characteristics from neoclassical theory, one of which is the conviction that employment and production are controlled via the goods market, instead of the labor market. However, Keynes bases economic wealth and development not on the quantity of produced goods, but on the liquidity of an economy. This is called "*liquidity preference*" (cf. Keynes, 1936, p. 376).

Reviewing Keynes' foundations, it becomes now visible how growth theory is connected to theories and hypotheses about innovation and innovation management and hence, why it should play a role in this study to answer the research question and reveal other questions related to the topic. With Schumpeter being the first to introduce innovations directly as a growth driver and Keynes shifting the perspective onto entrepreneurs, their investment decisions and customer demand, valuable theoretical basics have been set for the further development and later link to innovation management theory. Before connecting the dots and coming to innovation management, the development of modern endogenous growth theory is displayed to get an insight into the current economic understanding.

Based on *post-Keynesian* theory and the *Harrod-Domar model* (Harrod, 1939; Domar, 1946) which links the maximum amount of investments to the rate of savings and which also introduces both the technological progress and investors' behavior (*animal spirits*) as growth accelerators (cf. Harrod, 1939, p. 14), Robert Merton Solow (1956) and Trevor Swan (1956) have established the so-called *Solow-Swan model*. This model investigates the economy's output. It sees output as a per capita entity rather than on an aggregate level. The model postulates that, if technological progress and saving rate are identical, the income per capita of different countries converge against each other over time (cf. Solow, 1956, p. 73; Barro & Sala-i-Martin, 1992). This confirms the above-mentioned theory of innovation adoption by less innovative countries of Aghion & Howitt (2006, p. 269). Solow and Swan became famous for their proposal that the capital intensity of an economy remains constant if it is at a level at which the capital stock and depreciation of goods are equal. This status is called a *steady state*. According to Solow (1956, p. 70) and Swan (1956, p. 338), this would always be the case in the long run.

As most neoclassical models the Solow-Swan growth model combines the three main growth variables: capital, labor, and technology. Especially the latter is of great interest to the two economists. In contrast to Harrod and Domar who have taken the saving rate as the primary driver for growth, Solow and Swan accentuate the role of technological progress in that regard. However, the three fundamental neoclassical growth variables were only necessary for a long-term equilibrium not the short-term equilibrium. They postulate that production factors exhibited decreasing returns over time. Additionally, their marginal utility would decrease at a certain point. The only factor that lengthened the time before additional entities of production factors became obsolete, which would lead to a long-term equilibrium – the steady state – was the technological change. (Cf. Solow, 1956, p. 85; Swan, 1956, p. 338).

The Solow-Swan model has been criticized due to its missing explanation of the origins of saving, consumption decisions and technological progress. Especially the latter is the main source of criticism. Technological progress is still assumed exogenous. According to the model, technological progress is assumed to constantly grow and lead to constant growth rates over time. Because of that, long-term growth is determined by exogenous factors and, hence not explained in the model nor in any other neoclassical model (cf. Mankiw, Phelps & Romer, 1995, p. 280; Jones, 2019, p. 859). An exception to this is the extension of Cass (1965) and Koopmans (1965) who have been the first to include an endogenous form of the saving rate. Because the neoclassical theory is comprised of various perspectives, extensions, and accumulation of heterogeneous views on economic growth which all share certain fundamental assumptions, Weintraub (2007) calls the neoclassical theory a “metatheory”.

From reviewing the central positions of the neoclassical growth theory, it becomes clear that the fundamental perspective has shifted away from seeing growth only in a macroeconomic context onto a microeconomic view. Especially Schumpeter and Keynes have initiated that perception by explaining growth with innovations, on the one hand, and by including entrepreneurs’ perspective, on the other hand. As pointed out, exogeneity remains the central aspect of criticism and prevents us from assuming that companies’ innovation effort is relevant for economic growth and is a changeable and manageable leverage for performance increase.

Because of that and as the last step, another big field of growth theory besides the classical and neoclassical – the **endogenous growth theory** – must be discussed. In fact, it will be demonstrated that economists have managed to continue the development of economic discussions about growth towards a business perspective while accepting technological progress as a key driver. Nelson & Winter (1985) build an “evolutionary theory” on economic growth driven by innovations. In that, they are the first ones to mention explicitly innovations as drivers of economic growth since Schumpeter in 1911. However, their scientific focus lies on the analysis of industrial and organizational economic developments from the perspective of businesses “[…] operating in a market environment” (Nelson & Winter, 1985, p. 3; compare also Nelson & Winter, 1982).

With this in mind, both scientists have also initiated discussions about the role of R&D expenditures in driving growth of entrepreneurs’ and managers’ businesses, motivated by the huge amount of money that is frequently pumped into this sector. They state that “[…] much of the firm behavior could be more readily understood as a reflection of general habits and strategic orientations coming from the firm’s past than as the result of a detailed survey of the remote twigs of the decision tree extending into the future.” (Nelson & Winter, 1985, viii). Moreover, Nelson and Winter perceive such efforts as a response to changes of other central variables that drive the economic and business development, e.g. changes of supply or demand and changes of technology (cf. Nelson & Winter, 1985, p. 163).

In contrast to their predecessors, Nelson & Winter (1985, p. 8) do not accept the classical and neoclassical assumptions that actors in the market would make entirely rational investment decisions based on total market information which in the long-run would lead to economy-specific equilibria. Instead, they underpin the necessity to shed light on the uncertainty in an entrepreneur's and manager's decision-making process. Furthermore, Nelson and Winter introduce the term "routine" (Nelson & Winter, 1985, p. 14) which would include "regular […] patterns" (ibid.) of expenditures, such as R&D. The connection between evolutionary/endogenous theory and earlier work is also recognized by Nelson and Winter who refer to the necessity of modeling the Schumpeterian competition concept (cf. Nelson & Winter, 1982, p. 114). Consequently, this should go hand in hand with an investigation of firm-specific characteristics and the interplay of firm dissimilarity and industry specifications (cf. Nelson & Winter, 1985, p. 30) which is exactly what this thesis intends to do.

According to (Nelson & Winter, 1985), technological changes come into play when firms intend to maximize their profits. Therewith, it allows the connection between a macro- and microeconomic perspective. Nonetheless, Nelson and Winter postulate that firms are not driven by maximization. Instead, companies would rather tend towards a convenient level of profit. Consequently, the model does not aim for a state of equilibrium as is suggested by neoclassical models.

The basis of our research is the question concerning the effects that an increase of input and driving factors would have on the reaching of an equilibrium state (steady state). In that, endogenous theory distances itself from neoclassical theory and underpins the importance of discussing growth theory in advance. Accordingly, Nelson and Winter postulate the basic assumption (which is of great importance to our research focus) that entrepreneurs and managers do not achieve business growth and do not contribute to economic equilibrium by simply maximizing their inputs into the determinants of technological progress (on the business level). Instead, they would find themselves in an environment in which they have to consider various non-perfect market conditions (cf. Nelson & Winter, 1985, p. 37). These included non-full information and monopolies (cf. ibid, Nelson & Winter, 1985, p. 184). As a consequence, there is no one-way solution. Entrepreneurs and managers have to decide between investment options which all may promise a certain performance enhancement but are strongly dependent on the above-mentioned and other conditions.

Many thoughts and views of endogenous growth theory go back to the works of Paul Romer (1990) and Robert Lucas (1988). The role of competition in endogenous growth theory is a central one, although, it is characterized as "monopolistic" (Romer, 1990, p. 73). Romer and Lucas are described as having put technological change at the center of their investigations (cf. Morley, 2015; Romer, 1994, p. 16). Romer (1990, p. 71) argues that there are two levers through which growth by technological progress could be steered: population growth and capital accumulation. However, the latter alone would not be "sufficient" (ibid.).

On the other hand, Romer and Lucas agree with Nelson and Winter in not taking technological change as a given externality but as something that can be managed (cf. Romer, 1994, p. 4). The following represents the next major insight and basis for our research topic: Romer (1989, p. 13) assumes that R&D investments of individual companies may lead to knowledge acquisition by other companies due to insufficient knowledge protection. By that, Romer not only "ties the development of new ideas to the number of people working in the knowledge sector […] as effort devoted to R&D" (Morley, 2015) and links R&D efforts to economic growth in general, but also introduces a new dimension much clearer than his predecessors – acquisition as a result of competition.

In that context, Romer defines innovations as "nonrival" (Romer, 1990, p. 74) which means that anyone could use them. He calls this "spillovers" (Romer, 1990, p. 75). These effects imply that the marginal productivity of capital is not decreasing. This imposes a problem upon the theory of the importance of innovation as a considerable growth option. If innovations were in fact non-rival, then any effort put into researching and developing them would not only be obsolete but create a disadvantage relative to other competitors who could access these innovations without the obligation to invest in them and, consequently, without missing other opportunities worth investing as well. Thereafter, some form of protection and, coming along with it, an interference in market competition is needed. Patents and trademarks provide such protection. Grossman & Helpman (1990, p. 87) go further by suggesting that continuous investments in R&D would lead to long-term growth and a steady state at which growth would be constant, given that the market had a monopolistic competition structure.

Romer's work already combines and introduces important aspects which justify the frequent discussions on innovation management. Given that both technological progress and human capital which are the growth drivers in Nelson's and Winter's model are endogenous, Romer has been the first to imply that strategies regarding the management of innovations and the openness to the market are relevant growth considerations.

Romer (1990, p. 71) and Nelson & Winter (1985) have adjusted previous classical models with their assumption of non-perfect competition. Hence, full information should not be expected. This is another assumption (not yet hypothesis) on which this thesis' research question will be resolved. Entrepreneurs and managers must make and justify decisions about different business opportunities under the condition of imperfect markets. This results in uncertainty. This study intends to provide insights about two of such opportunities – innovating by (internal) research or by (external) acquisition. There are many more scientists who have contributed to the discussion about growth and innovations from various perspectives (some can be viewed in Table 13). However, these will not be further discussed as the key perspectives and findings relevant to our research topic have already been identified. The central theories of growth and their connecting or differentiating characteristics are illustrated in Table 1. This table gives an overview of the presented and discussed insights from leading economists of the last centuries.

Table 1: Characteristics of central growth theories

	Classical theory	Neoclassical theory	Keynesian theory	Endogenous/ evolutionary theory
Economic view	macroeconomic	macroeconomic	macro- and microeconomic	microeconomic
Economy development	non-stationary, perfect markets	non-stationary, perfect markets	non-stationary, perfect markets	non-stationary, semi-/non-perfect markets
Main growth drivers	exchange & trade; market forces (invisible hand)	labor, capital & technology (capital linked to saving rate)	liquidity (investment/ savings & supply of money)	technology & human capital
Role of innovation	none	none (general)/ central (Schumpeter)	indirectly considered through investments	central (but to be protected)
Role of entrepreneur/ manager	none	considered but inferior	central	central
Role of technology	none	central but exogenous	important	central & manageable
Economic target	tendency towards equilibrium state (long-term)	steady state (when capital intensity remains constant) (long-term)	short-term growth and long-term steady state through capital saturation	convenient level of profit (Nelson/ Winter); long-term equilibrium if supply = demand

(Source: own representation)

Based on these insights we agree on central assumptions for the purpose of clarity about our research fundament and argumentation. These **central assumptions** are as follows:

- The economy is in a non-stationary state of ever-changing circumstances
- Technological progress is amongst the drivers of economic and business growth
- Technological progress is endogenous and manageable
- Investments are amongst the determinants of technological progress
- Innovations are a form of investments
- Innovations are a growth driver

Regarding the here-presented assumptions about investments and innovations, it is specifically not mentioned, if it is referred to as business investments and innovations, or economic investments and innovations. The growth theory mostly derives implications about these variables from a macroeconomic view which mostly deals with economic growth. As has been discussed, this perspective shifts onto a microeconomic perspective in the late 20th century. Especially the last of the above assumptions is the result of the many presented relationships between growth, technological progress, investment, and innovation. At the same time, this assumption is the fundamental motivation for this thesis. If innovations really drive growth, they may drive business performance as well. If so, under which conditions do they do that? The above-listed assumptions and results which are drawn from previous theories will (partly) be the basis and task for upcoming regressions to verify.

After having reviewed the central theories on economic growth and development, one may pose the question of what the purpose and gain of this is. The revision of those theories has three fundamental purposes: First, we have gained insights about where innovation management has come from and how it has evolved based on historical theoretical developments. Second, we have reason to assume that innovation (management) is linked to growth. We have an idea which areas are impacted (knowledge, technology, capital etc.). Third, we are able to value innovations in the scope of past experiences and we can build on resulting (above-mentioned) assumptions about economic and business dynamics. In fact, our hypotheses will be based on those assumptions and theories as well. The following section is devoted to providing the basic models and theories on the concept of innovation and innovation management and what it all covers, solely from a business perspective.

3.2 Introduction into strategic innovation management

Theoretical models, which try to explain innovation and innovation management can be classified according to two perspectives: a macro- and a micro-perspective (cf. Braun-Thürmann, 2005), pp. 66–85). ***Macro-level models*** account for views on innovations which emphasize their impact on societies and economies. The Schumpeterian theory is seen as the foundation of this kind of innovation model. Typical for macro-level models of innovation is the assumption that firms and organizations have to accept innovation-related and environmental circumstances such as the overall impact of disruptions and innovations on economy and businesses as exogenous and non-influenceable by firms and organizations (cf. Howitt, 2009, p. 16).

Despite his suggestions towards a macro-level understanding, Schumpeter has also set the foundations of micro-level theories. He has come to the conclusion that pioneering work would not only come from economic self-interest but was based on psychological motives (cf. Schumpeter, 1911, p. 138). Hence, an entrepreneurial component of innovation is given. ***Micro-level models*** are also based on endogenous growth models, e.g. by Romer (1990) or Lucas (1988), which also assume such entrepreneurial controllability. The connection between growth and innovation (management) theory becomes obvious once again.

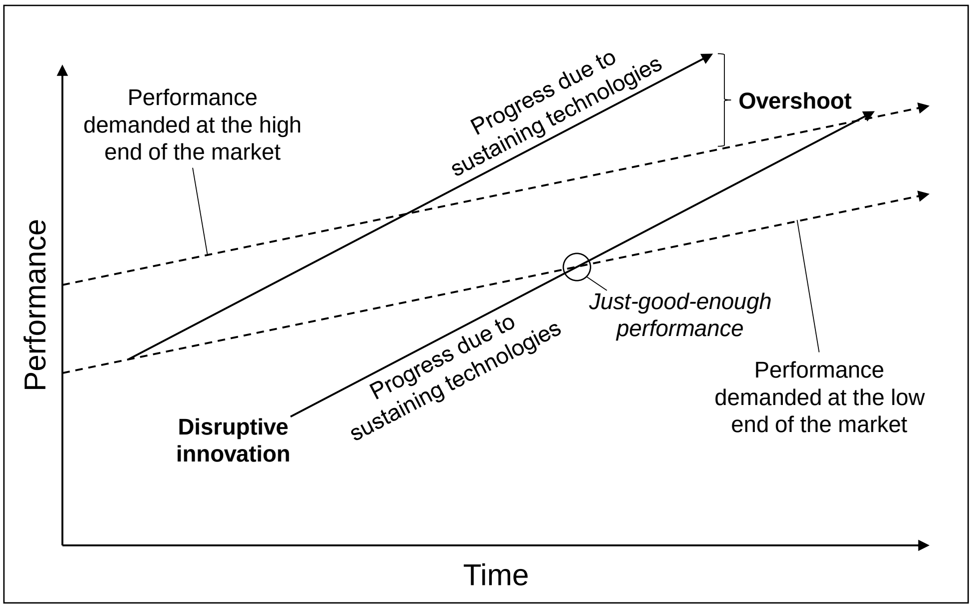
At this stage, it needs to be pointed out that seeing innovation and its effects as part of a given conglomerate of exogenous circumstances, given the fact that mostly companies, despite national innovation efforts, are the key drivers of developing new solutions of either kind, be it product innovations, organizational changes in the shape of process innovations or others, seems hazardous. As a consequence, this study will focus on an innovation understanding which belongs to the micro-level perspective. In fact, this perspective is going to be the baseline for the upcoming regressions as the predominant intention is to measure a specific form of firm performance under the influence of different kinds of innovation. The underlying assumption of micro-level innovation models, as they deal with how innovations are organizationally managed, is that corporations of any kind do have an influence on which, when, how, and how many innovations are developed (cf. Braun-Thürmann, 2005, p. 84).

It becomes notable that the term innovation management can also be seen from the two perspectives, both macro and micro, i.e. in the societal-economic and the business/managerial context. But what exactly is innovation management? And why is it important? In order to answer these questions, we will look at fundamental problems that companies face regarding innovation processes and take up the recently gained knowledge about growth theories.

The addressed problem is that existing products, services, and other solutions are continuously and incrementally refined by businesses. Over time, this leads to an *overshoot* of the solutions' features, i.e. these solutions offer more than what is needed by customers and what they are willing to pay. Thus, existing solutions will eventually stop satisfying customers' demands at the end of their life cycle. New solutions are required. In fact, there is a need for continuous innovation as a response to market changes, some of which are disruptive and, themselves, originate in innovations from other competitors.

This has been introduced as the "**innovator's dilemma**" by US American economist Clayton Magleby Christensen (1997, p. 15). At its core, the innovator's dilemma describes the problem that innovations are, at the beginning of their life cycle, inferior to existing comparable solutions in most dimensions. Accordingly, these innovations usually would attract only a subset of the market. In addition to that, they come along with great risk and rather low margins in the beginning (cf. Christensen, 1997, p. 12). Christensen has shown that these innovations are necessary to meet customers' changing needs and demands over a longer period of time. Figure 11 illustrates how disruptive innovations create the necessity to continuously innovate, how existing solutions create an overshoot and that these will eventually be substituted by disruptive innovations. These innovations are just-good-enough solutions regarding most dimensions of the "old" offerings. However, in key dimensions, e.g. user comfortability, these solutions meet current (and possibly future) customer needs and may create new needs.

Figure 11: Disruptive innovation model (innovator's dilemma)

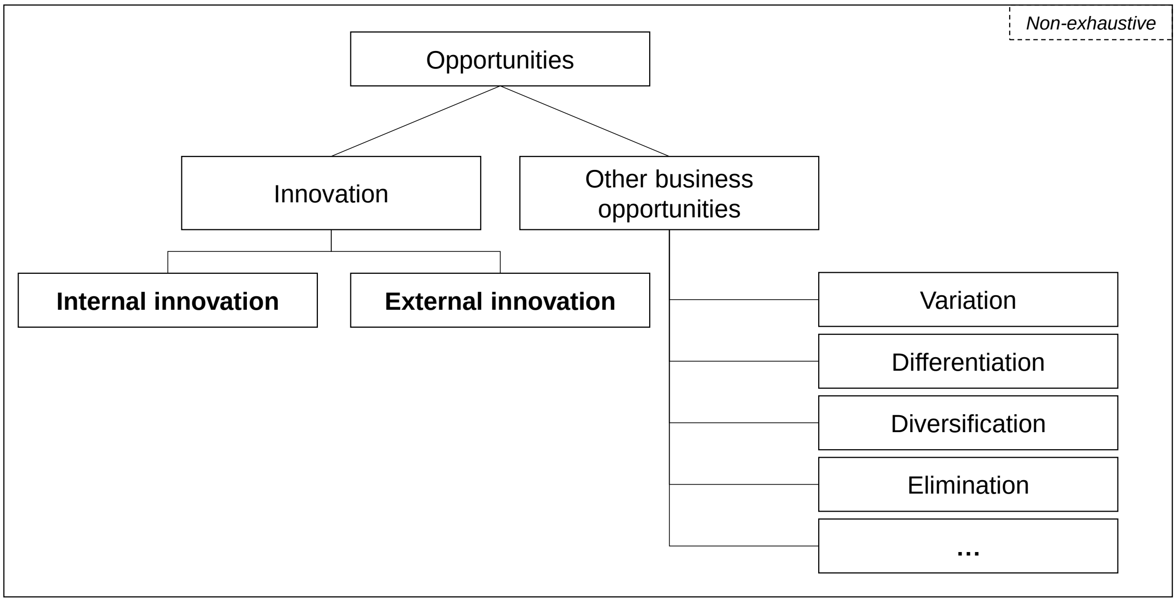


(Source: based on Christensen, 1997, p. 12)

The innovator's dilemma demonstrates the **urgency and importance** of our research focus. As has been deduced from previous Sections, a crucial problem for managers and entrepreneurs is the question of **how** to innovate. In combination with Romer (1994, p. 21) introduced problem of (hostile) knowledge acquisition, several questions come up. Should managers rather decide to buy another company to acquire innovations, knowledge, technology, and all the other aspects that come along with an acquisition, or should they rather focus on using internal knowledge, capabilities and resources to develop innovations on their own? You may call that the "**manager's dilemma**". Managers and entrepreneurs need to constantly decide between different business opportunities. At this point, innovation management comes into play.

As can be seen in Figure 12 various forms of **business opportunities** regarding a company's portfolio can be distinguished, e.g. *innovation*, *variation*, and *elimination*. In our case, we do not restrict ourselves to the view of products but include all general corporate solutions. It can be understood that "innovation" as a business opportunity implies more significant changes to the corporate portfolio, maybe even the radical kind of changes. On the other hand, variations refer to rather slight changes to existing solutions, comparable to incremental innovations (as previously mentioned in Section 2.1). However, the most interesting aspect of this model is that business opportunities, which every entrepreneur or manager faces, include the elimination of previous innovations or existing solutions in a company's portfolio. This underpins the perspective highlighted by the innovator's dilemma. Obviously, innovation management means **weighing opportunities up** against each other.

Figure 12: Business Opportunities (manager's dilemma)



(Source: based on the theory of Vernon, 1979)

In order to answer these questions, we need to understand the innovation (management) processes beforehand. Dougherty (2012) names four central product **innovation development processes**: *product, capabilities, business,* and *strategy*. As we do not solely restrict our analyses to product innovations, the model and the term "product" will be modified to "solution"[5] in the following explanation and in Figure 13 which is an illustration of Dougherty's work. The understanding and implications of the model remain unchanged. According to Dougherty, the development of an innovative solution would demand a multifunctional collaboration of experts from various fields of expertise. The key here was to meet customer needs (cf. Dougherty & Hardy, 1996, p. 1123). These needs would often be multidimensional and could not be viewed from just one perspective. Dougherty (1992, p. 179) has worked out that especially in large companies, the knowledge of what customers need is often scattered across the different corporate departments and is not centralized. However, as especially "[…] authority over strategy needs to be centralized […]" (Dougherty, 2008, p. 175), it is necessary to merge the departmental perspectives. Dougherty also highlights that the development of innovations needs to be done in "collaboration" (Dougherty, 1992,

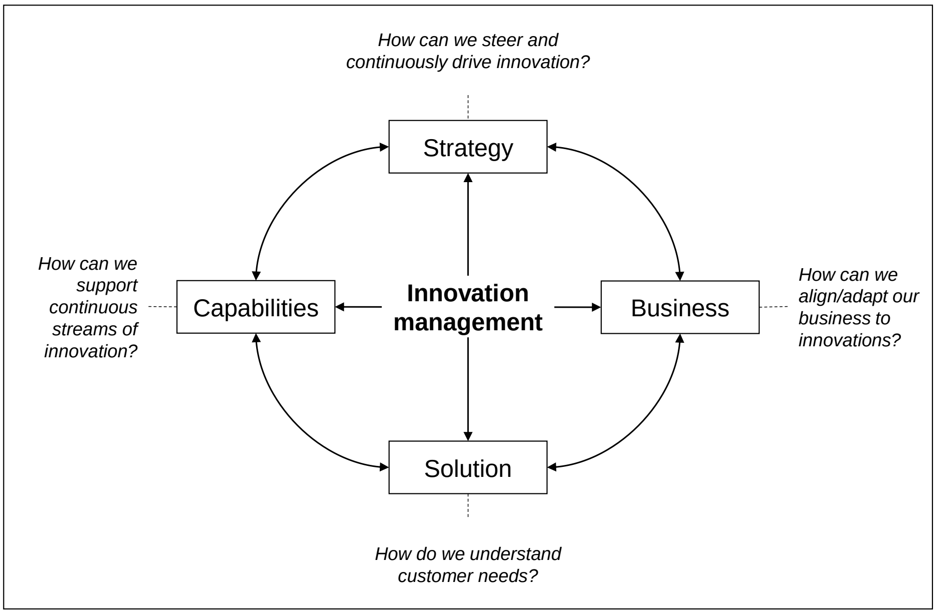
[5] With the term "solution" we intend to cover all possible customer-oriented forms of company offerings.

p. 179) with other sources of expertise from multiple functions within the firm. That implies corporate innovators from different corporate functions to work closely together (cf. Cooper & Kleinschmidt, 1986). This, however, would be difficult as "[…] departments are like different "thought worlds" […]" (Dougherty, 1992, p. 179).

This is where the second development process comes into play. According to Dougherty (2008, p. 177; cf. Dougherty, 2001), the different functional teams within a company would have to invest in and build up **capabilities** to contribute to the corporate innovation process from their perspective. Often, this process would be prohibited by the leadership of the different departments or even by the company's leadership itself arguing that investments would be too costly and time-consuming. This way of thinking would often come along with concerns about short-term financial targets. Consequently, the problem of prohibition needed to be resolved by a changed mindset and openness of managers towards innovations. This coincides with Schumpeter's assumption of psychological and personal criteria that are relevant aspects of entrepreneurship and in the innovation process and management (cf. Schumpeter, 1911, p. 138). On top, managers and leaders should understand innovations as a long-term objective and develop business models and structures to cope with the necessary and defined innovation objectives given that value creation is perceived as "[…] a long-term working relationship with customers […]" (Dougherty, 2001, p. 612). This seems to imply that internal efforts are more likely to take effect in the long run. However, this question will be clarified in our analyses.

Having established internal responsibilities regarding innovation development and having developed the necessary multifunctional capabilities and organizational structures, Dougherty identifies, yet, another problem. Without leadership directing all these (internal) efforts to innovate and without weighing opportunities up against each other to invest in the right ones at the right time, business departments do not work efficiently together, and capabilities will not unfold their innovative potential. This last aspect is referred to as strategy development (cf. Dougherty, 2012). Strategic managers would have to focus on long-term investments to fulfill innovation objectives. And in general, they would initiate, formulate, and drive these long-term innovation objectives in the first place.

Figure 13: Corporate innovation (management) development processes



(Source: based on Dougherty, 2012)

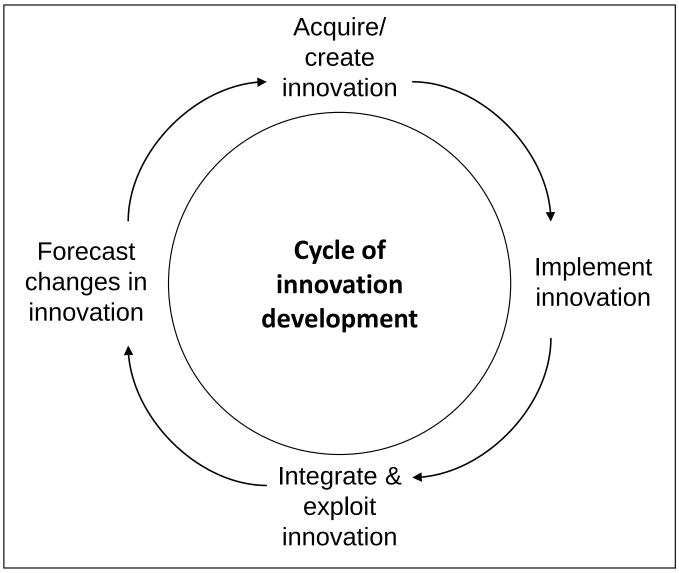
The strategic development process is exactly the perspective from which we look at this thesis' research question and accounts also for the term "strategic" in *strategic innovation management*. Furthermore, the innovation management model by Dougherty describes the organizational and hence, the internal form of innovation effort which is referred to as **internal innovation** in the following (cf. White & Bruton, 2011, p. 26).

There are various models which explain the other innovation option. This other option is here referred to as **external innovation,** that is innovation acquisition. For example, White & Bruton (2011, p. 22) describe the innovation process as a cycle and refer to innovation as the acquisition of technology. Note that, for our purposes and understanding, the here-presented version of the cyclical innovation process model (compare Figure 14) is modified by the exchange of the term "technology" with "innovation". Nevertheless, the discussion of the different terms and definitions related to innovation will not be resumed at this point. Instead, it is noted that White & Bruton understand innovation as the recurrence of certain managerial steps and refer to it as "technology" in that case (cf. ibid.).

Thus, the cycle of innovation would include a forecast in the changes of technology based on scientific, technical, and market insights before acquiring and implementing it. The final step would be the exploitation of that technology before the process restarts. This model is interesting due to two facts. First, White & Bruton suggest that technological change would drive innovations and not the other way around as is assumed by endogenous growth theory.

If accepted both perceptions this would lead to innovations and technological change or progress affecting each other. Second, White & Bruton assume a never-ending (cyclical) process of innovating. Both these assumptions cope with Christensen's described dilemma and additionally emphasize that, if innovation efforts were to be analyzed, the time variable was of great importance. This brings up another question which should be taken into account within our upcoming analyses: Do innovations by acquisition and innovations by internal development efforts have a short-term or rather a long-term effect on firm performance? In other words, where do the two presented innovation options (internal or external) unfold a greater impact – in the short run or in the long run? Is the decision for or against the one or the other innovation option even conditioned by the time of their execution?

Figure 14: Cyclical innovation process model



(Source: based on White & Bruton, 2011, p. 22)

Batterink (2009, p. 134) provides a model of how these technologies, knowledge, innovations, and the like can be integrated into the buying firm. He distinguishes three "levels of R&D integration": *system standardization*, *structural linking* and *process re-design* (ibid.). These are introduced as levels of *technological relatedness* between the buying and the bought corporation. Batterink postulates that increased technological relatedness increases innovation synergies and eventually results in an increase in the firm's performance (ibid.). This brings up another question for our regression analyses to consider: Is external innovation in the form of company acquisition influenced by the technological closeness, e.g. represented by both the acquirer and the acquisition target being in the same industry? Is innovation, regardless of whether it is internal or external, influenced by the industry in general?

The above-presented models equip us with enough knowledge that we can develop one last definition before going into hypotheses development:

Definition 6: Innovation management
Innovation management is the package of all activities that account for the creation and handling of innovations and related business opportunities over time in order to meet current customer needs. As such, internal innovation management includes the four development processes: solution, capabilities, business, and strategy. External innovation management includes the handling of innovation acquisition from outside the organization itself.

3.3 Hypotheses development and refinement of the research focus

We recall beginning this chapter and the discussion of the historical development of various growth theories with the assumption of innovation targeting economic growth of either entire economies (macro-perspective) or individual actors, e.g. companies and organizations (micro-perspective). So far, basic theories and models have been elaborated. Nonetheless, the conditions under which innovation does lead to financial improvements and growth are rarely explained and tested in recent literature, although new technologies, i.e. computational support and new data may provide a proper baseline for testing. Exceptions prove the rule. One exception is Mcnamara, Haleblian & Dykes (2008, p. 114): “In examining the role of environmental conditions, we extend existing research”. This thesis intends to follow this idea and elaborate on new insights into the conditions of innovation effects on firm performance.

In fact, this intention and the before-presented theories and insights from economic science, already, lead to the central assumption that innovations do have an effect on firm performance. But, is this really the case? There are numerous papers and research results from various perspectives on innovation or performance which have been published over the last decades. Few of them from which we conclude our own to be tested hypotheses are presented in the following. We attend to the research question of this thesis and hypothesize:

Hypothesis 1 (H1): ***(a)*** *Internal,* ***(b)*** *external innovation leads to an improvement of corporate financial performance.*

In the process of reviewing the literature on innovation and firm performance in the context of this thesis, **two basic perspectives** from which innovation and performance and their relationships to other factors are investigated, have been identified. These comply with our definitions of internal and external innovation in Section 2.1.

One way of dealing with competition are investments in R&D as a representative of our above-defined **internal innovation**. In that regard, diversification seems to play an important role. Accordingly, Hitt, Hoskisson & Kim (1997, p. 788) find both evidence that a large R&D intensity on average comes along with a lower degree of diversification. This could be explained if taking acquisition as a form of innovation or resource diversification and R&D as a substitutional decision option to acquisition. Hence, companies who invest in acquisitions (external innovation) would consequently have less capital to invest in R&D (internal innovation). Additionally, the decision for one or the other is often a matter of strategic direction. Zhao (2009, p. 1172) provides evidence to support the suggestion that acquisitions are "innovation-motivated". There are arguably firms which strategically focus more on investments in acquisitions than R&D and vice versa. We want to investigate the effects of both options on performance regardless of companies' strategic directions. As well as that, it is also of importance to understand, if and how the one innovation option influences the effect on the performance of the other. Sampson (2007, p. 366) offers a starting point by discussing the positive relation between so-called "R&D alliances" and firm innovation. In that, he implies synergy effects of both interacting with other companies for innovation and resource exploitation and the usage of own internal resources. Do such synergies exist? If so, a significant moderation of innovation effects by combinations of internal and external innovation should be found. We hypothesize:

Hypothesis 2 (H2): *Internal and external innovation influence each other's effects on corporate (financial) performance when carried out at the same time.*

Hitt, Hoskisson & Kim (1997, p. 778) also bring the international perspective into the discussion, hypothesizing that international diversification had a non-linear relationship with R&D intensity. Other economists link R&D intensity to organizational measures such as organizational slack (cf. Greve, 2003a, p. 688). And yet others connect R&D intensity to firm size, e.g. measured by market share (cf. Ettlie, 1998, p. 3). Surely, these investigations provide interesting and important insights, but they omit fundamental questions about the conditions of innovation (especially internal and acquisition) effects on firm performance. Parthasarthy & Hammond (2002, p. 80) offer a model that explains innovation frequency with high levels of external integration. However, they do not explain under which conditions this explanation holds, nor under which conditions this effect is enhanced or diminished. Nevertheless, they provide a clear model which puts a certain form of performance, here the frequency of innovation, in a relationship with both a form of what may be understood as external innovation, here integration, and R&D intensity. Similarly, Liu (2011, p. 2634) establishes a model of R&D intensity explaining innovation performance. Generic models like these which directly determine internal innovation, e.g. with R&D measures or other variables, on firm performance, will be checked with our first two hypotheses.

In the course of investigating innovation effects on performance, a comprehensive analysis must be conducted to rule out probable other effects. Do innovations take effect long after their publication or implementation respectively? This issue is still unresolved and not perceived as major in recent papers. Thus, we hypothesize:

Hypothesis 3 (H3): ***(a)*** *Internal,* ***(b)*** *external innovation has a long-term influence on corporate (financial) performance.*

Batterink (2009, p. 134) who, as mentioned focuses on **innovation synergies** based on technological relatedness, is just one example of how scientists and economists often view innovation based on a single or few aspects. Unwittingly, he has implied such a long-term effect as hypothesized above because synergies usually take time to evolve. The question is also, whether innovation effects on firm performance, if approved, are simply linear or, if internal or external innovation share another form of relationship with performance:

Hypothesis 4 (H4): ***(a)*** *Internal,* ***(b)*** *external innovation has a significant non-linear effect on corporate (financial) performance.*

The second option to deal with innovation and performance issues is the acquisition of competitors as a form of **external innovation** which has been illustrated with the cyclical innovation process model (Figure 14) and introduced in Section 2.1. In fact, firm acquisition has been identified as one of the two most discussed issues regarding innovation and performance in the research phase of this thesis. On the one hand, Batterink (2009, p. 54) postulates that acquisitions in the form of M&A deals would negatively influence a firm's innovation performance. He bases his hypothesis on both technological and non-technological M&A deals following Ahuja & Katila (2001, p. 197). On the other hand, he simultaneously states that open innovation by licensing-in, outsourcing and other cooperation had a positive effect on innovation performance of firms. In addition to that, Mishra & Slotegraaf (2013, p. 708) show that acquisitions affect post-acquisition invention importance. Datta & Roumani (2015) shift the focus onto a more success-oriented approach by investigating knowledge acquisitions and post-acquisition innovation performance. In doing so, they build on Romer's

(1989, p. 13) theory that knowledge acquisition played an important role for innovation and success.

Obviously, effects on performance can be viewed from a post-decision perspective. However, this thesis intends to provide pre-decision implications. Opinions which combine both a pre-acquisition and a post-acquisition view on innovation effects on firm performance are rare (cf. Wang & Hui, 2017, p. 3). Note, that firm acquisition is not always perceived as a means to innovate. Nonetheless, it is mostly either understood as a catalyst for firm performance and growth respectively, or as a resistance to competition (cf. Harrod, 1939, p. 14; Howitt, 2009, p. 20). This fact itself demands a proper investigation of the influence of firm acquisition and its related measures on performance.

In this regard, especially **leverage** and **diversification** seem to have attracted scientists' attention. For example, Hitt, Hoskisson & Kim (1997, p. 775) postulate: „International diversification has a positive effect on firm innovation." However, this relationship would be negatively moderated by the degree of product diversification (cf. Hitt, Hoskisson & Kim, 1997, p. 778). This means that the positive effect of internationalizing the business is diminished if a firm increases its variety of product/solution offerings. They also find a non-linear relationship between international diversification and firm performance (cf. Hitt, Hoskisson & Kim, 1997, p. 773).

Choi, Kumar & Zambuto (2016, p. 1188) present the hypothesis that firms with greater engagement in excessive exploration would exhibit significant leverage increases. The explanation for that were the increasing costs for equity. At the same time increased leverage would come along with an increased exploitation of a company's prior knowledge (cf. Choi, Kumar & Zambuto, 2016, p. 1187). Diversity seems to be an important factor, not only in the frame of internal business but also when other firms are acquired. Thus, Lin (2015, p. 33) finds a connection between the relatedness of an acquisition and **exploitation** or **exploration** respectively. Thereafter, related acquisition was associated with exploitation and unrelated acquisition with exploration (ibid.).

Alliances are one shape of exploring new knowledge. Vanhaverbeke, Duysters & Noorderhaven (2002, p. 721) focus their work on these and hypothesize that alliances would more often be formed in the shape of acquisitions if the alliance crossed national borders. Furthermore, they connect alliance formation to a company's role in an M&A deal. Firms with more alliances would be more likely to be the acquirer (cf. ibid.). Li, Qiu & Wang (2019, p. 4) link alliances to what they call innovation output. They describe innovation output as the number of patents which result from innovation creation. Thus, alliances would enhance innovation output, especially, if they were formed amongst companies with similar underlying technologies. Rothaermel & Hess (2007, p. 902) choose a different setting as they solely refer to alliances with new technology providers and connect them to enhanced innovation output. Besides these opinions, alliance formation and its effects on innovation and performance is a frequently discussed issue in economic science. Sometimes this issue is referred to as unions, innovation promotion, or networking (cf. Bradley, Kim & Tian, 2017, p. 1; Pennings & Harianto, 1992, p. 356), sometimes the investigation focuses on network density and innovation outcome (cf. Schilling, 2015, p. 10) (see sources in Table 13 as an indication). As can be seen from innovation and firm performance literature, alliance formation of various shapes, be it acquisitions, networks or other forms, seems to positively affect firm performance and innovation output. Yet, these findings lack an explanation under which conditions alliances sink in. Regarding acquisition-related conditions we hypothesize:

Hypothesis 5 (H5): *Acquisition-deal characteristics significantly affect on corporate (financial) performance: In case of an acquisition (external innovation),* ***(a)*** *diversification positively affects corporate (financial) performance,* ***(b)*** *the size relation between acquirer and target affects corporate (financial) performance,* ***(c)*** *the target's affiliation to a high-technology industry positively affects corporate (financial) performance.*

Staying outside company borders, Zajac, Golden & Shortell (1991, p. 173) explain innovativeness with the degree of market competition. Jansen, van den Bosch & Volberda (2006, p. 1665) assign a moderating effect to the environmental competitiveness. Such competitiveness would negatively moderate the relationship between exploratory innovation and financial performance and positively moderate the relationship between exploitative innovation and financial performance. Chandra, Osorio-Rodarte & Primo Braga (2009, p. 25) are more precise in finding an explanation for the relatedness of innovation to competition. They argue that innovation was a way to "escape" competition and agree with Aghion & Howitt (2006, p. 278), Acemoglu et al. (2018, p. 3457), and Acemoglu, Aghion & Zilibotti (2006, p. 39) who emphasize the importance of industry closeness to a "technological frontier", on the one hand, and that competition plays an important role for the productivity of a firm. Regarding high-technology industries Ransbotham & Mitra (2010, p. 2079) imply a central role in the context of acquisitions (see also Higgins & Rodriguez, 2006, p. 358). Again, industry is taken up as a determinant of innovation. In this case, industry is assigned to the motivation to innovate. Is the industry both in which the observed and innovating firm is active and in which an acquired firm is active another determinant of innovation effects on firm performance?

Liao et al. (2010, p. 23) approach this topic generally by referring to "industry structure". They find that such a structure would "[…] moderate the relationship between knowledge acquisition, absorptive capacity and innovation capability." The relationship would presumably become clearer if what is hypothesized by Nain & Wang (2018, p. 4) is true. In fact, they find that: "Horizontal minority stake acquisitions are followed by an increase in industry output prices and price-cost margins, and this increase is more pronounced in industries with greater barriers to entry" (ibid.). Obviously, industry characteristics affect M&A deals with minor participation of the acquirer. Is this transferable to internal innovation and other industry specifics as well?

In their book about innovation output measurement Kleinknecht & Bain (1993, p. 24) already highlight the positive relationship between R&D (internal innovation) and market concentration. However, they point out that this relationship is different when market concentration and innovation output are directly related. Nain & Wang (2018, p. 5) provide yet another insight. They find evidence that returns (of an M&A announcement) of firms is explained through industry concentration of the customers' industries. Vanhaverbeke, Duysters & Noorderhaven (2002, p. 720) postulate that within the same industry, alliances are rare and that, if these alliances were formed, it was most likely to be in the shape of an acquisition. This implies, that companies rather decide to overtake or eliminate competitors through acquisitions than collaborate with these. Obviously, the fear of unwanted knowledge acquisition is pervasive. Assuming, that Aghion & Howitt (2006, p. 280) are right about the importance of industry closeness to a technological frontier, the industry of a company drives innovation efforts and activities. Hence, there has to be a relationship between the extent of (internal and external) innovation efforts and industry affiliation. We hypothesize:

Hypothesis 6 (H6): *A firm's industry affiliation moderates innovation effects on corporate (financial) performance.*

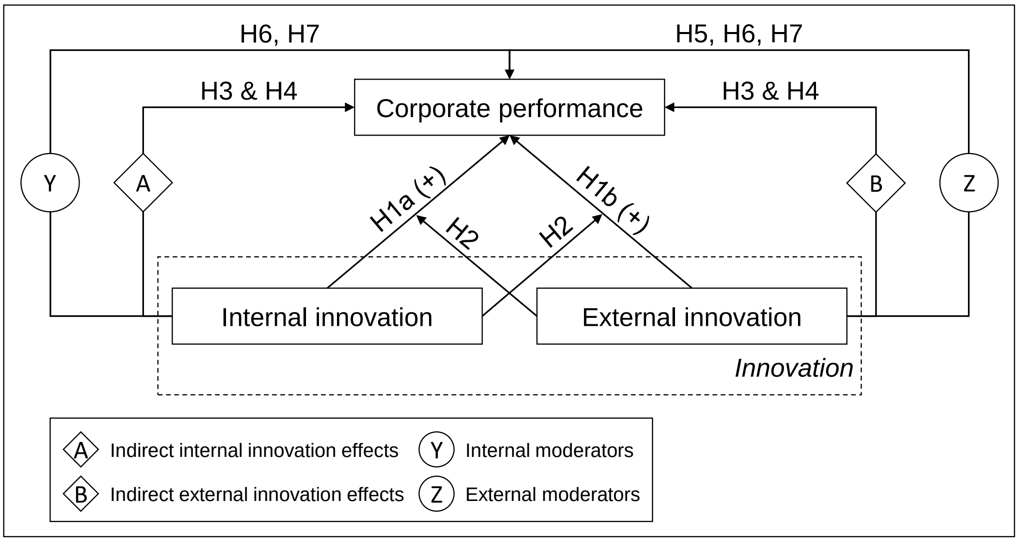
The issue of missing investigations about the conditions of the innovation effects on performance as is mentioned further above, is partly taken up by Leiponen & Helfat (2011, p. 644) who state: "A positive association between multiple locations of R&D and the amount of innovation output is mediated by the extent of external knowledge sourcing that firms utilize in their innovation activities." In this particular case, the relationship between R&D locations and innovation output is conditioned on external knowledge. In the context of our research focus, we are looking for these kinds of conditions. The reason is, that in contrast to most above-mentioned and below-following sources, this thesis pursues to be an initial lead for entrepreneurs and managers to orientate themselves when confronted with investment decisions with a given (innovation) budget and the need to consider basic conditions and eventualities.

White & Bruton (2011, p. 21) allocate different areas influencing both internal and external innovation management. Nevertheless, a last major issue that is not covered by recent economic discussions but is of great importance to managers and entrepreneurs who must consider all eventualities when making decisions, is the time dependency of investment success and innovation effects respectively. Is the effect of innovation on firm performance bound by the date on which it is carried out? To answer this, we hypothesize:

Hypothesis 7 (H7): ***(a)*** *The time period of an innovation significantly moderates its effect on corporate (financial) performance.* ***(b)*** *Innovation effects on corporate (financial) performance are moderated by the consequences of financial crises.*

In order to get a clearer understanding of what has been hypothesized and is tested in the following, Figure 15 provides an illustration of the fundamental research model. The model shows that innovation is not assumed to simply take direct effect on performance but under various conditions and relationships (“A”, “B”) and by moderation of other influences (“Y”, “Z”). Again, this model intends to close the gap that existing specific and pragmatic tools and models view either effects on innovation or performance or both but do not investigate conditions on innovation effects on performance which would provide data-based support in the decision-making process of entrepreneurs and managers much better.

Figure 15: Research model



(Source: own representation)

4. Data and empirical methodology

4.1 Data sources and allocation

4.1.1 Description of data sources

The presented measure calculations and results from regression analyses are, on the one hand, based on the financial annual data from *Compustat North America* which is a database of *Standard & Poor's*. It contains fundamental information of US American and Canadian publicly held companies. The database is provided by the *Wharton Research Data Services* (WRDS) of *Wharton University of Pennsylvania* and has been accessed through a students' account of *TU Dortmund University*. On the other hand, the dataset containing information about M&A deals of US American firms has been accessed through *Eikon*. Eikon is a database provided by *Refinitiv* which is jointly held by *Blackstone Group LP* (55%) and *Thomson Reuters* (45%) since October 2018 (cf. Scuffham, 2018) after it has been entirely owned by Thomson Reuters before. Eikon makes real-time market and fundamental data available to its customers. TU Dortmund University owns several Eikon accounts through which the M&A-datasets were acquired.

Initiated by the Chair of Innovation Management at TU Dortmund University and in joint cooperation with other professorships and chairs, a document has been created which matches firm names from Eikon with company names from Compustat and assigns them to the uniquely identifying *Global company key* (GVKEY) which is a six-digit number key from Compustat. In comparison to other identifiers, the GVKEY remains constant over time. The matching file includes *Standard and Poor's 500* (S&P 500) peers which have been listed between 2004 and 2019 and other companies as well. It matches their names, which are often spelled differently in Eikon and Compustat, using the fuzzy match option offered by *Alteryx*. Alteryx is a computer software which allows the processing of large datasets by commands such as merging, joining, transforming etc. The matched names of Eikon to the spelling in Compustat allows the assignment of Eikon firm names to a unique GVKEY. That way both financial and acquisition data can be merged at a later stage during this study.

The matching of companies of both databases to a GVKEY produces a peer set of 1,378 companies of which 1,202 can be assigned to the S&P 500 index. This index is of major interest due to the superior availability of important financial information and the assumption that, first and foremost, big companies exhibit an active acquisition behavior (cf. Dougherty, 1992, p. 179). The S&P 500 index lists the 500 biggest US American companies by market capitalization (cf. S&P Global, 2020) and thereby optimally aggregates companies with a high number of publicly available and complete financial statements during the observed time period, which is a necessity for this study to include as many observations per peer without gaps as possible. For this study's purpose, annual financial data from 18,637 companies were collected from Compustat summing up to 167,755 observations. The underlying time period for this thesis covers a 16-year time span from 1st January 2003 to 31st December 2018. The data can be accessed in Compustat's category "Fundamentals Annual".

Throughout this work, companies are understood as the consolidation of both company parents and their corresponding subsidiaries as we understand that acquisition and internal innovation decisions are both made in mutual agreement and affect all parts of a company's conglomerate, at least with regards to its public representation and customers' perceptions. Also, it is argued that innovations, if successfully adopted from acquired targets, are made available to all divisions and subsidiaries of a parent firm (compare Sampson, 2007, p. 370). One example is provided by Volkswagen which uses few platforms to produce the entire fleet across all its subsidiaries[6]. Consequently, the financial dataset from Compustat contains only companies with the consolidation level "C" which equals combined parent and subsidiary accounts.The chosen screening variables, before saving our query from Wharton, are "STD" which represents North America-specific standardized annual data and restated interim, "D" for a domestic population source, instead of an international one, and "USD" for US dollars to be the underlying currency.

The acquisitions dataset from Eikon supplies 9,992 observations of 636 companies of which all are or have been part of the S&P 500 index. This set contains acquirer- and target-specific, as well as deal-specific information such as the deal size, the percentage acquired, the announcement date, and many others. Due to difficulties of access and an enhanced ability of comparison to faculty owned data, the Eikon file has been provided by the Chair of Innovation Management. The collected data is not restricted to only active companies as both active and inactive firms provide valuable insights into their financial development. That way a possible *survivorship bias*[7] is already controlled for.

[6] This applies only to those subsidiaries which focus on car production. Other firms like *MAN* use different production platforms. The platform strategy will also be targeted for the electric vehicle market (Volkswagen AG, 2020).

[7] Survivorship bias describes the falseness of statistical test results due to a biased selection of only active companies which could possibly lead to an overestimation of performance measures.

4.1.2 Allocation and preparation of data

Before proceeding with the necessary data preparation, it is most important to note that this study intends to provide insights about the difficulties of creating valid regression models. Because of this, not only the found results are presented as it is done throughout numerous papers of similar methodologies and issues but also the development process (Section 4.3).

After both the financial and acquisitions data are collected, the next step is to separately calculate all measures which will or might be of interest during the study. To do so, first, the financial data from Compustat is imported into *Stata* which is the underlying statistical software used for this thesis to process the data. Stata is based on the programming language *C*. The used version for this study is *Stata/MP 15.0* on *Windows 10* as the underlying operating system.

After the import of the financial data of the 18,637 companies from Compustat into our Stata coding file (20200605_Code_Data_DH.dta), all observations with the industry format “FS” for financial services are dropped which leaves us with 149,096 observation of 18,637 companies. Financial services in Compustat include banks, insurance companies, brokers, real estate, and other financial services. Such corporations tend to report their financial statements under different reporting standards and therefore it is decided that these observations should not be compared to the other companies with an industry format “IND” (industrial). Fortunately, as the unchanged peer number proves, those financial service companies have all provided financial data in an industrial format as well. Additionally, all duplicate observations and non-US American companies are dropped which confines our focus on companies of the same nation, which allows us to already control for possible nation-specific effects that might occur when comparing peers cross-country-wise. The final raw financial dataset upon which the later measure calculations are based consists of 128,317 observations of 16,022 different companies.

For the purpose of calculating measures and regressors for the final regression analyses relevant literature with the main focus on “A+”-rated journals according to (VHB, 2020), with specific focus to the topics “innovation”, “acquisition”, “performance” and various combinations of these, has been screened as a first step. Out of these journals, the found measures are aggregated, imported into excel to drop duplicates, clustered, sorted, and assigned to their citations.

Why is this an important and effective pre-step before the actual computation of measures in Stata? Quantitatively screening regressors and measures which are repeatedly used in literature allows us to identify fundamental components of a significant model and to understand possible shifts of the research focus away from measures used during the previous decades to measures that have arrested attention in the modern and more recent study landscape.

Table 2 presents the identified categories of measures. Basically, there are four categories constantly recurring in literature: environmental measures, firm-specific measures (e.g. firm size or other financial KPIs, measures that can be linked to innovation, and measures regarding the area of mergers & acquisitions. The choice of the *dependent variable* (DV) or the *independent variables* (IVs) varies across papers and journals. At this stage of the study, the clusters in Table 2 are strong indicators that characteristics of firm performance, internal innovation effort, and external innovation acquisition are related to each other or even affect each other. At least, their collective relationship has apparently drawn attention to scientific research.

Table 2: Recurring categories of measures in screened literature

Measure level-1-category	Measure level-2-category	Measure level-3-categories
Environment	Country-specific	-
	Industry-specific	-
	Institutional	-
	Other dummies	-
	Social	-
	Time-specific	-
	Uncertainty	-
Firm	Accounting	Assets; Equity & capital; Performance & income statement
	Finance	-
	Slack	-
	Strategic & organizational	-
Innovation	Alliances & networks	-
	Knowledge & innovation	-
	Patents	-
	R&D & expenditures	-
M&A	Acquirer	Acquirer M&A history; Acquirer structure; Acquirer performance; Acquirer size; Acquirer slack
	Deal	Acquirer-to-target relatedness; Offer type; Deal term; Deal value; Deal financing
	Post-M&A	Acquisition performance; Post-M&A growth; Post-M&A innovation; Post-merger integration
	Target	Target age; Target financials; Target firm type; Target pre-patents; Target size

(Source: own representation)

The above-shown measure categories are further aggregated and analyzed based on their formulae as well as on the feasibility of calculating them with the existing data from Compustat and Eikon. In addition to that, some of the measures appear not to be computable but can be approximated by making some slight changes to them. In the end, 85 distinct basic measures were chosen to form the measurement basis of our Stata code, although not all measures will be found to be fit for the later regression models. In addition to the calculated measures, *time*-, *state*- and *industry-dummy variables* are included accounting for differences originating in the observed time period, in the state (US) of the firms' headquarters as well as in the industry type approximated by a four-digit *standard industry classification* code (SIC). This code standard was established in 1937 by the United States and consists of the first two digits indicating the "major group", the third digit indicating the "industry group", and the last digit representing the "industry sector" (cf. United States Department of Labor, 2020). A final dummy variable (also known as *indicator variable*) added to the Stata code is a *financial crisis* identifier which equals one, if the observation dates back to the years 2008 to 2012 (five years after the global financial crisis). This dummy is chosen to control for possible crisis anomalies in the explanation of the research focus.

Out of the initial clusters from Table 2 groups that are both aligned to the findings from literature and are of actual interest for this thesis are developed. Accessorily, these groups are arranged and created respectively in such a way that it simplifies the computation in Stata. Table 13 (see appendix) presents these groups and measures. Apparently, our calculations are based on the assumption that models aiming to explain financial, innovation and acquisition characteristics should contain *environmental*, *firm*, *investment*, *innovation* and *acquisition measures*. The firm variables are divided up into *general firm measures*, e.g. size and growth variables, *slack measures*, *liquidity measures*, and measures that represent different forms of *profitability*. Innovation variables are restricted to variables representing a certain position of expenditures, e.g. capital, total, or R&D expenditures. Also, one would include patent variables in this category. This thesis focuses on what is understood as innovation effort, instead of innovation output. Hence, as the latter would be described through patent data, such measures will not be included in the presented regressions. Lastly, acquisition measures include deal specifics as well as combined ratios of firm, deal or environmental measures (e.g. *target high-tech industry rate* which indicates whether the target is a high-tech company).

First, the so-called *industry variables* are calculated. For that goal not only data on our final S&P 500 peers have been collected but also of all 16,022 available companies for the underlying time span. The computation continues with firm variables and *firm-industry variables*. The latter describes KPIs that are based on both industry and firm variables. The following *firm-acquisition variables* are derived from firm variables but are associated with acquisition characteristics in literature. Lastly, firm indicator variables cover the above-mentioned state and industry dummies, as can be seen in the code and in Table 13.

Next, all financial data besides the calculated measures, the time variable (*fyear*) and the company identifier (*gvkey*) are dropped. The Compustat data code is saved and we continue with the Eikon dataset to compute all acquisition-related variables: *acquisition variables* and *acquisition indicator variables*.

Finally, both the calculated variables based on Compustat and Eikon data are merged into one file. That allows us to calculate even more measures (e.g. *acquisition-firm variables*) which combine data from both sets, e.g. the acquirer-target relatedness (*_AcqTargRelSizeI*) which divides a firm's acquisition deal value per year by the market value of the acquirer of that year.

The merging of both files results in (20200307_Stata_Data_Merged_DH.dta with) 133,904 total observations of 16,297 companies because there are certain firms which are included in Eikon but are not part of the Compustat file. Again, we drop all unnecessary columns and duplicate rows. As our final step, the merged data file which contains all companies is merged again with a version of the Compustat file in which all columns except *gvkey* have been dropped beforehand. The merge produces an indicator variable "*_merge*" which shows whether the data has been used only from the first file (*_merge* == 1), only from the second file which contains only the *gvkey* (*_merge* == 2) or matched from both files (*_merge* == 3). All except the matched data (*_merge* == 3) are dropped which leaves us with a document that contains only our S&P 500 peers and all calculated measures. This step may not seem very straightforward but allows us to both save a file with all calculated measures for all companies (20200307_Stata_Data_Merged_DH.dta) and a file with all calculated measures containing only our S&P 500 peers (20200307_Stata_Data_Merged_SP500_DH.dta) separately from one another.

The data file containing all companies is the basis for calculating firm-industry variables, i.e. measures that put firm specifics (e.g. size, growth) in relation to the entire corresponding industry. The latter data file will be used for our regressions because the focus of this study is the examination of the S&P 500 peer set. This is also the underlying panel data sample and contains 16,048 observations of companies which have been listed in the 16-year time span. In the following we proceed in a new Stata coding file (20200605_Code_Control_Models_GEE_DH.dta). However, before the creation of controls-only models, the foundations of empirical regression models and their requirements must be understood.

4.2 Introduction into econometric foundations and requirements

The first step of establishing a model to observe an underlying behavior, circumstance, or development is the generation of a so-called **controls-only model** which contains important components (regressors) that explain a large portion of the dependent variable but are not the main interest of the research. Such control variables can be considered factors that have a known influence on the dependent variable.

In our case, as the three subtopics of the research focus – performance, innovation, and acquisition – will be explained, we will not only look at a single model but at different versions of our targeted final controls-only model throughout this thesis. “Different versions” means that variables, which are significant in explaining the DV (corporate financial performance) are repeatedly added to the model while other variables are excluded. We will always align with the common and theory-based practice which is explained in the following.

Well-known for their work and findings in the theory of econometrics, Carl Friedrich Gauss (1821) and Andrey Markov have established fundamental assumptions and requirements known as the ***Gauss-Markov assumptions*** which need to be satisfied, in order to guarantee a model’s econometric correctness and freedom from adulterant noises that are triggered, if unwanted effects are not considered in the model and corrected beforehand. Such effects originate in relationships between unobserved or ignored issues and the DV, as can be seen in the following Section 4.2.1.

To better understand how regressions are constructed and why the Gauss-Markov assumptions play such an important role when generating models, we must look at the theoretical background of econometrics.

4.2.1 Cross-sectional data models

Take the standard model of a **simple linear regression**:

$$y_i = \beta_0 + \beta_1 x_i + u_i \tag{1}$$

Adding multiple independent variables to the model, leads to a **multiple linear regression**:

$$y_i = \beta_0 + \beta_j x_{ij} + u_i \quad \text{or} \quad \boldsymbol{y}_i = \boldsymbol{x}_i' \beta + \boldsymbol{u}_i \quad \text{or} \quad Y = X\beta + u \tag{2}$$

Here, y_i describes the dependent measurement which is explained through the independent variables x_{ij}. The parameters β_j are indicators for the influence of x_{ij} ceteris paribus on y_i, while j represents the number of so-called *regressors* and i represents an index for the respective sample (in our case it is represented by the GVKEY which, again, represents an individual company) (cf. Wooldridge, 2013, p. 12). It is this latter index i that gives ***cross-sectional data models*** their name because it runs with the individual company and, hence is ever-changing, if multiple individuals/companies are observed. These companies are all observed at one certain point in time which is why time t is fixed and not displayed in any cross-sectional function. The error term u_i contains all unobserved effects which cannot be displayed by the regressors. This term will be of special interest at a later stage of this thesis (see Section 4.3.3).

Because the true model is usually unknown due to complexity, the reality cannot be entirely rebuilt with a congruent regression model. Therefore, regressions are estimated:

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_j x_{ij} \tag{3}$$

The basic form here is subject to specific assumptions, without which a *causal identification*[8] of the parameters would not be possible. These basic assumptions are known under the name **Gauss-Markov assumptions** (or Gaussian assumptions) (cf. Gauss, 1821; Wooldridge, 2013, p. 59). In compliance with the Gaussian assumptions the parameter $\hat{\beta}_j$ is an undistorted parameter estimator. It is, then, the ***B****est* ***L****inear* ***U****nbiased* ***E****stimator* (BLUE), i.e. the best unbiased estimator that a regression estimation can put forth. This principle is called ***Gauss-Markov theorem*** and is essential to any work with such data.

The assumptions for cross-sectional data models are as follows:

C1 **Correct Specification & Linearity** ($Y = X\beta + u$)

Misspecifications are either caused by superfluous regressors or by omitting relevant variables (*omitted variable bias*). In both cases, the parameter estimator would not be BLUE anymore. In the case of an omitted variable bias, it would even not be

[8] We speak of identification, if the parameter can be estimated.

unbiased (true to expectations), i.e. not correct in its expected value. At the same time, we assume linearity in parameters.

C2 **Random Sample Selection**

In order to avoid *endogeneity*, it is assumed that all sample data is randomly selected, i.e. that they are not consciously chosen or manipulated. This assumption will, as can be seen in Section 4.3.3, be violated in the case of a so-called *sample selection bias* (cf. Heckman, 1976).

C3 **No Multicollinearity**

In the case of multicollinearity, our parameter estimators $\hat{\beta}_j$ would not be BLUE anymore, because regressors could be described through a multiple of other regressors and hence, superfluous regressors would be present in our model.

C4 **Strict Exogeneity** $(E(u_i|X) = 0 => Cov(X,\ u_i) = 0)$

Strict exogeneity, also referred to as *zero conditional mean* (Wooldridge, 2013, p. 86), describes the feature that parameter estimates hit, in their expected value (on average), the true value and, thereby, reproduce reality. To do that, the corresponding regressor and error term must not be correlated with each other (cf. Wooldridge, 2010, p. 54). Closely connected with the term exogeneity is *consistency*. In such a case the estimator would, at the least asymptotically, i.e. for specifically large samples, converge against the true value. Consistency is considered the absolutely minimal assumption, without which any causality of parameter estimators and, thereby, *inference techniques* (hypothesis tests) would not be existent and applicable, respectively. In any case, we need exogeneity to provide consistency. Exogeneity is, on the contrary, not an exhaustive requirement for consistency but a necessary one. At the same time, inconsistency is the case if there is endogeneity (cf. Wooldridge, 2010, p. 61). Methods of resolution are e.g. the *two stage least squares* (2SLS*)*-method (cf. Wooldridge, 2010, pp. 96–98) and an *instrumental variable estimator*, respectively (cf. (Wooldridge, 2010, pp. 89–96). For the special case of *sample-induced endogeneity* the so-called *Heckman Correction*, which will be discussed in Section 4.3.3, comes into play.

C5 **Homoscedasticity** $(Var(u_i|X) = \sigma)$

This describes the assumption of sample-independent error term variances σ. Only when *homoscedasticity* is present, the standard errors of the parameter estimators can be robustly estimated and the results of hypothesis tests (especially significance tests and confidence intervals) are on average correct. In practice, when heteroscedasticity ($Var(u_i|X) = \sigma_i$) is the case, a so-called *feasible generalized least squares* (FGLS) estimator is used. This estimator, however, is only asymptotically (i.e. for very large samples) BLUE because it estimates the error term variance in advance. If necessary, one could determine a robust parameter estimator variance, so that, at least (despite inconsistent parameter estimates) hypothesis tests would be feasible. (Cf. Wooldridge, 2010, pp. 176–180)

C6 **Normal Distribution of Error Terms** $(u \sim N(0, \sigma^2 I_n) => \widehat{\beta_j} \sim N(0, \sigma^2 I_n))$

The normal distribution of error terms is another basic assumption for the application of inference methods which, although not being part of the classic Gauss-Markov theorem are, nonetheless, mentioned at this point due to their importance for modeling in general and modeling with panel data on which is about to be the focus of this section. If error terms are normally distributed, so are their parameter estimators. If our error terms are *identically and independently distributed* (i.i.d.) they are also normally distributed. This, again, requires the mentioned homoscedasticity and non-correlation of the error terms. Only with the satisfaction of this sixth assumption inference methods are generally applicable. (Cf. Antonakis et al., 2014, p. 111)

In case of non-compliance with one or more of these assumptions the mentioned or similar methods of resolution follow. Additional assumptions may be made (cf. Wooldridge, 2010, pp. 161–273). The same applies to so-called *time series data models*.

4.2.2 Time series data models

The above-introduced model represents the case of cross-sectional data models where the observations are invariant (fixed) on the time dimension and examined individuals, often represented by companies, countries, or other institutional bodies, vary so that our sample consists of more than one observed individual.

In the now discussed case of ***time series data models***, the time dimension is set to be variant with $t \in \boldsymbol{N}$, where t represents a sequence of natural numbers where the interval is based on a chosen entity. At the same time, the number of observed individuals i is restricted to one which results in:

$$y_t = \beta_0 + \beta_j x_{tj} + u_t \quad \text{or} \quad \boldsymbol{y}_t = \boldsymbol{x}_t' \beta + \boldsymbol{u}_t \quad \text{or} \quad Y = X\beta + u \tag{4}$$

or

$$\hat{y}_t = \hat{\beta}_0 + \hat{\beta}_j x_{tj} \tag{5}$$

respectively. Consequently, time-series data models describe the case where one particular individual at different points in time is observed. For that case, the Gauss-Markov theorem also applies but requires different assumptions to be satisfied, in order to be able to correctly estimate models and use inference methods. These are as follows:

T1 **Stationarity & Weak Dependence** ($u \sim N(0, \sigma^2 I_n) => \widehat{\beta_J} \sim N(0, \sigma^2 I_n)$)

Stationarity describes the independent distribution of variables from t. In other words, the information content of a sample must be independent of the time period from which it has originated. This assumption is often violated in a time series context. To preserve at least asymptotic correctness of time-series estimations one should try to secure the state of *weak stationarity*. This describes the case where the expected value and variance (of x_t) are finite and from t independent constants. At the same time, it describes the fact that the auto-covariance (of x_t) is only dependent on the time difference h. Stationarity can formally be described as follows:

$$\mathrm{E}(x_t) = \mathrm{E}(x_{t-1}) = \mu < \infty \ \wedge \tag{6.1}$$

$$\mathrm{Var}(x_t) = \mathrm{Var}(x_{t-1}) = \sigma_x^2 < \infty \ \wedge \tag{6.2}$$

$$\mathrm{Cov}(x_t, x_{t-1}) \ independent\ from\ t \tag{6.3}$$

Weak dependence describes the case when the relationship between x_t and x_{t+h} must converge fast enough against zero for $h \to \infty$. "loosely speaking, a stationary time series process $\{x_t : t = 1,2, \ldots\}$ is said to be weakly dependent if x_t and x_{t+h} are "almost independent" as h increases without bound" (Wooldridge, 2013, p. 382; cf. Ha & Howitt, 2007, p. 735).

T2 **No Multicollinearity**

This assumption is also a requirement for time-series data models.

T3 **Contemporaneous Exogeneity** ($E(u_t|x_t) = 0 => \ Cov(x_t,\ u_t) = 0$)

The problem with strict exogeneity is that it is often violated in the context of time series data. As described above, strict exogeneity "implies that the error at time t, u_t, is uncorrelated with each explanatory variable in *every* time period" (Wooldridge, 2013, p. 350). For contemporaneous exogeneity, this is only the case for the same time period ($t = s$). For $t \neq s$ this is only required by strict exogeneity. Consequently, in the case of *contemporaneous exogeneity* ($E(u_t|x_t) = 0 \to \ Cov(x_t,$ $u_t) = 0$) the estimator would at least reproduce reality correctly for the same time period t. Why is contemporaneous exogeneity so important? Asymptotically, i.e.

when working with large samples, basic econometric characteristics are required in order to be able to derive certain significance tests and apply other inference methods when repeating an experiment often enough and observing many time series, respectively. As mentioned before, this would result in consistency which has been introduced as the minimal assumption for econometric methods to work and be valid.

T4 **Homoscedasticity** $(Var(u_t|X) = \sigma)$

Homoscedasticity (see cross-sectional data models) is also a basic requirement for time series data (cf. Wooldridge, 2013, p. 402).

T5 **Freedom from Autocorrelation** $\mathrm{Corr}(u_t, u_s) = 0 \;\forall\; t \neq s$

Autocorrelation is often referred to as ***serial correlation***. It is explicitly stated here that autocorrelation of our variables is not a problem and can frequently occur in time series data. What is of interest and covered by this assumption here is the freedom from autocorrelation of the error term. Serial correlation describes the case when error terms are correlated across time. Consider two different points in time: t and s, where $t \neq s$. For these time periods we, if assuming autocorrelation, consider the error terms to correlate with each other so that $\mathrm{Corr}(u_t, u_s) = 0 \;\forall\; t \neq s$ which originates in $\mathrm{Cov}(u_t, u_s|X, \alpha_i) = 0 \;\forall\; t \neq s$.

The consequence of serial correlation is that any estimated parameter estimator variance would be inconsistent which would result in inference methods not being applicable and the parameter estimator not being BLUE. The goal of correctly applying hypothesis tests is to avoid such type of correlation which is why we assume freedom from autocorrelation and will test for it during our estimations and regression analyses.

In case the hypothesis of autocorrelation cannot be rejected as per upcoming significance tests one usually makes use of a so-called FGLS-estimator. However, it is only asymptotically (for specifically large samples) BLUE because it estimates the error term variance in advance. An alternative but much more difficult approach to correct for autocorrelation is to simply specify an alternative model. This is often strongly restricted to the data availability and, usually, puts a lot of pressure on the respective scientist. (Cf. Wooldridge, 2013, p. 353)

T6 **Normal Distribution** $(u \sim N(0, \sigma^2 I_n) \rightarrow \widehat{\beta_J} \sim N(0, \sigma^2 I_n))$

As is required for cross-sectional data models the normal distribution of error terms is also needed in the context of time series data models for inference methods to properly function.

Note that the above-mentioned assumptions for both cross-sectional data and time series data refer to estimations with o*rdinary least squares* (OLS). OLS estimation approach can no longer be held as best practice for panel data models. Other estimation methods for cross-sectional and time series data models may need other assumptions which are not further discussed here.

4.2.3 Panel data models

The question is, what happens if cross-sectional and time series data are combined. So-called *seemingly unrelated regressions* (SUR) are based on such combination. These models combine both a varying time index t and a variation of observed individuals i so that

$$\boldsymbol{y}_{it} = \alpha_i\, \boldsymbol{x}'_{it}\beta_i + \boldsymbol{u}_{it} \tag{7}$$

The problem with this type of regression is that it assumes that the parameter vectors α_i and β_i can vary with i.

***Panel data* models** (also referred to as *longitudinal data models*) are based on the assumption that $\beta_i = \beta\ \forall\ i$. That implies, that the parameters are equal for every individual. This makes sense because there can exist variables in a model which all have the same effect on the dependent variable for the same observed individual. Nonetheless, panel data models allow a so-called *time-invariant heterogeneity* which is described by individual-specific characteristics α_i. These vary only over different individuals i. That makes sense, as well, and becomes clear when taking an employment example into consideration. Imagine, we wanted to estimate the effect of trainings on the employment situation of employees or applicants for a job. Then, there would be unique properties to every individual which would not vary over time, e.g. education, age, experience etc.

Consequently, panel data models can be structured as follows:

$$\boldsymbol{y}_{it} = \alpha_i\, \boldsymbol{x}'_{it}\beta_i + \boldsymbol{u}_{it} \tag{7}$$

There are numerous possibilities for estimating panel data models. *Pooled OLS* (POLS) is one method that deals with data sets as if they were a large cross-section with observations with $t \sim T$ different time periods and $n \sim N$ different individuals. However, this implies that we disregard unobserved, time-invariant effects as if we had no data of them. Then those effects would become part of the error term $v_{it} = \alpha_i + u_{it}$ when $y_{it} = x'_{it}\beta + v_i$. Thereby, POLS ignores the panel data structure. Theoretically, this can lead to valid estimations but only, if these effects are not correlated with x_{it}. This would lead to $\mathrm{Cov}(x_{it}, \alpha_i) \neq 0$ and, eventually to x_{it} correlating with the error term v_{it}. For such cases POLS is inconsistent. In other cases, POLS is consistent but not efficient. (Cf. Wooldridge, 2010, pp. 169–173) "Because panel data require replication of the same units over time, panel data sets, especially those on individuals, households, and firms, are more difficult to obtain than pooled cross sections" (Wooldridge, 2013, p. 11). Therefore, we introduce two consistent ways of estimating panel data models: *random-effects* (RE) and *fixed-effects* (FE). Before doing so in a more detailed manner, we have to take a look at the assumptions for panel data models because they not only reveal more distinctions between panel data, cross-sectional data, and time series data but also reveal the main difference between RE- and FE-models.

The assumptions for panel data models are as follows (cf. Wooldridge, 2013, pp. 509–511):

P1 **Correct Specification & Cross-sectional Independence** ($Y = X\beta + u$)

As is the case with cross-sectional data, we assume that the used model is correctly specified and does not leave out any relevant variables to avoid an omitted variable bias. In addition to that, we assume that the sample is random from the cross-section.

P2 **Classic Error Terms**

P2.1 **Homoscedasticity** ($\mathrm{Var}(u_{it}|X, \alpha_i) = \mathrm{Var}(u_{it}) = \sigma_u^2$)

This remains an important assumption, regardless of whether we work with cross-sectional, time series, or panel data.

P2.2 **Freedom from Autocorrelation (**$\mathrm{Cov}(u_{it}, u_{is}|X, \alpha_i) = 0$)

For panel data models it is essential to avoid autocorrelation of error terms. If the hypothesis of autocorrelation cannot be rejected the asymptotic solution is the same as with time series data: an FGLS-estimator which is consistent but only asymptotically BLUE.

P3 **Strict Exogeneity** ($\mathrm{E}(u_{it}|X, \alpha_i) = 0 \Rightarrow \mathrm{Cov}\left(x_{isj}, u_{it}\right) = 0 \wedge \mathrm{Cov}(\alpha_i, u_{it}) = 0$

P4 **(Non-)Correlation with Unobserved Effects**

P4.1 **Correlation of Regressors with Unobserved Effects** ($\mathrm{Cov}(x_{it}, \alpha_i) = 0$)

The major difference between a RE-model and a FE- model is that the random-effects model assumes that the unobserved individual-specific effects are not correlated with each explanatory variable so that $\mathrm{Cov}(x_{it}, \alpha_i) = 0$.

That way the RE-estimator is not only consistent but also asymptotically BLUE and asymptotically normally distributed.

P4.2 Non-correlation of Regressors with Unobserved Effects

$(\mathrm{Cov}(x_{it}, \alpha_i) \neq 0)$

The FE-estimator needs the regressors x_{it} to be correlated with the unobserved effects α_i to be consistent, BLUE, and normally distributed. In that case, both POLS and RE would be inconsistent.

If P1-P3 and P4.1 are satisfied, then the RE-estimator is asymptotically BLUE. If P1-P3 and P4.2 are satisfied, the FE-estimator is BLUE. But what is RE and FE exactly?

RE is really a *generalized least squares* (GLS) estimator (cf. Wooldridge, 2013, p. 493). It allows us to model the unobserved effects α_i as part of a composite error term because they correlate with both the regressors x_{it} and the error terms u_{it}. Such modelling results in idiosyncratic errors u_{it}. They are also called a time-varying error term "[…] because it represents unobserved factors that change over time and affect $\mathrm{y_{it}}$" (Wooldridge, 2013, p. 460).

Fixed-effects models, on the other hand, treat unobserved effects α_i as if they were parameters. They can be estimated by applying a *within transformation* or as a *least squares dummy variables* (LSDV) regression. The first one (*within-estimator*) is the FE-estimator adjusted by its means. The latter represents the unobserved effects through several dummy variables and estimates the resulting multiple regressions.

4.3 Development of controls-only models

Now, that fundamental types of regressions have been introduced and understood and that basic assumptions for panel data models have been developed, we can proceed with what has initially been the purpose of these assumptions and the intention of presenting them – the generation of controls-only models as a first step of modeling our economic and managerial relationships of interest. The merged dataset from the previous Stata code containing only the S&P 500 peers is used. All missing values of dummy variables, measures that are calculated based on dummy variables, and acquisition measures are replaced with zeroes. Missing values for dummies represent nothing but zeroes and missing values for acquisition-related measures indicate that an observed company does not show any acquisition activity throughout the observation period. Due to their size and based on the assumption that Eikon covers all of the acquisition data of the companies that are part of its data bank, it is assumed that the missing of information about acquisition measures indicates that there has, in fact, not been any such activity by the individual monitored company. This is a very strict assumption, but it can be justified by the huge gain in the number of observations which would otherwise be automatically dropped by Stata when estimating regressions.

Now it is time to apply the recently gained theoretical knowledge of regression models and basic assumptions to our data. In the following, the econometric approach will be demonstrated and explained in alignment with the basic assumptions for panel data models (P1-P4).

4.3.1 Correct Specification and cross-sectional independence

In accordance with our established hypotheses (Section 3.3), the underlying idea of our approach to answering the research question is to translate it into one regression model that attempts to explain the effects of internal innovation effort and external innovation acquisition respectively on corporate financial performance. Consequently, we choose a DV which represents this performance and investigate direct and moderating innovation effects of corresponding measures on it. In doing so, we investigate the conditions of innovation effects on performance. The chosen DV is the firms' *EBIT-margin* for reasons which are explained in the upcoming Section 5.1.1.

As described in Section 4.1.2 we have both observations on a large number of individuals, in our case the S&P 500 companies which have reported their financial standpoints, as well as a time span of 16 years. Obviously, simple cross-sectional data models or simple time series data models would not do the job of validly preparing our observations for inference methods. Hence, we find ourselves confronted with a combination of both. Also, as has just recently been deduced, SUR- or POLS-models do not acceptably handle the case of longitudinal data. This leads us into the direction of panel data models. Random-effects or fixed-effects models come to mind. Deciding between these two options is essential to proceed with our regressions and analyses, which is why, as an initial step, we prefer testing for assumption P4 to analyzing the panel data assumptions in their usual order.

To test whether to choose an RE-model or an FE-model, the ***Hausman specification test*** (in short: *Hausman test*) is conducted. However, a starting model containing variables that might be relevant is needed beforehand. This is very difficult to forecast as it is what ultimately needs to be found out with our regressions. Therefore, all variables available in the beginning are used, leaving out the ones that strongly correlate with each other. At this stage, "strong correlation" is defined as a *Pearson's correlation coefficient* of higher than 0.5 (Stata command: *pwcorr*). This results in an initial model on which Hausman test can be applied.

The **Hausman test** is a frequently used test to choose between a random-effects model and a fixed-effects model (cf. Tambe & Hitt, 2014, p. 61; Mishra & Slotegraaf, 2013, p. 717; Bloom, Schankerman & van Reenen, 2013, p. 1369; Wang & Lu, 2013, p. 36; Kleis et al., 2012, p. 50; Krasnikov, Mishra & Orozco, 2009, p. 161; Rothaermel & Hess, 2007, p. 909). It was developed by Hausman (1978). Under the null hypothesis, the random-effects model is preferred to the fixed-effects model because the FE-model would then be inefficient. If the null hypothesis can be rejected (depending on the choice of the significance level α), one should use FE instead of RE because then RE would even be inconsistent (cf. Hausman, 1978, p. 1268). Despite the frequent use of this test, there are also critics among scientists. Schilling (2015, p. 12) states that one should not (only) consider the Hausman test but rather look at other characteristics of the underlying data. Clark & Linzer (2015, p. 407) add: "Instead, the decision must be based on the amount of data in a study and the level of correlation between regressors and unit effects."

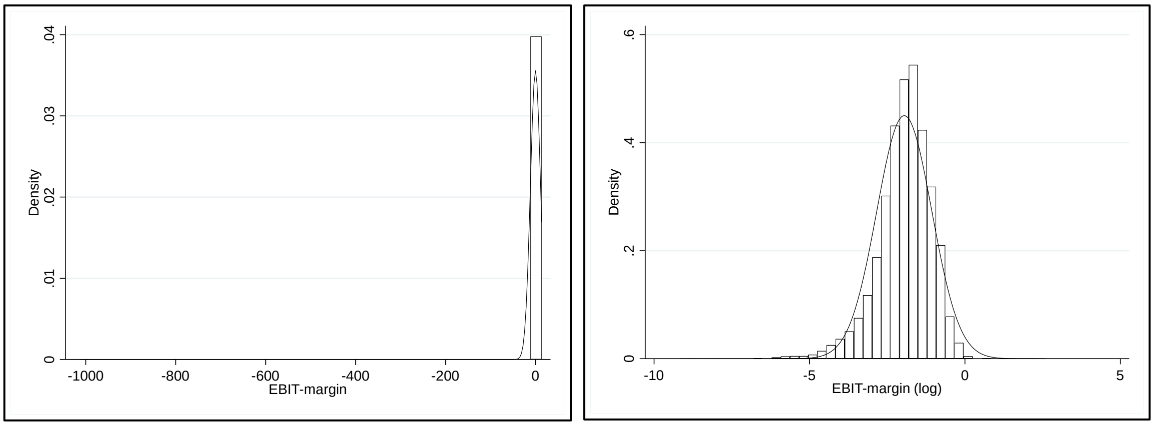
In our case, both data characteristics and the results from Hausman test would be combined to conclude which model type to choose. However, the Hausman test drops our indicator variables. To make sure of the right interpretation of the test results, Hausman is recomputed with standardized measures (using *std* command). The result remains the same in that dummy variables are still dropped. This implies, that these variables are collinear with one or many of our other predictor variables or with whatever variable is specified as panel variable (here: *gvkey* and *fyear*). We conclude that the indicators do not vary within panels and FE-estimation would not be appropriate as it assumes just that variation (cf. Wooldridge, 2013, p. 485). Nonetheless, the Hausman test's results indicate that an FE-model should be chosen because the null hypothesis is rejected. However, the Hausman test's results cannot be trusted when relevant variables like our dummies are simply dropped. A possible explanation could be that Hausman drops dummies due to high correlations. Another explanation is that Hausman only considers variables with similar coefficients in both models (RE and FE). This dilemma of contradicting factors regarding the implications and interpretation of the Hausman test demands to overthink the choice of the model type.

Ballinger (2004) introduces the ***generalized estimating equation*** (GEE) as a new status quo of modeling panel data regressions. He points out that GEE would be able to "[…] estimate more efficient and unbiased regression parameters relative to ordinary least squares regression in part because they permit specification of a working correlation matrix that accounts for the form of within-subject correlation of responses on dependent variables of many different distributions, including normal […]" (Ballinger, 2004, p. 127). In other words, it allows a certain degree of correlation between residuals which OLS does not. According to Liang & Zeger (1986, p. 14) the coefficients and standard errors estimated with GEE would be asymptotically normally distributed. Ballinger (2004, p. 130) adds that GEE should be used for significance tests of both "main effects and interactions" regardless of whether IVs were "categorical or continuous". "GEE estimates are the same as those produced by OLS regression when the dependent variable is normally distributed and no correlation within response is assumed" (ibid.). "GEE is an extension of the generalized linear model […] to correlated data such that valid standard errors of the parameter estimates can be drawn" (Cui, 2007, p. 210; cf. Nelder & Wedderburn, 1972).

For this exact reason the Gaussian assumptions are also applicable for GEE, with the exception being P4. Nonetheless, the usage of GEE demands a proper fitting of the model. The user is obliged to make three specifications in advance. First, the so-called ***family*** needs to be set. The family describes the "[…] distribution of the dependent variable […]" (Ballinger, 2004, p. 131). The nature of our data suggests that EBIT-margin is approximately normally distributed (Figure 16) which would lead us onto the Gaussian model type. Consequently, *gauss* is set as the underlying model family.

The ***link function*** is the second option and offers to choose from the specifications: *identity*, *cloglog*, *logit*, *probit*, *nbinomial*, and *log*. The link function is described as what would make GEE "[…] techniques part of a larger family of log-linear models, nonlinear and distinct from multiple linear regression in the link function but linear and familiar in terms of the string of regression parameters […]." (Harrison 2002, p. 454 cited as per Ballinger, 2004, p. 131). We intend to control for outliers of our regressions by taking the natural logarithm of our DV. Stata suggests choosing *log* as the link function for that. At this point, we must anticipate the later identified need to cluster our data to meet Gaussian assumptions. This result is derived and explained further below in this section. However, clustered data demand an independent link function which is why it is set as *ident*. Nevertheless, outliers can still be accounted for by taking the logarithm of the DV in advance (during the measure calculation step).

Figure 16: Distribution of the dependent variable (EBIT-margin) (Stata output)



(Source: own representation)

The next option to be selected is the ***correlation structure*** of the dependent variable (cf. Ballinger, 2004, p. 133). Stata (2020a) provides information about the different GEE options and their equivalents to other regression types and commands in Stata. Accordingly, one would have to select *exchangeable* as the correlation structure because GEE would then be equivalent to the RE-model specification (*xtreg, re*) in Stata which is what has been the initial idea and copes with our data and research intention. This would also cope with Horton & Lipsitz (1999, p. 161) who suggest *exchangeable* as the right choice for our clustered data. Pan (2001, p. 122) and Ballinger (2004, p. 134) suggest the so-called *QIC*[9] test. We apply the QIC test to all variations of the correlation structure option in our GEE model. The results show that the QIC score for the model with a DV's correlation structure set as *independent* is in fact the lowest with, still, a high score of 1,106.48. Ballinger (2004, p. 134) postulates that "[…] the score that is the lowest (closest to zero) is judged to be the best […]." Consequently, *ind* is chosen as the correlation structure for the underlying regression model. The QIC test also underpins that *ident* is the right choice of link function as the test does not allow *log* for our data in Stata. Liang & Zeger (1986, p. 16) emphasize that the right specification of the correlation structure would be rather less important, compared to the specification of the distribution.

After having specified the correct model options for GEE in Stata and a starting model version, we still lack a proper choice of the right variables to completely align with assumption P1. The measures which are in the end included in the controls-only model are chosen based on the following procedure: The maximum number of variables is included in the model

[9] The QIC is a criterion that can be "[…] used to select the best working correlation structure in GEE analyses" Cui (2007, S. 210).

without adding variables of a Pearson correlation coefficient of higher than 0.5 (as explained further above). As a third step, every variable with the lowest *t-tested* significance (using *xtreg, re*)[10] is either dropped or exchanged by its correlated substitutional[11] variable that has initially been excluded. As a fourth step, all measures, regardless of their significance, are sequentially replaced by their strong correlating alternative measures to investigate which of the substitutes increases the adjusted coefficient of determination – the in-between-R-squared ("*R-sq: between*")[12] – the most.

This procedure is justified by two reasons: On the one hand, we are not interested in the stand-alone-impact and -significance of the controls-only model and its *control variables* (CVs). Instead, it is simply the intention to test whether the IVs which cope with the research focus of this thesis, if added to the corresponding controls-only model, would not only be significantly explaining the corresponding DV but also improve the explanation power of the original controls-only model. The plan is to test whether our IVs are still significant for the explanation of the corresponding DV if the underlying controls-only model already exhibits a high explanation power. If the controls-only model did not exhibit such high explanation power, one could assume that the value added to the model through an IV of interest could be simply explained with the poor choice of rather less significant CVs. The second justification for this approach is the inclusion of variables of all identified relevant measure categories (as is comprehensively explained in Section 4.1.2. The best measures of those categories to explain our DV are chosen. The final step for the creation of the controls-only model is the dropping of more variables, to increase the model's R-squared.

Assumption P1 not only dictates the correct specification in the sense of taking all the relevant variables into the underlying model but also a normal distribution of the error terms and thereby of the residuals of each estimated regression. A **normal distribution** of the residuals is a necessary assumption to apply inference (see Section 4.2.3). There are different possibilities to test this in Stata: the ***skewness*** and ***kurtosis test*** (cf. D'agostino, Belanger & D'agostino Jr., 1990) (Stata command: *sktest*), the ***Jarque-Bera test*** (cf. Jarque & Bera, 1980, 1981) (Stata command: *jb6*), and the ***Shapiro-Wilk test*** (cf. Shapiro & Wilk, 1965) (Stata

[10] GEE, as it is fitted above, is equal to RE-model computation (cf. Stata, 2020b).
[11] Substitutional in that regard refers to variables of the same measure category as defined in Table 2.
[12] The in-between-R-squared makes sense when using and RE-model as it is constructed to account for the variance between separate panel units. The FE-model (within estimator) would require an investigation of the within-R-squared.

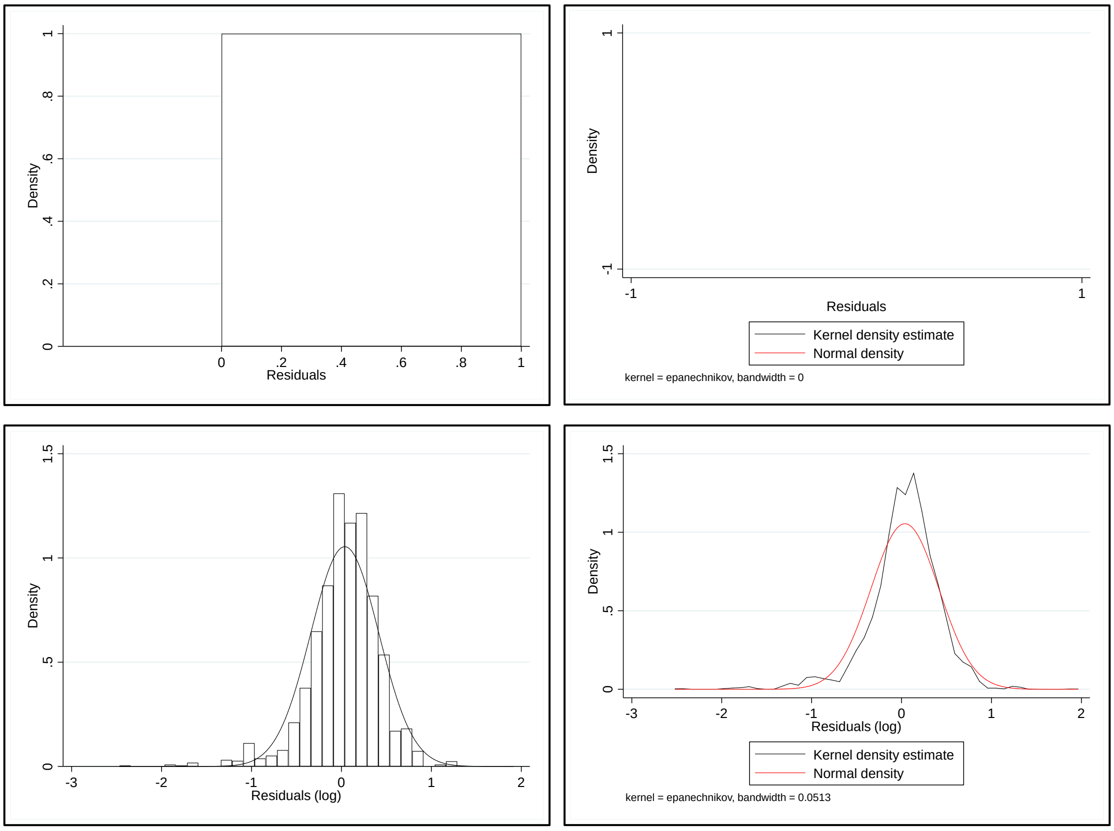
command: *swilk*). All these tests have been conducted. Unfortunately, they are all found to be inapplicable for computational and data-driven reasons.

These difficulties lead us to a procedure that is of more visual nature. The underlying data is examined by computing histograms of the **density distribution function** as well as the **kernel density estimate**[13] of the predicted error terms ($\hat{u}_i$) (residuals) of the clustered data. The closeness of the data to the normal distribution with regards to its skewness and kurtosis can be revealed. As a result regarding our controls-only model, the values for skewness and kurtosis should be optimized (see Figure 17). This is achieved by taking the natural logarithms of the DVs as anticipated above. Note that the non-normality of the DVs' and IVs' distributions is not of concern. As the Gaussian assumption demands, only the non-normality of the residuals of the underlying model are of concern. The non-normality is found to be of acceptable degree based on the graphical analysis of the histograms which show some outliers which is not surprising due to the longevity of the sample.

Another issue regarding P1 is **multicollinearity**. While correlation describes a bivariate relationship, collinearity is a multivariate phenomenon. This would make a derivation of multicollinearity from strong correlations of single pairs of variables a difficult, nearly impossible task, albeit such pairwise correlation might function as a useful indication of possible multicollinearity. This is why our controls-only model has previously been adjusted by not including pairs of measures which are correlated above a coefficient of 0.5. However, economists justify the assumption of non-multicollinearity in their samples with the same few methods.

[13] The kernel density estimate is computed to ensure what is implied by the general distribution function. It is a statistic and non-parametric method to determine the density distribution function of a random variable. As an advantage to histograms kernel density estimate do not withhold information visually due to binning of data. The red line offers an easy comparison to the normal case of a variable distribution.

Figure 17: Density distribution function (left) and kernel density estimate (right) of residuals



(Source: own representation)

Some predict that multicollinearity will not be of concern if the model does not show a higher *variance inflation factor* (VIF)[14] than the self-set threshold of 10.0 (cf. Wang & Lu, 2013, p. 35; O'Brien, 2007, p. 679–681). Others rely on the *condition number test* (Stata command: *collin*) which indicates how large the determinant of a square matrix $(X^T X)$ is (cf. Belsley, 1989; Belsley, Kuh & Welsch, 1980, p. 101) and which should not exceed the threshold of $\eta = 30$ (cf. Belsley, Kuh & Welsch, 1980, p. 164). We apply all these methods to rule out problematic measures but still ensure that all measure categories are represented in the controls-only model. Yet, we do not solely rely on these tools.

Kalnins (2018, p. 3–4) shows that methods like the VIF or the condition number test enhance the production of “**type 1 errors**”[15]. Especially, when correlations exhibited a coefficient around 0.3 Kalnins (2018, p. 9) would often find type 1 errors.

He also introduces **criteria** that indicate the presence **of multicollinearity** in the model (cf Kalnins, 2018, p. 25): First, the mentioned pairwise correlation of around 0.3 would indicate

[14] The VIF is the ratio of the variance of a model with multiple terms over the variance of the model with a single variable.
[15] Type 1 errors occur when the null hypothesis of a significance test is falsely rejected.

such an error. As a second requirement, the coefficients of both correlated variables would have to show coefficients of the opposite sign, if they were correlated positively (positive correlation coefficient) and coefficients of the same sign, if they were correlated negatively. As a third and last criterium, a variable would cause multicollinearity, if its correlation with the DV was either of the opposite sign of the beta or not statistically different from zero. Kalnins (2018, p. 25) accentuates that multicollinearity may be present if "all" the criteria would hold. We apply this approach to our data and find that two variables (*l1._AvgIndSizeA4* and *l1._AvgIndSGA4*) are correlated above the threshold of 0.3 (~0.54). Both variables also fulfill the second and third criterium. Consequently, one of them (*l1._AvgIndSGA4*) is substituted with another variable (*l1._AvgIndSalesGrowth5Y*) and the model is rechecked for the three criteria. In fact, now two other variables (*l1._IndCon4* and *l1._FirmSizeSales*) show signs of multicollinearity based on the first criterium. Fortunately, the second and third criterium do not hold for each of them and the model is now assumed free of multicollinearity and correctly specified. Assumption P1 is tested up to computational limits and can be considered satisfied. We continue with assumption P2.

4.3.2 Homoscedasticity and freedom from autocorrelation

Homoscedasticity

Assumption P2 demands classic errors in the sense of homoscedasticity and freedom from autocorrelation. Starting with assumption P2.1, which is **homoscedasticity,** we come across frequently used conventional tests, one of which is the ***Breusch-Pagan test*** (cf. Breusch & Pagan, 1979). It actually tests the existence of heteroscedasticity ($\mathrm{Var}(u_{it}|X,\alpha_i) = \mathrm{Var}(u_{it}) = \sigma_i^2$) with its null hypothesis being the presence of homoscedasticity ($\mathrm{Var}(u_{it}|X,\alpha_i) = \mathrm{Var}(u_{it}) = \sigma^2$). The idea is to regress the squared residuals on all the regressors of the main regression and to estimate the parameters. Under the null hypothesis, these parameters would all be equal to zero. A similar test is the so-called ***White test*** by White (1980) which represents a specific version of the Breusch-Pagan test. Unfortunately, both tests work with samples where N is small and T is large, which is not the case here. Baum (2000) offers a workaround solution specifically for Stata with the *xttest2*. Despite the fact, that our data shows large samples across companies and relatively small samples across time, Stata confronts the executioner of this Stata command with the problem that there are too few observations across panels.

The same problem occurs with other tests for cross-sectional dependencies in panel data like ***Friedman's chi-square distributed statistic*** (cf. Friedman, 1937), ***Free's Q distribution*** (cf. Frees, 1995) or ***Pesaran's statistic*** (cf. Pesaran, 2004). Another consideration for testing heteroscedasticity is the ***Goldfeld-Quandt test*** (cf. Goldfeld & Quandt, 1965) which assumes a specific form of heteroscedasticity induced by a specific regressor. It is useful when the underlying regression contains an indicator variable among the regressors. All of them intend to bridge the gap of testing for heteroscedasticity but fail due to the missing of enough "common observations" in Stata. Our options for testing heteroscedasticity, given our specific panel data structure, seem limited. This issue is postponed, and it is proceeded with assumption P2.2 – freedom from autocorrelation.

Freedom from autocorrelation

P2.2 demands freedom from autocorrelation of the error terms. To test this, the *Breusch-Godfrey test* (cf. Breusch, 1978; Godfrey, 1978) and *Durbin-Watson test* (cf. Durbin & Watson, 1950) come to mind. Both are problematic because they are not supported in Stata.

An alternative is the so-called ***Wooldridge test*** (cf. Wooldridge, 2002, p. 282; Drukker, 2003). The null hypothesis of the test is that the residuals from the regression of the first-differenced variables have an autocorrelation of -0.5 (cf. Wooldridge, 2002, p. 283). Hence, if the null hypothesis is rejected there is enough evidence that autocorrelation is present (based on a chosen significance level α). Stata provides an implementation of testing autocorrelation of the idiosyncratic errors of a linear panel data model by conducting the *xtserial*. We find evidence of strong autocorrelation. As the test result "Prob > F = 0.0000" demonstrates, we are obliged to correct the model's standard errors. This problem and the problem of (not yet proven) heteroscedasticity is attended to by clustering the data using the *Huber-White sandwich estimator* (cf. Huber, 1967). Therefore the *vce(robust)* command is applied in Stata as has been anticipated further above (cf. Wooldridge, 2010, p. 446).

Clustering our data helps to **identify heteroscedasticity**. If the standard errors of the coefficients increase in the regressions with clustered data, we can assume homoscedasticity. If the standard errors do not increase, a certain degree of heteroscedasticity must be expected. The results are not univocal. About half of the CVs of the controls-model exhibit lower standard errors in the clustered case. Consequently, it is assumed that heteroscedasticity cannot be completely ruled out (cf. Wooldridge, 2003, 134).

4.3.3 Exogeneity

The last major issue that remains is the one linked to assumption P3: the issue of endogeneity. As has been described in Section 4.2.1, endogeneity arises between IVs and the error term. In that case, both are correlated, which means that the explanation power of the correlated IV is influenced by unobserved effects. There are four different **sources of endogeneity** to be distinguished, three of which frequently occur in other research fields as well (cf. Rutz & Watson, 2019, p. 481–484).

Omitted variable bias

The first is the **omitted variable bias**. As is known from Section 4.2.1, this bias occurs when relevant IVs are excluded from the regression model, e.g. because they cannot be observed due to missing data. These unobserved but still relevant effects are then part of the error term. The following exemplary cross-sectional equation (for the reason of simplicity) demonstrates that:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 z_i + u_i \tag{8}$$

We assume z_i is a non-observable regressor which influences y_i. Instead, the model

$$y_i = \beta_0 + \beta_1 x_i + v_i \tag{9}$$

with $v_i = \beta_2 z_i + u_i$

is specified. In case the regressors x_i and z_i would be correlated, an endogeneity problem would occur because then x_i would also be correlated with the error term v_i which is forbidden as per assumption P1. This type of endogeneity is controlled for by including measures of all the as necessary identified categories to explain firm performance. (Cf. Wooldridge, 2010, p. 54; Antonakis et al., 2014, p. 100–102).

Errors-in-variables bias (measurement error)

The second source of endogeneity is caused by a so-called ***errors-in-variables bias***, also known as *measurement error*. We assume the model

$$y_i = \beta_0 + \beta_1 x_i + u_i \tag{10}$$

and that exogeneity of x_i would be the case. For a moment, we are also assuming x_i to be incompletely observable. Thus, instead of this true regressor, we would measure m_i and a measurement error v_i as per:

$$m_i = x_i + v_i. \tag{11}$$

If inserting equation (X second of above) into (X) one would get

$$y_i = \beta_0 + \beta_1(m_i - v_i) + u_i \tag{12}$$

or $y_i = \beta_0 + \beta_1 m_i + f_i$

and f_i would correlate with m_i which would then be an endogenous regressor. (Cf. Wooldridge, 2010, p. 55; Antonakis et al., 2014, p. 103)

To avoid this, the case of errors-in-variables bias is controlled for by using a sample of only US-American companies with only one reporting standard and an identical observation period, an identical measure calculation and identical data banks which are amongst the most comprehensive. That way, it can be justified that the underlying samples are consistent and free from errors-in-variables biases. (Cf. Rutz & Watson, 2019, p. 484)

Simultaneous equation bias (simultaneity)

A ***simultaneous equation bias*** represents the third source of endogeneity and describes the problem when "[…] one or more explanatory variables are caused simultaneously and reciprocally with the specified dependent variable in a model […]" (Rutz & Watson, 2019, p. 483). This problem occurs whenever dependent and independent variables are determined simultaneously within the same equation system. This can be clarified with another example. Let us assume we wanted to reproduce the influence of an output volume m_i of a product on its market price p_i:

$$m_i = x_i + v_i. \tag{13}$$

Thus, the input m_i would obviously have a negative ($\beta_1 < 0$) effect of the price p_i. The output volume can be varied by the corresponding company. At the same time, companies can, in the case of large demand but low supply, increase the price so that

$$m_i = \alpha_0 + \alpha_1 p_i + v_i \tag{14}$$

with $v_i = u_i + w_i$. $\quad$ (15)

Thus p_i would be determined through m_i and u_i and thence be correlated with the error term u_i as per equation (13). However, this should be precluded in equation (14) because p_i is a regressor here. An endogeneity problem arises. (Cf. Wooldridge, 2010, p. 55: Antonakis et al., 2014, p. 110)

In the context of our data and research topic, an example for simultaneity could be that innovation would not only be significant in explaining firm performance but also vice versa. A clear ceteris paribus explanation of innovation on the corporate financial performance would not be possible. To avoid such an econometric problem, we follow Attig et al. (2013,

p. 21) who suggest lagging all possible IVs. The intention and effect are that the DV will most certainly not have any significance in explaining an IV whose value has been measured one or more periods before. We argue that corporate financial performance of the current period ($t = 1$) does not significantly (i.e. not at all) explain any IVs, especially not innovation measures, of the previous period ($t = 0$). For that reason, all CVs of our controls-only model as well as the later added and to be tested IVs are lagged by one period (year). An exception to this is, on the one hand, the financial crisis indicator and the dummy variables as they are either themselves time variables and their lagging would cause disorder and confusion, or they are as dummies neither affected nor explained by firm performance in general.

On the other hand, all acquisition-related measures (based on Eikon data) are not lagged. We argue that firm performance does not directly affect acquisition measures, e.g. if an acquisition is hostile or if the target is a high-tech company. Furthermore, company-related financial measures are supposed to have a longer-term orientation. Imagine that a company invests in R&D. The benefit and pay-off from this kind of investment will arguably take effect on a longer time horizon than simply one year. Batterink (2009, p. 134) provides an M&A framework which demonstrates how innovation in the form of R&D gradually sinks in and is integrated into the firm depending on the technological relatedness between target and acquirer. This model can be transferred onto the time dimension, i.e. the process and extent of R&D sinking in and realizing profits is also dependent on how much time has passed since the investment. At least, this is the predominant assumption and must be verified in the course of the upcoming regression analysis.

Sample selection bias (induced endogeneity)

The last possibility of endogeneity is the so-called *induced endogeneity*. Imagine we wanted to reproduce the effect of university education on wages. If we took university graduates as our sample all other effects, e.g. personal abilities which the investigated group exhibits, would also have to be considered. Because one could not rule out that wages were influenced by exactly these personal factors. Another example is the attendance of advanced training for employees as an effect on their technical capabilities. If employees could determine their attendance on this training by themselves, one could not assume a random experiment. For instance, especially those employees with a higher technical interest and hence a probably higher technical capability beforehand would attend such training. Endogeneity would be existent. This type is known as ***self-selection***.

Both presented examples would represent an adulteration of the results of significance tests. Samples would not be randomly chosen but based on certain shared characteristics. Hence, such samples would not be representative of the entire population. Heckman (1979, p. 153) explains: “Sample selection bias may arise in practice for two possible reasons. First, there may be self-selection by the individuals or data units being investigated. Second, sample selection decisions by analysts or data processors operate in much the same fashion as self selection.” In such cases, parameter estimators would be inconsistent and inference methods would be applicable. Wolfolds & Siegel (2019, p. 434) point out that an endogeneity problem would only occur when probable effects, such as the here-presented personal capabilities of university students, would be observable and could accordingly be controlled in the model. Otherwise, estimation results would be inconsistent: “When selection instead occurs on unobservable variables, the approach is more challenging” (ibid.).

The sample selection problem can be subdivided into two problems: *truncation* and *treatment* (cf. Wolfolds & Siegel, 2019, p. 444). Truncation describes the problem that occurs when relevant untreated samples are not included due to missing data. This often occurs when trying to investigate a “subset” (cf. Certo et al., 2016, p. 2642; Wooldridge, 2010, p. 790; Wolfolds & Siegel, 2019, p. 434) of a sample. In the case of the treatment problem the data of all treated and untreated samples are available. Usually one would create a model which includes both the investigated or treated group and a non-investigated group. Nevertheless, due to a non-random choice of the groups, one would have had induced endogeneity already. This case of endogeneity of an originally exogenous model that copes with all Gaussian assumptions (P1-P3) is called *sample-induced endogeneity* (cf. Certo et al., 2016, p. 2640). How should such a case of induced endogeneity be handled? “The Heckman method […] is one way to address this issue” (Wolfolds & Siegel, 2019, p. 434). With that, Wolfolds & Siegel refer to the *Two-step method*, also known as *Heckman correction* which has been established by Heckman (1979).

Before conducting this method, we go back to examining our data regarding the truncation and treatment problem. Only companies of the S&P 500 index are included in the model. This choice is justified with better access to detailed financial information. However, now it can be argued that data of the untreated (non-S&P 500) companies were missing and that a treatment problem was present. Moreover, due to our non-random choice of sample endogeneity might be induced. This is eradicated by including relational industrial measures into the model. For instance, the average industry size (*_AvgIndSizeA4*) controls for the difference of the observed peer's size and that of its corresponding industry competitors. More CVs like this are included (Section 5.1.2). Hence, there is arguably no need to conduct the Heckman correction. Assumption P3 can be assumed satisfied. Coming to a preliminary conclusion, our controls-only model is aligned with all Gaussian assumptions for panel data models and it can be continued with the inclusion of the necessary IVs to investigate our hypotheses in the following chapter.

5. Results and discussion

5.1 Explanation of final regression measures

5.1.1 Dependent variable

We reclaim the intention of this thesis which is the investigation of internal and external forms of corporate innovation on corporate financial performance. As per our definitions (Section 2.2) performance is understood as a variable that measures the financial business success.

As has been discussed, performance as well as the measurement of it can be viewed from various perspectives. As an example, different forms of income, e.g. foreign income (cf. Christensen et al., 2015, p. 21), income to employees (cf. Cornett & Tehranian, 1992, p. 224), or net income (cf. Bendig et al., 2018, p. 21; Saboo et al., 2017; Rothaermel & Hess, 2007, p. 910) can be found in management literature as exemplary performance variables. Many measures are already excluded from model considerations due to their composition and the lack of available data on their components from Compustat or Eikon.

Li, Qiu & Wang (2019, p. 8) present *return on assets* (ROA) as the predominant measure of corporate financial performance. ROA can be calculated as either the operating income before interest and taxes divided by the firm's revenues, or the net income divided by assets (cf. Bendig et al., 2018, p. 19; Zhao, 2009, p. 1174; Hitt, Hoskisson & Kim, 1997, p. 778; Cornett & Tehranian, 1992, p. 224). Obviously, some economists use measures stand-alone while others prefer composite variables such as ratios of two or more stand-alone measures. Another finding is that ratios in the shape of returns are well-represented in the economic scientific landscape. For instance, the *return on equity* (ROE) (cf. Tam, 1998, p. 86; Cornett & Tehranian, 1992, p. 224; Pennings & Harianto, 1992, p. 368) is a measure that emphasizes the capital side of corporate resources, as does *return on capital employed* (ROCE) which is a ratio where *earnings before interest and taxes* (EBIT) is the enumerator. ROCE has the advantage of putting the focus on what is essential for considering innovation as a later tested IV – the investment perspective. It describes how much of the employed capital comes back as earnings. Another similar measure is the *return on investment* (ROI) which divides the EBIT by investment amount itself.

All these KPIs can be classified as measures of profitability as they target the firm's income and profit situation. In that, they do illustrate the success and performance which is a major target of every business. The unfortunate problem is that some of these measures consist of inputs that are not in all cases reported. For instance, the ROE as per Cornett & Tehranian (1992, p. 224) only leaves 709 observations in our data due to its stock market-based denominator which is rarely available. It also reveals the second problem of many found KPIs which is the relatedness to stock data. The problem with stock data is that it is highly affected by various influences, some of which originate from outside companies' borders. For instance, Tidd & Ciaran (2007, p. 109) highlight that the impact of R&D on the stock market was "[…] difficult to judge […]". (Hall, 1993, p. 608) even questions the relationship between innovation and stock market data. He doubts that it is consistently analyzable. Pakes (1985, p. 396) notices some noisiness in this regard. Noisiness describes all influences on the corresponding measure which cannot be clearly explained and distinguished from the intended effects of interest. If taken such a measure as the DV there would be a significant and large portion of the measure which would be explained by the error term of the regression model. This is to be avoided as our intention is to establish a model where its maximum explanation power comes from intentionally included and observable variables rather than from unobserved effects.

Consequently, a measure which is free of any noisiness and unwanted influences is needed. A measure which solely reflects the firm's own and clean performance must be found. This rules out every measure which is based on capital market or stock market information. Measures like the market value, Tobin's Q, market capitalization, or even the *enterprise value* (EV) are based on stock data such as the preferred stock, closing price or common shares outstanding.

To minimize the noisiness, a performance DV that is very close to the firm's own business activities and operations must be considered. A measure that is often referred to as the operational result is the firm's EBIT. EBIT is both part of the reporting as per US-GAAP[16] and IFRS[17] and is therefore directly available in Compustat. Originally EBIT is calculated by adding tax, interest and other financial expenses to and subtracting tax, interest and other financial income from the profits. Alternatively, it can be measured as adding both interests and taxes to the net income of a firm. In other words, the operating profit is derived from subtracting all operating and some non-operating (e.g. interest or derivatives) expenses from revenues.

However, the EBIT alone does not entirely reflect the company's profitability and performance respectively. It is subject to environmental influences. Imagine a situation of financial crisis and imagine that markets were becoming more short-term protective as a reaction to that crisis. The demand would decrease, and the firm would presumably not sell as much of its products or services as before. As EBIT is indirectly determined by revenues through profit, it would be affected by the decline in demand, although the company would still be operationally profitable and as competitive as before since it has not operationally changed. Accordingly, the performance of its operating business model has not changed as well.

As we want to rule out influences from outside company borders as much as possible[18], we put the firm's EBIT in relation to its revenues to calculate the EBIT-margin. The ratio is also referred to as *return on sales* (ROS) (cf. Tam, 1998, p. 86) . It is important to note that the term "return" is not clearly specified and often used for different purposes. Because of this, it is advised not to use ROS interchangeably for EBIT-margin. As can be seen below (Section 5.1.2), this only creates confusion upon the slight differences between our DV and some of the variables which have been chosen to explain it.

The EBIT-margin combines multiple advantages. First, it is a measure of corporate financial performance which complies with our definition in Section 2.2. As such we understand a firm's profitability. At the same time, it is not directly connected to stock measures or substantially disrupted by other unobservable influences. Instead, the EBIT-margin is directly

[16] US-GAAP stands for United State Generally Accepted Accounting Principles.
[17] IFRS stands for the International Financial Reporting Standards and is the internationally predominant standard for reporting corporate financials.
[18] Note that ruling out all other influences is not possible for any company that interacts with its environment. Our intention is therefore to minimize such influences by firstly choosing the right DV.

connected to a firm's operative business performance because it is the result of a firm's business model's efficiency. It reflects the strategic orientation of a firm and thereby of entrepreneurs' or managers' ability to make the right decisions and steer the company towards success. On top of that, the EBIT-margin does not directly contain any acquisition or innovation partition but can be influenced by both internal and external innovation because it is a reported output quantity. As such it reflects all four dimensions and development processes that are part of successful innovation management (as per Section 3.2). This includes the strategic development which is led by entrepreneurs and managers. EBIT-margin (*_EbitMarginlog*) is set as the regression model's dependent variable and its natural logarithm is calculated to capture outliers (see Section 4.3.1).

5.1.2 Control variables

Much effort has gone into developing the controls-only model. Control variables have the purpose of ideally capturing all known influences on underlying DV and minimize the explanation portion coming from unobserved effects. Thus, the choice of a CV must be justified with its significance in explaining the DV, in our case the EBIT-margin.

Starting with **firm variables**, size effects are controlled for by including the firm size (*_FirmSizeSales*) as a CV. Another *general firm measure* is the firm asset growth (*_AssetsGrowth*) which is calculated as the difference of a firm's assets in period t and in period $t-1$ divided by the latter. As EBIT-margin itself is a *profitability measure* it is explained by other measures of profitability as well. The market value (*_MarketValueI*) (cf. Tam (1998, 88), which equals a firm's liabilities divided by common ordinary equity, and Tobin's Q (*_TobinsQ*) (cf. Krasnikov, Mishra & Orozco, 2009, p. 159; Bharadwaj, Bharadwaj & Konsynski, 1999, p. 1014), which basically describes a firm's market value over its book value, are such measures. In our case, we calculate the Tobin's Q slightly differently as can be seen in Table 13.

We follow economists Li, Qiu & Wang (2019, p. 8) by including the ROA (*_ROAI*) as the last profitability measure. Interestingly, in some papers (e.g. Zhao, 2009, p. 1175) this variable is calculated by dividing the operating income before interest and taxes by the revenues instead of by firm assets, which the name would suggest. In that, it is related to the name "return on sales". As discussed above, the ROS and the ROA respectively, are very closely related to EBIT-margin. The major difference is that the EBIT does also include non-operating income and expenses which is arguably the better choice for the DV as it includes exactly the expenses that interest us – those that flow into investments and innovation (of any kind). Nonetheless, the ROA needs to be added to the model because it makes up for a large portion of the explanation power of the controls-only model. That, again, allows us to be sure of any later tested and found significances and explanation power of our IVs.

To continue, ***liquidity measures***, e.g. the leverage ratio (*_LeverageRatioI*) (cf. Bradley, Kim & Tian, 2017, p. 8), the cash flow (*_CashFlowI*) (cf. Dutordoir, Verbeeten & Beijer, 2015, p. 39), the solvency (*_Solvency*) (cf. Gulati e al. (2009), the market-to-book ratio (*_MBRatio*) (cf. Jie He et al., 2020, p. 12; Zhao, 2009, p. 1175; Bali & Hovakimian, 2009, p. 1800) and ***slack measures*** such as the absorbed slack and unabsorbed slack (cf. Greve, 2003b, p. 692; Dinesh & Miller, 2008, p. 813) improve the explanation power of the controls-only model (compare Section 4.3).

The conclusion from theory has been that innovation can be understood as a form of corporate investment and expenditure (Section 3.1). There are two basic forms of corporate expenditures: the *operational expenditures* (OpEx) and the *capital expenditures* (CapEx) which both add up to the *total expenditures* (TotEx). While OpEx describes all ongoing operational expenditures with a short-term orientation to finance daily business, CapEx defines all investment expenditures directed towards long-term assets. Thus, CapEx includes also innovation expenses which are already controlled for by our chosen innovation IVs and is therefore not included as a CV. OpEx, however, needs to be at least considered because it represents the partition of expenditure which is not related to our later innovation IVs, although it is denied an inclusion into the model due to correlation problems. We follow previous papers which suggest including pension expenditures (*_PenEx*) measured as pension and retirement expenses over the number of employees (cf. Healy, Palepu & Ruback, 1992, p. 153) and marketing intensity (*_MarketingIntI*) as the difference of *selling, general, and administrative expenses* (SG&A). These measures build the group of ***investment variables***.

Another measure category which finds its place in the controls-only model is the one of **environmental variables**. Although it has been argued that every noise or external influence must be eradicated, this cannot be entirely guaranteed. As a consequence, such noises are controlled for by including measures such as the industry dynamism which equals an industry's average five-year sales growth (*_AvgIndSalesGrowth5Y*) (cf. Fang, 2011, p. 158; Kim & Finkelstein, 2009, p. 641; Gerhart & Milkovich, 1990, p. 679), the industry concentration (*_IndCon4*), often referred to as "technological turbulence" (Bendig et al., 2018, p. 47; cf. Krasnikov, Mishra & Orozco, 2009, p. 159; Zheng Zhou & Bingxin Li, 2012, p. 1098) or the average industry profitability (*_AvgIndProf4*) (cf. Choi, Kumar & Zambuto, 2016, p. 1190). Apparently, environmental variables are in the context of this thesis understood as variables measuring the industry environment which is why they are calculated on the level of *industry groups* (four-digit SIC) instead of *major groups* (two-digit SIC) as per Choi, Kumar & Zambuto (2016, p. 1190). Environmental measures are only included to control for external effects and to take all other companies with available data into account. In doing so, environmental variables also allow (to some extent) to control for a treatment problem which would lead to induced endogeneity (see Section 4.3.3).

The last category contributing to our set of CVs are the ***firm-industry variables***. These measures benchmark the respective firm to its industry competitors, again using the four-digit SIC as competitor peer group. We follow Gosh (2004, p. 219) and include the relative size by sales (*_RelFirmSizeS4*) to the model (see also Renneboog & Vansteenkiste, 2019, p. 657; Brown & Laverick, 1994, p. 93) as well as the relative asset growth (*_RelAsset-Growth4*) and the relative profitability (*_RelFirmProf4*). Both the *environmental* and the *firm-industry variables* justify the establishment and repeated merging of the two data files in Stata, with one containing only data on our S&P 500 peers (20200307_Stata _Data_Merged_SP500_DH.dta) and the other one containing data for all available companies on Compustat and Eikon (20200307_Stata_Data_Merged_DH.dta) (see Section 4.1.2).

Another not to be disregarded category of variables is the *indicator variable* (or dummy variable) category. For the upcoming regressions, three forms of dummy variables are distinguished: time indicators, state indicators and industry indicators.

Time indicators range from the year 2003 (*_T03*) to 2018 (*_T18*). State dummies include the acquirers' home state (US) (e.g. *_AB* for Alabama). Companies may fall under different jurisdictions or may face different circumstances like rent and sales market. Therefore location-dependent influences must be expected. Industry indicators are defined as the two-digit SICs. Apparently, the argumentation for environmental measures does not hold in this case. Whereas the intention of using four-digit SICs before was to closely look at a firm's industry and how it moderates innovation effects, the purpose of deepening the scope onto two-digit SICs for environmental and firm-industry measures is to include as many peers per observation and per "industry" as possible. All indicators are part of the model because they not only control for possible external effects from time, location or industry circumstances but they are also object of interesting tests, especially regarding moderation (see Section 5.2).

5.1.3 Independent variables

Recalling our hypothesis (**H1**) the main question to be investigated in this thesis is whether innovation determines or even improves corporate financial performance and, if so if this is due to internal innovation (effort) or external innovation (acquisition). For this reason, the provision of a measure for both introduced forms of innovation is required. Most economists suggest two different measures to capture **internal innovation**: CapEx and R&D in various forms, e.g. R&D intensity, growth or stand-alone. As CapEx includes expenditures in both innovation and all other investment goods, it cannot clearly document innovation effects on performance. CapEx is dropped. Instead, R&D intensity which is described as affecting “innovation performance” (Liu, 2011, p. 2634) is chosen. The question remains which type of R&D measure to use. In order to comprehensively illuminate effects from internal innovation on performance and to be sure about drawing the right implications from regression results, multiple measures are chosen as IVs to be tested. These measures are R&D intensity over assets (*_RDIntensityA*) and stand-alone R&D (*_RDIntensity*).

For the part of **external innovation** (acquisition) two different perspectives are central: the quantity of firm acquisitions in the sense of the number of acquired companies and in the sense of the value per acquisition in US-dollars. The first perspective is taken into account by estimating the total number of firm acquisitions of a company in period t (*_AcqCountTotal*). Secondly, the value per acquisition is estimated as an average value of the acquirer’s firm acquisition per period t (in USD) (*_AvgDealVal*).

These four presented variables are the **key stand-alone IVs** around which regressions in this thesis are built and hypotheses are tested (compare **H1**). Basically, five types of analyses are executed in the following: stand-alone effects, cross-IV effects, strong-lag (long-term) effects, u-shaped effects, and moderation effects. With **cross-IV** effects influences of an internal innovation IV on an external innovation IV and vice versa are described (compare **H2**).

With **strong-lag IVs** we calculate and estimate our four key IVs by lagging them two and three periods. This way it can be analyzed, if internal innovation (effort) and external innovation (acquisition) have a significant long-term effect on corporate financial performance and, if this effect is stronger than in the short-term of ≤ 1 year (compare **H3**).

Moderator variable analyses are again subdivided into three investigations: **general moderator variables**, (acquirer) **industry moderator variables,** and **time moderator variables**. The first kind examines, if other probably related entities, e.g. the average rate of hostile acquisitions per acquirer per period (*_HostAcqRate*) or whether the acquirer purchases on average and per period high-tech targets (*_TargHighTech*) significantly influence innovation effects on performance. High-tech targets are classified as such if they belong to a certain industry. These industries are shown in Table 3. The second category, the industry moderators, allow an examination of whether internal or external innovation effects on corporate financial performance are affected by the acquirer's industry. Time moderators are analyzed analogously.

Table 3: High-tech target industries

Industries
Healthcare Equipment
Pharmaceuticals
Aerospace & Defense
Telecommunications Equipment
Electronics
Chemicals
Computers & Peripherals
Machinery
Semiconductors
Internet Software
Other Materials
Other High Technology

(Source: own representation)

5.2 Presentation and interpretation of regression results

Table 4 presents the descriptive statistics for the panel data sample. As it reports information for both the logged EBIT-margin (DV) and all CVs, the table reveals the final controls-only model. Panel A of the table shows the summary statistics and unfolds the number of observations for the entire (S&P 500) sample, which is 16,048, and the means of every variable. For the underlying peer set of (formerly) S&P 500 companies, the mean of EBIT-margin is 18.9%. This means that a firm's earnings before interest and taxes make on average up for about a fifth of its revenues. The extreme minima and maxima (whose values cannot be properly interpreted) show the restrictions to our data in that companies may either falsely report their financials or the underlying data bank (Compustat) may miscalculate the given information. Nonetheless, these outliers, once again, justify the logging of our DV.

Panel B of the table shows the correlation matrix of the DV and all CVs. The matrix presents the bivariate Pearson correlation coefficients. Note that some of these coefficients are higher than 0.3 or even 0.5. High correlations between the DV and a CV are allowed. A high correlation between different CVs can come along with the problem of multicollinearity. However, this problem has been ruled out following the procedure as per (Kalnins, 2018) in Section 4.3.1.

Table 4: Descriptive statistics for the panel data sample (S&P 500) (controls-only model)

Panel A: Summary statistics for the panel data sample (S&P 500) (controls-only model)					
Variable (lagged)	Obs	Mean	Std.Dev.	Min	Max
EBIT-margin (log)	13,367	-.189	11.219	-1013	13.49
Industry size (A)	13,559	11905.25	58675.16	.056	1830000
Industry growth (S)	13,510	4.755	37.498	-86.953	1276.124
Industry growth (A)	13,524	153.012	3435.704	-.998	98851.06
Industry profitability	10,711	-1.524	12.359	-537.112	.536
Industry dynamism	13,668	42.063	241.343	.021	6676.08
Industry concentration	13,698	1.12e+09	5.01e+09	0	7.48e+10
Firm size (S)	13,442	12525.11	29148.81	-12500	497000
Asset growth	12,318	475.257	52608.4	-1	5840000
Absorbed slack	10,451	.343	4.387	.005	422.087
Unabsorbed slack	10,687	2.182	5.104	0	337
Leverage ratio	12,060	.26	.257	0	11.647
Cash flow	13,106	.102	.121	0	1
Solvency	11,757	37.279	878.658	0	48492.5
Market-to-book ratio	11,715	4.851	78.247	-1734.676	6274.015
ROA	12,832	.111	.224	-14.768	1.535
Market value	13,409	2.734	29.158	-1083.427	1405.769
Tobin’s Q	10,179	1.641	2.429	-.326	188.441
Relative size (S)	13,311	169.306	15578.65	-228.671	1790000
Relative growth (A)	12,172	325.318	35574.22	-10900	3920000
Relative profitability	6,304	.331	9.924	-455.592	220.666
PenEx	11,795	4.216	7.576	-48.386	432.967

Marketing intensity	6,539	.192	.182	-.447	3.799
Financial crisis	16,048	.316	.465	0	1
Number of observations	16,048				

Panel B: Correlations (controls-only model)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) EBIT-margin (log)	1.000											
(2) Industry size (A)	0.004	1.000										
(3) Industry growth (S)	0.003	-0.015	1.000									
(4) Industry growth (A)	0.001	-0.007	0.007	1.000								
(5) Industry profitability	-0.002	0.016	-0.013	-0.002	1.000							
(6) Industry dynamism	0.005	0.108	0.052	0.000	-0.010	1.000						
(7) Industry concentration	0.003	0.695	-0.028	-0.008	0.021	0.048	1.000					
(8) Firm size (S)	0.007	0.147	0.000	-0.006	0.009	-0.010	0.212	1.000				
(9) Asset growth	0.003	-0.005	0.025	0.001	-0.002	0.028	-0.009	0.001	1.000			
(10) Absorbed slack	-1.000	-0.007	0.000	-0.001	0.001	-0.004	-0.007	-0.013	-0.002	1.000		
(11) Unabsorbed slack	-0.009	-0.088	0.030	0.010	-0.007	0.058	-0.106	-0.194	0.001	0.017	1.000	
(12) Leverage ratio	-0.018	0.031	0.025	0.010	0.006	0.020	-0.034	-0.060	0.006	0.018	-0.096	1.000
(13) Cash flow	0.002	-0.074	0.040	-0.014	-0.018	0.016	-0.112	-0.169	-0.007	0.008	0.411	-0.065
(14) Solvency	0.001	-0.010	-0.003	-0.001	0.002	-0.009	-0.009	-0.014	-0.005	-0.000	0.002	-0.046
(15) Market-to-book ratio	0.000	-0.001	-0.006	-0.001	0.000	0.002	-0.005	0.006	-0.002	0.000	-0.019	0.014
(16) ROA	0.043	-0.018	-0.012	-0.013	0.001	0.021	0.042	0.057	-0.023	-0.039	-0.001	-0.302
(17) Market value	-0.000	0.005	0.001	0.001	-0.003	-0.004	-0.001	0.026	0.002	0.000	-0.019	-0.022
(18) Tobin's Q	-0.005	-0.024	0.067	0.003	-0.014	0.018	-0.039	-0.078	0.005	0.018	0.105	0.453
(19) Relative size (S)	0.001	-0.010	-0.002	-0.001	-0.003	0.002	-0.007	0.011	-0.001	-0.001	-0.017	-0.005
(20) Relative growth (A)	-0.000	-0.010	0.000	-0.000	0.000	0.000	-0.003	-0.003	0.040	0.000	0.016	-0.023

(21) Relative profitability	0.001	0.004	-0.001	-0.002	0.003	-0.011	0.011	0.003	-0.001	-0.002	0.013	-0.066
(22) PenEx	0.010	0.090	0.026	0.018	-0.024	0.050	0.039	0.241	-0.010	-0.012	-0.065	-0.021
(23) Marketing intensity	0.012	0.005	-0.031	-0.022	0.031	-0.077	0.181	-0.032	-0.031	-0.006	-0.160	0.159
(24) Financial crisis	0.012	0.005	-0.039	-0.020	0.012	-0.064	0.004	0.010	-0.014	-0.012	0.028	-0.062
Variables	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(13) Cash flow	1.000											
(14) Solvency	0.084	1.000										
(15) Market-to-book ratio	-0.003	0.002	1.000									
(16) ROA	-0.077	-0.025	0.019	1.000								
(17) Market value	-0.016	0.004	0.143	-0.015	1.000							
(18) Tobin’s Q	0.162	0.038	0.031	0.031	-0.013	1.000						
(19) Relative size (S)	-0.022	-0.001	-0.001	-0.003	-0.000	-0.010	1.000					
(20) Relative growth (A)	0.008	0.001	0.001	-0.045	0.004	-0.006	-0.000	1.000				
(21) Relative profitability	0.018	-0.002	-0.004	0.052	-0.004	-0.067	-0.001	0.007	1.000			
(22) PenEx	-0.044	-0.007	0.012	-0.037	0.010	-0.024	-0.002	0.016	-0.015	1.000		
(23) Marketing intensity	0.045	0.070	0.036	-0.084	0.024	0.285	-0.018	-0.018	-0.012	-0.153	1.000	
(24) Financial crisis	0.051	0.022	-0.028	0.027	0.003	-0.140	-0.015	-0.004	0.029	0.024	0.016	1.000

Note. Panel A shows the summary statistics for the controls-only model. All variables are shown for period *t*. EBIT-margin (log) is the model’s dependent variable (DV). All other variables are the chosen control variables (CVs). Panel B shows the bivariate Pearson correlation coefficient of all variables of the controls-only model and of the DV. The underlying sample consists of all companies which have been listed at S&P 500 between the beginning of 2003 and the end of 2018 (fiscal) and whose data is available on Compustat or Eikon.
(Source: own representation)

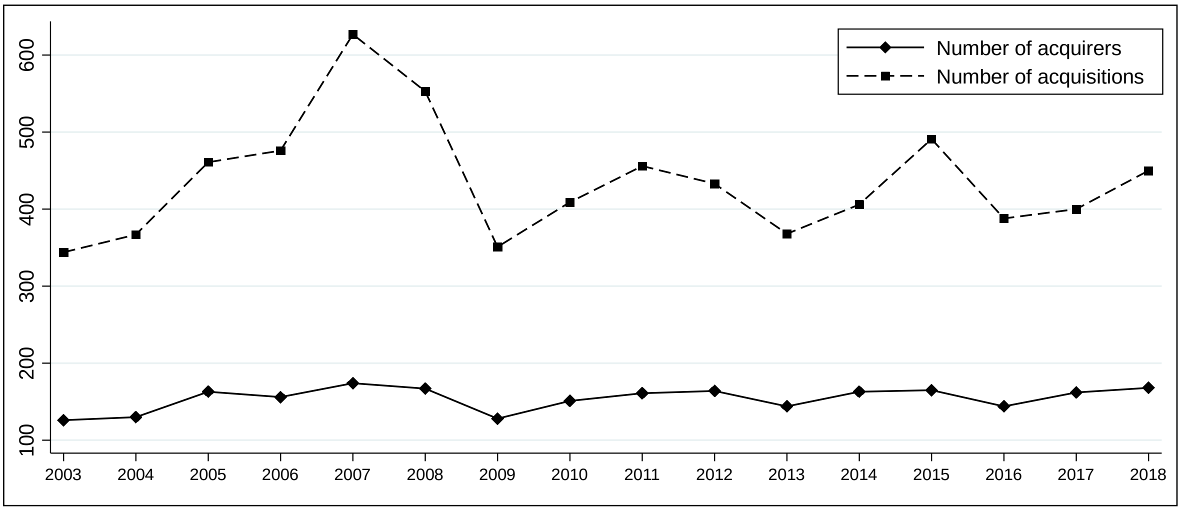
The underlying sample consists of companies which have been listed at the S&P 500 index between the beginning of 2003 and the end of 2018 and whose data is available on Compustat and/or Eikon. Table 5 shows how many of these companies have engaged in acquisitions during that time span. Over the entire 16 years, 2,466 companies bought other companies with a total of 6,958 acquisitions. Figure 18 confirms Mcnamara, Haleblian & Dykes' (2008, p. 113) theory that acquisitions come in waves. The number of acquirers has been almost constant over the 16 observed years. Local minima occur about every three to four years. Acquisitions, on the other hand, show larger variations, although extrema cope with those of the number of acquirers. The number of acquisitions and the number of acquirers seem to affect each other. What one may only carefully suggest regarding acquirers, become more obvious regarding acquisitions. The number of both has experienced its lowest value (128 acquirers, 358 acquisitions) and the strongest decline in the year 2009. The negative development has begun in 2007 when acquisitions have been at their highest (627) and suggests that during financial crises firms tend to keep their money and not invest in M&A deals.

Table 5: Acquisition sample distribution by year (S&P 500)

Year (fiscal)	Number of acquirers	Number of acquisitions
2003	126	344
2004	130	367
2005	163	461
2006	156	476
2007	174	627
2008	167	553
2009	128	351
2010	151	409
2011	161	456
2012	164	433
2013	144	368
2014	163	406
2015	165	491
2016	144	366
2017	162	400
2018	168	450
Total	2,466	6,958

(Source: own representation)

Figure 18: Number of acquirers and acquisitions by year (S&P 500)



(Source: own representation)

It has been hypothesized that innovation leads to an improvement in corporate financial performance (**H1**). We have identified two forms of innovation: internal and external innovation. Whereas the first kind deals with innovation efforts of internal research and development of new products, services, technologies etc., external innovation is connected to firm acquisitions and, with that, the acquisition of innovation through external sources. Four key innovation measures have been identified and tested. The results are presented in Table 6.

R&D intensity (A)$_{t-1}$, *R&D intensity*$_{t-1}$, *Acquisition count*$_t$ and *Average deal value*$_t$ are all significant in explaining the EBIT-margin of firms, if included stand-alone into the model (models (2) to (5))[19]. The internal innovation measures are significant at a level of $\alpha = 0.001$ (for *R&D intensity (A)*$_{t-1}$) and $\alpha = 0.01$ (for *R&D intensity*$_{t-1}$). External measures are significant at a level of $\alpha = 0.05$. However, external innovation loses its significance when combined with all other innovation measures (model 6). This suggests that when investing in both internal and external innovation, the latter becomes obsolete for steering a company's performance. However, note that our significance levels are chosen rather conservatively. We continue with these four key innovation IVs.

Table 6 also demonstrates that the R&D expenditures divided by assets (*R&D intensity (A)*$_{t-1}$) and the number of acquisitions per firm per year (*Acquisition count*$_t$) have each a much larger parameter estimate than the other two innovation measures. If a company increases

[19] Note that for the post-regression results all measures are referred to by their measure label, whereas for pre-regression calculations only code names as per Stata code were presented (e.g. *_RDIntensityA* → *R&D intensity (A)*$_{t-1}$). An assignment of the variable labels to their code names can be found in Table 13.

its proportion of R&D to its assets by 10%, the stand-alone model (model 2) suggests that this company will decrease its EBIT-margin on average by approximately 37.6%. This is a large impact. Despite the return on assets and the absorbed slack (in the controls-only model which is model 1 of the table), there is no other variable which exhibits both such a large parameter estimator and a significant effect like the R&D intensity divided by firm assets. The reason for this is the nature of our measure *R&D intensity (A)*$_{t-1}$. It describes a fraction, i.e. proportion of R&D to assets, whereas *R&D intensity*$_{t-1}$ is an absolute variable measured in US-dollars, as is *Average deal value*$_t$.

Interestingly, the stand-alone measure of simple R&D expenditures (*R&D intensity*$_{t-1}$) shows an opposite sign of its parameter estimate compared to the intensity over assets. Apparently, a firm can increase its EBIT-margin by raising investments into R&D as long as its proportion to assets is not increased as well. Although, the parameter estimate (with 0.0000360 in model 3) is much lower compared to *R&D intensity (A)*$_{t-1}$. This translates into a much greater effect size. With every invested 1,000 US-dollars the company can ceteris paribus increase its EBIT-margin by about 3.6% on average.

We shift the focus onto external innovation. Note that both external innovation measures show positive estimates as none of them is a calculated ratio but a direct linear IV. *Acquisition count*$_t$ is an average ratio of a counted variable which, again, needs to be interpreted differently compared to above-discussed internal innovation IVs. With every additionally made firm acquisition on average, a company can ceteris paribus increase its EBIT-margin on average by approximately 2.2% (model 4). The parameter estimate becomes negative when all innovation measures are included (model 6) suggesting that when investments flow into research and development, acquisitions become harder to finance and more difficult to bear for a company.

The parameter estimate of *Average deal value*$_t$ is the lowest of the reported innovation IVs. This is due to its measurement by millions of US-dollars. According to model 5, with every on average invested 100 million US-dollars in an acquisition per year a firm’s EBIT-margin ceteris paribus increases by about 0.09%. Obviously, the average of how much a firm invests in one acquisition (*Average deal value*$_t$) does not affect company performance as much as the number of acquisitions per period (*Acquisition count*$_t$). This conclusion would certainly have been different if EBIT had been taken stand-alone as DV instead of its margin. In that case, bigger companies would arguably have a higher EBIT just because their investment volumes were larger due to their individual size. This disturbance is controlled by taking the margin as DV. In conclusion, it does not matter so much, if a company is big and has a large investment budget to buy large competitors.

Note that the number of observations has diminished from 16,048 to 3,562 due to the inclusion of numerous CVs and IVs at the same time. This number will stay constant over most of the upcoming regressions. Also note that Table 6 does not show any industry, time, or US-state indicator variables for reasons of simplicity. However, these are always included when referring to "CVs" or "control variables" in a table. To avoid a dummy variable trap, three significant dummies – one industry dummy (with SIC being *_27*), one time dummy (*_T04* for the year 2004) and one state dummy (*_KY* for the state of Kentucky) – have been excluded from our regressions. Another notation is that the external innovation measures are observed and reported for period t, whereas all other measures (expect *Financial crisis*$_t$) are based on period $t-1$. Consequently, all these effects take effect one period later while external innovation acquisition affects EBIT-margin in the same period in which it is initiated. These results all lead to the confirmation of our central question and **H1**. Apparently, innovation (both internal and external) significantly influences a firm's financial performance.

Table 6: Regressions of the panel data sample with stand-alone IVs (S&P 500)

	(1) EBIT-margin (log)	(2) EBIT-margin (log)	(3) EBIT-margin (log)	(4) EBIT-margin (log)	(5) EBIT-margin (log)	(6) EBIT-margin (log)
			Control variables			
Industry size (A) $_{t-1}$	-0.00000863*	-0.00000900*	-0.00000850*	-0.00000861*	-0.00000867*	-0.00000886*
	(0.00000400)	(0.00000359)	(0.00000419)	(0.00000402)	(0.00000402)	(0.00000379)
Industry growth (S) $_{t-1}$	-0.000545	-0.000566	-0.000619	-0.000524	-0.000562	-0.000667
	(0.000370)	(0.000382)	(0.000375)	(0.000375)	(0.000370)	(0.000393)
Industry growth (A) $_{t-1}$	0.0000148	0.0000182*	0.0000138	0.0000141	0.0000146	0.0000166*
	(0.00000789)	(0.00000779)	(0.00000778)	(0.00000773)	(0.00000782)	(0.00000742)
Industry profitability $_{t-1}$	-0.000597	-0.000884	-0.0000522	-0.000709	-0.000559	-0.000219
	(0.00177)	(0.00156)	(0.00177)	(0.00178)	(0.00177)	(0.00155)
Industry dynamism $_{t-1}$	0.00000299	0.00000797	0.00000474	0.00000348	0.00000364	0.0000113
	(0.0000242)	(0.0000248)	(0.0000241)	(0.0000238)	(0.0000243)	(0.0000246)
Industry concentration $_{t-1}$	4.65e-12	6.05e-12	3.97e-12	4.35e-12	4.62e-12	5.10e-12
	(4.89e-12)	(5.10e-12)	(4.84e-12)	(4.83e-12)	(4.88e-12)	(4.96e-12)
Firm size (S) $_{t-1}$	-1.63e-08	-4.94e-08	-0.000000602	-0.000000223	-4.31e-08	-0.000000950
	(0.000000422)	(0.000000402)	(0.000000552)	(0.000000454)	(0.000000425)	(0.000000618)
Asset growth $_{t-1}$	0.0000745	-0.00275	-0.000794	0.000104	0.000163	-0.00405
	(0.00377)	(0.00420)	(0.00377)	(0.00368)	(0.00378)	(0.00412)
Absorbed slack $_{t-1}$	1.360***	1.877***	1.275***	1.329***	1.353***	1.784***
	(0.314)	(0.466)	(0.303)	(0.309)	(0.313)	(0.444)
Unabsorbed slack $_{t-1}$	0.0560***	0.0444**	0.0573***	0.0562***	0.0563***	0.0454**
	(0.0157)	(0.0158)	(0.0156)	(0.0157)	(0.0157)	(0.0154)
Leverage ratio $_{t-1}$	-0.0267	-0.0666	0.00423	-0.0114	-0.0212	-0.0176
	(0.138)	(0.127)	(0.140)	(0.139)	(0.138)	(0.128)
Cash flow $_{t-1}$	-0.740**	-0.461*	-0.682**	-0.712**	-0.739**	-0.349
	(0.226)	(0.214)	(0.226)	(0.226)	(0.226)	(0.216)
Solvency $_{t-1}$	0.00000298	0.00000363	0.00000125	0.00000229	0.00000285	0.000000959
	(0.0000177)	(0.0000184)	(0.0000179)	(0.0000178)	(0.0000177)	(0.0000188)
Market-to-book ratio $_{t-1}$	-0.000227***	-0.000258***	-0.000215**	-0.000223**	-0.000226***	-0.000241***
	(0.0000673)	(0.0000660)	(0.0000677)	(0.0000683)	(0.0000671)	(0.0000663)
ROA $_{t-1}$	5.679***	5.842***	5.522***	5.634***	5.674***	5.622***
	(0.562)	(0.578)	(0.563)	(0.560)	(0.562)	(0.574)
Market value $_{t-1}$	0.000316	0.000275	0.000310	0.000313	0.000317	0.000263
	(0.000379)	(0.000351)	(0.000374)	(0.000379)	(0.000379)	(0.000343)

Tobin's Q $_{t-1}$	0.0748**	0.0962***	0.0813**	0.0768**	0.0753**	0.108***
	(0.0255)	(0.0245)	(0.0256)	(0.0255)	(0.0255)	(0.0247)
Relative size (S) $_{t-1}$	-9.93e-08	-0.00000126	0.000000546	0.000000218	6.57e-09	-0.000000262
	(0.00000243)	(0.00000222)	(0.00000244)	(0.00000241)	(0.00000243)	(0.00000220)
Relative growth (A) $_{t-1}$	-0.0000343	-0.0000356	-0.0000353	-0.0000365	-0.0000354	-0.0000389
	(0.0000947)	(0.0000934)	(0.0000941)	(0.0000943)	(0.0000942)	(0.0000919)
Relative profitability $_{t-1}$	0.0000561	0.000488	-0.0000440	0.0000161	0.0000352	0.000355
	(0.000529)	(0.000575)	(0.000524)	(0.000531)	(0.000531)	(0.000569)
PenEx $_{t-1}$	0.00941***	0.00995***	0.00873***	0.00945***	0.00945***	0.00913***
	(0.00231)	(0.00231)	(0.00224)	(0.00230)	(0.00230)	(0.00223)
Marketing intensity $_{t-1}$	-1.762***	-2.135***	-1.691***	-1.736***	-1.752***	-2.050***
	(0.264)	(0.323)	(0.267)	(0.264)	(0.264)	(0.318)
Financial crisis $_t$	0.103	0.0923	0.106*	0.105*	0.103	0.0961
	(0.0528)	(0.0507)	(0.0523)	(0.0525)	(0.0528)	(0.0495)
Independent variables						
R&D intensity (A) $_{t-1}$		-3.755***				-4.040***
		(0.593)				(0.568)
R&D intensity $_{t-1}$			0.0000360**			0.0000476***
			(0.0000116)			(0.0000119)
Acquisition count $_t$				0.0221*		0.0115
				(0.00896)		(0.00728)
Average deal value $_t$					0.00000878*	0.00000536
					(0.00000366)	(0.00000320)
Constant	-3.452***	-3.369***	-3.434***	-3.448***	-3.452***	-3.338***
	(0.203)	(0.209)	(0.201)	(0.203)	(0.203)	(0.206)
Observations	3,562	3,562	3,562	3,562	3,562	3,562

Robust standard errors in parentheses: * p < 0.05, ** p < 0.01, *** p < 0.001

Note. The above table shows generalized estimation equations (GEE) each with a different chosen key innovation measure. The equations consist of the DV (*EBIT-margin$_t$ (log)*), the controls-only model with its CVs and the IVs which represent internal innovation measures (*R&D intensity (A)$_{t-1}$*, *R&D intensity$_{t-1}$*) and external innovation measures (*Acquisition count$_t$*, *Average deal value$_t$*). All CVs except *Financial crisis$_t$* and all internal innovation IVs are lagged by one period (year). All external innovation IVs are not lagged. Indicator variables to control for industry, time, and location effects are part of the controls-only model but are not reported above.
(Source: own representation)

Another main interest is the investigation of whether internal and external innovations are substitutional decision options for entrepreneurs to manage. This can be analyzed by testing interaction terms of both innovation type variables for their significance. Table 7 shows that internal and external innovation does not significantly affect each other's influence on innovation performance (models 2, 3 and 5). An exception to this is model 4 which shows a significance of the interaction between *R&D intensity*$_{t-1}$ and *Acquisition count*$_{t}$. EBIT-margin of a firm is on average increased by 0.0004% per increased entity of *R&D intensity*$_{t-1}$ *x Acquisition count*$_{t}$, that is, if R&D investments and the number of acquisitions are increased at the same time. However, this effect is small. Despite the fact that this significance is eradicated when all measures of innovation are included in the regression model (model 6), these results, given the positive coefficient (model 4), imply that managers can apparently realize synergy effects when investing in R&D and firm acquisitions at the same time, at least to some small extent.

For the interaction of internal innovation and a firm's average deal value per period, the result is another. An attempt to explain this could be that the amount of money invested in R&D equals the minimization of the maximal investment budget for acquisition activities. In other words, whatever amount is invested in R&D cannot be invested in acquisitions at the same time. Nonetheless, the number of acquisitions is on average not diminished by the invested amount in R&D. In conclusion, the amount of money invested in R&D does not affect the influence of the sheer number of acquisitions on firm performance. This is a positive message for entrepreneurs who can apparently invest in R&D and buy as many firms as possible without having to worry about changing performance effects as long as the total invested money value is not affected. **H2** cannot be confirmed.

Table 7: Regressions of the panel data sample with cross-moderator variables (S&P 500)

Variable	(1) EBIT-margin (log)	(2) EBIT-margin (log)	(3) EBIT-margin (log)	(4) EBIT-margin (log)	(5) EBIT-margin (log)	(6) EBIT-margin (log)
CVs	-	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)	(-)
R&D intensity (A) $_{t-1}$	-4.040***					-3.525***
	(0.568)					(0.677)
R&D intensity $_{t-1}$	0.0000476***					0.0000463***
	(0.0000119)					(0.0000131)
Acquisition count $_t$	0.0115					0.0328*
	(0.00728)					(0.0129)
Average deal value $_t$	0.00000536					0.0000114***
	(0.00000320)					(0.00000338)
R&D intensity (A) $_{t-1}$		-0.0298				-0.329
x Acquisition count $_t$		(0.161)				(0.195)
R&D intensity (A) $_{t-1}$			-0.0000427			-0.0000532
x Average deal value $_t$			(0.0000684)			(0.0000473)
R&D intensity $_{t-1}$				0.00000415**		-0.000000536
x Acquisition count $_t$				(0.00000134)		(0.00000194)
R&D intensity $_{t-1}$					1.26e-09	-1.24e-09
x Average deal value $_t$					(9.20e-10)	(7.18e-10)
Constant	-3.338***	-3.452***	-3.451***	-3.440***	-3.451***	-3.382***
	(0.206)	(0.203)	(0.203)	(0.203)	(0.203)	(0.203)
Observations	3,562	3,562	3,562	3,562	3,562	3,541

Robust standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note. The table shows generalized estimation equations (GEE) for the panel data sample with interaction terms between the four key innovation measures (each between one internal and one external innovation measure).

(Source: own representation)

Further investigations regard the long-term effects of innovation as shown in Table 8. For the underlying sample and thesis, "long-term" or "**strong-lag**" refers to effects which date back more than one period. Accordingly, Table 8 deals with both two- and three-period lagged innovation IVs. As a result, all presented lagged versions of all IVs except for *Acquisition count$_t$* show significant effects on EBIT-margin. Apparently, the number of acquisitions of previous periods does not affect the DV. Obviously, our assumption and decision not to lag *Acquisition count$_t$* for the key IV in the first place has been the right one.

A major insight is that the effects (parameter estimates) of all the four key innovation measures become stronger with every lag, that is the absolute value (distance from zero) is the greatest for the three-period lagged IVs. For all IVs except *R&D intensity (A)$_{t-1}$* the two-period lagged versions show stronger effects than the one-period lagged or non-lagged IVs from Table 6. For instance, an increase of R&D intensity over assets of 10% in period $t-3$ would now only lead ceteris paribus to a decrease in EBIT-margin of approximately 22.8% (instead of 37.6% as further above). Although, an additionally invested 100 million US-dollars in period $t-3$ lead ceteris paribus to a 0.12% increase of EBIT-margin on average in period t (instead of 0.09% as in Table 6). Model 9 includes three-period lagged internal innovation IVs and two-period lagged external innovation IVs. Again, all effects but the one of *Acquisition count$_{t-2}$* are significant for the determination of the DV. The number of observations has diminished for every model with lagged IVs because lagged variables cannot access data for the earlier periods (t = 2002 and 2001 respectively) because there is no data on them. Except for *Acquisition count$_t$* **H3** can be confirmed for all innovation IVs. Innovation does have a long-term influence on firms' performance. Consequently, managers and entrepreneurs must plan such activities long in advance.

Table 8: Regressions for the panel data sample with strong-lag IVs (S&P 500)

Variable	(1) EBIT-margin (log)	(2) EBIT-margin (log)	(3) EBIT-margin (log)	(4) EBIT-margin (log)	(5) EBIT-margin (log)
CVs	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)
R&D intensity (A) $_{t-2}$	-2.754***				
	(0.615)				
R&D intensity (A) $_{t-3}$		-2.276***			
		(0.569)			
R&D intensity $_{t-2}$			0.0000365**		
			(0.0000121)		
R&D intensity $_{t-3}$				0.0000388**	
				(0.0000128)	
Acquisition count $_{t-2}$					0.0104
					(0.00894)
Acquisition count $_{t-3}$					

Average deal value $_{t-2}$					
Average deal value $_{t-3}$					
Constant	-3.268***	-3.261***	-3.279***	-3.271***	-3.258***
	(0.218)	(0.221)	(0.213)	(0.219)	(0.213)
Observations	3,297	3,034	3,297	3,034	3,319

Variable	(6) EBIT-margin (log)	(7) EBIT-margin (log)	(8) EBIT-margin (log)	(9) EBIT-margin (log)
CVs	-	-	-	-
	(-)	(-)	(-)	(-)
R&D intensity (A) $_{t-2}$				
R&D intensity (A) $_{t-3}$				-2.553***
				(0.572)
R&D intensity $_{t-2}$				
R&D intensity $_{t-3}$				0.0000490***
				(0.0000126)
Acquisition count $_{t-2}$				0.00181
				(0.00769)
Acquisition count $_{t-3}$	0.0141			
	(0.00860)			
Average deal value $_{t-2}$		0.00000971*		0.00000802*
		(0.00000398)		(0.00000406)
Average deal value $_{t-3}$			0.0000121*	
			(0.00000491)	
Constant	-3.241***	-3.264***	-3.247***	-3.251***
	(0.219)	(0.214)	(0.219)	(0.219)
Observations	3,077	3,319	3,077	3,034

Robust standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note. The table shows generalized estimation equations (GEE) each with either a two-period or a three-period lagged version of the four introduced key innovation measures.

(Source: own representation)

As postulated further above, the relationship between *R&D intensity (A)$_{t-1}$* may not be a linear one. To be sure, squared versions of all four innovation measures have been tested for their significance for the explanation of the DV. Table 9 reveals that all our innovation measures also have a non-linear relationship with the DV. For *R&D intensity (A)$_{t-1}$* this relationship is an inverted U-shaped (with a negative coefficient of -7.361) and for the other three measures, it is a **U-shaped relationship**. This affirms what has been suggested before. On the one hand, an infinite improvement of the ratio of R&D intensity to firm assets will not lead to an infinite decline of EBIT-margin. The EBIT-margin's increase due to *R&D intensity (A)$_{t-1}$* will eventually reach its peak at a certain point and then cause the reverse effect and decrease. In other words, the negative effect of the R&D divided by assets will not set in right from the beginning but after it has surpassed a certain ratio threshold.

On the other hand, an increase in stand-alone R&D expenditures has been recognized as improving EBIT-margin. However, the significant squared measure suggests that low investments in R&D do not constantly improve the EBIT-margin but worsen the short-term financial situation until the amount of R&D invested by the firm surpasses a threshold above which managers and entrepreneurs can on average expect a performance improvement. Although, this improvement will be rather difficult to notice given the amount of other influences circumcising the business and given that the parameter estimate for $R\&D\ intensity_{t-1}^{2}$ is extremely low ($2.62e^{-9}$).

The estimated parameters of $Acquisition\ count_t^2$ (0.00165) and $Average\ deal\ value_t^2$ ($1.65e^{-10}$) are lower than for the estimated linear measures in Table 6. Model (6) of Table 9 includes all squared IVs. While both external innovation measures have lost their sign of significance from the model with all linear IVs included, model (6) of (Table 9) which includes all squared IVs shows that only $Average\ deal\ value_t^2$ turns out to be non-significant anymore. In contrast to its linear measure in Table 6 $Acquisition\ count_t^2$ does not change its sign when included together with the other IVs in the model (compare model 4 to 6 of Table 9) suggesting that the above interpretations hold. As a consequence, **H4a** and **b** can be confirmed. There are significant non-linear effects of internal and external innovation on performance.

Table 9: Regressions for the panel data model with (inverted) U-shape IVs (S&P 500)

Variable	(2) EBIT-margin (log)	(3) EBIT-margin (log)	(4) EBIT-margin (log)	(5) EBIT-margin (log)	(6) EBIT-margin (log)
CVs	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)
R&D intensity (A) $_{t-1}^2$	-7.361***				-7.409***
	(1.630)				(1.642)
R&D intensity $_{t-1}^2$		2.62e-09**			2.33e-09**
		(9.95e-10)			(8.91e-10)
Acquisition count $_t^2$			0.00165*		0.00131*
			(0.000677)		(0.000550)
Average deal value $_t^2$				1.65e-10*	1.46e-10
				(7.49e-11)	(7.95e-11)
Constant	-3.417***	-3.444***	-3.448***	-3.453***	-3.408***
	(0.197)	(0.203)	(0.203)	(0.203)	(0.197)
Observations	3,562	3,562	3,562	3,562	3,562

Robust standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note. The table shows generalized estimation equations (GEE) each with a squared version of the four key innovation measures: *R&D intensity (A)* $_{t-1}$, *R&D intensity* $_{t-1}$, *Acquisition count* $_{t}$, and *Average deal value* $_{t}$.
(Source: own representation)

Firm acquisitions can be determined by various characteristics which are shown in Table 10. It presents five additional acquisition-related independent variables. Model 2 to 6 include each one of the five additional IVs as well as the four innovation IVs and all CVs. Model 7 includes all the above at once. The acquisition-related IVs are $Hostile\ acquisition_t$ which is the rate of hostile acquisitions made by a firm per year, *Diversification$_t$* which is the average rate of a firm's divers M&A deals, *Geo-Distance (A-T)$_t$* which is the rate of within-nation acquisitions over the number of acquisitions per year, *Relatedness (A-T)$_t$* which is measured as the deal value divided by the acquirer's market value and finally *High-tech industry (T)$_t$*. The last listed measure is an indicator of whether a company operates in a certain industry which is defined as being related to high technology (as per Table 3). The results in Table 10 show that none of the additional acquisition-related IVs significantly affects the DV. This is surprising because one would at least suggest a certain significance of the target's industry. In fact, neither that nor any form of diversification (geographical or industry-wise) is important when buying a firm aiming to increase business performance. Model 7 (of Table 10) which includes all acquisition-related and key innovation IVs confirms that. In the end, **H5a-c** cannot be confirmed. Corporate financial performance is not significantly affected by specific deal characteristics as presented below.

Table 10: Regressions for the panel data sample with acquisition-related IVs (S&P 500)

Variable	(1) EBIT-margin (log)	(2) EBIT-margin (log)	(3) EBIT-margin (log)	(4) EBIT-margin (log)	(5) EBIT-margin (log)	(6) EBIT-margin (log)	(7) EBIT-margin (log)
CVs	-	-	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)	(-)	(-)
R&D intensity (A) $_{t-1}$	-4.040***	-4.043***	-4.027***	-4.044***	-4.068***	-3.985***	-4.040***
	(0.568)	(0.568)	(0.558)	(0.554)	(0.566)	(0.548)	(0.543)
R&D intensity $_{t-1}$	0.0000476***	0.0000476***	0.0000471***	0.0000477***	0.0000473***	0.0000469***	0.0000480***
	(0.0000119)	(0.0000119)	(0.0000118)	(0.0000118)	(0.0000118)	(0.0000118)	(0.0000116)
Acquisition count $_t$	0.0115	0.0114	0.0131	0.0110	0.0101	0.0191*	0.0144
	(0.00728)	(0.00727)	(0.00705)	(0.00717)	(0.00728)	(0.00827)	(0.00800)
Average deal value $_t$	0.00000536	0.00000533	0.00000613	0.00000524	0.000000109	0.00000700*	0.000000312
	(0.00000320)	(0.00000318)	(0.00000337)	(0.00000328)	(0.00000468)	(0.00000327)	(0.00000470)
Hostile acquisition $_t$		0.402					0.533
		(0.270)					(0.274)
Diversification $_t$			-0.0286				0.00956
			(0.0724)				(0.0709)
Geo-Distance (A-T) $_t$				0.00474			0.0892
				(0.0630)			(0.0542)
Relatedness (A-T) $_t$					0.00000298		0.00000305
					(0.00000271)		(0.00000265)
High-tech industry (T) $_t$						-0.0804	-0.146
						(0.0736)	(0.0779)
Constant	-3.338***	-3.340***	-3.339***	-3.338***	-3.339***	-3.343***	-3.346***
	(0.206)	(0.206)	(0.206)	(0.206)	(0.206)	(0.206)	(0.206)
Observations	3,562	3,562	3,562	3,562	3,562	3,562	3,562

Robust standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note. The table shows generalized estimation equations (GEE) for the panel data sample with selected acquisition-related IVs. These IVs are all observed at period *t*.

(Source: own representation)

So far, as central results for stand-alone, strong-lag, (inverted) U-shaped IVs, and also for other acquisition-related measures have been presented, the major objective and value-add of this thesis is to reveal conditional circumstances under which innovation affects corporate performance.

To do so, **two types of moderator variables** are tested. On the one hand, interaction terms containing both an innovation IV and an **industry dummy variable** indicating, in which industry the observed firm (not always the acquirer) operates, are tested. On the other hand, interaction terms with an innovation IV and a **time dummy variable** are presented. Furthermore, interaction terms with innovation IVs and the measure *Financial crisis*$_t$ are included in our tests. In addition to that, interaction terms with an external innovation IV and an indicator of whether an acquired firm is operating in a high-tech industry (as defined above) is part of our regression analyses. This latter type of moderator variables makes only sense in combination with external innovation IVs as they are both related to firm acquisitions.

The test results for internal innovation IVs are presented as panel A of our moderator regressions in Table 11 and for external innovation IVs as panel B in Table 12. Note that both tables show only interaction terms that are found to be significant for the explanation of EBIT-margin. This means that all interaction combinations of any industry or time dummy with an innovation IV which is not listed in the table is also not significant as per test results.

Table 11 illustrates that *R&D intensity (A)*$_{t-1}$ is moderated by the industries with the two-digit SIC being 01, 29, 49, 56, 70 or 99 which translate into the following industries: “Agricultural Production Crops”, “Petroleum Refining and Related Industries”, “Electric, Gas, and Sanitary Services”, “Apparel and Accessory Stores”, “Hotels, Rooming Houses, Camps, And Other Lodging Places”, “Nonclassifiable Establishments” (United States Department of Labor, 2020). Industries 01 (“Agricultural Production Crops”), 49 (“Electric, Gas, and Sanitary Services”), 56 (“Apparel and Accessory Stores”) and 70 (“Hotels, Rooming Houses, Camps, And Other Lodging Places”) moderate the effect of *R&D intensity*$_{t-1}$ on the DV. Except for industry 01, all other significant industry indicators show in interaction with *R&D intensity (A)*$_{t-1}$ a changed sign compared to the stand-alone innovation measure (compare model 2). The same phenomenon occurs for the other internal innovation IV (*R&D intensity*$_{t-1}$). We take two examples of the latter.

For instance, the coefficient of the interaction of *R&D intensity*$_{t-1}$ with industry 01 (model 8) indicates that, if a firm is operating in “Agricultural Production Crops” (ibid.) it is likely to decrease its EBIT-margin on average by approximately 17.8% with every additionally invested 1,000 US-dollars. However, with every additionally invested 1,000 US-dollars in R&D a company in industry 56 (model 10) increases its EBIT-margin by approximately 625%. In this case, if the EBIT-margin of a company has been for example 10%, the additional 1,000 US-dollars would lift it on average onto 72.5% (0.10 + 0.10 x 6.25). For industry 70 the on-average-increase would even lead to an increase of 784,200%. In our example with an EBIT-margin of 10%, such an increase would result in an EBIT-margin of 784.3%. This is impossible. It would indicate that a company's earnings before interest and taxes are more than 784-times higher than its revenues, which is simply not realistic. These results indicate either strong outliers within the observed industry or simply a low number of peers per industry. Again, this effect is too large, and considerations of non-linear effects come to mind. Nevertheless, these effects are not tested here.

This thesis does not purport to establish a fully functioning and fully explaining economic model. Instead, the intention is to reveal significant conditions (e.g. regarding industry affiliation, time of initiation, crises effects) which entrepreneurs and managers should consider in their decision-making process. The same difficulties apply for other industries and for time-related moderators as well. It is advised not to put much emphasis on the effect size of these moderator variables (which is also not the objective of this thesis) but to focus on the fact that industry and time dummy variables do moderate the internal innovation effect on performance.

To conclude, all significant industry moderators have a stronger impact on the DV than the corresponding stand-alone innovation measures reported in Table 6, given their higher absolute values of their coefficients. This justifies their testing and proves the importance of this thesis' research focus on conditions of innovation effects on performance. Apparently, for some industries (all the ones in Table 11 (panel A) the further above-drawn implications from stand-alone measures hold.

Continuing, **time moderators** are only significant for *R&D intensity*$_{t-1}$ and for the year 2008 and 2017. Surprisingly, there is no pattern to be found here. Also, moderators with *Financial crisis*$_t$ for both internal innovation measures are not significant for the DV's explanation.

Table 11: Regressions of the panel data sample with industry and time moderator variables for internal innovation IVs (Panel A) (S&P 500)

Variable	(1) EBIT-margin (log)	(2) EBIT-margin (log)	(3) EBIT-margin (log)	(4) EBIT-margin (log)	(5) EBIT-margin (log)	(6) EBIT-margin (log)	(7) EBIT-margin (log)	(8) EBIT-margin (log)
Control variables (CVs)								
Other CVs	-	-	-	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
Financial crisis	0.103	0.0923	0.0935	0.0848	0.0923	0.0943	0.0926	0.106*
	(0.0528)	(0.0507)	(0.0506)	(0.0504)	(0.0507)	(0.0509)	(0.0507)	(0.0523)
Independent variables (IVs)								
R&D intensity (A) $_{t-1}$		-3.754***	-3.734***	-3.757***	-3.754***	-3.748***	-3.756***	
		(0.593)	(0.592)	(0.594)	(0.593)	(0.593)	(0.593)	
R&D intensity $_{t-1}$								0.0000361**
								(0.0000116)
Moderator IVs								
R&D intensity (A) $_{t-1}$ x		-4.098*						
(1, if industry SIC = 1)		(1.692)						
R&D intensity (A) $_{t-1}$ x			244.7*					
(1, if industry SIC = 29)			(105.8)					
R&D intensity (A) $_{t-1}$ x				2136.6***				
(1, if industry SIC = 49)				(62.30)				
R&D intensity (A) $_{t-1}$ x					43.97**			
(1, if industry SIC = 56)					(15.24)			
R&D intensity (A) $_{t-1}$ x						1406.3*		
(1, if industry SIC = 70)						(709.1)		
R&D intensity (A) $_{t-1}$ x							16.94*	
(1, if industry SIC = 99)							(8.357)	
R&D intensity $_{t-1}$ x								-0.000178***
(1, if industry SIC = 1)								(0.0000433)
Variable	(9) EBIT-margin (log)	(10) EBIT-margin (log)	(11) EBIT-margin (log)	(12) EBIT-margin (log)	(13) EBIT-margin (log)	(14) EBIT-margin (log)	(15) EBIT-margin (log)	(16) EBIT-margin (log)
Control variables (CVs)								
Other CVs	-	-	-	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
Financial crisis	0.0983	0.106*	0.108*	0.0922	0.0918	0.106*	0.0814	0.103*

	(0.0519)	(0.0523)	(0.0525)	(0.0505)	(0.0507)	(0.0522)	(0.0514)	(0.0523)
Independent variables (IVs)								
R&D intensity (A) $_{t-1}$				-3.944***	-3.882***		-3.837***	
				(0.602)	(0.579)		(0.617)	
R&D intensity $_{t-1}$	0.0000359**	0.0000360**	0.0000360**			0.0000345**		0.0000347**
	(0.0000116)	(0.0000116)	(0.0000117)			(0.0000115)		(0.0000113)
Moderator IVs								
R&D intensity $_{t-1}$ x	0.125***							
(1, if industry SIC = 49)	(0.00369)							
R&D intensity $_{t-1}$ x		0.00625**						
(1, if industry SIC = 56)		(0.00194)						
R&D intensity $_{t-1}$ x			7.842*					
(1, if industry SIC = 70)			(3.618)					
R&D intensity (A) $_{t-1}$				1.556**				
x (1, if year is 2009)				(0.578)				
R&D intensity (A) $_{t-1}$					1.684*			
x (1, if year is 2017)					(0.701)			
R&D intensity (A) $_{t-1}$						0.0000433*		
x (1, if year is 2008)						(0.0000171)		
R&D intensity (A) $_{t-1}$							0.295	
x Financial crisis $_t$							(0.520)	
R&D intensity $_{t-1}$								0.00000576
x Financial crisis $_t$								(0.00000869)
Constant	-3.432***	-3.434***	-3.432***	-3.366***	-3.366***	-3.432***	-3.364***	-3.433***
	(0.201)	(0.201)	(0.201)	(0.210)	(0.210)	(0.200)	(0.209)	(0.201)
Observations	3,562	3,562	3,562	3,562	3,562	3,562	3,562	3,562

Robust standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes. The table shows generalized estimation equations (GEE) of the panel data sample, each with a different moderator variable for one of the four key innovation measures. Only significant moderator variables are presented. Consequently, all non-shown moderators are tested non-significant in explaining the DV. The presented moderator variables are either an industry moderator or a time moderator, i.e. an interaction term of an industry dummy with an internal innovation IV or an interaction term of a time dummy with an internal innovation IV. If not explicitly specified otherwise the term "industry" refers to the industry of the observed firm of the panel data sample. All IVs, except acquisition-related ones, are reported for period *t*-1. This table represents panel A of the industry and time moderator regression table.

(Source: own representation)

Analogously Table 12 shows the same results for our external innovation IVs. The effect of innovation is not moderated by financial crises. Hence, the decline in numbers of acquirers and acquisitions during and after financial crises (Table 5) can only be explained with the degree of uncertainty in the business environment. Interestingly, external innovation's effect on EBIT-margin is significantly affected by the affiliation of a corresponding target to a high-tech industry (compare model 5), if external innovation is measured by the average number of a firm's acquisitions per year (*Acquisition count*$_t$). If a target is a high-tech company an additional entity of *Acquisition count*$_t$ (an additional one acquisition on year-average) leads to a decrease of EBIT-margin of 4.8%. For *Average deal value*$_t$ there is no such significant moderator reported (model 8).

Apparently, **H6** which indicates significant moderation of innovation effects on performance by industry affiliation can be confirmed for some of the tested firm industries. Being a high-tech target only moderates the effect of acquisition frequency (count) on performance. Furthermore, **H7a** is affirmed for some of the years tested. A pattern is not notable. **H7b**, on the other hand, cannot be proven by the presented regression and test results.

Table 12: Regressions of the panel data sample with industry and time moderator variables for external innovation IVs (Panel B) (S&P 500)

Variable	(1) EBIT-margin (log)	(2) EBIT-margin (log)	(3) EBIT-margin (log)	(4) EBIT-margin (log)	(5) EBIT-margin (log)	(6) EBIT-margin (log)
Control Variables (CVs)						
Other CVs	-	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)	(-)
Financial crisis	0.103	0.105*	0.101	0.105*	0.106*	0.103
	(0.0528)	(0.0525)	(0.0525)	(0.0525)	(0.0527)	(0.0528)
Independent variables (IVs)						
Acquisition count $_{t}$		0.0220*	0.0212*	0.0225*	0.0547***	
		(0.00899)	(0.00903)	(0.00906)	(0.0157)	
Average deal value $_{t}$						0.00000948*
						(0.00000393)
Moderator IVs						
Acquisition count $_{t}$ x (1, if industry SIC = 1)		0.0416***				
		(0.0116)				
Acquisition count $_{t}$ x (1, if industry SIC = 29)			0.197*			
			(0.0783)			
Acquisition count $_{t}$ x (1, if industry SIC = 99)				-0.0324*		
				(0.0128)		
Acquisition count $_{t}$ x (1, if Targ. industry is high-tech)					-0.0482*	
					(0.0212)	
Average deal value $_{t}$ x (1, if industry SIC = 1)						-0.0000136**
						(0.00000448)
Constant	-3.452***	-3.448***	-3.448***	-3.448***	-3.454***	-3.453***
	(0.203)	(0.203)	(0.203)	(0.203)	(0.202)	(0.203)

Variable	(7) EBIT-margin (log)	(8) EBIT-margin (log)	(9) EBIT-margin (log)	(10) EBIT-margin (log)	(11) EBIT-margin (log)
Control variables (CVs)					
Other Cvs	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)
Financial crisis	0.103	0.103	0.110*	0.104*	0.104*
	(0.0527)	(0.0528)	(0.0527)	(0.0523)	(0.0528)
Independent variables (IVs)					
Acquisition count $_{t}$				0.0214*	
				(0.00921)	
Average deal value $_{t}$	0.00000899*	0.0000127*	0.00000864*		0.00000944**
	(0.00000369)	(0.00000578)	(0.00000362)		(0.00000352)
Moderator IVs					

Average deal value $_t$ x	-0.000638***				
(1, if industry SIC = 59)	(0.000160)				
Average deal value $_t$ x		-0.00000615			
(1, if Targ. industry is high-tech)		(0.00000732)			
Average deal value $_t$			0.000156**		
x (1, if year is 2004)			(0.0000559)		
Acquisition count $_t$				0.00247	
x Financial crisis				(0.00814)	
Average deal value $_t$					-0.00000899
x Financial crisis					(0.0000137)
Constant	-3.450***	-3.453***	-3.460***	-3.447***	-3.452***
	(0.204)	(0.203)	(0.203)	(0.203)	(0.203)
Observations	3,562	3,562	3,562	3,562	3,562

Robust standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes. The table shows generalized estimation equations (GEE) of the panel data sample, each with a different moderator variable for one of the four key innovation measures. Only significant moderator variables are presented. Consequently, all non-shown moderators are tested non-significant in explaining the DV. The presented moderator variables are either an industry moderator or a time moderator, i.e. an interaction term of an industry dummy with an external innovation IV or an interaction term of a time dummy with an external innovation IV. If not explicitly specified otherwise the term “industry” refers to the industry of the observed firm of the panel data sample. All IVs, except acquisition-related ones, are reported for period *t*-1. This table represents panel B of the industry and time moderator regression table.

(Source: own representation)

5.3 Discussion and alignment with theory

Some of the above-shown results cope with theories and hypotheses from economic science, some of them do not and, again, some others have not even been investigated until now. In the following, further implications are drawn from the regression analysis and aligned with the relevant theory and literature.

First, the influences of both internal and external innovation on corporate financial performance have found to be significant. This is the major insight on which all the following implications are based. It shows that entrepreneurs and managers can, indeed, manage their businesses' performance by increasing their efforts in innovation. Our results from Table 6 which contains the stand-alone IVs confirm **H1a** and **H1b**. The table also demonstrates that (Schumpeter, 1911) implications about innovations being driven by industrial corporations can be confirmed in that companies experience an on average increase in business performance when engaging in innovative activities. Consequently, suggestions that M&A deals were negatively related to what Batterink (2009, 54) calls "innovation performance" must be denied.

It has also been confirmed that **H2**, which suggests significant interaction effects between internal and external innovation, holds (Table 7). At least, for direct R&D investments and the frequency of buying other companies, the interaction effect is significant. Managers and entrepreneurs can expect synergy effects when both engaging in internal innovation and frequent acquisition activities (based on the number of acquisitions but not on the invested money in acquisitions)[20]. These results do not support the general theory of significant synergy effects between combinations of both internal and external innovation as implied by Sampson (2007, p. 366).

Confirming **H3**, our results show that innovations can effectively carry out a long-term effect on firm performance. Especially internal R&D needs time to completely sink in and realize performance improvements. However, this does not rule out short-term effects. *Acquisition count$_t$* is the only IV (as per Table 8) that does not show a significant long-term effect on performance. This underpins our choice of one-period lagged internal innovation IVs and non-lagged external innovation IVs as stand-alone measures.

[20] Note that Ransbotham & Mitra (2010, S. 2078) find only low synergistic private value from acquisitions effects. However, they understand synergies as an additional advantage/value that comes from acquired target resources, instead the combination of internal and external innovation, as it is presented and discussed here.

Apparently, managers and entrepreneurs need to preplan their innovation activities. Preplanning requires a well-functioning strategic management and a well-organized and well-implemented innovation management to continuously assure the company's competitiveness. This follows the four presented innovation development processes by Dougherty (2012) (Figure 13). The first three hypotheses also support the theory that companies can use innovations as a means to escape innovation as per Howitt (2009, p. 20), given that innovation increases performance (on average) and performance, as well as success, is directed towards a gain of market share, growth and competitiveness itself.

Restrictions to the above implications are imposed by the verification of **H4** regarding non-linear innovation effects. Performance improvement through increased innovation cannot be achieved ad infinitum. Instead, there is a maximum intensity of R&D over assets (*R&D intensity (A)*$_{t-1}$^{2}) above which further performance improvements cannot be realized (model 2 of Table 9). At the same time, pure investments in internal innovation (*R&D intensity*$_{t-1}$^{2}) and external innovation are only effective above a certain amount. Given the as significant tested effects of U-shaped external innovation effects, it is implied that acquisitions only make sense above a certain average number of acquisitions per year (acquisition experience) and amount of capital invested in acquisitions (acquisition commitment).

H5a-c cannot be confirmed as per estimated regressions. Managers and entrepreneurs evidently should not focus their intentions towards external innovation investment on whether the bought firm comes from another industry, is related to the acquirer regarding firm size or is a high-tech target. The latter disproves that, as is suggested by Ransbotham & Mitra (2010, p. 2076) the relationship between the affiliation of a company to a high-technology industry and the importance of external innovation acquisition would be significant. However, the theory that high intensity of R&D would on average come along with a relatively low degree of diversification, as postulated by Hitt, Hoskisson & Kim (1997, p. 788), may be supported by our results (compare model 3 in Table 10). These show that the coefficient of R&D intensity (*R&D intensity*$_{t-1}$) declines when diversification is included in the model. Yet, this result is insufficient to clearly derive a negative relation between R&D intensity, its impacts on performance and diversification. Further research is necessary. Significant diversification effects in the sense of globalization or internationalization on innovation as suggested by Pilat et al. (2009, p. 86) are at the best case supported. Yet, their moderation effect on performance has not been investigated but demands further analysis.

Regarding environmental and externally given conditions in the form of industry affiliation and time dependency, our results allow mixed implications (Table 11 and Table 12). Only a few industries and years show significant moderation effects regarding innovation and performance. However, managers should always consider these two factors whenever confronted with innovation investment decisions. This is an interesting addition to what has been suggested by endogenous growth theory. Obviously, not only doe industrial/business innovations and technological progress affect economic growth bottom-up but also vice versa. Industrial and cyclical circumstances apparently also influence innovation effects on business growth or performance respectively in a top-down direction.

Restrictions to the model must be considered as other influences on the decision for and success of innovation and company performance may be present. Managers' and entrepreneurs' decisions are always subject to personal and psychological perceptions and preferences as suggested by Keynes (1936). Also, as discussed, outliers, false reportings and the general assumptions imperfect market information (cf. Romer, 1990; Lucas, 1988; Nelson & Winter, 1985) limit the explanation ability of the presented results.

6. Conclusion and outlook

6.1 Summary and conclusion

The underlying thesis has given top priority to the investigation of innovation effects on corporate performance. The fundamental research question has been:

"Can innovation be bought?"

Around this issue, multiple sub-problems and questions have been deduced. As such it has been questioned:

Should innovation be bought? Is there evidence that innovation efforts and acquisitions directly or indirectly affect corporate financial performance for the better and that innovation efforts and acquisitions should be considered important tools to improve a company's competitive position?

Given the results from regression analyses about both internal and external stand-alone variables measuring corporate financial performance (Table 6), these questions can be answered with a clear "yes". Evidence has been found that both internal innovation efforts and external innovation acquisitions both directly and moderated by industry and time specifications significantly affect corporate financial performance. Positive coefficients of internal (*R&D intensity*$_{t-1}$) and external innovation show that managers and entrepreneurs can and should use innovations as tools and targets to make their companies more successful, competitive, and resistant to future disruptions. A restriction to these conclusions is provided by the negative coefficient of *R&D intensity (A)*$_{t-1}$.

It has also been asked: Is the decision for or against the internal or external innovation option conditioned by the time of their execution? Again, this question must be affirmed given the significant long-term relationships (Table 8).

In summary, entrepreneurs and managers should use innovations but estimate their investments accordingly with their firms' characteristics and resources. Given the results from regressions with strong-lag IVs (table 8) entrepreneurs and managers have to do so by long-term preplanning. Innovation both realizes short- and long-term effects on performance. All these insights lead already to the answering of the thesis' research question:

"Yes, innovations can be bought."

However, this is not an unrestricted conclusion. The first restriction is connected to non-linear effects. It has been asked: Is there a maximum amount of money spent on innovations above which such investments become unprofitable? Is there a non-linear relationship between innovation and firm performance? It has been discussed that managers cannot simply increase their businesses' performance by infinitely raising their investments in innovations, especially regarding internal innovation. Above a certain point, these become unprofitable and hence managers and entrepreneurs find themselves in the inevitable situation to weigh their opportunities of either innovation option up against each other. Through the analysis of the squared versions of the chosen innovation measures non-linear effects have been revealed (Table 9). The negative coefficient of *R&D intensity (A)*$_{t-1}^2$ demonstrates that companies' spendings on internal innovation (R&D) in relation to the resources (assets) should not exceed a certain threshold. Positive coefficients of the other squared IVs indicate that low portions of R&D, acquisitions and money spent on acquisitions lead to a diminishing effect on firm performance.

Managers and entrepreneurs are bound to their decisions, not only from an organizational perspective but also to realize certain targeted effects. Given the U-shape of these innovation variables, performance improvements just set in above certain thresholds of effort and investment.

Another issue has been: Should companies rather buy other companies to acquire the corresponding innovations and all other resources with it, or should they rather focus on internal efforts to research and develop innovations themselves? The question of weighing opportunities up against each other has been introduced as the "**manager's dilemma**". However, this question cannot be clearly answered like the above. Results show that innovation is a complex field which not only touches many different aspects of a business (e.g. production, marketing, controlling, procurement, management) (compare White & Bruton, 2011, p. 16) but are also influenced by other circumstances such as industry affiliation and the time of execution of an engagement in such opportunities. Regressions demonstrate that the industrial area of the business sometimes influences the effectiveness of innovation attempts and activities towards performance. This counts for both acquirer and target industries. Also, the year in which innovations are initiated can have such an influence. Although, both industry and time moderation does not allow any suggestions about possible patterns. For instance, financial crises do not moderate either internal or external innovation effects, which might have been expected beforehand.

In a nutshell, entrepreneurs and managers are obliged to connect and prepare their business unit towards innovation, with regard to harmonizing the innovation solution itself, the corporate capabilities, the business from an organizational and operational perspective as well as the strategy and direction of the firm. This final conclusion is what has been missing from literature and science discussions about innovations – the actual and conditional effects of innovation on performance and hence a justification for managers and entrepreneurs to set and pursue corporate innovation goals (cf. Mcnamara, Haleblian & Dykes, 2008, p. 114; Batterink, 2009). Only those companies that notably dedicate their efforts to innovation will survive in the long run as only these companies will be able to adjust to disruptive market changes and stay competitive (cf. Engelen, 2020, p. 3).

6.2 Outlook and future research obligations

What remains unresolved in this thesis is the investigation of two aspects. On the one hand, the results regarding the moderation of financial crisis on innovation effects have shown that before-assumed relations and dependencies cannot always be confirmed. Obviously, the financial crisis of 2007/08 has not influenced internal or external innovation effects. Moreover, all other examinations in this study are based on data, which is presumably normal, meaning that no abnormal environmental circumstances and corresponding influences could be expected. But what happens, when the unexpected and unusual becomes the new norm? Do innovation effects on firm performance substantially change in times of crises?

Crisis management has not just been present since the beginning of growth and strategic innovation management theory but long before. Financial disasters like the Great Depression in the 1930s, political changes like the break-out of wars in either physical or economic manner, global environmental crises such as short-term weather catastrophes, long-term climate change or global pandemics like COVID-19 presumably lead to different results and demand a different strategic innovation approach compared to what is presented and discussed here. In the best case, such further research would lead to a better understanding of the interrelationships of uncertainty, customer perception, corporate innovation, and performance improvement both business- and economy-wise.

Secondly, only few conditions for the effects of innovation on corporate performance, i.e. industrial, time-bound, and acquisition-related circumstances, are presented in this study. What other aspects would significantly condition the relationship between corporate innovation and performance? These aspects remain, indeed, “largely unexplained” (cf. King, 2004, p. 198).

Despite the criticism of not dealing with the conditional effects of innovation on performance, it must be noted that each scientist surely possesses specific expertise on the topic he/she examines. However, as this expertise has recently been used to deeply investigate all possible effects of the corresponding topic on various aspects, amongst which there are innovation and performance, the focus should easily shift onto further investigating conditions under which innovation leads to performance improvements and revealing additional restrictions upon innovation effects.

The main criticism of the screened journals and other sources persists as modern innovation discussions consistently revolve around those various relations of certain aspects with either innovation or performance, but rarely around the conditional effects of the earlier on the latter. It is up to economic science to fulfill its original purpose of supporting businesses in their decision-making processes with data-driven insights.

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Appendix

Table 13: Calculations and groups of measures

Name of measure	Label of measure in Stata	Calculation of measure	Related sources
		Environmental variables	
Industry size (A) $_{t-1}$	l1._AvgIndSizeA4	Industry average of assets $_{t-1}$	
Industry growth (S) $_{t-1}$	l1._AvgIndGrowthS4	Industry average of ((sales $_{t-1}$ - sales $_{t-2}$) / sales $_{t-2}$)	Zhou, Gao & Zhao, 2017
Industry growth (A) $_{t-1}$	l1._AvgIndGrowthA4	Industry average of ((assets $_{t-1}$ - assets $_{t-2}$) / assets $_{t-2}$)	
Industry profitability $_{t-1}$	l1._AvgIndProf4	Industry average of ((Revenues $_{t-1}$ - COGS $_{t-1}$ - R&D $_{t-1}$ - SG&A $_{t-1}$) / assets $_{t-1}$)	Choi, Kumar & Zambuto, 2016; Zhou, Gao & Zhao, 2017
Industry dynamism $_{t-1}$	l1._AvgIndSales-Growth5Y	Industry average of 5-year sales growth	Fang, 2011; Gerhart & Milkovich, 1990; Kim & Finkelstein, 2009
Industry concentration $_{t-1}$	l1._IndCon4	$\sum$ (industry average of sales $_{t-1}$)^2	Bendig et al., 2018; Krasnikov, Mishra & Orozco, 2009
		Firm variables	
Firm size (S) $_{t-1}$	l1._FirmSizeSales	Revenues $_{t-1}$	various
Asset growth $_{t-1}$	l1._AssetsGrowth	(assets $_{t-1}$ - assets $_{t--2}$) / assets $_{t-2}$	
		Slack measures	
Absorbed slack $_{t-1}$	l1._AbsorbedSlack	SG&A $_{t-1}$ / revenues $_{t-1}$	Dinesh & Miller, 2008; Greve, 2003b
Unabsorbed slack $_{t-1}$	l1._UnabsorbedSlack	Current assets $_{t-1}$ / current liabilities $_{t-1}$	Dinesh & Miller, 2008
		Liquidity measures	
Leverage ratio $_{t-1}$	l1._LeverageRatioI	Debt $_{t-1}$ / assets $_{t-1}$	Bradley, Kim & Tian, 2017
Cash flow $_{t-1}$	l1._CashFlowI	Cash $_{t-1}$ / assets $_{t-1}$	Dutordoir, Verbeeten & Beijer, 2015
Solvency $_{t-1}$	l1._Solvency	Cash $_{t-1}$ / long-term debt $_{t-1}$	Gulati, Lavie & Singh, 2009; He et al., 2020
Market-to-book ratio $_{t-1}$	l1._MBRatio	Market value of (equity $_{t-1}$ / (assets $_{t-1}$ - liabilities $_{t-1}$)	Bali & Hovakimian, 2009; He et al., 2020; Zhao, 2009
		Profitability measures	
EBIT-margin $_t$	_EbitMargin	EBIT$_t$ / revenues $_t$	Kastalli, van Looy & Neely, 2013; Tam, 1998; Visnjic, Wiengarten & Neely, 2016
ROA $_{t-1}$	l1._ROAI	Operating income before interests and taxes $_{t-1}$ / revenues $_{t-1}$	Bendig et al., 2018; Hitt, Hoskisson & Kim, 1997; Li, Qiu & Wang, 2019; Zhao, 2009
Market value $_{t-1}$	l1._MarketValueI	Liabilities $_{t-1}$ / common ordinary equity $_{t-1}$	Tam, 1998
Tobin's Q $_{t-1}$	l1._TobinsQ	(Closing price $_{t-1}$ x common shares outstanding $_{t-1}$ + preferred stock capital $_{t-1}$ + longterm debt $_{t-}$	Bharadwaj, Bharadwaj & Konsynski, 1999; Krasnikov, Mishra & Orozco, 2009

		$_1$ + current liabilities $_{t-1}$ + current assets $_{t-1}$) / assets $_{t-1}$	
		Firm-industry variables	
Relative size (S) $_{t-1}$	l1._RelFirmSizeS4	Firm revenues $_{t-1}$ / industry revenues $_{t-1}$	Brown & Laverick, 1994; Gosh, 2004; Renneboog & Vansteenkiste, 2019
Relative growth (A) $_{t-1}$	l1._RelAssetGrowth4	Asset growth $_{t-1}$ / average industry asset growth $_{t-1}$	
Relative profitability $_{t-1}$	l1._RelFirmProf4	Firm profitability $_{t-1}$ / average industry profitability $_{t-1}$	
		Investment variables	
PenEx $_{t-1}$	l1._PenEx	Pension and retirement expense $_{t-1}$ / employees $_{t-1}$	Healy, Palepu & Ruback, 1992
Marketing intensity $_{t-1}$	l1._MarketingIntI	(SG&A $_{t-1}$ - R&D $_{t-1}$) / assets $_{t-1}$	Bendig et al., 2018; Mizik & Jacobson, 2007; Raassens, Wuyts & Geyskens, 2014
		Innovation variables	
R&D intensity (A) $_{t-1}$	l1._RDIntensityA	R&D $_{t-1}$ / assets $_{t-1}$	Bendig et al., 2018; Flammer & Kacperczyk, 2016; Jinyu He & Wang, 2009; Healy, Palepu & Ruback, 1992; McAlister, Srinivasan & Kim, 2007; Pennings & Harianto, 1992; Zhao, 2009 - R&D / revenues: Bahadir, Bharadwaj & Srivastava, 2008; Bharadwaj, Bharadwaj & Konsynski, 1999; Cassiman & Veugelers, 2006; Choi, Kumar & Zambuto, 2016; Demsetz & Villalonga, 2001; Ettlie, 1998; Greve, 2003b; Katila & Chen, 2008; Miller & Le Breton-Miller, 2011; Ravichandran, Han & Mithas, 2017; Rothaermel & Hess, 2007; Subramaniam & Youndt, 2005 - R&D / employees: Adams, Bessant & Phelps, 2006; Benson & Ziedonis, 2009; Greve, 2003a; Hitt, Hoskisson & Kim, 1997; Katila & Chen, 2008; Kivimäki et al., 2000; Parthasarthy & Hammond, 2002; Steenkamp & Fang, 2011
R&D intensity $_{t-1}$	l1._RDIntensity	R&D $_{t-1}$	Kleis et al., 2012; Leiponen & Helfat, 2011; Schilling, 2015; Wadhwa, Bodas Freitas & Sarkar, 2017
		Firm indicator variables	
Region/State (dummy)	_[state]	1, if specific US state	
Industry (dummy)	_[industry]	1, if a specific industry	
Time (dummy)	_[time]	1, if a specific fiscal year	
		Acquisition variables	
Acquisition count $_t$	_AcqCountTotal	Count of deals $_t$	Hitt, Hoskisson & Kim, 1997; Karim & Kaul, 2015 (proxy: acquisition experience)

Average deal value $_t$	_AvgDealVal	∑ deals $_t$ / count of deals $_t$	He et al., 2020
Hostile acquisition $_t$	_HostAcqRate	∑ (1, if deal attitude is hostile) $_t$	He et al., 2020
Diversification $_t$	_DiversDealRate	∑ (1, if acquirer industry is target industry) $_t$	Zhao, 2009
Geo-Distance (A-T) $_t$	_AcqTargGeoDist	∑ (1, if acquirer nation is target nation) $_t$	As proxy for Internationalization/Globalisation/International Diversification: Benson & Ziedonis, 2009; Guadalupe, Kuzmina & Thomas, 2012; Hitt, Hoskisson & Kim, 1997; Kashmiri & Mahajan, 2017; Leiponen & Helfat, 2011; Puranam, Singh & Zollo, 2006; Wadhwa, Bodas Freitas & Sarkar, 2017; Zheng Zhou & Bingxin Li, 2012
Acquisition indicator variables			
High-tech industry (T) $_t$	_TargHighTechIndRate	∑ (1, if target industry is high-tech industry) $_t$ / count of deals $_t$	Rubera & Kirca, 2012
Acquisition firm variables			
Relatedness (A-T) $_t$	_AcqTargRelSizeI	Average deal value $_t$ / market value of target $_t$	He et al., 2020; Zhao, 2009
Time indicator variables			
Financial crisis $_t$	_FinancialCrisis	1, if year is 2008/2009/2010/2011/2012	

(Source: own representation)

Affidavit

Eidesstattliche Versicherung
(Affidavit)

Haas, Daniel
Name, Vorname
(Last name, first name)

166420
Matrikelnr.
(Enrollment number)

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(Title of the Bachelor's/ Master's* thesis):

Can innovation be bought? - An empirical analysis of innovation acquisition effects on corporate performance

*Nichtzutreffendes bitte streichen
(Please choose the appropriate)

Dortmund, 05.06.2020
Ort, Datum
(Place, date)

Unterschrift
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