ACQUISITION BEHAVIOR IN HIGH-TECHNOLOGY INDUSTRIES

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THE ROLE OF PRODUCT DIVERSIFICATION, TECHNOLOGICAL CHANGE, AND IP PROTECTION

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ZUSAMMENFASSUNG (GERMAN SUMMARY)

Die zahlreichen Unternehmensakquisitionen in Hochtechnologiebranchen sind einem intensiven Wettbewerb geschuldet, der durch immer kürzere Produktlebenszyklen, komplexere Produktdesigns und extreme Netzwerkeffekte geprägt ist. Die vorliegende Forschungsarbeit hat zum Ziel, die genauen Umstände, die zu technologiegetriebenen Akquisitionen führen, in Form von relevanten erklärenden Einflussfaktoren theoretisch herzuleiten und empirisch zu untersuchen.

Das Hauptargument dieser Arbeit besteht in der grundsätzlichen Differenzierung zwischen verschiedenen technologiegetriebenen Akquisitionen, welche sich wiederum unterschiedlich auf die Unternehmensleistung auswirken können. Bisher wurde dieser Umstand in empirischen Untersuchungen über die Auswirkungen von Akquisitionen nur unzureichend berücksichtigt. Demnach besteht ein zentraler wissenschaftlicher Beitrag dieser Arbeit in einer tiefergehenden und empirisch differenzierenden Beschäftigung mit dem Motiv der technologiegetriebenen Akquisition. Darüber hinaus ist der hier gewählte empirische Fokus auf eine Industrie als Antwort auf die komplexen Zusammenhänge innerhalb einzelner Branchen zu verstehen. Nur durch detaillierte Informationen über die Wertschöpfung und die jeweiligen Produktstrategien der untersuchten Unternehmen kann ein nachhaltiger Erkenntnisgewinn bei der Identifikation bestimmter Verhaltensmuster erzielt werden, der bei Berücksichtigung auch zu einem konsistenteren Bild bei ergebnisorientierten Analysen von Akquisitionen dienen sollte.

Die empirischen Analysen der drei aufeinander aufbauenden Hauptkapitel basieren auf Paneldaten über die (U.S.-amerikanische) EDA Industrie, welche Software zur Entwicklung von Halbleiterprodukten wie Mikroprozessoren herstellt und die in der Einleitung dieser

Arbeit (Kapitel 1) näher beschrieben wird. Die Branche ist von einem sehr hohen Innovationsdruck geprägt, der sich auch in überdurchschnittlich häufigen Akquisitionsaktivitäten wiederspiegelt.

In der ersten Analyse (Kapitel 2) wird die grundsätzliche Differenzierung zwischen unterschiedlichen technologiegetriebenen Akquisitionen mit Hilfe von Charakteristiken und Veränderungen im Produktportfolio empirisch belegt. Dabei werden „expansive" und „defensive" Akquisitionen definiert und mit Hilfe von Produktinformationen approximiert.

Darauf aufbauend führt die zweite Analyse (Kapitel 3) zusätzliche Kontingenzfaktoren ein, die über die generelle Veränderung von Produktportfolios hinausgehen. Konkret bedeutet dies eine gezieltere Untersuchung bezüglich der Frage, wann welche Unternehmen bestimmte andere Unternehmen akquirieren. Hierfür wird ein technologischer Trend innerhalb der Branche definiert, welcher neben einer allgemeinen Notwendigkeit zur Anpassung insbesondere die Nachfrage nach bestimmten Produkten forciert. Die Ergebnisse zeigen, dass der hier identifizierte technologische Wandel an sich in diesem stark volatilen Umfeld keine Veränderung in der Akquisitionshäufigkeit hervorzurufen scheint. Jedoch zeigt sich weiter, dass bestimmte Firmen während der Phase der technologischen Veränderung häufiger in bereits besetzten Produktsegmenten akquirieren − sich somit auf die bereits bestehenden Kompetenzen konzentrieren und nicht in neue vielversprechende Segmente hinein diversifizieren.

Die dritte Analyse (Kapitel 4) betrachtet die Rolle von Patenten im speziellen Kontext von Software-Akquisitionen. Grundsätzlich zeigt sich in den vorherigen zwei Untersuchungen, dass das durch Patente gemessene Konstrukt der *absorptive capacity*, welches häufig genutzt wird, um Akquisitionsverhalten bzw. -erfolge zu erklären, im

Vergleich zu den produktbasierten Maßen weniger bis gar keinen Erklärungsgehalt aufweist. Die speziellen Ergebnisse dieser dritten Untersuchung zeigen, dass die Häufigkeit der Existenz von Patenten bei Akquisitionen abhängig vom neu akquirierten (EDA) Produkttyp ist. Darüber hinaus leistet die Analyse einen Beitrag zur allgemeinen Patentdiskussion und leitet entsprechende Implikationen für zukünftige Untersuchungen in Hochtechnologiebranchen ab.

Die Arbeit endet mit einer ergänzenden integrierten Modellschätzung aus den ersten beiden Hauptkapiteln, bevor die eigentliche Schlussbetrachtung in einer Diskussion und generellen Empfehlung für zukünftige Forschungsarbeiten mündet.

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ABBREVIATIONS

Bn.	Billion
CAGR	Compound Annual Growth Rate
Df	Degrees of freedom
EBITDA	Earnings before interest, taxes, depreciation, and amortization
EDA	Electronic Design Automation
EDAC	Electronic Design Automation Consortium
Eds.	Editors
ESL	Electronic Design Level
Et al.	Et alii (and others)
FE	Fixed effects
IC-BE	Integrated Circuit – Back End
IC-FE	Integrated Circuit – Front End
IP	Intellectual property
IPC	International Patent Classifications
IT	Information Technology
Log	Logarithm
M&A	Mergers and Acquisitions
NAICS	North American Industrial Classification System
NBER	National Bureau of Economic Research
Nm	Nanometer(s)
RBV	Resource Based View
RE	Random effects
R&D	Research and Development
SoC	System on a Chip

S&P 500	Standard and Poor's 500
U.S.	United States (of America)
USD	United States Dollar
USPTO	United States Patent and Trademark Office
VIF	Variance Inflation Factor

1. INTRODUCTION

This introductory chapter starts by outlining the general motivation for this work and the conceptual positioning of its research. This is followed by an overview of the focal industry of the empirical analyses – the electronic design automation (EDA) industry. After a brief reflection upon the benefits and caveats of single-industry analyses, the different data sources are described. Finally, a closing section presents an introduction to regression analysis on count data as well as a general description of the structure of panel data and the benefits of the analysis of such data structures.

1.1. Motivation of research

The understanding of firm behavior is one of the most consistently analyzed subjects within the disciplines of business research and economics. Not only are the activities of each commercial organization a result of its respective internal processes and decisions. They are also embedded within a complex and ever-evolving system of market participants, societal stakeholders, and technological change. The survival of each organization is the most basic underlying motive by which every corporate-level action can be understood. To achieve long-term survival firms compete for limited resources in defined markets by constantly increasing their productivity. As a result of this Darwinian survival-of-the-fittest principle in (more or less) free markets, Schumpeter (1946) described the construct of creative destruction, in which new businesses emerge and replace old incumbents. New technologies often trigger this process by increasing efficiency, effectiveness or making room for new business models. Established firms constantly need to adapt to these changes in order to stay competitive and not to fall victim to creative destruction. The resulting pressure to innovate is especially high in knowledge-intensive high-technology (high-tech)[1] industries, where innovations can often be radical in nature, rendering former core-capabilities obsolete and give rise to new competitors. In combination with short product-life cycles and strong network effects, this generates high-risk environments in which strategic flexibility is essential. One way to achieve this strategic flexibility is to rely on the acquisition of necessary knowledge from external sources as a means to react to technological changes. An acquisition not only guarantees a fast and effective supplement to a set of competences, it is also less risky (and often more feasible) than the internal development of a similar technology, as established firms often battle with organizational limitations when it comes to internal innovation processes (March, 1991).

In contrast to those beneficial factors, there are obviously some effects that can hinder mergers and acquisitions (M&As)[2] from happening or from being successful. For example, the so-called *winner's curse* can result in a substantial price premium that exceeds the potential (future) value of the target company (Roll, 1986). Another crucial aspect is the type of integration of the former independent company into the buying firm's organization (Puranam, Singh, and Zollo, 2006). Often, cultural differences between the involved parties turn out to be irreconcilable, leading to the loss of innovativeness and the simultaneous drain of key personnel. The latter is especially problematic in industries where critical competencies exist in the form of tacit knowledge.

The potential issues described above are just some examples of things that can go wrong before, during, or after making an acquisition, which is often regarded as one of the

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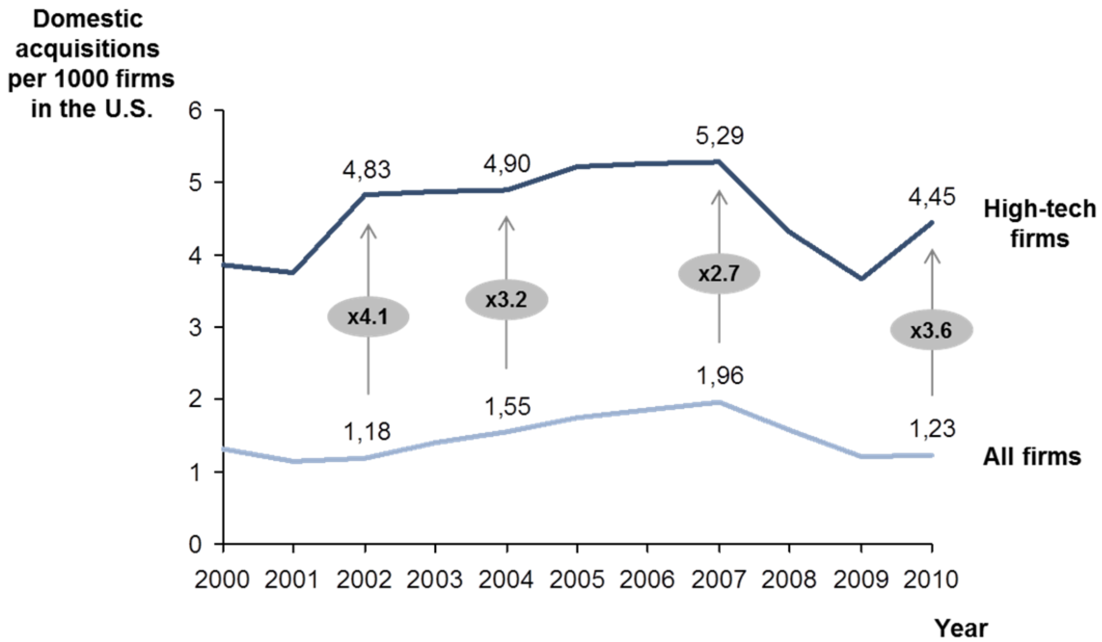
[1] The definition of high-technology industries in this thesis is in line with TechAmerica's (2013) definition according to the North American Industrial Classification System (NAICS). Therefore, we mainly refer to industries that fall under the NAICS categories of 'High-tech manufacturing', 'Communication services', 'Software services', and 'Engineering and tech services'.

[2] In the remainder of this thesis, the terms acquisition, merger, M&A and takeover are used interchangeably.

most challenging management tasks. Therefore, it should not come as a surprise that almost two-thirds of all mergers reduce rather than create value (BCG, 2003).

Despite these difficulties, M&A activities are not declining. Especially in the high-tech sector, M&As apparently seem to be a very popular managerial instrument. Between 2000 and 2010, the intensity of domestic acquisitions[3] in U.S. high-tech industries has been significantly higher than the average M&A activity across the whole U.S. economy. As Figure A shows, high-tech firms have been acquiring between 2.7 and 4.1 times more often during the last decade.

Figure A: Domestic acquisition intensity among high-tech firms and all firms in the U.S.



Source: Own illustration based on information from the Zephyr M&A database, TechAmerica (2013), and the United States Census Bureau (2013).[4]

3 Here, domestic means that both, the acquirer and the target have to be located in the U.S.

4 The number of acquisitions has been drawn from the Zephyr database. Only announced acquisitions are counted. No distinction has been made between different types of investments (minority or majority stake investments). The number of U.S. firms in the respective industries is provided by the United States Census Bureau. The TechAmerica definition of high-tech industries was taken in form of the NAICS from 2007. Only industry classes that exist during the whole analyzed period have been included, which leads to a rather conservative calculation of high-tech acquisition intensity.

The above picture clearly indicates that in high-tech industry settings, the necessities and potential benefits of acquisitions are given priority over possible drawbacks. However, little empirical research has been done to identify the actual driving factors behind high-tech acquisitions. From a management perspective, the apparent clarity of the above phenomenon is sorely reduced, and becomes a rather fragmented and hazy picture when we look at the firm level and actual business operations. In addition, existing empirical models do not necessarily reflect the realities of the fast-paced and dynamic industries analyzed. This thesis aims to address this weakness in empirical literature.

1.2. The different perspectives on acquisitions in empirical research literature

In the attempt to identify and confirm theoretical principles behind acquisitions, empirical management research provides a pattern of different approaches. To acknowledge this work's contribution, this section provides an introduction to the conceptual landscape of management research views on (high-tech) acquisitions, in which this thesis has its distinct place and function. Some aspects of the different concepts and arguments can also be found in the main chapters. Yet, the concluding statement about the positioning of this work within the greater context of M&A research is necessary for the appreciation of the main chapters and the whole thesis in this format.

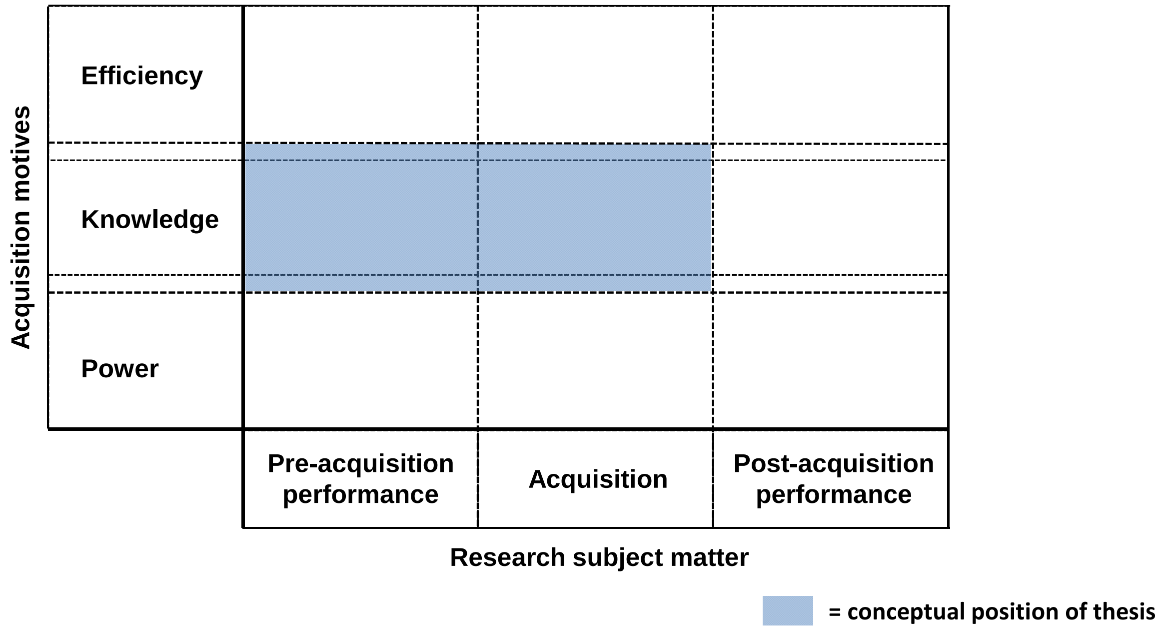
Corporate acquisitions are a very popular subject to analyze, and the ease with which M&As may be recorded and measured certainly plays its part. However, the landscape of empirical research literature is quite diverse.

At the very outset, we can distinguish between different perspectives on acquisitions that have substantial ramifications on the conceptual and empirical research approach and the resulting implications. Research implies different motives behind acquisitions, with Trautwein

(1990) being one of the first who provided a theoretical overview of *theories of merger motives,* based on which he then distinguished *merger as rational choice, merger as process outcome*, and *merger as macroeconomic phenomenon* at the most abstract level. However, especially during the last two decades, 'knowledge' itself, often embodied in technology, has played an important role in acquisition decisions that clearly transcends the traditional theoretical classifications. For example, Krishnan, Hitt and Park (2007) identify achieving higher levels of efficiency, enlarging capabilities (complementarity) or gaining more market power as the three main motives behind acquisitions. In his recent dissertation, McCarthy (2011) empirically analyses acquisitions with respect to the more tactical motives of *new product*, *new region*, *cost synergy*, and *market share*. However, at the most abstract level, most merger motives can be classified into efficiency, knowledge and (market-) power related motives. The more tactical motives will be discussed in the empirical analyses in this thesis.

Apart from the various implied motives, we can also distinguish studies according to the exact subject matter analyzed around the event of an acquisition, in other words, the type of dependent variable. Following the logic sequence of the events around an acquisition, there are three distinct conceptual periods similar to the pre- during- and post-stages noted by Appelbaum *et al.* (2000a, 2000b). Everything that happens before, and culminates in, an acquisition can be associated with the first period, the pre-stage. Pre-acquisition performance as such represents all possible interpretational dimensions that can be utilized to describe and measure the state of an organization prior to an acquisition. Another subject matter is the type of the acquisition and the target itself within the during-stage. For example, firms can purchase differently sized blocks of shares from the target company or they can deliberately buy firms in a particular foreign market. Following this logic, the third group of analyses takes a closer look at post-acquisition performances. As it is the case with pre-acquisition performance, this can be understood in the form of different dimensions, such as financial results or innovation-related aspects. Figure B illustrates this conceptual classification of empirical studies on acquisitions.

Figure B: Thesis positioning within the landscape of empirical research on acquisitions



Source: Own illustration.

Although the different motives can be separated conceptually, a practical clear-cut distinction is very difficult. The dotted lines between the different acquisition motives on the y-axis indicate this difficulty, which clearly is most apparent in the practical distinction between efficiency and knowledge driven acquisitions on one side, and power and knowledge driven takeovers on the other.

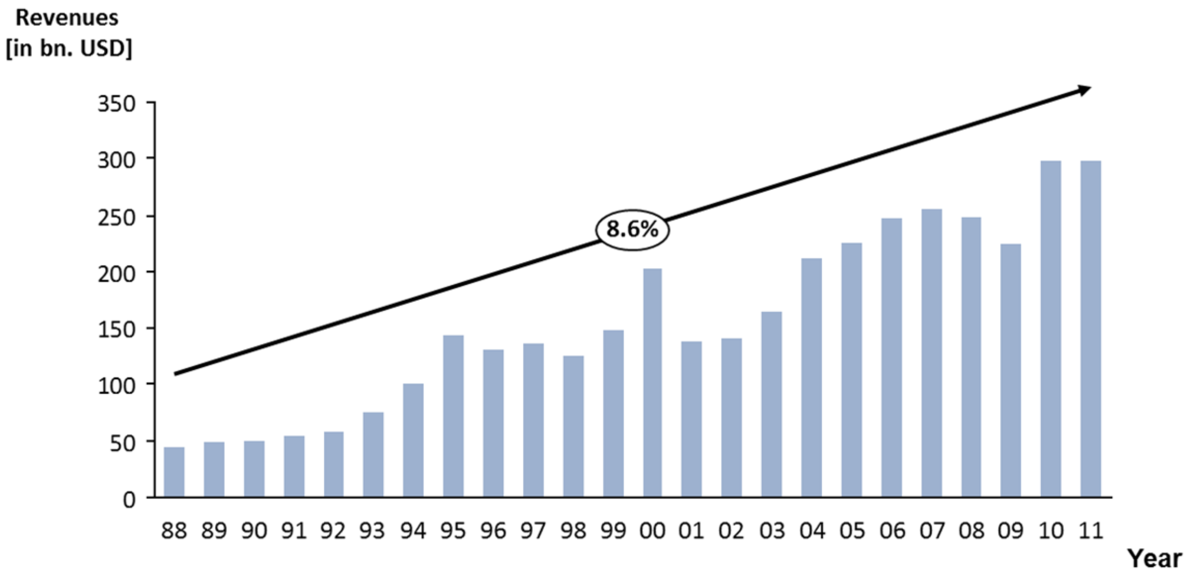
The shaded area in Figure B indicates the conceptual position of this thesis. As indicated above, the focal high-tech setting of this study suggests the prevalence of technology-driven acquisitions since knowledge-based resources can be seen as essential for almost every strategic decision within these industries (Kogut and Zander, 1992). The validation of this particular motive is tested in Chapter 2, while the subsequent parts clearly build on those results. With regard to the concrete subject matter, this thesis is about the explanation of acquisition behavior. More specifically, it aims to reveal moderating factors predicting the number of (patent-oriented) acquisitions.

1.3. The role of EDA within the semiconductor sector

While most of the theoretical arguments in this thesis can be applied to a broad range of high-tech industries, most hypotheses and all empirical tests are based on a single industry, namely the EDA industry. This section will provide a brief introduction to the setting of this industry, a description of the basic purposes and functionalities of EDA products and a short introduction to the industry itself. The special emphasis of this chapter is to illustrate the highly competitive environment of EDA firms and the immense pressure to innovate. Ultimately, this industry description aims to establish the EDA industry as an appropriate example of a very dynamic high-tech industry for the remainder of this thesis.

The EDA industry is an integral part of the semiconductor sector. In terms of end products, we can divide semiconductors into three main categories. The most prominent product type is the microchip (or microprocessor), which is the main processing unit in every personal computer device including laptops, tablets, and smartphones. Memory chips represent the second product category followed by the third main product category, rather standardized ‘low-end’ chips for routine processing purposes. Figure C shows the global sales of the semiconductor sector from 1988 to 2011.

Figure C: Worldwide semiconductor sales (1988–2011)



Source: Own illustration based on data from Statista (2012).

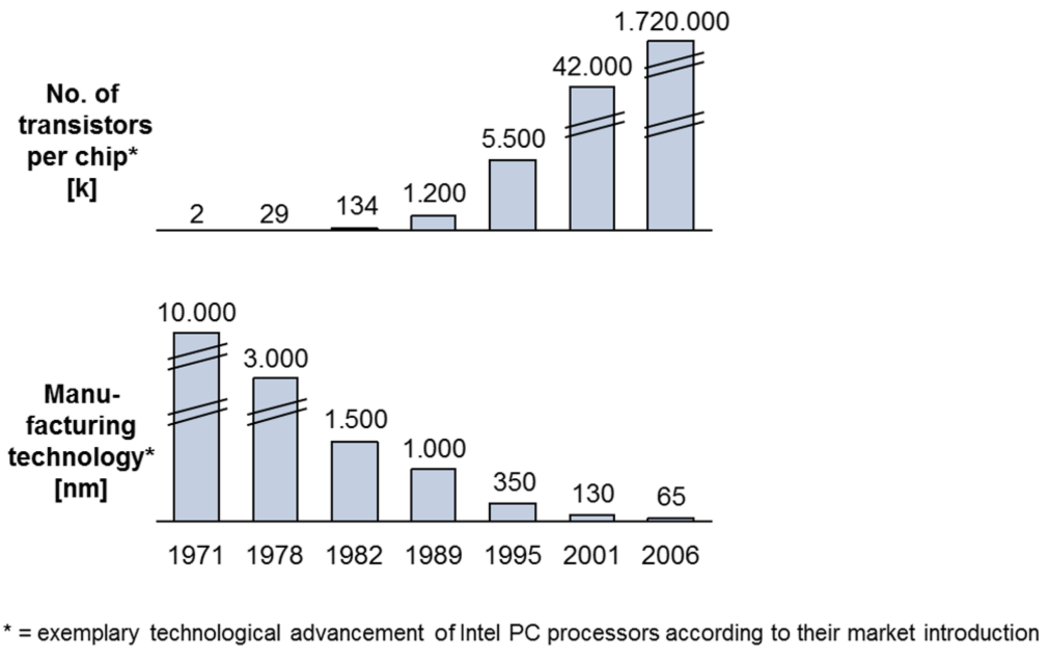
Also apparent in this data is the cyclical nature of the semiconductor business, which is very much bound to the global economic climate. This is an important topic for chip manufacturers as they typically have to build up their production capacities to cater for high demand. These capacities turn into liabilities during economic dips and put pressure on chip prices, which in turn leads to less capacity. As a consequence, prices usually stabilize again and feed the next costly increase in capacities, when the economy recovers.[5]

Apart from these cyclical nuances in sales, the figures show an impressive growth of this still rather young industry. Global revenues grew significantly during the period from 1988–2011 which means a compound annual growth rate (CAGR) of 8.6 percent. This development is not surprising given the proliferation of semiconductors in consumer products.

[5] The challenge for chip manufacturers to cope with cyclical demands is a very crucial aspect in the economies of the semiconductor industry. However, this topic is not essential for this work. Please see Tan and Mathews (2010) for a comprehensive analysis of this subject matter.

The root cause for the immense success of semiconductors is technological progress coming through the realization of *Moore's Law*. Gordon Moore (1965), who was one of the co-founders of Intel, the world's largest designer and manufacturer of microprocessors, made the prediction that the amount of transistors on a single microchip roughly doubles every 24 months. Until today, chip manufacturers successfully followed that law. One of the main drivers behind this development is the constant improvement of the chip manufacturing process. The increase in transistors always went along with smaller manufacturing scales. Smaller dimensions have major ramifications on the performance of microchips. A smaller manufacturing scale not only pushes the envelope in terms of raw speed, power consumption, or heat emission. It also lowers manufacturing costs and improves performances of mid-tier and low-end microprocessors, making it possible to have these devices in more and more home appliances and everyday products like televisions, cars or toys. Figure D illustrates the rapid development of chip complexities from 1971 to 2006.

Figure D: Chip evolution from 1971 to 2006



Source: Own illustration based on information from Intel (2013).

This constant improvement of chip performance also comes with an increase in complexity. Today, a modern microchip hosts several billion transistors on a surface the size of a fingernail. Interconnections between these transistors form millions of logic gates which have to work together efficiently in terms of chip performance and reliability. Moreover, diverse former adjacent sub-systems like hardware and memory controllers are being built into the chip itself very often, also known as System on a Chip (SoC) design (Birnbaum, 2004; Linden and Somaya, 2003).

1.3.1. What EDA does

Given the extreme complexity of modern microchips and the vast technological advancements that are being introduced to markets, EDA software is used to automate large parts of the chip conceptualization and design process. Thus, EDA firms act as suppliers and technical consultants for chip manufacturers and developers like Intel or AMD.[6] Supporting chip designers and engineers, EDA tools provide a high level of abstraction, automatically transforming new architectures into a blueprint for physical manufacturing (including defined placements and routings). The use of EDA software also allows for fast and cost-efficient testing and validation through virtual emulation software. This is extremely important as a chip design process is characterized by much iteration and many verification steps (see Figure G in the appendix). On the way to a marketable product, each non-physical prototyping step saves time and cost.

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[6] Due to the ever increasing challenges in chip design and manufacturing we can observe a trend towards a division between these two businesses. So called fabless firms specialize in the development of new chip designs. Owning the intellectual property (IP) they often license out their chip architectures to other chip design specialists or directly assign chip manufacturers with the production. These specialized chip manufacturers are called foundries.

Different EDA tools operate on different abstraction levels along the chip design process, also known as the '*design flow*' (Birnbaum, 2004). Within this flow, all design tools need to be highly integrated to ensure that different design disciplines and specialists can communicate and exchange data with each other seamlessly. The chip design flow can be roughly divided into three sub-categories/phases, the Electronic System Level (ESL), IC Front-End (IC-FE) and IC Back-End (IC-BE) design (Birnbaum, 2004).[7] A new chip design passes through each sub-category in these consecutive phases with much iteration within and across the phases. In essence, the different tools work on different levels of abstraction that assist designers and engineers during the design process. With the assessment of the type of existing product portfolios, it is possible to characterize the positioning of each EDA firm, upon which a large part of the empirical tests in this thesis will be based. Therefore, a more detailed description of the actual product categories will be given in the respective chapters, as necessary. Although this can produce brief redundancies it also improves the reading process since most of the explanatory variables utilized are closely tied to the main product variables, which are not necessarily comprehensible intuitively.

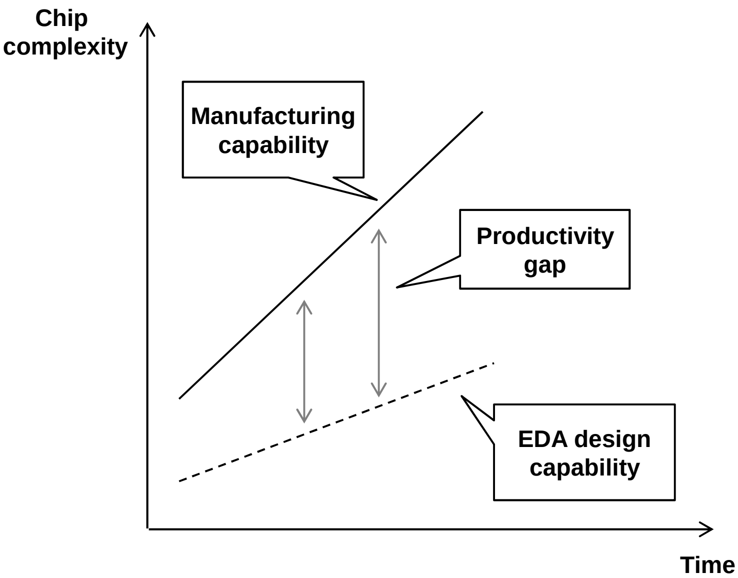
1.3.2. The pressure to innovate

Compared to the crucial role of EDA tools in the chip development process, the industry is relatively small in terms of revenue. For example in 2011, the combined revenue of the three largest EDA firms, which account for more than 50 percent of the global EDA industry at least for the last 15 years, was roughly 3.6 billion USD (Cadence Design Systems, 2011; Mentor Graphics, 2011; Synopsys, 2011), which was less than seven percent of the

[7] Please also see Figure G in the appendix.

revenue of Intel of 53.4 billion USD in that year (Intel, 2011).[8] Moreover, the industry faces a permanent high pressure to innovate. The existence of the so-called *design gap* or *productivity gap* is a good indicator of this pressure. As illustrated in Figure E, this gap represents the enormous challenge that chip design software firms face. Manufacturers of silicon-based chips constantly invent smaller-scale manufacturing processes, and they need corresponding design software to realize the advantages and address the challenges of miniaturization. In other words, while a new manufacturing process is being developed, chipmakers approach EDA software firms to incorporate corresponding features into their products. This leads to the productivity gap in which design software has to catch up with technological advancements (Birnbaum, 2004).

Figure E: The productivity gap in the semiconductor/EDA industry



Source: Own illustration based on Birnbaum (2004, p. 20).

[8] One of the most prominent topics within the EDA industry has always been the relative small financial share in the chip value chain. Based on a study made for the EDA Consortium (EDAC), the U.S. association of EDA companies, the costs for EDA tool licenses makes up for roughly around 10 percent of the overall costs during the chip design process, which translates into 1–1.5 percent of the total revenues of chip vendors (International Business Strategies, 2003).

Within this very progressive environment, only a few large (U.S.-based) firms account for the majority of global revenues (Sangiovanni-Vincentelli, 2003). According to Gary Smith EDA, more than 70 percent of EDA revenues in 2009 were generated by the top five players in the industry – all of them public U.S. companies (Solid State Technology, 2010). At the same time, the constant need for technological change creates fertile niches in which new ideas and technologies can evolve in the form of new EDA ventures, while entry barriers in terms of required capital are low. The diverse landscape of young and innovative specialist firms represents an attractive pool of knowledge and talent. Therefore, it is not surprising that the EDA industry is characterized by a high frequency of corporate acquisitions (Wagner, 2010).

1.4. The strengths and weaknesses of single industry analyses

The narrow industry focus in this thesis makes it possible to take a very close look at acquisition behavior and to take into account within-industry differences that can play a pivotal role motivating corporate takeovers. On the other hand, such a focused approach comes with some inherent caveats.

Although discussed in greater detail in the main chapters, the special character of the coming empirical analyses is worth preceding with a general summary of the respective trade-offs of differently-scoped empirical analyses. The rationale behind this is twofold: First, the very general discussion about the implications of differently-scoped empirical analyses is appropriate for all three subsequent empirical studies. Therefore, this preceding explanation works as a universal frame valid for the whole thesis. Second, the reflection about alternative-scope-related empirical research designs at this early point supports the reader in putting the methodology in this work into perspective as being just one possible approach. However, the single industry approach can be seen as an appropriate methodological answer to scholars calling for a more consistent approach in innovation related M&A research (e.g. Schulz, 2008).

The scope of an empirical analysis has fundamental ramifications for the interpretation and generalization of its results. In one case, a study can feature a very large-scale set of data across almost all industries. Inferring very general conclusions based on such studies is entirely feasible, since the data is very representative. As with all econometric analysis, we can only interpret average effects across whole datasets. Consequently, a broad validity very often comes at the cost of limited depth, leaving out industry and firm-specific contingency factors. Therefore, on the other side of this conceptual continuum between generalizability and situational consideration, case studies can address the shortcomings of very broad research scopes. These single examples can validate theory or large-scale empirical results at the level of the firm or a particular organizational unit. They can also generate insights uncovering new cause-effect relationships and therefore enrich our understanding of contingent economic behavior, which in turn can then trigger new larger-scale empirical analyses.

The choice of the "right" scope of the empirical research does not only depend on the specific research question, but it also hinges on the availability of proper data. In the case of this work, the research direction and the data situation fit together very well. It represents a kind of middle ground between the two most extreme forms of research scope indicated above. The analyses in this thesis are based on a panel data set about a single industry. Making arguments about the necessity of more single-industry analyses in acquisition research, the analyzed data in the current research features detailed information about the firms of that industry. Although very specific in nature, similar data can theoretically be obtained from other industries to cross-validate and further legitimize the results presented.

1.5. Data source description

The main purpose of this section is to provide a description of the data sources on which the empirical analyses in this thesis are based. While not all data are utilized in every analysis this description functions as an overview and general reference for the three main chapters that follow.

The studies below feature datasets of varying size for their respective empirical analyses. This is partly due to diverse selection criteria and variables being appropriate for the different purposes of the studies. Further, although the datasets have been larger immediately after the merging and filtering processes, the nature of the left-truncated datasets leads to unavoidable cut-offs for the multivariate regression analyses.

At the very core of the analyzed dataset are the detailed EDA industry descriptions by Gartner Dataquest and Gary Smith EDA. Those consulting agencies published annual reports providing an overview of firms in the global EDA industry for the period 1996–2006. These include information about the specific sub-segments in which the firms are active, allowing us to track the type and breadth of firm-specific activities within the EDA industry over time.

Despite an international industry structure, the large majority of global revenue comes from EDA firms based in the U.S. (Lebret, 2007). The decision to solely focus on firms with their origins in the U.S. allows controlling for any country effects without losing global information about specific trends and developments. In a second step, matching financial data for all public U.S. firms from the Compustat database was obtained. Respective patent information was sourced from the database of the National Bureau of Economic Research (NBER). Information about the M&A activity of the firms comes from the Thomson One Banker database.

For the purposes of this work, an acquisition is defined as a purchase that leads to a corporate equity stake of more than 50 percent of another company (Desyllas and Hughes, 2009). This excludes deals resulting in minority stakes and the repurchasing of a company's own shares. Also excluded are corporate deals involving non-EDA companies, such as IT service companies. Through this strict data treatment, we are able to clearly interpret every acquisition as an event following which the acquiring party has full control over the target and full formal access to the firm's technological competencies. Starting with a sample of 468 acquisitions conducted by public U.S. EDA firms between 1996 and 2006, every acquisition entry was manually evaluated using these rules, resulting in a final set of 247 before any empirical analysis was conducted. Furthermore, qualitative triangulation through secondary sources such as conference papers and presentations or relevant online trade journals (e.g., *EE Times*) ensured the filtering was appropriate.

From the NBER database 16,446 patents have been extracted, of which 2,748 were applied for prior to our chosen time period (1996–2006). These latter patents are used to calculate starting patent stocks in 1996. Before the matching process, 84.2 percent of all patents are in the IPC categories 'G' (Physics) and 'H' (Electricity). Almost 13.9 percent are in the 'B' (Performing Operations, Transporting) and 'C' (Chemistry, Metallurgy) categories.[9]

[9] Owing to our narrow industry focus we want to avoid any patent selection bias. Therefore, we estimated all of our models with two versions of our patent data. One version included only patents belonging to the more industry-related categories 'G' and 'H' and one version included all patents. The reported models in this dissertation include all patents since the results do not differ in any qualitative or quantitative manner.

1.6. Analyzing count data

This section aims to lay some theoretical groundwork for the subsequent empirical analyses. Apart from the more intuitive explanations, the formal descriptions are mainly based on the very well written work by Tutz (2010) and the seminal contribution by Cameron and Trivedi (1998).

1.6.1. The negative binomial distribution

The main research interest in this thesis is to understand the acquisition behavior of firms. To capture and measure this behavior, the number of acquisitions[10] is the dependent variable in all empirical models in this work. This has some implications for the choice of the particular regression model, which is used for the multivariate analyses.

The classic linear regression model assumes a normally distributed, continuous and metric dependent variable. Obviously, the number of acquisitions is a discrete count measure that does not comply with the classic assumptions, in that it cannot be negative and usually is not normally distributed. The most basic model for the distribution of count-based events is the Poisson distribution. It calculates the probability of certain draws as follows:

$$f(y) = P(Y = y) = \frac{\lambda^y}{y!} e^{-\lambda} \qquad \text{for} \qquad y \in \{0, 1, 2, \ldots\}, \tag{1}$$

where Y is the event (specifically the number of acquisitions) and λ is the expected value of the random variable ($\mathrm{E}[Y] = \lambda$). The specialty of this distribution is the assumption of *equidispersion*, which means that the expected value is equal to the variance, meaning $\mathrm{E}(Y) =$

[10] To be more specific, different subgroups of acquisitions are analyzed in this thesis depending on the respective chapter.

$var(Y) = \lambda$ (Tutz, 2010, p. 888; Cameron and Trivendi, 1998, p. 4). Thus, the Poisson distribution is only determined by one parameter (λ).

This assumption is very limiting, particular regarding real-life events. Very often, we observe a greater variability, which is also known as *overdispersion*. This can be the case when certain events predominantly show very low values while higher values are rare. For example, when we look at entire populations, most people will visit a doctor only a few times a year, whereas a smaller group might be far more frequent visitors. This skewed distribution regarding the number of events would solidify the larger the sample gets. A Poisson model does not consider this overdispersion as it is too strict in its assumptions.

The negative binomial distribution is more flexible in this regard, as it introduces a second parameter in its probability function:

$$f(y) = \frac{\Gamma(y+\nu)}{\Gamma(y+1)\Gamma(\nu)} \left(\frac{\mu}{\mu+\nu}\right)^{y} \left(\frac{\nu}{\mu+\nu}\right)^{\nu} \qquad \text{, with } y = 0, 1, 2, \ldots \quad (2)$$

Hence, we have two parameters (λ and ν) determining the distribution. Γ describes the function $\Gamma(\nu) = \int_0^{\infty} t^{\nu-1} e^{-t} dt$ and we get the expected value of $E(Y) = \mu$ and the variance of $var(Y) = \mu + \frac{\mu^2}{\nu}$ (Tutz, 2010, p. 889).

Because of the flexibility of the negative binomial model, it is the model of choice in all empirical analysis in the subsequent chapters. Alternative distribution models like Poisson or zero-inflated specifications have also been tested. However, none of these alternative specifications proved to be superior concerning model fit (in terms of comparing log-likelihood values) over the negative binomial setting in any of the analyses.

1.6.2. Interpretation of the regression coefficients

The special characteristics of count variables also demand some special consideration when modeling the regression itself. Again, starting with the ordinary linear regression:

$$\mu = \beta_0 + x_1\beta_1 + \ldots + x_i\beta_i \ , \qquad (3)$$

where we have an expected value $\mu = \mathrm{E}(\mathrm{Y}|x_1, \ldots, x_i)$ being in a linear relationship with the independent variables $x_1, \ldots, x_i$ (Tutz, 2010, p. 889). In this setting, a non-negative dependent (count) variable cannot be properly estimated as it also allows for negative outcomes. Therefore, the classic model must be extended:

$$\mu = h(\beta_0 + x_1\beta_1 + \ldots + x_i\beta_i). \qquad (4)$$

The extension happens in such a way that h is a transformation function that prevents μ from becoming negative. Usually, this transformation function is a loglinear operator, so that:

$$\mu = exp(\beta_0 + x_1\beta_1 + \ldots + x_i\beta_i). \qquad (5)$$

The linear characteristic can still be maintained by logarithmizing the expected value:

$$\log(\mu) = \beta_0 + x_1\beta_1 + \ldots + x_i\beta_i \ . \qquad (6)$$

However, the linear effect only indirectly influences μ through log(μ). This has ramifications for the interpretation of the coefficients of the independent variables. In order to illustrate this, we can see the non-linear relationship as follows:

$$\mu = e^{\beta_0}\left(e^{\beta_1}\right)^{x_1} \dots \left(e^{\beta_i}\right)^{x_i}. \tag{7}$$

Thus, an increase of the variable $x_j$by 1 would lead to

$$\mu = e^{\beta_0}\left(e^{\beta_1}\right)^{x_1} \dots \left(e^{\beta j}\right)^{x_j+1} \dots \left(e^{\beta_i}\right)^{x_i}, \tag{8}$$

and would change the expected value by the factor $e^{\beta j}$ (Tutz, 2010, p. 890). The multiplicative effect of $e^{\beta j}$ leads to a more general interpretation compared to a classic linear regression model. Given the case of an increase by one, $\beta_j = 0$ means no change in the expected value. $\beta_j > 0$ would imply $e^{\beta j} > 1$ and result in an increase of μ. In the case of $\beta_j < 0$ we get $e^{\beta j} < 1$ and therefore a diminishing effect on μ (Tutz, 2010, p. 890).

1.7. Panel data analysis

In this section, the emphasis is on a general description of panel data structures, through which the multivariate empirical analyses in this thesis are conducted. By providing a fundamental econometric understanding, the benefits of panel data compared to cross-sectional and longitudinal data are shown. This chapter tries to provide an intuitive and application-oriented understanding. The formal descriptions and aspects are mainly based on an article by Brüderl (2010).

1.7.1. Panel data structure

The characteristic feature of panel data can be described as a combination of cross-sectional and time series data. In other words, a panel structure represents a certain number of repeated measures over time (T) of a group of individuals, firms or other subjects of interest (N). Therefore, $T \cdot N$ represents the total number of observations of a balanced panel dataset. In the case of unbalanced data, the size of the group of individuals and the number of observations can vary within the sample. This can be the case when firms cease to exist due to bankruptcy or acquisitions, or when they appear as new subjects as they become part of a certain index like the S&P 500. Unbalanced datasets are very common in empirical management literature.

1.7.2. Benefits of panel data analysis

The general goal of empirical analyses is to identify cause-effect relationships. While natural scientists can set up and repeat experiments within a controlled environment, social scientists very often have to rely on data from surveys or from special databases. The interpretation of the latter type of data is more difficult, because data generation usually cannot be repeated under the same conditions and information about these conditions at that time is always limited. This makes it very difficult to derive reliable statements about causal effects, since it is not possible for social scientists to control for every possible influencing factor at the time the information was collected.

The structure of panel data helps mitigate the effects of this issue. This advantage becomes clearer when we compare panel data with cross-sectional types of information. For example, assuming the analysis of the performance of professional athletes, one could measure their results at a particular competition. Possible explanatory variables could be physical characteristics like height, endurance, or strength. It is likely that the type and length of the prior training could also be important predictors. Based on this one time measurement, a cross-sectional regression analysis of the athlete's performance could have the general structure of a linear regression as was already shown in equation (3):

$$\mu = \beta_0 + x_1\beta_1 + \ldots + x_i\beta_i \; . \qquad (3)$$

However, this estimation would only be based on one measurement at a particular time. Thus, the weakness of this cross-sectional approach is that it only considers inter-individual differences and it potentially ignores intra-individual and time-dependent developments, which could influence the individual performances, too. In addition, there are usually unobserved individual differences (unobserved heterogeneity) to be controlled for. As panel data consist of observations at several consecutive times (e.g., performance measure on every competition weekend) it allows for the analysis of intra-individual and time-dependent developments, and thus for the control of unobserved heterogeneity. Following the example above, it is possible that athletes with some special training perform better. Hence, in a cross-sectional analysis special training would have a positive influence on the individual performance.

A simple model with special training being the only explanatory variable, the cross-sectional model would estimate the difference of the average performance between athletes without and with some special training at the same time (t) the so-called 'between-estimation' (Brüderl, 2010, p. 965). It can be formally written as:

$$y_{i,t_0}^{T} - y_{j,t_0}^{L} \; , \qquad (9)$$

where y is the performance, T stands for the special training and L stands for less or normal training. With this method the true causal effect of the special training cannot be estimated correctly as the cross-sectional approach only compares two different groups of athletes who most likely differ in more aspects than in their special training.[11] The actual causal effect of special training can only be identified through the within-estimator, which compares the dependent variable (performance) of the same person (athlete) at the time before and after the treatment (the special training):

$$y_{i,t_1}^{T} - y_{i,t_0}^{L}\ . \qquad (10)$$

Assuming, that there are no other time-dependent effects, the true effect of special training could be estimated correctly.

Both, between- and within-estimation play a crucial role in panel regressions as they can be addressed simultaneously. There are two general approaches to analyzing panel data, namely the fixed-effects (FE) and the random-effects (RE) model.

The FE regression only shows the effect of the within-estimator by only considering changes over time within a respective individual subject and not between different individuals. To understand how FE estimation works we can start with a basic model with error components:

[11] A causal relationship through cross sectional analysis can only be shown in the case if the two groups of a between-estimation are completely identical except of the respective treatment (here: special training), which is a very unrealistic assumption.

$$y_{it} = \beta_1 x_{it} + v_i + \varepsilon_{it} \text{ ,} \tag{11}$$

where v_i and ε_{it} together form the error term (u) consisting of an individual error (v_i which is assumed constant over time) and an idiosyncratic error (ε_{it} which represents the remaining unobserved errors that vary over time and between individuals). The constant β_0 is not included in the equation, as it would be collinear with v_i, which can also be understood as an individual constant (Brüderl, 2010, p. 967). The components v_i and ε_{it} also form the error term of cross-sectional regression. However, it is not possible to distinguish between the two different types of errors in a cross-sectional setting. This is the advantage of panel data. The FE estimation 'normalizes' the measured effects by calculating average values over time for every individual, which leads to the following equation:

$$\overline{y}_i = \beta_1 \overline{x}_i + v_i + \overline{\varepsilon}_i \text{ .} \tag{12}$$

The normalization happens when we subtract equation 12 from equation 11 and we get the following FE model:

$$y_{it} - \overline{y}_i = \beta_1 (x_{it} - \overline{x}_i) + \varepsilon_{it} - \overline{\varepsilon}_i \text{ .} \tag{13}$$

The time-constant error term v_i is eliminated through the subtraction. As a consequence, the FE estimator measures the deviation of the variables relative to the specific average values of every person. Referring back to the example of the athletes, it would only measure the effect of the special training. However, it is possible that athletes who engage in the special training are better per se (e.g., more talented). This would mean that they self-selected themselves into the special training. Although the FE model does not identify between-differences, it still controls for them, whether they are known or not. On the other hand, this benefit comes at a cost, as there may be a danger of ignoring important between-differences that are essential for the interpretational evaluation of the model. Moreover, the FE estimator does not allow for time-constant variables like gender or country of origin. The RE model can address both, the within- and the between-differences and can be written as follows:

$$y_{it} = \beta_0 + \beta_1 x_{it} + v_i + \varepsilon_{it} \; . \qquad (14)$$

Unlike in the FE estimator, the effects from v_i are not treated as being constant. Rather, v_i is considered to be normally distributed, hence random. The combined influence of within- and between-estimations is only possible under the condition that v_i is uncorrelated with the independent variables. In our example this would imply that there are only non-systematic unobserved individual differences and self-selection does not exist. In the case of self-selection the quality of the RE estimator depends on the magnitude of the between-variance in comparison to the within-variance. The larger the relative between-variance, the less biased is the RE estimator.

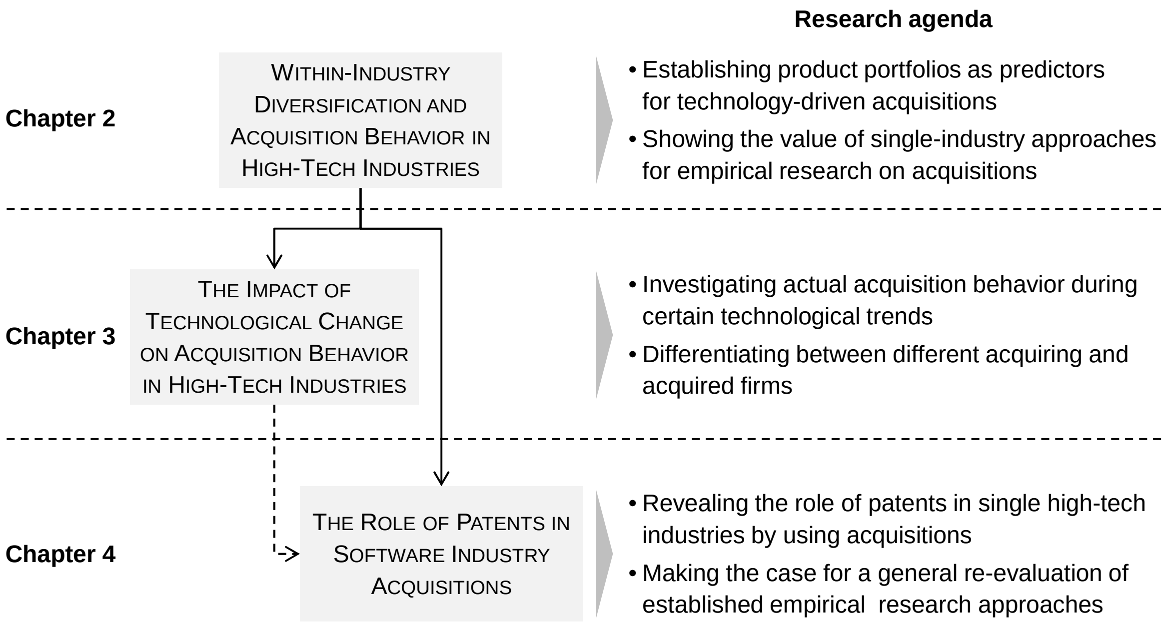
A vigorous debate continues about how and when to choose which estimator. Although the Hausman test is a common tool, the ultimate choice of the respective model should depend on the type of data and the empirical setting of the respective analysis to weigh between bias and variance (Clark and Linzer, 2012).

1.8. Thesis structure and main research goals

This thesis consists of three main empirical analyses. Each aims to contribute to the understanding of acquisition behavior from different angles. However, the three parts are conceptually intertwined and partly built on each other. The hypothesized models in Chapter 2 test and verify basic assumptions about technology driven acquisitions by utilizing unique product information, which will be explained below in greater detail. The main results confirm common assumptions about motives behind high-tech acquisitions while also forming the foundation for the more distinct and explorative chapters that follow. More specifically, the main research goal in Chapter 2 is to conceptually and empirically show the predictive potential of characteristics and changes in product portfolios with respect to acquisition behavior. Chapter 3 further utilizes this product information to expand the range of contingency factors by introducing a technological trend and illustrating its impact on the acquisition behavior. In addition, the model also distinguishes between different kinds of firms according to the types of products they offer. Therefore, not only the effect of the trend on each firm's acquisition activities is part of the empirical model, but also its particular impact on the behavior of specific types of firms. Hence, the main research goal of the third chapter is to better understand the effects of technological trends on the acquisition behavior of particular firms in high-tech industries.

Chapter 4 essentially examines the role of patents for acquisitions in high-tech industries. It was also motivated by the results from the first two main chapters but takes a different conceptual path. The apparent inferior explanatory power of patent-measured absorptive capacity in the prior empirical models begs the fundamental question about the role of patents in software-based industries and their use as innovation-related indicators in management research in general. Similar to the second chapter, the empirical model distinguishes between different kinds of EDA firms according to the type of new products they add to their existing product portfolio through acquisitions. Acquisition behavior is further narrowed down to corporate takeovers involving targets with patents. With this very distinct single-industry approach, a rather new and exploratory attempt is made to contribute to the general patent discussion. Figure F illustrates the conceptual concept of the three empirical studies in this thesis.

Figure F: Thesis main research structure overview



Source: Own illustration.

After the three main chapters, the results of a complementary integrated analysis with the explanatory variables from Chapter 2 and 3 are presented and discussed in Chapter 5. The thesis concludes with a brief summary and research outlook in Chapter 6.

2. WITHIN-INDUSTRY DIVERSIFICATION AND ACQUISITION BEHAVIOR IN HIGH-TECH INDUSTRIES

ABSTRACT

In this chapter we attempt to explain acquisition dynamics in a single high-tech industry. Utilizing a unique dataset that features within-industry characteristics such as activities in product categories we distinguish different reasons for corporate takeovers, specifically expansive and defensive acquisitions. We show that intra-industry diversification strategies have a significant positive impact on the number of acquisitions. At the same time, we confirm a positive relationship between the qualitative breadth of product portfolios and acquisition activities. Our findings show that there is a need to distinguish between the reasons behind acquisitions, and to consider and address qualitative product characteristics in future empirical research on acquisitions in order to reliably explain observed dynamics.

2.1. Introduction and extant literature

For commercial organizations, acquiring another firm is often a critical event that is associated with a high degree of uncertainty. The potential improvement of the acquirer's market position through a takeover usually comes with a broad set of possible risks. Acquisition plans often look good on paper, appearing to be mutually beneficial arrangements, but may turn out to be very difficult to realize. Depending on a variety of conditional factors like technological distance (Folta, 1998), acquisitions can be unsafe for all parties involved, often resulting in sub-optimal post-acquisition performances (Agrawal and Jaffe, 2000; Cartwright and Schoenberg, 2006). However, despite these potential ambiguities, firms have not stopped acquiring other firms. Acquisitions are a common and accepted means to realize corporate strategies, and especially in high-tech industries with innovation-based competition (Inkpen, Sundaram, and Rockwood, 2000).

The complexities of corporate acquisitions are reflected in the extant literature on the topic. We can broadly distinguish between those theories that explain the motives of acquisitions and those that focus on the impact of takeovers. In the latter theories, researchers have used success measures such as financial performance (Agrawal and Jaffe, 2000) and innovation performance (Ahuja and Katila, 2001) and have analyzed moderators like organizational fit (Cartwright and Cooper, 1993; Nahavandi and Malekzadeh, 1988), knowledge and market relatedness (Cassiman *et al.*, 2005; Cloodt, Hagedoorn, and van Kranenburg, 2006) and the post-acquisition integration process (Jemison and Sitkin, 1986; Puranam, Singh, and Zollo, 2006). Analysis of explanatory factors for the success or failure of corporate acquisitions has so far produced ambiguous results. In a meta-analysis on post-acquisition performance King *et al.* (2004) found the independent variables used to be lacking any consistent explanatory power. They suspected that there are *"significant opportunities remaining for knowledge creation"* (p. 198).

We argue that one underlying reason for the limited amount of undisputed knowledge about acquisition performance is the presence of unchallenged implicit assumptions about certain motives for acquisitions. This deficit in M&A research already has been identified by Trautwein (1990) who criticized strategy scholars for dominantly implying non-tested efficiency theory in their prescriptions on "*the choice of acquisition mode"* (p. 283).

Research focusing on the results of acquisitions without controlling for why the acquisitions happen in the first place overlooks important influences. This also involves the question of why similar firms might differ in their acquisition behavior. Implicitly assuming there are certain motives behind corporate takeovers can be the first step towards inconsistent results, since this approach overlooks more differentiated interpretations for particular acquisition activities that can have different performance implications.

Based on the abovementioned theories, we identify a broad set of acquisition motives such as efficiency-related reasons (e.g., economies of scale or transaction costs), increasing market power (e.g., growth theories, access to new markets or distribution channels), and external technology sourcing (e.g. resource-based theories or diversification theories).[12] In the realm of acquisition behavior in high-tech industries, most empirical research projects assume a motive of external sourcing of knowledge and technology (e.g., Blonigen and Taylor, 2000; Grimpe and Hussinger, 2008; Prabhu, Chandy, and Ellis, 2005), that is, things that are *"beyond the boundaries of the firm"* (Desyllas and Hughes, 2008, p. 158). This treats every acquisition the same, and is a simplistic assumption that is inconsistent with reality.

[12] The recent doctoral thesis by McCarthy (2011) is one of the few exceptions that analyze different acquisition motives across different industries.

Depending on a firm's competitive position, technology-driven acquisitions can serve different purposes. Specifically, they can originate from expansive strategies (i.e., the goal of diversifying into new businesses) or from the need to defend existing businesses. As a consequence, ex-post evaluations of these acquisitions should take different ex-ante goals into account. In a relatively rare case Ahuja and Katila (2001) have successfully integrated distinguishing acquisition purposes into their quantitative analysis. We follow the same reasoning, factoring the different motives behind acquisitions into the analysis and addressing the question (in a more differentiated manner) of what drives companies to take on the often difficult challenge of acquiring other firms, especially in a high-tech context.

In order to analyze the behavior of individual companies, we need an understanding of particular competitive positions within the given firms' respective markets. For quantitative analyses, this suggests several prerequisites.

To begin with, it is essential to have proper measurements with which to assess competitive positions when considering a company's individual situation. We need firm specific data that can be linked to concrete commercial activities to act as an indicator for the motivational factors behind acquisitions. One common means of achieving this is to use secondary data such as patent information as an explanatory indicator to describe and explain the existence of technology-driven acquisitions (e.g., Desyllas and Hughes, 2008). Patents can offer an appropriate measure of a company's competency in dealing with issues of IP protection and patent evaluation, as well as being a proxy for accumulated knowledge (stocks). However, the number and quality of patents does not mirror the number and quality of the company's marketable products (Acs and Audretsch, 1989), and therefore can hardly mirror individual competitive positions. We deal with these requirements by utilizing a unique dataset that features information on the different types of products offered by each company. This allows for a detailed evaluation of the competitive positions of firms in a single industry, without neglecting their internal competencies and technological knowledge (Breschi, Lissoni, and Malerba, 2003; Pavitt, 1998). Incorporating commercial activities means we have a very clear indicator of the qualitative differences between market participants since the product strategy of a firm is a direct result of its past strategic resource commitments (Miller and Shamsie, 1996; Mintzberg, 1978).

In addition, our arguments go beyond the simple employment of qualitative market data. A given firm's behavior is always contingent on an environment which is largely defined by the market in which it operates. We want to analyze differences within a single industry, in contrast to Schoenberg and Reeves' (1999) analysis of the determinants of different acquisition patterns between industries. As most industries are populated with firms that have diversified within that industry (*related diversification* in Rumelt's [1974] terminology) it seems logical to assume this aspect is very important when analyzing firm behavior and performance (Li and Greenwood, 2004). In addition, the probability of a firm engaging in an acquisition apparently decreases the more distant are the industries involved (Folta, 1998; Folta and O'Brien, 2008). This is also supported by the finding that acquiring firms can best realize benefits within a related-business context (Kim and Finkelstein, 2009). Consequently, we follow Stern and Henderson's (2004) line of argument that within-business diversification has a crucial impact on firms' viability.[13] Further, our single-industry setting answers the call by Schulz (2008), who sees *"in depth studies of specific industries"* (p. 19) as the next logical

[13] From a conceptual point of view 'within-industry diversification' and 'within-business diversification' as suggested by Stern and Henderson (2004) have the same meaning in this thesis.

step after asserting the incommensurateness of generalizing principles and scientific rigor in the literature about mergers and innovation.

To account for within-industry characteristics, we create segment classes based on a detailed understanding of the industry and link these to our detailed information about sub-segment activities. In focusing on a single industry, we also test Patel and Pavitt's (1997) claim that product variety in an industry usually goes alongside a relatively broad technological homogeneity – another argument for focusing on qualitative differences within a single industry setting.

To summarize, we see a substantial gap in empirical acquisition research that to date has at best insufficiently accounted for within-industry differences. Our research approach acknowledges the individual qualitative characteristics of industry players as essential drivers of corporate behavior. On this basis, we argue that it is necessary to use information about the differences in product/service offerings of the individual firms in a single industry. This also includes an in-depth understanding of the technologies and trends involved in order to truly grasp and analyze the motives for and drivers of acquisitions. On this basis, we take a closer look at the acquisition dynamics of a single high-tech industry, the EDA industry. Unlike most prior research, we account for the complementary characteristics of products and the interlinkage and relationships of different product categories when deriving hypotheses about firm behavior. This enables a differentiated testing of existing theories and also provides new arguments for explaining within-industry dynamics. Specifically, our analysis addresses the following questions: is detailed information about product and industry characteristics useful when differentiating between distinct acquisition motives? Do diversification strategies have a significant impact on acquisition activities? Does the qualitative breadth and complexity of existing businesses have an impact on the frequency of acquisitions?

The remainder of this chapter is structured as follows. In the next section we develop our hypotheses. Subsequently, we introduce our methods. After reporting our findings the chapter closes with a general discussion and proposals for future research.

2.2. Theory and hypotheses

Particularly in technology-driven industries, where competitive advantages depend heavily on a firm's technological competency, acquisitions are implicitly associated with the motive of accessing external knowledge. One can argue that this behavior is a consequence of rational managerial decisions aimed at improving the company's competitive position. However, this does not explain why management looks for potential (and expensive) acquisition targets in the first place. In this section we provide a full theoretical framework, beginning with the main principles of our reasoning and ending with the derivation of our hypotheses.

2.2.1. General theoretical underpinnings

The resource-based view (RBV) of the firm provides a theoretical foundation for the root cause of frequent corporate acquisitions and their assumed technology focus. Organizations compete against each other on the basis of their core competencies, which translate into core (end-) products (Prahalad and Hamel, 1990). Especially in a highly volatile setting these competencies must constantly adapt to the characteristics of the relevant industries and the dynamics of their technological environments. Although every top executive should, in theory, embrace this externally-imposed requirement, it often calls for almost perfect cognitive and calculative capabilities that are unrealistic as a strategic management paradigm (Cockburn, Henderson, and Stern, 2000; Levinthal and March, 1993). Previous research that was focused on the internal mechanisms of organizational adaption, and ultimately on the survival of the firm, found considerable restricting factors. For the most part, the process of adaptation happens through organizational learning, which is heavily influenced by past experience and encoded into routines (Levitt and March, 1988). The more successful they are, the more strongly these routines will be embraced and promoted. Positive experience with established routines sets off a feedback mechanism which leads to path dependencies in learning, also known as competency traps (Levinthal and March, 1993; Levitt and March, 1988; March, 1991). The approach labeled *exploitation* with a focus on efficiency and execution, is the objectively preferable strategy in a stable environment where expectations about future revenues are certain and competitive activities are easily observed. In contrast, *exploration* is characterized by variation, risk-taking, flexibility and innovation, a set of activities which is more appropriate for new product creation and market diversification strategies (March, 1991). Inherent mechanisms for learning, also known as learning myopia, tend to favor exploitation over exploration, as core competencies and capabilities simultaneously enhance and inhibit internal development (Leonard-Barton, 1992). Focused short-term (exploitative) strategies have a higher probability of success than (explorative) strategies that explore new (technological) territories and have vague goals. Additionally, as decision-makers are evaluated according to the outcome of their implemented policies, routines geared towards focused short-term goals are generally preferred internally. At the same time, these exploitative strategies' high success rates rapidly increase confidence, supporting the belief of those that implement them that they can cope with almost all changes within their domain (Levinthal and March, 1993). Moreover, the operational requirements of exploitation-focused activities hinder the effective management of explorative strategies, which is also mirrored in the literature on ambidextrous organizations (e.g., Tushman and O'Reilly, 1996). Thus, over time the higher average success rate of exploitative strategies will inevitably suppress exploration plans and activities. This well-observed structural momentum of organizational inertia can put the long-term survival of successful companies at risk, as soon as inevitable exogenous changes in the environment make it necessary to adjust once-successful routines (Hannan and Freeman, 1984; Leonard-Barton, 1992; Levinthal and March, 1993).

Technology portfolios reflect firms' past problems, interests and capabilities, which in turn mirror their past organizational learning. In consequence, a firms's technological competencies are also subject to (evolutionary) path dependency and inertia (Dosi, 1982; Garud and Kanøe, 2001; Leten, Belderbos, and van Looy, 2007; Teece, Pisano, and Shuen, 1997).

As product life cycles tend to become shorter, fast-changing technological regimes lead to volatile markets marked by a great deal of uncertainty about future developments. Environmental changes in the form of technological discontinuities can either enhance or diminish existing competencies within an industry (Tushman and Anderson, 1986).

2.2.2. Theoretical arguments and hypotheses

Established companies with institutionalized capabilities may suffer from *incumbent inertia* (Lieberman and Montgomery, 1988). Moreover, as they benefit from a healthy business they face the dilemma of having large financial resources while at the same time being confronted with many codified routines and much bureaucracy. Hence acquisitions, as a mechanism for learning, play a critical role in high-tech industries and can be seen as a very attractive solution, allowing established industry players to react to environmental dynamics and complement their portfolio of competencies without falling victim to *"the tyranny of the served market"* (Hamel and Prahalad, 1991, p. 83). In this way, organizations can maintain their efficiency-focused core operations and concentrate on exploitative activities (Teece, Pisano, and Shuen, 1997). At the same time they can browse for potential candidates to complement their existing competencies and ultimately extend their product/service offerings without transferring existing inertial tendencies into new ventures (Vermeulen and Barkema, 2001). Industry-wise, the attractiveness of technology-driven acquisitions is increasing with the intensity of external technological dynamics and opportunities (Dushnitsky and Lenox, 2005). Therefore, technology-driven acquisitions can be regarded as a logical result for our case, which focuses on an industry at the very forefront of technology.

RBV literature suggests that the complementarity of acquirer and target is one of the main success factors for corporate acquisitions occurring in a related-industry context (Harrison *et al.*, 1991). The general need for integrated and embedded products and processes strongly supports the view that bringing together a mix of products and services to get a more complete business portfolio creates value (Breschi, Lissoni, and Malerba, 2003; Kim and Finkelstein, 2009; Krishnan, Joshi, and Krishnan, 2004). This has a direct influence on the observable breadth of product/service offerings of the acquiring company. Pavitt (1998) notes that technological diversification usually anticipates product and market diversification.

Given the mechanisms of inertia described above, the extension of technological competencies and diversification into new sub-segments can easily be realized through expansive acquisitions similar to McCarthy's *"explorative acquisitions"* (2011, p. 73), but on a single-industry level. Compared to organic growth, external knowledge-sourcing clearly has benefits in terms of less uncertainty about the content and outcome of knowledge accumulation. In a fast-moving environment, where time to market is a crucial success factor, corporate acquisitions (and subsequent integrations) can also allow for a much faster realization of the intended knowledge growth. Of course, not every decision to diversify must necessarily be realized through an acquisition.

However, based on our arguments above, we suggest that business-enlarging activities are likely to have a positive effect on the acquisition activities of firms during the period in question. Expansive acquisitions in high-tech industries are expected to complement existing product/service lines and, in turn, are an outcome of diversification strategies. Using the portfolio of existing product offerings as an indicator for technological diversification, we pose our first hypothesis:

> ***Hypothesis 1:*** *Within a single high-tech industry a positive change in product diversification from t-1 to t has a positive influence on the total number of acquisitions of the diversifying firm in t.*

While firms in high-tech industries might depend on acquisitions as a prime mean to diversify into new product categories, they also maintain their existing businesses and defend their competitive positions. Exploitative strategies tie up substantial internal resources, as they typically focus on a broad set of activities including continuous product development, customer relationship management, and business process engineering. The aforementioned *tyranny of the served market* (Hamel and Prahalad, 1991) can therefore not only prevent companies from engaging in new businesses but can also hinder the adoption of new technologies in existing product categories.

The broader an existing product portfolio and its different technologies, the more expensive it will be to keep these products current and in turn justify the investment in customer loyalty. For instance, customers of (EDA) software vendors expect constant updates and customized solutions for their specific needs, in the same way that a hardware manufacturer needs to constantly refresh its product portfolio to offer the latest functionality. Thus, companies are bound by their existing products because customers demand compatibility with legacy products without having to sacrifice enhanced function. Both, the breadth of a product portfolio and its qualitative range can inhibit firms from pursuing new technological approaches to existing solutions. More diverse and heterogeneous products tend to need a more complex organizational set up. More managerial resources are needed to coordinate an elaborate internal network between different organizational sub-units with formal workflows, interfaces and steering boards which, as is well known, inhibit adaptation and change processes (Grant, Jammine, and Thomas, 1988). This resource binding lock-in effect can lead to situations where firms cannot afford to, or do not want to, invest in technologies which break with existing technological paradigms and may cannibalize their existing products. Nevertheless, new technological paradigms might result in superior products and threaten established businesses, eventually provoking short periods of radical change (Tushman and Anderson, 1986). The more diverse and dynamic a technological environment, the greater is the probability of such an event. Capron and Mitchell (1998) show that within-industry (horizontal) acquisitions can potentially reconfigure existing businesses through an exchange of resources, resulting in improved business capabilities across all functional disciplines.

Hence, for established players the acquisition of externally-developed ideas can be seen as a strategy suitable for defending (as opposed to ‘extending’) market positions and for reacting to new technological paradigms within existing product segments similar to McCarthy's *"exploitative acquisitions"* (2011, p. 73) but on a single-industry level. This is expected to be even more crucial the more diverse and differentiated ('qualitative breadth') the offered product portfolios are. Consequently, we argue that a firm's propensity to acquire increases with the qualitative breadth of its existing product portfolio.

> ***Hypothesis 2:*** *The qualitative breadth of the existing product portfolio of a given company in t-1 is positively associated with the total number of its corporate acquisitions in t.*

2.3. Methods

In addition to the initial data source description, this section provides a more detailed introduction to the employed dataset of this specific analysis. This is followed by a formal overview and a descriptive analysis of the utilized variables.

2.3.1. Data

The merged and unbalanced panel dataset consists of 51 firms and 304 observations. Complete information is available for 43 firms and 230 observations. Due to the one year time lag of most of our independent (change measuring) variables and due to very limited observations in 1997 our final regression analyses cover the time period 1998–2006 and include 39 firms with 187 observations.

Whilst this reduction is sizeable, we considered it necessary to arrive at a high level of data quality. Next to reductions due to definitional criteria (as in the case of acquisitions) there are those related to the usual filtering to eliminate false positives (as in the case of company names for patents). Thus, other single-industry studies will unavoidably face most of the reduction as well and pure sample size cannot be considered an issue - especially since single-industry analyses with similarly-sized datasets have been successfully conducted in the recent past (e.g., Soh, 2010). Keeping in mind that multi-industry studies often have even less firms per industry than is the case here representativeness for the industry at hand seems not an issue. Additionally, the VIF values of 1.06 to 2.05 indicate that multicollinearity is not an issue in our analysis, either (Kleinbaum *et al.*, 1998).

2.3.2. Model and variable description

Dependent Variable

Our dependent variable is the number of acquisitions completed by a given firm in a given year. Since in this way we measure the intensity of acquisition activity by means of a discrete and non-negative number of events (acquisitions), we employ a random effects negative binomial model which is common for the case of count data (Cameron and Trivedi, 1998).[14]

Independent Variables

To test our hypotheses we generate two explanatory variables. The first of these, *product diversification*, is used to test our first hypothesis and indicates a given firm's observed diversification strategy, by comparing the relative proportion of a firm's occupied product categories in t-1 with its relative share of product categories in t.[15] If the relative fraction in t is larger than the one in t-1 (and the absolute number of product categories in t is

[14] We use Hausman tests to decide between fixed- and random-effects model specifications being more appropriate.

[15] We use relative measures to account for any dynamics regarding the total number of sub-segments. However, estimations with absolute figures yield identical results in terms of sign and significance of the coefficients.

larger than the number in t-1) the *product diversification* variable (div_{it}) is equal to unity, otherwise it is zero. In detail, *product diversification* for a single firm is calculated by:

$$product\ diversification\ (div_{it}) \rightarrow \frac{s_{it}}{S_t} - \frac{s_{it-1}}{S_{t-1}} = \begin{cases} 1, if\ div_{it} > \ 0\ and\ s_{it} > s_{it-1} \\ \quad\quad 0, if\ otherwise \end{cases} \tag{15}$$

where s is the number of product categories occupied by firm i and S is the total number of product categories existing in the EDA industry in year t.

Our second hypothesis assumes a positive relationship between the qualitative breadth and complexity of the existing business (*product portfolio breadth*) and the intensity of acquisitions. We consider a time lag of one year to allow the qualitative complexity of the product portfolio to show an effect on the observed acquisition behavior. This allows us to avoid any endogeneity and to reduce bias from differences in accounting methods or financial statement consolidation (Desyllas and Hughes, 2008). As we want to account for the degree of qualitative breadth and complexity, we incorporate information from the EDA product landscape into the *product portfolio breadth* variable. As indicated above, three main product categories are created, namely: ESL, IC-FE and IC-BE (Birnbaum, 2004). Thus, the value of *product portfolio breadth* indicates how many different main categories a given firm i is active in during a given year t. The three main product categories allow us to map distinct differences within an existing product portfolio. Due to the existence of some non-categorized sub-segments in the data, the variables can all take on zero values. Therefore, we measure the qualitative breadth and complexity of the existing product portfolios of a given company for every year on a scale from zero to three.[16]

Control Variables

Since our analysis deals with firm behavior based on competitive strategies in technology-driven industries, we need to control for differences in innovation inputs and outputs. The reason for controlling for investments in research and development (R&D) is straightforward, as internal R&D can be a substitute for external technology-sourcing through acquisitions (Hitt, Hoskisson, and Ireland, 1990). To account for different levels of R&D input we calculate the variable *R&D intensity* as the ratio of R&D expenditures to net sales (Blonigen and Taylor, 2000).

Patent-related measures have become well-established in addressing *R&D output*. According to the notion of absorptive capacity a firm's ability to identify, acquire and utilize new knowledge is positively influenced by its knowledge stock, which mirrors the accumulated knowledge of the past (Cohen and Levinthal, 1990). As a proxy for innovation-related output, *R&D output* is calculated according to the standard perpetual inventory formula (Hall, 1990). We normalize the patent stock according to the size of the organization (Grimpe and Hussinger, 2008; Hussinger, 2008).[17] This also allows us to address the considerable variation in firm size in the EDA industry, which would lead to an undervaluation of the patent stocks of smaller and relatively less patent-active firms without normalization.

[16] See Tables 16–19 in the appendix for a detailed descriptive overview of the annual distribution of firms within the three main product categories and *product portfolio breadth*. As an alternative to a simple count of main categories, an exponential relationship between the number of main categories and complexity does not lead to qualitatively different results.

[17] While Grimpe and Hussinger (2008) use assets, Hussinger (2008) divides the discounted patent stock by the number of employees. Blonigen and Taylor (2000) perform similar calculations measuring R&D intensity by normalizing through total assets. Similar to our later argument, we consider net sales to be better suited as a proxy for firm size in the EDA industry than assets or number of employees.

Therefore *R&D output* is used as the ratio of patent stock to net sales (as a proxy for firm size):

$$R\&D\ output_{it} = \frac{[(1-\delta) patent\ stock_{it-1} + patents_{it}]}{net\ sales_{it}}\ . \tag{16}$$

In accordance with previous work the depreciation rate (δ) is set at 15 percent (Hall, 1990). In addition to the years 1996–2006 all available patent information from before 1996 (2.748 patents) was utilized to avoid a truncation bias in the calculation.

Other aspects such as firm size, growth and financial performance indicators can have an important influence on corporate acquisition behavior and are integrated as control variables (Desyllas and Hughes, 2008). To account for different firm sizes we employ the natural logarithm of the respective total net sales (*firm size*).[18] Accordingly, we use the *growth* variable to control for firm growth, which is calculated as the annual growth in net sales for each firm (i) as follows:

$$Growth_{it} = \frac{sales_{it} - sales_{it-1}}{sales_{it-1}}\ . \tag{17}$$

To control for and measure financial success we use operating *profitability*. This is calculated as the ratio of earnings before interest, taxation, depreciation and amortization (EBITDA) to net sales. *Liquidity* is calculated as the ratio of current assets to current liabilities, and accounts for a company's *"ability to meet its short-term obligations from its current assets"* (Desyllas

[18] Since we deal with software companies, total net sales might represent the actual size of a firm's business more correctly than total assets. An alternative measure would be number of employees, which did result in qualitatively similar results to total sales.

and Hughes, 2008, p. 164). Furthermore, we control for *leverage*, which addresses the financial risk a firm is exposed to since this could influence management decisions and in turn foster or inhibit acquisitions. The annual *leverage* is calculated as the ratio of long-term debt to common equity.

Ultimately, we acknowledge the influence of more general developments and time trends that are beyond our research focus, in short, the institutional and economic environment of the particular industry and we use the *industry's annual acquisitions* of all analyzed firms in a given year as an additional control variable to proxy for this influence. With the exception of this last control variable we employ a one year time lag for all other variables. Table 1 has verbal explanations for each variable while Table 2 summarizes the descriptive statistics.

Table 1: Variables description

Variables	Description
Dependent Variable	
Number of annual acquisitions	The number of corporate acquisitions made by a focal firm in *t*
Independent Variables	
Product diversification	A dummy which equals unity, where the relative footprint in terms of occupied product segments of a given firm in *t* is larger than in *t-1*
Product portfolio breadth	Indicates how many main product categories a given firm is selling in in *t*
Control Variables	
R&D intensity	Ratio of R&D expenditures to net sales of a given firm in *t*
R&D output	Ratio of discounted patent stock to net sales of a given company in *t*
Firm size	Natural logarithm of net sales of a given firm in *t*
Growth	Annual growth rate of a given firm, taking net sales in *t* compared to *t-1*
Profitability	Ratio of earnings before interests, taxation, depreciation and amortization to net sales of a given firm in *t*
Liquidity	Ratio of current assets to current liabilities of a given firm in *t*
Leverage	Ratio of long-term debt to common equity of a given firm in *t*
Industry's annual acquisitions	Number of corporate acquisitions of all firms in the dataset in *t* *

*only acquisitions which meet the criteria of this analysis are counted.

Table 2: Descriptive statistics, correlation matrix, and variance inflation factors

	Variable	Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	VIF
1	Number of annual acquisitions	0.545	1.137	0.000	7.000	1.00											
2	Product diversification	0.182	0.387	0.000	1.000	0.43 **	1.00										1.23
3	Product portfolio breadth	1.390	1.128	0.000	3.000	0.42 **	0.34 **	1.00									1.29
4	R&D intensity	0.270	0.192	0.032	1.993	-0.03	0.12	0.08	1.00								1.62
5	R&D output	0.319	0.450	0.000	3.319	-0.10	-0.15 **	-0.21 **	0.26 **	1.00							1.31
6	Firm size	5.478	1.702	1.703	9.036	0.22 **	-0.10	0.02	-0.50 **	-0.29 **	1.00						2.05
7	Growth	0.240	0.689	-0.645	6.462	0.08	0.15 **	-0.01	0.36 **	0.12	-0.32 **	1.00					1.23
8	Profitability	0.143	0.288	-1.490	0.783	0.23 **	-0.06	0.07	-0.50 **	-0.37 **	0.61 **	-0.19 **	1.00				1.87
9	Liquidity	2.944	2.069	0.314	14.812	-0.16 **	-0.03	-0.26 **	0.16 **	0.22 **	-0.30 **	0.08	-0.14	1.00			1.23
10	Leverage	0.097	0.425	-1.915	1.929	0.01	0.05	0.00	0.00	0.03	0.16 **	0.00	0.04	0.02	1.00		1.06
11	Total annual acquisitions	12.738	5.687	4.000	22.000	0.21 **	0.13	-0.02	-0.03	-0.12	-0.09	-0.03	-0.03	0.08	-0.04	1.00	1.06

** $p < 0.05$

2.4. Results

Table 3 provides the estimation results for our negative binomial models. We can support our first hypothesis in Model 1, as we find a positive relationship between the observed diversification into additional product categories and the number of acquisitions. Our second hypothesis is also supported: the broader, and therefore more complex, the portfolio of the products offered, the more acquisitions are being conducted by the company in question. The third model includes both of our explanatory variables and again confirms our hypotheses.

Of the control variables employed, *R&D output* shows weak to moderate significance levels in Models 2 and 3, indicating the importance of absorptive capacity, which has been well established in the past (Cohen and Levinthal, 1990). Further, the positive significant effects of g*rowth* and *industry's annual acquisitions* support that factors like recent success in terms of business growth and the economic and institutional environment of an industry influence acquisition decisions alongside our hypothesized drivers. Put differently, the more the business was growing in t*-1* the more acquisitions are being conducted in t to continue that growth path. This trajectory of successful management resulting in more acquisitions should not come as a surprise. All other control variables (*liquidity*, *R&D intensity*, *leverage*, and *profitability*) are mostly non-significant, probably because, due to our single-industry setting, all included firms make similar use of their internal resources since they share similar business models and experience the same pressure to innovate.

We use likelihood ratio tests to control for the general fit of our models. As can be seen, these confirm that the final model specification with both hypothesized explanatory variables has the best fit.

Table 3: Negative binomial panel regression analyses on the number of annual acquisitions

Variable	Model 1		Model 2		Model 3	
Product diversification	0.953 ***	(0.256)			0.843 ***	(0.250)
Product portfolio breadth			0.601 ***	(0.181)	0.467 ***	(0.177)
R&D intensity	0.507	(1.066)	0.217	(1.076)	0.355	(1.090)
R&D output	0.743	(0.502)	0.887 *	(0.467)	0.953 **	(0.433)
Firm size	0.351 **	(0.172)	0.304 *	(0.159)	0.372 **	(0.151)
Growth	0.300	(0.184)	0.534 ***	(0.173)	0.421 **	(0.173)
Profitability	0.845	(0.722)	1.208	(0.745)	0.810	(0.719)
Liquidity	-0.276 *	(0.141)	-0.097	(0.127)	-0.148	(0.134)
Leverage	-0.214	(0.367)	-0.175	(0.366)	-0.265	(0.358)
Industry's annual acquisitions	0.075 ***	(0.021)	0.080 ***	(0.020)	0.073 ***	(0.020)
Likelihood ratio test for nested model 1					5.70**	
Likelihood ratio test for nested model 2					11.52***	
Wald χ^2 (df)	48.06 (9)***		46.81 (9)***		61.96 (10)***	
Log Likelihood	-133.1957		-136.1062		-130.3465	
Observations (Groups)	187 (39)		187 (39)		187 (39)	

*** p < 0.01; ** p < 0.05; * p < 0.1

All significance tests are two-tailed. The values in parentheses are standard errors.

2.5. Conclusion and discussion

In this chapter, we examine the acquisition behavior of firms (and managers) within a single high-tech industry utilizing qualitative market knowledge and product information to address an important gap in the literature, specifically to analyze in more detail the relevance of the different drivers behind acquisition activities.

The contribution of this analysis is threefold. First, our model clearly shows the significant explanatory substance of qualitative industry characteristics for acquisition behavior. Combining detailed product information allows us to confirm theory-based hypotheses on motivational factors behind acquisition activities in the EDA industry. We can identify specific and distinct drivers within the analyzed set of intra-industry acquisitions that are in line with extant theory.

More specifically, the significant relationship between the existence of an active diversification strategy and the respective number of acquisitions strongly supports our first hypothesis. In fast-paced industries, firms inevitably face organizational and institutional limitations affecting their innovation activities, and seem to realize their diversification strategies to a considerable extent through expansive corporate takeovers. The above-mentioned mechanisms of organizational learning seem to favor internal exploitative strategies despite the potential challenges of post-merger integration. Against this background, the purchase of external knowledge presents a very attractive alternative compared to the internal development of new competencies. This interpretation is further supported by the fact that all observed acquisitions take place within one single industry – where companies operate in similar fields of knowledge and share similar corporate cultures – which mitigates to some degree the risk associated with the integration of former independent businesses, making post-merger integration a less important issue.

Methodologically, one could suggest that diversification and the number of acquisitions measure similar phenomena and are therefore naturally and unavoidably correlated (and thus not really distinguishable). However, the preferences and motives of firms or management cannot be observed directly (Desyllas and Hughes, 2009), so this is hard to test. Since neither acquisitions nor extensions of product portfolios are random events, we think it is plausible to suggest that the decision to acquire another company is made with a clear idea about the substitutive or complementary effect of the acquisition and the implied product portfolios being bought through it. As our analysis is about the different motivations behind acquisitions, we assume every observable extension of product portfolios is the result of deliberate managerial decisions. Our model shows that these observable managerial decisions are positively related to the number of acquisitions, which confirms our theoretical arguments about organizational limitations and learning in high-tech environments. The significant positive effect is certainly a logical implication, but it is not obvious given the number of other possible instruments that could achieve this managerial goal, such as internal growth or any form of joint corporate activities (Folta, 1998).

In addition to diversification, we also measure the qualitative breadth and complexity of product portfolios to account for the types (and sizes) of competitive positions within the EDA industry affecting acquisitions (beyond the effect of firm size on the latter which we account for in our model). *Product portfolio breadth* is defined by the number of different categories represented by existing products and measures the degree of specialization of the given company's product offerings. The broader a firm's qualitative product diversity the more acquisitions we observe, supporting our hypothesis about the greater corporate organizational complexity and cognitive occupation that comes with constant incremental development of a broader product portfolio. Keeping existing products up-to-date and accounting for the constantly-evolving needs of existing customers therefore leads to a greater impetus to acquire external know-how within existing product categories.

The significant positive influence of both independent variables strongly supports our arguments for the relevance of organizational limitations and innovative activities in high-tech markets and their implications for acquisitions.

As concerns our control variables, R&D-related factors provide a mixed picture. The relatively lower importance of R&D intensity could be due to the focused industry setting chosen for this analysis since it is likely that all the firms included have similar levels in terms of their relative commitment to internal R&D. Innovation output measured by patent stocks (*R&D output*) has a significant positive effect in Models 2 and 3. Therefore, even at a single-industry level, there seems to be sufficient variation in innovation output to explain differences in acquisition behaviors. Our findings thus also support the appropriateness of the absorptive capacity concept alongside the existence of important additional strategic factors influencing acquisition behavior aimed at technology sourcing.

Our results are also in line with important arguments made by Stern and Henderson (2004) whose analysis shows that in order to understand within-industry acquisition behavior, one needs to grasp the qualitative characteristics and governing principles of each industry, which also further supports our single-industry approach. In this approach, while patents may indicate the ability to identify, integrate and use (new) IP, the number and quality of patents does not necessarily mirror the breadth and quality of the relevant company's marketable products (Acs and Audretsch, 1989). This might be even more applicable in highly specialized and technology-driven industries where external knowledge-sourcing through acquisitions is very often the only way to react appropriately to rapid change and new trends.

Moreover, patents are often used solely as defensive measures to prevent competitors from entering certain markets ('defensive patenting'). Therefore, an increase in patent stock does not necessarily mean an improvement in internal technological competency, advances in product quality or a broader set of commercial products.[19] Thus, for research purposes, it can be very difficult to provide clear interpretations of changes in patent portfolios what

[19] A recent example comes from 2011; Google's attempt to purchase 6,000 patents from the insolvent communications company Nortel was blocked. These patents include important mobile technology standards and would have put Google in a better position to defend its mobile communication business in the future. In the end, a syndicate led by Apple, Microsoft and Sony outbid Google and strengthened their own position against possible infringement cases.

constitutes another argument to take product data as a proxy for technological competence and innovative performance instead. This is especially true for industries, where patents are less common (Bessen and Hunt, 2007; Prabhu, Chandy, and Ellis, 2005). Third, and most importantly, inferring qualitative market characteristics and trends, which would also inform us about a firm's service and product strategies, is difficult to accomplish by means of patent data analysis.

The highly significant influence of the *industry's annual acquisitions* variable suggests the existence of institutional effects (i.e., industry and/or time trends) that play a role in observed corporate acquisition behavior. This strongly hints at the complex dynamics we have to acknowledge and control for when explaining corporate behavior in general, and thus supports again a single-industry approach. It also supports the conclusion of King *et al.* (2004) that the ambiguity of research results about the success factors of M&As can be explained by the complex decision processes behind every corporate acquisition. In turn, implicit generalizing assumptions about the motivations and goals of acquisitions could be responsible for inconsistent results in at least some of the existing research about M&A outcomes.

As a second contribution, our research shows the relevance and importance of qualitative information as a means of describing industry players within their industries, and ultimately, of understanding their behavior. Although most high-tech industries share a set of common characteristics like high pressure to innovate, they differ substantially in terms of market structure, specific trends and dynamics. Our understanding of the EDA industry and its offerings along the microchip design flow makes it possible to classify firms according to their expertise, reflected in the specific set of their products. Therefore, we show that it might not be enough to simply count products, patents or R&D expenditures to predict the acquisition behavior of firms. Rather it seems necessary to evaluate data in their specific context. This leads us to the third contribution of this analysis, which underscores the general call for considering within-industry differences when analyzing the acquisition behavior of firms (Stern and Henderson, 2004). Whilst analyses across industries are valuable for certain research questions, the qualitative differences between single industries could easily be overlooked and leveled out in multi-industry analyses, contributing to ambivalent results with potentially limited practical relevance, as reported by King *et al.* (2004). Large-scale quantitative analyses are prone to overlook competitive differences and strategies within industries, which can lead to interpretational limitations. This might also account for why the majority of research on acquisition drivers is based on case studies which especially applies to single-industry analyses. Our unique dataset allows us to leverage value of both quantitative and qualitative data in order to shed light on takeover motives within one industry based on a number of observations significantly larger than in case studies.

In terms of limitations, our analysis does not account for the characteristics of the targets of the acquiring firms, which could help to confirm our hypotheses even more strongly. Owing to the large number of smaller-sized EDA firms, not all deals could be enriched by information about the targets' sub-segment activities. In order to prevent our sample size from being even further reduced and the number of acquisition events becoming too small, we decided to solely focus on the acquirers' characteristics and the thorough understanding of the industry to test our hypotheses.

Likewise, we are not able to track acquisition activities that take place solely between privately-held companies. Future research should attempt to utilize more data that include the acquisition activities of private companies, but we anticipate major issues in obtaining such data.[20] Moreover, private companies' institutional environments can be very different to those of public companies. Therefore, this limitation can be regarded as another layer of control helping to derive valid conclusions from our results.

Additionally, our data does not include the wide activities of new venture funding and minority stakes, through which incumbents frequently invest in and prepare for future technologies. The interpretation of these institutional agreements should be different from that of majority acquisitions. Funding and ownership of shares do not involve long-term commitment and risk-sharing at the same level as the total acquisition of another company (Folta, 1998). Financing new start-ups can be described as seeding: hoping some investments turn into growth opportunities, and eventually yield useful knowledge and contribute to the investing firm's success. On the contrary, acquiring more than 50 percent of another organization can be regarded as more of an ex-post confirmation of an already convincing performance, making up for the potential hurdles and conflicting interests that come with the consolidation of two companies.

The coverage and analysis of more single high-tech industries is a logical step towards testing more general applicability of our results. The EDA sector could be the beginning of a thread of single-industry analyses, each one incorporating product-specific characteristics and testing our hypotheses. Based on our experience, this will certainly require considerable time and resources since every industry differs in its qualitative characteristics but it holds the promise to be capable of moving beyond the limitations indicated by King *et al.* (2004).

[20] This especially concerns the completeness of such a dataset, as we experienced ourselves. We therefore feel that the limitations we outlined for our analysis are general analyzability limitations in our field, rather than weaknesses resulting from limited data gathering efforts since these are prohibitively high for private firm data.

To sum up, our study confirms that acquisition decisions should always be analyzed with the industry context and the specific situation of single companies in mind – a statement likely to meet favorably with both, researchers and managers. While our product-related explanatory variables implicitly confirm the strong technology focus of acquisitions in the EDA industry, we incorporate additional qualitative situational factors which allow us to carry out a more fine-grained analysis of the motives behind corporate takeovers. We see this analysis as a step towards more 'context-related' empirical research in acquisition analyses, which potentially links quantitative data methods with relevant qualitative industry information. As mentioned above, this also includes institutional pressure and managerial trends which play a critical role in horizontal acquisition activities (Haunschild, 1993; Haveman, 1993). In this way our work (by means of contingent empirical models that bring together acquisition drivers, moderating factors and respective response variables) provides more meaningful and consistent results for practitioners as well as more differentiated analyses, that should ultimately enable better managerial decisions and more reliable empirical findings in this important field of research.

3. THE IMPACT OF TECHNOLOGICAL CHANGE ON ACQUISITION BEHAVIOR IN HIGH-TECH INDUSTRIES

Abstract

This chapter contains a contingent empirical analysis of the acquisition dynamics within the EDA industry. In order to do justice to the complexities of today's modern competitive environments, our methodical approach integrates external trends and fundamental strategies at a narrow industry level. Using detailed qualitative and quantitative data, we show that particular groups of EDA firms significantly contribute to the acquisition activity of the industry at particular times. The timing of these acquisitions hinges on the existence of industry specific technological change, which brings higher levels of uncertainty. Based on our results the identified industry trend by itself has no significant influence on acquisition activities. On the contrary, we provide empirical evidence that specialized firms pursue focused and defensive acquisition strategies during times of greater uncertainty.

3.1. Introduction

High-tech industries are characterized by rapidly changing technological regimes and competitive structures. This volatility inevitably produces a diverse set of distinct business conditions that are highly relevant to corporate strategies and behavior. Commercial organizations have to establish and defend their competitive positions within these fast-paced environments on the basis of their (technological) competencies. In doing so, corporate acquisitions seem an appropriate means to achieve and maintain a high level of competitiveness in markets marked by technology-based competition (Inkpen, Sundaram, and Rockwood, 2000).[21]

Although there is a large body of empirical management research literature on the M&A phenomenon (especially since the 1980s) most of this work focuses on outcomes of corporate takeovers. Researchers have acknowledged the complexity of acquisitions largely by looking at the broad range of potential aspects that could have an influence on the post-merger financial performance (Agrawal and Jaffe, 2000) or innovation output (Ahuja and Katila, 2001). Several moderating factors like organizational fit (Cartwright and Cooper, 1993; Nahavandi and Malekzadeh, 1988), knowledge and market relatedness (Cassiman *et al.*, 2005; Cloodt, Hagedoorn, and van Kranenburg, 2006) or the post-acquisition integration process (Jemison and Sitkin, 1986; Puranam, Singh, and Zollo, 2006) have been analyzed but no consistent picture has emerged. King *et al.* (2004) found that that inconsistency is often due to a substantial lack of explanatory value of the independent variables used.

Another important explanation for the mixed and inconsistent results of M&A ‘success-research’ could be the simultaneous inclusion of several industries and businesses

[21] According to the Financial Times (2011) between 2000 and 2009 almost one fourth of the global M&A deal value was generated in ‘telecommunications’, ‘media and entertainment’, and ‘high technology’ industries.

and the insufficient consideration of different strategic positions and intentions of single firms within their respective environments. We believe that it is worth taking a closer look at the conditions preceding corporate acquisitions in order to legitimately evaluate their success. Therefore, our analysis aims to incorporate specific circumstances and drivers that lead to corporate takeovers at the level of an individual industry.

Relatively few researchers have tackled the question of why acquisitions at the industry level are being conducted in the first place (Schoenberg and Reeves, 1999). Different reasons and motives behind M&A activities might be of different importance depending on the respective industry examined. Even more disparity can be anticipated if we understand an industry to consist of different product/service sub-segments and hence of strategic groups, each characterized by distinct technological developments as well as special competitive landscapes and business models (McGee and Thomas, 1986; Porter, 1980). Therefore, individual corporate behavior is very much the result of a function with a very specific set of variables such as the particular environment including technological trends and developments within the sphere of suppliers and customers (Ahern and Harford, 2012), the individual strategic position which is characterized by the type and breadth of product portfolios, and institutional factors which also have a direct influence on management agendas and political decisions within a firm.

When it comes to the particular timing of acquisitions, the assumptions for our analysis are drawn from research on the phenomenon of merger waves which has been thoroughly analyzed by scholars in the fields of financial and general economics (e.g. Andrade, Mitchell, and Stafford, 2001; Gort, 1969). These empirical analyses try to unveil the drivers behind the clustering of acquisition behavior over time. Although adopting a more long-term macroperspective, empirical findings feature contingent effects of particular trends on different industries (Harford, 2005). Merger wave researchers suggest a more reactive rationale behind acquiring firms and often look at influencing factors outside the immediate control of the affected companies, like deregulation (Andrade, Mitchell, and Stafford, 2001) or economic and technological shocks (Harford, 2005).

Although this seems counterintuitive to management scholars who conceptually tend to see companies' decision makers navigating competitive industries, we think that an integration of a more evolutionary understanding of firm decision making that integrates isomorphic mimicry and other industry-level aspects (see e.g., DiMaggio and Powell, 1983) better matches reality and could lead to more consistent insights.

The better integration of external effects in empirical management research becomes even more relevant since today's modern industries are increasingly either dependent on or producers of advanced technologies. Moreover, as the pace of technological change accelerates constantly, managers of high-tech firms have to consider these dynamics very often outside their direct influence in their strategic decisions: up to the point where corporate actions remind us of quick reactions rather than of outcomes from conscious strategic decision-making processes.

Hence, we attempt a more focused and contingent analysis of firm behavior in general and of acquisition behavior in particular. This implies that we will concentrate on the EDA industry described above. In order to assess corporate behavior appropriately it is crucial to understand the competitive environment within which the firm is primarily active. Moreover, each firm competes on the basis of its competencies, which are ultimately embodied in the specific products and services the firm offers and that its customers are willing to pay for

(Prahalad and Hamel, 1990). Our data features detailed information about the types of products of each firm. Together with a thorough understanding about the EDA industry, we can identify different strategic players as well as relevant industry specific trends.

Hence, we ask the following research questions: Does technological change have a significant impact on the acquisition behavior in high-tech industries with constant pressure to innovate? Do firms with different product portfolios behave differently in the face of these technological changes?

The remainder of this chapter is structured as follows: the next section gives an overview of the theoretical underpinnings of our assumptions and hypotheses, which will partly be derived in conjunction with the description of a particular technological trend within the EDA industry during the analyzed period. This is followed by the description of the methodology of our analysis. After reporting its findings, this main chapter closes with a general discussion and suggestions for future research.

3.2. Theory

In the following section, we will provide the theoretical foundation for our analysis of acquisition behavior in high-tech industries. Since our empirical analysis is based on contingent assumptions, we provide theoretical arguments for three different questions, all of which are interrelated: *The question of why* is about the underlying reason why we observe so many acquisitions in high-tech industries. *The question of when* deals with theoretical explanations that look at the specific timing of acquisitions. Finally, we want to find arguments for the *question of who*, by looking into the different rationales for different types of potential takeover targets.

The question of why?

The sheer speed at which modern technological regimes change, makes the concepts of core competencies (Prahalad and Hamel, 1990) and dynamic capabilities (Teece, Pisano, and Shuen, 1997) even more relevant. Within ever changing environments firms need to build and retain internal resources. These provide the basis from which they compete for the goodwill of their customers. This is especially true for high-tech industries in which new technological paradigms frequently force participants to adapt.

The process of adaption very much involves the concept of organizational learning, which is prone to some limitations itself. Restricted and influenced by past experiences and routines, organizations are prone to path dependency and have the tendency to prefer exploitative over explorative activities. Conservative and short-term oriented projects are given priority at the expense of more fuzzily defined and long-term endeavors (Leonard-Barton, 1992; Levinthal and March, 1993; Levitt and March, 1988; March, 1991). In addition, firms need to devote a considerable amount of managerial resources and financial assets to solve the needs of current customers who use their existing technologies and products, a situation also known as *"the tyranny of the served market"* (Hamel and Prahalad, 1991, p. 83; Slater and Mohr, 2006). Especially in high-tech industries, these inertial momenta can inhibit firms from effectively adapting to changing conditions. We can see the result of adaption via product portfolios, since existing offerings are the result of internal value creation that results from a firm's past experience (Dosi, 1982; Garud and Kanøe, 2001; Leten, Belderbos, and van Looy, 2007). Eventually, technological discontinuities can render existing competencies obsolete (Tushman and Anderson, 1986). Thus, from the perspective of an established company, corporate takeovers are an attractive managerial tool to react to environmental changes while minimizing cumbersome internal explorative actions (Teece, Pisano, and

Shuen, 1997). In fact, Dushnitsky and Lenox (2005) found that the intensity of external technological dynamics is positively correlated with the attractiveness of technology-driven acquisitions.

Based on the arguments above, we assume acquisitions are technology driven for our analysis of high-tech industries in general and especially for our chosen industry of interest, the EDA industry.[22] Technology is embodied in an organization's products and services. Therefore, we take information about the firms' individual offerings as a proxy for its internal technology.

The question of when?

Past research suggests that there is a strong relationship between acquisitions and timing. Numerous scholars have analyzed the phenomenon of the clustering of acquisitions over time that are also known as merger waves (Andrade, Mitchell, and Stafford, 2001; Gort, 1969). Very often, a higher frequency of corporate acquisitions is due to economic disturbance or economic shocks (Gort, 1969; Jensen, 1986). These shocks can come from economic, technological, or regulatory environments of an industry and firms use acquisitions as a means to adjust to the new conditions in this respect (Harford, 2005). In 1969, Gort identified rapid changes in technology as one of the most important shocks that can happen to an industry.[23] These shocks alter expectations about future developments as well as evaluations of business

[22] In addition to the results of Chapter 2, the technology driven character of acquisitions within the analyzed EDA industry was also confirmed through exploratory qualitative analyses and triangulation through secondary sources like trade journals.

[23] This has been confirmed by a number of scholars subsequently (e.g., Andrade, Mitchell and Stafford, 2001; Harford, 2005).

alternatives in all affected firms. As a result, one can observe heightened and increasingly synchronized acquisition behavior at times of strong technological change.[24]

The question about the particular timing of acquisitions is strongly bound to the underlying reasons for corporate mergers and the specific industry. Research on merger waves has shown the fruitfulness of incorporating industry specific information instead of more macroeconomic variables in the attempt to understand (clustered) acquisition behavior (Mitchell and Mulherin, 1996). Harford (2005) identified and described specific merger waves and the reasons behind them for the industries he analyzed. One of his findings was that he could attribute distinct reasons to every single industry at different times. This confirms our general research question about acquisition behavior and our methodology of concentrating on a single industry, although our sample is the most specific and industry focused we encountered in this regard. The field of merger wave research described above is certainly much broader in scale and concerns more visible (larger) acquisition waves. However, the link between technological change and more frequent acquisitions is undeniable and will be tested in this work at a single-industry level. Our detailed information and understanding about the EDA industry allows us to identify and describe a significant technological change and its impact on a very specific population of firms.

The question of who?

On our way to dissecting acquisition behavior for a single industry, we want to go beyond the simple count of acquisitions at particular times. In our attempt to identify which types of firms acquire and which firms are being acquired we have to consider the differences between the industry's strategic groups. Although all members are equally exposed to

[24] It seems appropriate to mention that capital liquidity is a general prerequisite to allow technological change starting merger waves, which was also pointed out by Harford (2005).

technological change some might be affected differently since firms differ greatly even within the same industry or market (Stern and Henderson, 2004). As described above, we take the structure of individual product portfolios into account for qualitative differences between participants. This approach is consistent with academic work that acknowledges the importance of the effect of within-industry diversification on corporate performance (Li and Greenwood, 2004).

We limit our set of acquisitions to deals within the analyzed industry.[25] This focus allows us to only analyze corporate acquisitions that are closely tied to the actual (technological) developments of the core business, which is important to derive credible interpretations. This is further supported by scholars who found that diversifications into industry-specific or 'related' fields have been identified to be very beneficial for the respective acquirers (Breschi, Lissoni, and Malerba, 2003; Folta and O'Brien, 2008; Kim and Finkelstein, 2009; Krishnan, Joshi, and Krishnan, 2004; Rumelt, 1974). From a theoretical point of view there are a number of possible explanations for more related or unrelated acquisitions going from portfolio theory (minimizing risk) over agency theory (managers taking individual advantages as agents) to institutional theory (mimetic behavior) (Zhou, 2011).

The relatedness principle can also be transferred to a single-industry level. Thus, contemplating technology-driven acquisitions within a single industry at times of particularly strong technological change allows us to distinguish between two generic types of takeover strategies. The first can be characterized as 'expansive', meaning that the acquirer extends its activities into new product-/service-categories within the boundaries of its industry. Considering technological change as the triggering mechanism and acquisition as the preferred

[25] Please see Section 3.4. for more detailed information about our set of acquisitions.

mode of knowledge accumulation this would imply that promising business opportunities emerged in a category that has not previously been served by the acquirer.

The second generic type of takeover strategy can be described as 'defensive' in that the acquiring firm purchases an organization that offers products/services in sub-categories or product segments in which the acquirer already has an interest. In the wake of technological change, this would imply advances in core business areas leading to new mandatory features and functionalities in product portfolios already offered. Our definitions of 'expansive' and 'defensive' are very much related to the aforementioned 'relatedness' term. However, as 'related acquisitions' refer more to inter-industry differences, we think that our distinction is more appropriate in this single-industry setting.[26]

In our analysis, we will define the major characteristics of acquirers as well as the type of takeover strategies that emerge from technological change by observing the targets and their particular products.

3.3. The impact of the 90 nanometer (nm) manufacturing scale and hypotheses

Every introduction of a smaller chip manufacturing scale means a significant—and usually exponential—increase in complexity. A decrease in scale not only means that one piece of silicon can usually host almost twice the number of transistors and features new functionalities, it also implies new challenges in the optimization of all performance indicators like heat emission or power consumption. Moreover, while the fundamental principle of transistors and logic gates remains largely unchanged, the management of all

[26] Please see Chapter 2 for a more focused empirical analysis about the distinction between 'expansive' and 'defensive' acquisitions.

interdependencies between the different functional parts within a microchip becomes more crucial.

For the purpose of our analysis, we can regard the introduction of a smaller manufacturing scale as a rapid change of technology for the EDA industry. The decreased dimensions inevitably have direct effects on all design and simulation tools within the chip design flow. Therefore, EDA firms experience an even greater pressure to adapt and complement their software tools during the transition time from one scale to another.

The introduction of the 90 nm chip scale is a well-documented technological change with important implications for the EDA industry. At the beginning of 2004, Intel started to release its first 90 nm microprocessors to end customers (Intel, 2013). In fact, a vigorous discussion about the implications of more complex chip architectures at 90 nm scales can be observed starting in 2003 (Goering, 2004), which makes sense given the lead times that are necessary to design and test new chip architectures.

Against the background of the limitations to organizational learning and adaption mentioned above, we might expect a general positive relationship between a step towards more advanced chip manufacturing technology and acquisition activity levels within the EDA industry:

> ***Hypothesis 3:*** *The introduction of the new (90 nm) chip mass manufacturing technology has a positive impact on the number of acquisitions within the EDA industry.*

Apart from expecting a general increase in acquisition behavior, our data also allows us to take a more differentiated look into the dynamics of the EDA industry. The introduction of the 90 nm chip manufacturing scale led to an increase in design implementation costs substantially driven by activities covered by EDA tools at the ESL. Around 2003 and 2004, industry insiders and experts became quite vocal on the growing importance of ESL tools in the wake of more complex microchips. For example, a study from International Business Strategies (2003) says that *'the design environment is evolving from being focused on IC chip designs to focusing on system designs, which means that the design skill base of IC vendors will need to increasingly address system-level architectural capabilities'* (p. 36). The same study notes that the implementing costs for chip design more than doubled with the introduction of 90 nm manufacturing scales. More notably, this increase in costs was mainly driven by a disproportionate rise in 'architecture' und 'verification'—two design disciples belonging to the most abstract ESL part of the chip design flow (Birnbaum, 2004). In another trade article from 2004, a general manager of one of the largest EDA firms was quoted as saying '*We think current processes are going to break down as you go to 100 million-gate chips. […], we think the problems are so severe that some level of ESL deployment is going to be inevitable'* (Goering, 2004).

Detailed product information allows us to distinguish between firms with and without ESL software in their existing product portfolios. We consider the acquisition of a target that offers ESL products as more unrelated compared to an acquisition of a target with non-ESL products when the acquirer has no ESL products in its product portfolio beforehand.

Since there is an apparently strong demand for design work at a high abstraction level, we would expect non-ESL firms to diversify into the untapped ESL business in their attempt to skim off high margins and therefore, to pursue expansive acquisition strategies. In addition, diversification along the value-added design chain is very feasible considering the integrated nature of the chip design flow, where ESL is a new endpoint extending the chain by one module. Complete design suites from only one EDA supplier ensure perfect compatibility and reduce implementation efforts for any interfaces with third parties (Sperling, 2012):

Hypothesis 4a: *EDA firms without ESL products react to the 90 nm chip technology through an expansive strategy by acquiring targets with ESL products.*

In opposition to this expansive acquisition motive, 'non-ESL firms' could also prefer defensive acquisitions which would follow the rationale of more related corporate takeovers similar to McCarthy's definition of '*explorative acquisitions*' (2011, p. 73).

This would imply that firms without any ESL products will focus on their existing (IC-FE and IC-BE software) product lines and strengthen those by acquiring (innovative) targets from the same sub-segments. Within a very dynamic environment, that focused strategy could also be reasonable since a business extension usually means more organizational efforts and operative friction losses (Grant, Jammine, and Thomas, 1988). Moreover, in the wake of great technological change it seems logical to prepare your core business for any future challenges before eventually reaching out for new business areas; even if there is a strong demand. In addition, by acquiring similar targets, competition in the industry is decreased and margins can potentially be improved. Thus, a second (competing) hypothesis can also be posed as follows:

> ***Hypothesis 4b:*** *EDA firms without ESL products react to the 90 nm chip technology through a defensive strategy by acquiring targets within product segments they already occupy.*

Hypotheses 4a and 4b represent competing outcomes of a typical economic trade-off decision. Generally, both make sense in the context of high-tech industries and testing these fine-grained hypotheses based on observable acquisition behavior can only be achieved using the detailed industry-level data that is at our disposal.

3.4. Methods

Due to the specificity of each empirical analysis, it is necessary to provide a more detailed description of the employed dataset in addition to the initial data source description of Chapter 1.5. Furthermore, this section provides a descriptive analysis of all employed variables.

3.4.1. Data

Because of missing data and left truncation, the resulting unbalanced dataset consists of 36 firms and 178 observations. Compared to the first study from Chapter 2, we lose some firms and observations because of the more rigid selection criteria that are due to the subject matter of this analysis; in that we wanted to make sure that every firm in this database considers the EDA business as one of its core fields of commercial activity. Therefore, we can make sure that we have a cohort of firms that is equally involved in the technological progress in that industry. The years 1996 and 1997 have been excluded from our analyses owing to there being too few data points. For the purpose of this analysis, our dataset is sufficiently large. Similarly-sized data has been used successfully in the recent past (e.g., Soh, 2010). VIF values of 1.17 to 3.75 indicate multicollinearity is unlikely to be an issue in our analysis (Kleinbaum *et al.*, 1998).

3.4.2. Model and variables description

Our dependent variable is the number of acquisitions being conducted by a given firm in a given year. Therefore, we employ a random effects negative binomial maximum likelihood model for our regression analysis (Cameron and Trivedi, 1998).[27]

Independent variables

Our first explanatory variable represents the change in microchip complexity going from 130 nm to 90 nm in mass production. The first large-scale introduction of 90 nm microprocessors happened in 2004 (Intel, 2013). Considering usual lead times within the semiconductor industry, and especially the chip design business, we consider this trend to have already been fully established in 2003. Further confirmation comes from publications and articles about the coming of the 90 nm chip scale and its implications for chip design in 2003. As our time period runs from 1998–2006, our new *90 nm* variable equals zero up until including 2002, and becomes unity from 2003.[28]

Utilizing our detailed product information we are able to summarize and distinguish between the different product-related EDA main categories, namely ESL, IC-FE, and IC-BE plus ‘others’, which represents all non-categorized product segments. To distinguish between ESL and non-ESL offering firms we employ two dummy variables. The *(firm w/) ESL products* variable is equal to equity if a respective firm offers products in the ESL sub-segment in a given year. Contrary to this, the *(firm w/) only non-ESL products* variable

[27] The Hausman test is used to decide between fixed- and random-effects model specifications.
[28] Taking absolute years can be a rather rough timeframe for the described trend since high-tech industries often change quicker than years. That is why we altered the length of the time trend to check the robustness of our model, as is described in the results section.

indicates whether a company is *only* offering IC-FE and/or IC-BE but no ESL in a given year. The residual sub-category 'others' is not included in the model, yet it prevents the other two dummies from being perfectly correlated.[29] Besides this technical argument, we cannot classify 'others' along the chip design flow and therefore reliably evaluate their existence. For the latter two explanatory variables, we allow for a one-year time lag in order to avoid any endogeneity and to reduce biases from different accounting methods (Desyllas and Hughes, 2008).

Control variables

Our employed model controls for different levels of innovative activity, firm size, and financial performance as these factors showed significant effects on the propensity to acquire in past M&A research.

Internal R&D can work as an alternative to acquisitions of external know-how (Hitt, Hoskisson, and Ireland, 1990). Therefore, we consider different levels of R&D activity, calculating the variable *R&D intensity* as the ratio of R&D expenditures to net sales (Blonigen and Taylor, 2000). In addition to R&D input, the level of respective output is a well-accepted indicator of the capability to identify and absorb new intellectual property (Cohen and Levinthal, 1990). Also known as absorptive capacity, this innovative output is calculated by the patent stock of the respective firm (Hall, 1990). The standard perpetual formula is used, which is then normalized by firm size proxied by net sales (Grimpe and Hussinger, 2008; Hussinger, 2008).[30] Normalization allows mitigation of the issue of large size disparities between industry participants that would relatively undervalue the patent stock of smaller and

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[29] *(firm w/) ESL products* and *(firm w/) only non-ESL products* have a correlation of -0.55 at a significance level below 0.05 (see Table 6).

[30] To normalize patent stock, Grimpe and Hussinger (2008) use assets and Hussinger (2008) uses employees to account for firm size.

less patent-rich EDA firms. Thus, we calculate *R&D output* as the ratio of patent stock to net sales:

$$R\&D\ output_{it} = \frac{[(1-\delta) patent\ stock_{it-1} + patents_{it}]}{net\ sales_{it}}. \qquad (16)$$

The depreciation rate (δ) is set at 15 percent (Hall, 1990). Although our data only covers the years 1996–2006 all available patent information before 1996 (2,748 patents) was used to avoid truncation bias for the calculation.

To control for size related differences in firm behavior, we employ a *firm size* variable by using the natural logarithm of the net sales of a given company.[31] Similarly, we use the change in annual net sales ('sales') for each firm i and year t to control for firm growth as follows:

$$Growth_{it} = \frac{sales_{it} - sales_{it-1}}{sales_{it-1}}. \qquad (17)$$

Controlling for financial success we calculate *profitability* as EBITDA to net sales. In order to account for a company's ability to meet its short-term obligations from its current assets, *liquidity* is calculated as the ratio of current assets to current liabilities. Although we analyze the influence of particular industry trends on firm behavior, we acknowledge that our identified effects do not present a complete picture of the total economic and institutional environment for a particular industry. Therefore, we include *industry's annual acquisitions* in

[31] Compared to the often-employed value of total assets, net total sales are better suited to represent the size of software firms. The number of employees can act as an alternative to net sales and produces qualitatively similar results when used in our estimations.

a given year as a proxy variable to mirror more general, industry-wide behavioral patterns beyond the individual specifics of the firm. Except for the latter, we employ a one-year time lag for all described control variables for the same reasons we lagged two of our independent variables (*[firm w/] ESL products* and *[firm w/] only non-ESL products*). Table 4 gives an overview of the used variables while Table 5 and Table 6 provide the descriptive statistics.

Table 4: Variables description

Variables	Description
Dependent variable	
Number of annual acquisitions	The number of corporate acquisitions made by a focal firm in *t*
Independent variables	
new 90 nm technology	A time dummy which indicates the existence of 90nm manufacturing scale for chip mass production
(firm w/) ESL products	A dummy which indicates the existence of ESL products within respective product portfolios of a given firm in *t*
(firm w/) only non-ESL products	A dummy which indicates the existence of non-ESL products (non categorized product excluded) within respective product portfolios of a given firm in *t*
Control variables	
R&D intensity	Ratio of R&D expenditures to net sales of a given firm in *t*
R&D output	Ratio of the discounted patent stock to net sales of a given company in *t*
Firm size	Natural logarithm of the net sales of a given firm in *t*
Growth	Annual growth rate of a given firm taking net sales in t compared to *t-1*
Profitability	Ratio of earnings before interests, taxation, depreciation and amortization to net sales of a given firm in *t*
Liquidity	Ratio of current assets to current liabilities of a given firm in *t*
Industry's annual acquisitions	Number of corporate acquisitions of all firms in the dataset in *t* *

*only acquisitions are counted which meet the described criteria of this analysis.

Table 5: Descriptive statistics

	Variable	Mean	S.D.	Min.	Max.
1	Number of annual acquisitions	0.573	1.158	0.000	7.000
2	new 90 nm technology	0.427	0.496	0.000	1.000
3	(firm w/) ESL products	0.309	0.463	0.000	1.000
4	(firm w/) only non-ESL products	0.404	0.492	0.000	1.000
5	90 nm techn. * ESL products	0.168	0.375	0.000	1.000
6	90 nm techn. * only non-ESL products	0.112	0.317	0.000	1.000
7	R&D intensity	0.274	0.195	0.032	1.993
8	R&D output	0.335	0.456	0.000	3.319
9	Firm size	5.494	1.715	1.703	9.036
10	Growth	0.249	0.696	-0.645	6.462
11	Profitability	0.143	0.292	-1.490	0.783
12	Liquidity	2.912	1.940	0.314	14.812
13	Industry's annual acquisitions	12.652	5.650	4.000	22.000

Table 6: Correlation matrix and variance inflation factors

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	VIF
1	Number of annual acquisitions	1.00													
2	new 90 nm technology	-0.03	1.00												3.75
3	(firm w/) ESL products	0.45 **	0.16 **	1.00											3.24
4	(firm w/) only non-ESL products	-0.27 **	-0.25 **	-0.55 **	1.00										3.15
5	90 nm techn. * ESL products	0.15 **	0.52 **	0.67 **	-0.37 **	1.00									3.83
6	90 nm techn. * only non-ESL products	-0.07	0.41 **	-0.24 **	0.43 **	-0.16 **	1.00								2.68
7	R&D intensity	-0.04	-0.03	-0.01	0.20 **	0.00	0.06	1.00							1.64
8	R&D output	-0.12	0.20 **	-0.04	-0.13	0.05	0.05	0.25 **	1.00						1.50
9	Firm size	0.22 **	0.14	0.17 **	-0.44 **	0.14	-0.20 **	-0.52 **	-0.31 **	1.00					2.32
10	Growth	0.07	-0.21 **	-0.09	0.10	-0.11	-0.08	0.37 **	0.12	-0.32 **	1.00				1.28
11	Profitability	0.24 **	0.03	0.13	-0.27 **	0.07	-0.09	-0.50 **	-0.38 **	0.62 **	-0.19 **	1.00			1.93
12	Liquidity	-0.17 **	-0.07	-0.29 **	0.19 **	-0.24 **	0.08	0.17 **	0.26 **	-0.27 **	0.10	-0.12	1.00		1.24
13	Industry's annual acquisitions	0.22 **	-0.35 **	-0.11	0.17 **	-0.22 **	-0.07	-0.03	-0.11	-0.06	-0.04	-0.02	0.02	1.00	1.17

** $p < 0.05$

3.5. Results

Table 7 shows the results of our negative binomial regression models. Most obviously, our third hypothesis does not hold true in any of the employed models meaning that the introduction of the 90 nm chip production scale by itself has no significant effect on the number of acquisitions within the EDA industry. As a robustness check, we adjusted the length of the 90 nm time dummy and employed different lengths from one to three years always yielding insignificant results. Models 2 and 3 include all of our three explanatory variables, where Model 3 features contingency effects (interactions) through which we can simultaneously test our third and fourth hypotheses. Looking at the interaction effects, we can confirm that EDA firms without any ESL products acquire significantly more from 2003: the time when chip design became increasingly more complex and ESL products experienced strong demand due to the smaller manufacturing scale at 90 nm. So far, this empirical result confirms our reasoning for expecting higher acquisition activity levels from firms without ESL products. Further support for one of our fourth-numbered hypotheses comes from the fact that EDA companies that already offered ESL software products did not seem to be affected by the introduction of smaller chip scales. More precisely, these types of companies show significantly higher acquisition activities during the entire time period analyzed.

To see whether Hypothesis 4a or 4b hold true we provide a simple descriptive overview of all mergers involving ESL offering targets from 1998–2006. Although 4a and 4b are competing hypotheses, we can find good arguments for both, since they represent a typical economic trade-off decision. That is why we are interested in the actual behavior of strategic groups within the single high-tech industry setting analyzed. As can be seen in Table 8, out of the six acquirers involved in ESL takeovers, five had already been offering ESL products prior the respective mergers. Only one company taking over an ESL target before 2003 (in 2000) did not offer any ESL related products. Conversely, firms without ESL products apparently kept acquiring within their already occupied product categories, which means that they followed a more focused acquisition strategy in relation to their core business. Therefore, we can reject Hypothesis 4a and note strong support for 4b.

Growth and *industry's annual acquisitions* continuously show significant positive effects on the number of acquisitions in all models. Their high significance levels clearly hint at a strong relationship between recent business growth and its continuation through corporate takeovers (for the *growth* variable). Moreover, unobserved general dynamics seem to play an important role in addition to our identified industry trend (for *industry's annual acquisitions*). Most other control variables (*R&D intensity, patent stock, profitability,* and *liquidity*) remain insignificant in all tested and reported models. This can be explained by the analysis' focus on a single industry where the similarities in innovation activities, business models, and utilization of internal resources cannot explain a large portion of the differences between industry players in terms of acquisition behavior. Likelihood ratio tests confirm the superior explanatory power of the largest employed model.

Table 7: Negative binomial panel regression analyses on the number of annual acquisitions

Variable	Model 1		Model 2		Model 3	
new 90 nm technology	0.124	(0.257)	0.125	(0.266)	-0.408	(0.640)
(firm w/) ESL products			1.407 ***	(0.542)	1.418 **	(0.564)
(firm w/) only non-ESL products			0.326	(0.561)	-0.211	(0.616)
90 nm techn. * ESL products					0.350	(0.678)
90 nm techn. * only non-ESL products					1.912 **	(0.865)
R&D intensity	-0.336	(1.211)	0.071	(1.110)	0.295	(1.154)
R&D output	0.430	(0.587)	0.470	(0.496)	0.595	(0.498)
Firm size	0.224	(0.187))	0.248	(0.162)	0.318 *	(0.165)
Growth	0.427 **	(0.192)	0.552 ***	(0.187)	0.585 ***	(0.190)
Profitability	1.336	(0.766)	1.157	(0.746)	1.176	(0.758)
Liquidity	-0.225	(0.142)	-0.104	(0.133)	-0.109	(0.136)
Industry's annual acquisitions	0.084 ***	(0.020)	0.086 ***	(0.020)	0.082 ***	(0.020)
Likelihood ratio test for nested model 1			6.06 **		12.51 **	
Likelihood ratio test for nested model 2					6.45 **	
Wald χ^2 (df)	37.04 (8) ***		42.89 (10) ***		52.40 (12) ***	
Log Likelihood	-138.2325		-135.2020		-131.9792	
Observations (Groups)	178 (36)		178 (36)		178 (36)	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

All significance tests are two-tailed. The values in parentheses are standard errors.

Table 8: ESL deals during the analyzed period from 1998 to 2006

Target	1998	1999	2000	2001	2002	2003	2004	2005	2006	Acquirer
Analogy		1								Avant*
Avant				1						Synopsys*
Axis Systems						1				Verisity*
C Level Design				1						Synopsys*
Cascade							1			Synopsys*
Chrysalis Symbolic Design		1								Avant*
Co-Design Automation					1					Synopsys*
First Earth						1				Mentor*
Get2Chip						1				Cadence*
Orcad		1								Cadence*
Summit Design									1	Mentor*
Verisity								1		Cadence*
Visual Software			1							Xilinx
Total ESL deals	0	3	1	2	1	3	1	1	1	
Total annual deals	**19**	**24**	**20**	**10**	**12**	**19**	**14**	**6**	**7**	
Annual share of ESL deals	0%	13%	5%	20%	8%	16%	7%	17%	14%	

* = Acquirer has been offering ESL software before.

3.6. Conclusion and discussion

In this study, we proposed to integrate different explanatory factors for acquisition behavior in order to better understand the dynamics in very dynamic high-tech industries. Our results show that the rise of the 90 nm process for mass production by itself had no significant influence on the number of acquisitions within the EDA industry. Despite the undeniable increase of complexity in chip design, we cannot identify a corresponding change in general EDA acquisition behavior in terms of frequency. A possible explanation could be that the constant pressure to innovate (productivity gap, see Figure E) overshadows the specific effects coming from the described technological change. We are far from generalizing the non-impactful nature of any industry trend on acquisition activities in high-tech industries. However, the insignificant effect of the technological change by itself further supports our call to utilize firm-specific characteristics that allow for more differentiated empirical analysis of the acquisition phenomenon. In fact, the confirmation of one of our competing hypotheses, 4b, reveals the existence of behavioral differences coming from strategic positions mirrored by product portfolios. Only by differentiating between different types of acquirers can we show a significant effect coming from a particular technological change within the industry. Moreover, the descriptive overview of ESL targets provides further insights about the takeover behavior of the different acquirers. Apparently, non-ESL firms do acquire significantly more within their already occupied product categories, namely IC-FE and IC-BE, making little attempts to diversify into the promising new ESL fields.

The confirmation of Hypothesis 4b instead of Hypothesis 4a is very interesting as it indicates that during times of technological change, firms seem to value their competency and expertise in already established product categories higher than any potential revenue growth in new (heavy demanded) but rather unknown product segments. Thus, we can confirm the existence of some basic principles and mechanisms of organizational learning. More related, and hence more secure, investments are preferred over more explorative activities (March, 1991). The fact that this behavior happens during a time of greater technological ferment makes sense as competition over technological leadership happens particularly during these periods (Tushman and Anderson, 1986). As the majority of corporate acquisitions take place in related businesses, intra-industry acquisitions should show a similar picture, but just at a different level. Corporate acquisitions serve very well as a valid measure for this kind of conclusion especially when controlled for internal R&D as a potential supplement.

The significant effect of *industry's annual acquisitions* suggests the existence of additional institutional effects in terms of micro- or macroeconomic environments even at a single-industry level. A stronger form of 'herd behavior' could not be identified since we could not find any support for Hypothesis 4a. Nevertheless, our initial statement about the complexities involved in corporate acquisition decisions is validated in this control variable.

An additional contribution of our analysis results from the utilization of detailed product information as an indicator of technological competence. Together with a comprehensive qualitative understanding about the actual value creation of the products offered along the chip design process, we were able to provide explanations for technologically motivated acquisitions that extend the literature by relating to more disaggregated levels.

In summary, our analysis focuses on technology-driven acquisitions and provides empirically tested explanations for certain patterns of acquisition behavior of firms within an industry at a particular time. The methodology of a single-industry focus delivers novel insights into the logic underpinning acquisition dynamics.

While such an approach is required to do justice to the complex circumstances in each individual (high-tech) industry, it also has its limitations. An analysis at this single-industry level requires detailed data that is not always available, especially in the case of industries that are larger in terms of aggregate sales volumes, less concentrated and/or more fragmented in terms of products. This also applies to a deep understanding of the actual products as well as knowledge of an industry's relationship with its customers.

Other limitations might come from the exclusion of minority stakes and venture capital or corporate venturing investments, which are known to be very common in high-tech industry environments. Although the omission of these activities may be a weakness of our approach, our strict selection criteria allow for a clearer interpretation of the included deals, which would not have been much improved by adding the aforementioned categories since minority stake investments are typically chosen when uncertainty about future developments is quite high. Conversely, corporate takeovers that result in full formal control over and responsibility for the target can be seen as an ex-post confirmation of an already convincing performance that is worth integrating into the acquirer's existing business. Along the same lines, our analysis also leaves out any form of inter-firm cooperation because again these reflect situations of greater potential uncertainty.

Future research on acquisition behavior might involve a stronger consideration of the various strategic characteristics of industry players. Our analysis has shown that the mere existence of a technological change or trend may not be enough to show any effect on hitherto dynamic industries. We would also encourage more empirical research on acquisition behavior in similar high-tech industries to further corroborate and confirm our findings, and provide evidence from beyond the EDA industry. One has to understand the complexities of a firm's business environment in order to evaluate its behavior and ultimately to offer better managerial implications. We hope that the value of following this convincing argument is apparent from this study.

4. THE ROLE OF PATENTS IN SOFTWARE INDUSTRY ACQUISITIONS

Abstract

This chapter addresses the apparent disconnection between patent portfolios and actual technological resources and knowledge in the high-tech sector in general and software industries in particular. In the fast-paced and complex industries of today, patent collection becomes part of competitive strategy replacing patent creation as a result of genuine innovative activities. This has some severe implications for empirical management research. Using acquisitions as an indicator for evaluation, we show the inappropriateness of patent-measured absorptive capacity and introduce product-related contingency factors to unravel patent policies in a single software industry, namely the EDA industry. Against the background of a variety of alternative IP protection mechanisms, we can also partly show that the feasibility of patenting has an inverse relationship with the degree of codifiable knowledge that is embedded in the software.

4.1. Introduction

For some time management researchers have tried to identify moderating factors influencing the outcomes of M&As. In the attempt many scholars concentrated on R&D intensive high-tech industries (e.g., Blonigen and Taylor, 2000; Cloodt, Hagedoorn, and van Kranenburg, 2006; Desyllas and Hughes, 2008; Ransbotham and Mitra, 2010). Compared to more traditional industries, high-tech settings feature a relatively high frequency of corporate acquisitions, which makes them very attractive for scientific analysis. One implied, and largely confirmed, assumption in the context of M&As in high-tech industries is that they are being conducted because of external technology sourcing as a means to expand or substitute one's own technology portfolio (Desyllas and Hughes, 2009) and to fight internal inertia (Levitt and March, 1988; Vermeulen and Barkema, 2001).

Explanations for the success or failure of technologically motivated acquisitions often feature arguments based on absorptive capacity (Cohen and Levinthal, 1990) or technological proximity (Cassiman *et al.*, 2005). Both concepts can trace their theoretical roots to the framework of organizational learning which can be classified into explorative and exploitative activities (March, 1991). In empirical studies, these theoretical frameworks are often measured and reflected by the number or type of patents applied for or granted.

The main thread of the arguments in this chapter builds on the results of the studies by Levin *et al.* (1987), Cohen, Nelson and Walsh (2000) and Hall and Ziedonis (2001), who empirically showed that patenting frequently is not the best option for firms seeking to appropriate their innovation returns. This is even more noteworthy in conjunction with the strong growth of high-tech sectors where we see a growing disconnection between the existence of patents and actual innovative activities of firms (Gobble, 2011). We can also observe an even more distorted relationship between software firms' innovative activities and their patenting behavior (Bessen and Hunt, 2007).

Because of the widespread use of patent-based measures in management research, the significance of this development must be addressed, especially in terms of the connection between innovation-based traits and acquisition behavior. We therefore state the following general implications for M&A research:

1. Software-based industries should be identified and treated differently in multi-industry samples of empirical research projects that use patent-based measures to explain acquisition behavior.
2. Since we can diagnose the extraordinary role of patents in software-based industries, there must be specific related mechanisms behind patent policies that could be contingent on other factors such as the type of products. We therefore call for single software-industry analyses to test new hypotheses unraveling the patterns of software patenting and the role of software patents in general.

We address these implications by conducting a quantitative single software-industry analysis about contingent factors that determine whether or not an acquired target has sometimes patented something before its acquisition. At the same time, we can identify different targets with different types of products, and whether these products are new to the acquirer or not. In addition, acquiring firms can regard existing patents to vary in importance depending on the target's product. It is also possible that targets have different mechanisms to protect their IPs that might be superior to patenting, something that also depends on the type of product produced and which is closely tied to the type of appropriability regime (Teece, 1986). More specifically, we ask the following research questions: To what extent do patents affect acquisition decisions in software industries? What types of products/businesses determine the existence of patents among acquired software companies? Is there an interconnection between the type of software products and the existence of patents?

To analyze these complex aspects we use a unique dataset that features detailed information about the firms and the type of products they offer within the EDA industry. Our hypotheses are also built on our thorough understanding of that particular industry which allows us to assess given product categories according to their role in the value creation process.

The remainder of this chapter is structured as follows. In the next section, we elaborate on the special role of patents in today's high-tech and software industries. On this basis, we formulate two rather general hypotheses. Next, we use our knowledge about the EDA industry to develop industry-specific hypotheses. After that, we provide a method description, subsequently report our findings, and close with a general discussion and implications for future research.

4.2. Scrutinizing the role of patents in high-tech industries' M&A decisions

In M&A research, one commonly accepted way to control for absorptive capacity and technological proximity is to measure the number and type of patents of the parties involved; i.e. the acquirer and/or the target (Ahuja and Katila, 2001). While this approach might sufficiently capture innovative activities in more traditional and more physical industries,[32] the role of patents becomes increasingly non-transparent in today's high-tech industries.

[32] By traditional and more physical we predominantly refer to businesses that create value based on industrial or mechanical engineering (i.e. the car and engine building industries), where innovations are embodied in physical products.

Although the arguments in this chapter are largely based on more recent developments, the first studies about the relative effectiveness of patents were published as early as 1987. In what came to be called the Yale Survey Levin *et al.* (1987) asked firms from different industries about their patent policy and which alternative mechanisms they used to appropriate returns from their innovations. On average, the firms in their multi-industry sample stated that appropriation methods like lead-time, learning curves and sales or service efforts were more effective than patenting. Secrecy as another mechanism of IP protection is also seen as being superior when we only look at process improvements (next to product improvements). These results are remarkable because of two things: First, the study was conducted with a multi-industry sample, meaning that high-tech industries like computers and semiconductors are only two out of 18 industries represented in the sample. Second, the study was conducted more than 25 years ago, when proliferation of information and product complexity were not nearly as developed as they are today.

This early multi-industry study makes it obvious that patent portfolios do not perfectly reflect the type of products and research the patenting firm's core business is based on. However, while variations in patent stocks can still serve as a good proxy for relative differences in innovative activities, recent developments in the increasingly important high-tech sectors lead to an ever growing disconnection between the characteristics of a patent portfolio and actual corporate activities and resources.

In order to defend themselves from potential accusations over patent infringements, firms try to gather as many valuable patents as possible without necessarily innovating themselves. Well filled *"patent war chests"* put them into a more powerful position to file countersuits in case of any accusations. As a result, sections of high-tech industries increasingly focus *"on the collection rather than the creation of innovation"* leading towards a *"patent bubble"*, in which the value of companies is determined by the patents they own and not by their actual innovative activities. In recent years, the rise of so-called patent wars between large high-tech companies is symptomatic of the abnormal use of patents and their increased importance to sustainable strategies (Gobble, 2011, p. 3).

One reason for this development is the increasing complexity of today's products. For example, a modern smartphone incorporates technologies from a wide array of disciplines like display technology, semiconductors, radio technology, software, storage, battery et cetera. Therefore, more and more firms become more prone to alleged patent violations as well as more likely to acquire patents for their war chests that have nothing to do with their core business or their core competencies (Gobble, 2011).[33]

4.3. The special case of software patents

In the context of high-tech industry research, another thread of arguments for a more differentiated treatment of patent-based measures comes from the very nature of the respective high-tech goods. Within the widely defined high-tech industries, there is a large variety of businesses and a corresponding range of IP protection. Within this range of businesses, the software-based sector plays a special role.

From an economic perspective, both the costs and the benefits of software patents generally appear to be potentially low. Several changes and relaxations of the U.S. patent law during the 1980s led to an institutional environment where *"software patents appear to have gained greater appropriability and become less costly to obtain in absolute terms over time*

[33] This increased patent application activity is also a topic in the study by Cohen, Nelson, and Walsh (2000). The authors note that firms in "*complex product industries, notably electronics,"* increasingly contributed to the number of patent applications (nine out of ten applications) in 1998 (p. 27).

and also possibly relative to other patents" (Bessen and Hunt, 2007, p. 162; see also Hall and Ziedonis, 2001).[34] Although there was undeniably an increase in software patents after these legislative changes, software firms do also face opportunity costs associated with the filing process itself and the publication of their knowledge.

Firms generating value by producing software have very effective ways to protect innovation apart from the application of patents. While physical products can be disassembled and examined, the access to source codes and algorithms in software products can be blocked and encrypted (e.g., Kanzaki *et al.*, 2008).

Therefore, one cannot make a definitive statement about the degree of importance of software patents for the affected firms. In a technology-driven environment, other forms of appropriability like secrecy, time to market or complementary services can be more effective than patenting (Bessen and Hunt, 2007; Cohen, Nelson, and Walsh, 2000; Levin *et al.*, 1987).

4.4. General theory and hypotheses for software acquisitions

The idiosyncrasies of high-tech patents and software patents in particular described above provide a starting point to form hypotheses about the moderating effects behind software- acquisitions involving patenting targets.

Since each acquisition usually features two independent parties,[35] our arguments will consecutively consider the target's perspective, the perspective of the acquiring party, and an integrated perspective.

[34] As this analysis focuses on U.S. firms the arguments made here solely focus on conditions in the U.S. patent system.

[35] Please see the data section for a detailed definition of the included deals.

From a target's perspective, one of the most important aspects about filing a patent is about the associated benefits and costs that result from patenting activities. One of the most important benefits from having a patent is the possibility of legally excluding others and the possibility of selling the right of inclusion.

While not perfectly substitutive, there are numerous alternative ways to efficiently protect new software IP and appropriate rents from related innovations, such as secrecy (Bessen and Hunt, 2007). Therefore, the associated costs and the resulting opportunity costs can be a critical factor in the decision to apply for a software patent. Based on the aforementioned Yale Survey by Levin *et al.* (1987) Cohen, Nelson, and Walsh (2000) surveyed firms on the reasons of preferring alternative mechanisms over patent applications. Among a sample of comparatively large manufacturing firms[36] the demonstration of novelty, disclosure and application costs have been the most important reasons for not patenting innovations.

The process of preparing and applying for a patent involves a number of necessary activities that often call for external specialists who are usually not part of a typical small to medium-sized software firm. This can include the work of patent lawyers and technology analysts. Additional monetary costs arise from the filing process itself. Based on the latest fee schedule of the United States Patent and Trademark Office (USPTO) (2003) and some additional information from patent attorneys (Quinn, 2011), the total costs can easily exceed

[36] The average firm in this sample has 22,027 employees with annual sales of 4.5 billion USD.

15,000 USD before the software patent is granted.[37] Even after the initial application costs, a mandatory patent maintenance fee has to be paid periodically.

Another cost factor is the time until the patent is finally granted by the respective institution of the legislation in order to legally enforce it. According to the latest available information from the USPTO (2003) the 'average patent application pendency' is 24.6 months. Especially in the rapidly evolving software sector, 24 months can often be too long to make patents a feasible option for IP protection.

All things being equal, the costs of patent application fees are more substantial the smaller the firm is. Since smaller firms are less likely to employ patent attorneys or IP specialists they are even more prone to encounter higher extraordinary costs than large corporations with dedicated law departments. While the absolute costs do not seem to be prohibitively high, they appear sufficiently large to influence the general patent policy of a software firm given the fact that there are alternative mechanisms of IP protection that can be achieved for significantly less (e.g., secrecy). In addition, the administration and organization of patent applications, patent portfolio management (patent defending) and possible licensing activities can potentially absorb management-resources, making it even more unattractive for smaller firms (Cohen, Nelson, and Walsh, 2000; Lanjouw and Schankerman, 2004; von Hippel, 1988).

Based on the above arguments about the relative costs of patent policies, we state the following hypothesis:

[37] We are aware of the discounted USPTO fees for smaller businesses (less than 500 employees) and non-profit organizations. The estimated costs of more than 15,000 USD already consider a firm with less than 500 employees. Not included in our estimation is the fact that small firms without any substantial tangible assets even tend to invest up to twice the amount into the preparation and formulation of a patent application (Quinn, 2011).

Hypothesis 5: *The average size of the acquired targets in t is positively associated with the number of acquired targets with patents in t.*

The general ability to identify, evaluate, and utilize "*new, external information*" is described by the concept of "*absorptive capacity*", which is considered *"a function of the firm's level of prior related knowledge"* (Cohen and Levinthal, 1990, p. 128). Measuring the level of past related knowledge by taking the discounted accumulated stock of patents or patent applications, absorptive capacity was born in a time when most patent applications were for physical products (Hall, 1990). At that time, the degree and quality of innovativeness of firms could very well be mirrored by their patent policies. In addition, most corporate takeovers involved parties generating revenue with physical products and holding patents on new technology embodied in these products. Thus, research legitimately used patent-measured absorptive capacity to explain-technology focused acquisition behavior and moderating factors of their outcomes.

The special case of software patents calls for a more differentiated view on the moderating role of absorptive capacity when we want to analyze the acquisition of patenting targets. All things being equal, the existing patent stock of a software company can be substantially different from its actual absorptive capacity, since patent portfolios are increasingly independent of the actual capabilities of the firm. From the inventor's point of view, the application for a patent can be the least desirable option to protect a new invention. For example, software code can very easily be copied, altered, and sold under a different name. Thus, secrecy and time to market are often regarded as preferred strategies (Cohen, Nelson, and Walsh, 2000; Levin *et al.*, 1987).

Patents can therefore over- or under-represent absorptive capacity depending on whether patents are preventively applied for or not seen as effective enough to protect innovations.

At the same time, it seems reasonable to assume that acquiring software firms do not necessarily expect potential targets to own patents as a prerequisite for a sustainable business because of the existence of a range of alternative ways to protect new IP (Bessen and Hunt, 2007).

However, from the acquirer's perspective the existence of target patents can also reduce uncertainty during the due diligence process and help to decide on acquisition decisions, especially in an international context (Ali-Yrkkö, Hyytinen, and Pajarinen, 2005). Furthermore, in the case of a firm that depends heavily on formal IP protection via patents, it seems reasonable to assume that patents are a very important element of its evaluation criteria for potential takeover targets (Ernst, 2003). As a consequence, this knowledge is also likely to trigger strategic patent behavior on the part of potential targets (Gick, 2008).

Given the ambiguity of the above arguments on the potential acquisition of patenting targets, we do not expect a significant net effect in either direction. Therefore, we propose the following hypothesis:

Hypothesis 6: *Absorptive capacity in t-1 is not significantly associated with the number of acquired targets with patents in t.*

Hypotheses 5 and 6 are applicable to all software industries in general and other high-tech sectors too. Although we acknowledge the disconnect between patent applications and actual activities, we can still observe patent applications from target firms prior to their acquisitions. In order to advance toward an understanding of existing patents in software industries a detailed understanding of the specific industry analyzed will be required. Therefore, our goal is to understand this patenting behavior and its moderating factors in order to assess the actual role of patents in M&A decisions. Apart from the already discussed patenting costs, which should be essentially independent from the type of (software-) technology or innovation, the aspect of disclosure should heavily depend on the actual products involved.

We interpret an acquisition as a signal of trust in the sustainable commercial value of the target's products. Based on our reasoning above, this does not necessarily have to correlate with the holding of patents (at least in software industries like EDA). Instead, we assume a more fine-grained patenting pattern depending on the type of software products.

Our data enable us to track the offered products of a target prior to its acquisition. We assess the number of product types that are new to the acquiring firm and to which of the above described three main EDA product categories (ESL, IC-FE, and IC-BE) they belong. By focusing only on diversifying ('expansive') acquisitions we exclude 'defensive' takeovers that only involve already offered product categories and do not lead to a broader portfolio of different types of products.[38]

The focus on newly acquired product segments allows for a more distinct interpretation of the involved patents. As patents can significantly decrease uncertainty and signal valuable knowledge, their importance can be seen to be especially important in a new product scenario with a significant commitment in the form of an acquisition. In other words, the absence of

[38] Please see Chapter 2 for a more detailed description and analysis of 'expansive' and 'defensive' acquisitions.

patents in this case hints at the relative unimportance of patent IP protection in that specific product segment, since the lack of patents did not prevent the (expansive) acquisition from happening.

To be more specific, we can rank the three identified EDA main product categories according to the extent to which their value can potentially be translated into codified knowledge, such as computer languages or algorithms, making ESL software the most non-technical product type and IC-BE software the most technical. In addition to the costs and resources described above, a successful patent application in the latter category would make focal knowledge freely available and easy to copy for competitors. Thus, the attractiveness and feasibility of patenting should have an inverse relationship with the degree of codifiable critical knowledge that is embedded in the software. Therefore, we expect the number of targets with patents to significantly depend on the type and number of new EDA products that have been added to the acquirer's product portfolio through its acquisitions. For the most technical—IC-BE software—we pose the following hypothesis:

> ***Hypothesis 7:*** *The number of new IC-BE products that have been acquired through acquisitions has a negative relationship with the number of acquired targets with patents.*

Following the same logic, we expect the opposite outcome from ESL software, being the most non-technical product category:

Hypothesis 8: *The number of new ESL products that have been acquired through acquisitions has a positive relationship with the number of acquired targets with patents.*

With regard to the codifiable critical knowledge, IC-FE software can be classified in between the very technical IC-BE and the rather abstract ESL tools. We think that the line of feasibility of IC-FE software patenting can be drawn within the IC-FE category itself. Thus, the overall feasibility to patent within this category can be positive or negative, depending on the respective types of new IC-FE products the acquirer diversifies into through its corporate takeovers. Therefore, we pose two competing hypotheses for the behavior of newly acquired IC-FE tools on the number of acquired targets with patents:

Hypothesis 9a: *The number of new IC-FE products that have been acquired through acquisitions has a positive relationship with the number of acquired targets with patents.*

Hypothesis 9b: *The number of new IC-FE products that have been acquired through acquisitions has a negative relationship with the number of acquired targets with patents.*

4.5. Methods

In this section, we provide a detailed overview of the employed dataset for this specific analysis. This also includes a descriptive analysis of the variables utilized in the empirical model of this study.

4.5.1. Data

Up until and including 1995, 2,748 patents have been applied for by the acquiring firms. These were used to calculate the starting patent stocks in 1996. After all matching and joining processes, 6,957 acquirer's patents were used to estimate our models. A separated database consists of targets with patents representing 49 percent of our total target sample (32 out of 65). The significant decrease in the number of deals compared to the records from Chapter 2 and Chapter 3 is due to the rigid filtering process applied to match the very detailed research questions of this study.

As our analysis features target characteristics, we need to consider the availability of data about on the acquired firms. Thus, acquisitions of sub-units or divisions of parent companies have been excluded, because we are not able to identify and isolate the specific products or patents affected by those deals. Furthermore, we excluded every deal involving a target not featured in the annual EDA reports, from where our product information comes. Ultimately, we did not consider acquisitions from the first year of our analyzed time period (1996) because we needed a reference point from which to start to analyze any changes in product portfolios. Following the rigorous criteria described above, we narrowed our initial set of 468 acquisitions (by public U.S. EDA firms between 1996 and 2006) down to 65.

Our final dataset consists of 289 observations covering the period 1997–2006 of which 225 observations are used in the models employed below.

4.5.2. *Model and variables descriptions*

The dependent variable in our models is the number of acquired targets with patents,[39] an absolute non-negative number of events. Therefore, a negative binomial maximum likelihood model is used (Cameron and Trivedi, 1998). Specifically, we employ a random-effects estimator as our sample almost perfectly represents the population of all U.S. based public firms of a certain industry (EDA). Therefore, the subset of individuals (firms) with zero intra-individual variance is of relevance, too, as we want to understand the role of certain contingent factors on certain acquisitions. As a result, by choosing the random-effects estimator, we avoid only analyzing *the group of the treated* (individuals [firms] with intra-individual variance greater than one) within our EDA industry dataset.

Dependent variable

In order to analyze the general importance of patents in the EDA industry and for acquisitions in particular, we adopt the number of annual acquisitions involving patenting targets as the dependent variable. In our data, a target is considered a patenting firm when it has applied for a patent at some point before its acquisition. Because of the special role that patents play in software industries described above, we regard the existence of a patent to suffice for interpretation. This is even more valid for small and medium-sized firms as they dominate the targets in our data.

Although this measurement does not control for the age of the patent, most of the targets had only applied for patents very recently. The average patent age per patenting target at the time of its acquisition was 3.3 years with a median of 3 years. Even more important, counting only the most recent patent applications prior to acquisition, we get a mean patent

[39] For sensitivity analyses, we also estimate the total number of acquisitions, which we will explicitly refer to below.

age of 1.9 years with a median of 2. Given the widely used method of patent stock calculation, where patents as old as five years are being considered to have at least some influence on the economic performance of an organization the implications of our dependent variable are in line with established research (e.g., Cloodt, Hagedoorn, and van Kranenburg, 2006; Heeley, Matusik, and Jain, 2007; Ransbotham and Mitra, 2010).

Independent variables

To test Hypothesis 5, we measured the size of the acquired targets using the number of the different types of products at the time of their acquisition. While this is arguably a rough approximation, it should be suited to work as a good indicator of relative size differences between the acquired firms, since all are acting in very similar businesses. We think it is reasonable to assume that a firm with a large number of different products in its portfolio will have to have a need for more specialized internal units dedicated to each product type, leading to more redundant and parallel work in similar sub-units. In addition, the organization and coordination of the production and distribution of the different product types will require more organizational management, and therefore absorb more overhead. To make the argument from the other end of the spectrum, in a specialized firm with only one type of product all functional units can solely focus on their tasks with direct communications to management. Thus, no extra organizational levels are needed to coordinate and control the activities in different product units, bundling and filtering information for the executive level. Although our firm size proxy is mainly derived from assumptions about the organizational setup of the targets and not about their raw economic power, it should show at least some positive correlation with the financial resources at the disposal of the respective organization. As there can be more than one acquisition in any one year, we take the average number of different product types of all acquired targets per year (*average target size*) as our target size variable to be included in our models.

To test Hypothesis 6, we measure the extent to which a firm relies on patents as an instrument of IP protection and to what degree this is going to influence its decision to acquire a target with patents itself. Often used as a proxy for absorptive capacity, we use Hall's (1990) standard perpetual inventory formula to calculate the discounted patent stocks for each firm. Rather than only counting and accumulating patenting activity, we want to put this into the relative perspective of the patenting firm. Thus, we normalize the discounted patent stock according to the size of the organization (Grimpe and Hussinger, 2008; Hussinger, 2008).[40] By calculating this *R&D output*, we also address the great variation in firm size in the EDA industry which would lead to distorted valuations across the varied spectrum of EDA firms. Thus, the ratio of patent stock to net sales forms our normalized *R&D output* variable:

$$R\&D\ output_{it} = \frac{[(1-\delta)patent\ stock_{it-1} + patents_{it}]}{net\ sales_{it}} \quad . \qquad (16)$$

As widely accepted in previous research the depreciation rate (δ) is set at 15 percent (Hall, 1990). We avoided truncation bias by also using patents from before 1996. To avoid any endogeneity issues the *R&D output* variable is lagged by one year.

40 While Grimpe and Hussinger (2008) use assets, Hussinger (2008) divides the discounted patent stock by the number of employees. Blonigen and Taylor (2000) perform similar calculations measuring R&D intensity by normalizing through total assets. Similar to our later argument, we consider net sales to be better suited as a proxy for firm size in the EDA industry than assets or number of employees.

The remaining hypotheses state assumptions about the effect of the number and the type of newly acquired product categories on the number of targets with patents. Three independent count variables measure the number of the acquired new types of products within the above described three main categories, IC-BE (*new BE*), IC-FE (*new FE*) and ESL (*new ESL*). We applied some general rules while generating these count variables. First, the acquisition of a new product type was not counted when the new product was not continued in the year after the acquisition. In that case, we assume there was no serious interest in the particular product that drove the decision to acquire the respective target. Second, we did not include the acquisition of a new product when the exact type of product had already been offered sometime before the acquisition, but was discontinued for whatever reason. As our analysis covers a ten-year period, we assumed that a short-term discontinuation of a certain product did not lead to an immediate loss of related competence within the organization and was therefore no new knowledge. Third, our left-truncated data makes it impossible to tell which products are new for the acquirer in 1996. Therefore all acquisitions in 1996 had to be omitted from the dataset.

Control variables

To improve the explanatory power of our model, we employ several control variables. Although we already measure R&D related output, we also need to control for R&D related input, which can be regarded as a substitute to outside company investments and can also contribute to the building of absorptive capacity (Ahuja and Katila, 2001; Puranam, Singh, and Zollo, 2006). Therefore, we calculate *R&D intensity* as the ratio of R&D expenditures to net sales (Blonigen and Taylor, 2000).

To accounting for the different firm sizes of the acquirers, we use the natural logarithm of the net sales (*firm size*) in our regression.

Liquidity as the ratio of current assets to current liabilities accounts for *'a firm's ability to meet its short-term obligations'* (Desyllas and Hughes, 2008, p. 164). It also helps to capture the effect of slack resources that can influence acquisition decisions in a very meaningful way (Jensen, 1986). Through *leverage*, we control for the level of financial risk of the respective company, which can influence strategic decisions. *Leverage* is calculated by the ratio of long-term debt to common equity.

Ultimately, we acknowledge that we cannot control for every aspect that can influence acquisition behavior in the EDA industry or any other industry. To capture at least some of the institutional effects, we employ another control variable that mirrors the acquisition behavior of the industry as a whole. This variable reflects the *industry's annual acquisitions* of the industry. With the exception of the last variable, all control variables are lagged by one year. Table 9 offers an overview of the variables used and Table 10 provides the descriptive statistics.

Table 9: Variables description

Variables	Description
Dependent variables	
Number of acquired targets with patents	The number of corporate acquisitions of targets with patents made by a focal firm in *t*
Number of annual acquisitions	The number of corporate acquisitions done by a focal firm in *t*
Independent variables	
Average target size	Average number of products of acquired targets of a respective firm in *t*
R&D output	Ratio of the discounted patent stock to net sales of a given company in *t*
New ESL	Number of newly acquired ESL (electronic system-level) products for a respective firm in *t*
New FE	Number of newly acquired FE (front-end) products for a respective firm in *t*
New BE	Number of newly acquired BE (back-end) products for a respective firm in *t*
Control variables	
R&D intensity	Ratio of R&D expenditures to net sales of a given firm in *t*
Firm size (acquirer)	Natural logarithm of the net sales of a given firm in *t*
Liquidity	Ratio of current assets to current liabilities of a given firm in *t*
Leverage	Ratio of long term debt to common equity of a given firm in *t*
Industry's annual acquisitions	Number of corporate acquisitions of all firms in the dataset in *t* *

*only acquisitions are counted which meet the described criteria of this analysis.

Table 10: Descriptive statistics, correlation matrix, and variance inflation factors

	Variable	Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	VIF
1	Number of acquired targets with patents	0.133	0.463	0.000	3.000	1.00											
2	Average target size	0.953	3.510	0.000	33.000	0.35 **	1.00										2.39
3	R&D output	0.365	0.633	0.000	6.616	-0.06	-0.09	1.00									1.62
4	New ESL	0.027	0.161	0.000	1.000	0.37 **	0.43 **	-0.07	1.00								1.29
5	New FE	0.142	0.588	0.000	5.000	0.49 **	0.52 **	-0.10	0.15 **	1.00							1.68
6	New BE	0.169	0.817	0.000	8.000	0.46 **	0.73 **	-0.04	0.37 **	0.60 **	1.00						2.54
7	R&D intensity	0.297	0.316	0.032	3.678	-0.01	-0.02	0.60 **	-0.03	0.01	0.02	1.00					1.83
8	Firm size (acquirer)	5.315	1.996	-0.306	18.063	0.11	0.09	-0.33 **	0.11	-0.01	0.00	-0.46 **	1.00				1.43
9	Liquidity	2.956	2.041	0.167	14.812	-0.13 **	-0.10	0.09	-0.08	-0.10	-0.05	-0.01	-0.17 **	1.00			1.06
10	Leverage	0.111	0.379	-1.915	1.929	-0.02	-0.02	-0.04	-0.02	-0.03	-0.03	-0.06	0.22 **	-0.01	1.00		1.06
11	Industry's annual acquisitions	6.516	2.250	2.000	9.000	0.12	0.02	0.05	-0.05	0.09	0.04	0.03	-0.12	0.01	-0.04	1.00	1.03

** $p < 0.05$

4.6. Results

The first comment to make on our empirical results is that neither the base model nor Model 2 have a statistically significant fit. Against the background of our hypotheses, it makes sense that we do not get a fitting model while we do not employ at least one of our hypothesized explanatory variables. In addition, the continued bad fit of Model 2 does not come as a surprise because of our assumption about the non-existence of any predictive power from the patent-measured absorptive capacity construct (*R&D output*). Hence, we can confirm Hypothesis 6.

We consider Hypothesis 5 to be supported, in that the *average target size* is positively associated with the number of patenting targets in Model 1. Model 3 shows the effect of the number of the newly acquired products within the three main product categories. New ESL products show a significant positive effect, as do new products within the FE category. However, new IC-BE tools do not have any significant effect on the dependent variable. These product-related effects also continue to show the same results in the fully specified model (Model 4). Here (in the fully specified model), average target size loses its significance. This is probably due to the relatively high correlation with the three new product variables (*new ESL*, *new FE* and *new BE*). A specified model without the three product variables shows a continued significance of the *average target size* variable while *R&D output* remains non-significant (not reported here).

Hence, we cannot confirm Hypothesis 7, which implies that the high proportion of codifiable knowledge in the IC-BE product category prevents applications for patents or any anticipation that patents are held by potential acquisition targets. However, our reasoning is strongly supported by the positive significant effects of the two remaining main product categories ESL and IC-FE. These two explanatory factors show consistent positive significant effects. Therefore, we can confirm Hypothesis 8 and reject Hypothesis 9b in favor of its oppositional counterpart, 9a. The acquisition of the technically more abstract ESL product category seems to foster the existence of targets with patents when new to the acquiring party. Apparently, IC-FE tools also fall into the same category.

Liquidity shows a significant negative effect as soon as our product-related explanatory variables enter the specification. Although varying slightly in strength, *industry's annual acquisitions* shows positive significant effects throughout all models. Table 11 shows the empirical results of our hypothesized models.

Table 11: Negative binomial panel regression analyses on the number of acquired targets with patents

Variable	Base model		Model 1		Model 2		Model 3		Model 4	
Average target size			0.079 ***	(0.027)					-0.010	(0.054)
R&D output					-0.152	(0.645)			0.248	(0.591)
New ESL							1.143 *	(0.593)	1.177 *	(0.638)
New FE							0.481 **	(0.193)	0.488 **	(0.194)
New BE							0.104	(0.130)	0.129	(0.185)
R&D intensity	-0.058	(1.033)	0.116	(0.944)	-0.227	(1.267)	0.358	(0.825)	-0.002	(1.202)
Firm size (acquirer)	0.171	(0.184)	0.167	(0.184)	0.177	(0.186)	0.228	(0.163)	0.237	(0.164)
Liquidity	-0.383	(0.234)	-0.402	(0.249)	-0.390	(0.238)	-0.421 *	(0.253)	-0.442 *	(0.264)
Leverage	-0.341	(0.838)	-0.202	(0.809)	-0.342	(0.841)	-0.144	(0.736)	-0.141	(0.743)
Total annual acquisitions	0.235 **	(0.091)	0.290 ***	(0.107)	0.232 **	(0.098)	0.301 ***	(0.108)	0.295 ***	(0.109)
Wald χ^2 (df)	9.14 (5)		15.31 (6)**		9.14 (6)		24.06 (8)***		23.89 (10)***	
Log Likelihood	-72.475		-68.928		-72.447		-63.997		-63.894	
Observations (groups)	255 (41)		255 (41)		255 (41)		255 (41)		255 (41)	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

All significance tests are two-tailed. The values in parentheses are standard errors.

4.7. Discussion and robustness tests

The detailed market data at our disposal allow us to empirically address very specific research questions. The dependent variable of this analysis not only accounts for the number of acquisitions. It is even more specific since it counts the number of a certain type of acquisitions, namely those involving targets holding patents.

Assuming that the takeover of another company indicates an ex-post appreciation of its past business performance (at least comparable to its purchasing price) our data allow us to test the explanatory power of different types of new products in the context of technology-driven acquisitions.

Next to relevant information for the acquiring firms, we are also able to integrate a set of target characteristics resulting in dyadic contingency factors. As the reasoning and interpretation at this high level of specificity leaves room for alternative interpretations, the integration of characteristics of both involved parties (the acquirer and the acquired target) allows us to address some potential criticism in this regard. For instance, our model does not control for the possibility of a patent-less firm being preferred over a firm with one or more patents. In other words, we cannot directly distinguish between the effect of patenting and a conscious or subconscious selection effect of the acquirer. However, by controlling for the addition of different EDA products through all acquisitions (involving targets with and without patents) the significant covariates support the validity our arguments.

As a sensitivity check, we also run an alternative model with the total number of acquisitions as the dependent variable. The results in Table 12 show a non-significant effect coming from *new ESL*, while *new IC-FE* remains significant. This less consistent picture is in line with our reasoning on the factors influencing acquisitions of patenting targets. The fact, that we get a weaker significant picture (also regarding the overall model fit) once every acquisition is included in the dependent variable supports our initial model. However, expecting the significant effects to completely disappear is not feasible, given that acquisitions with patents represent 49 percent of the total acquisitions in our sample.

Table 12: Negative binomial panel regression analyses on the number of annual acquisitions

Variable		
Average target size	0.020	(0.032)
R&D output	-0.178	(0.515)
New ESL	0.556	(0.459)
New FE	0.320 **	(0.144)
New BE	0.022	(0.127)
R&D intensity	0.119	(0.950)
Firm size (acquirer)	0.117	(0.142)
Liquidity	-0.071	(0.137)
Leverage	-0.278	(0.579)
Industry's annual acquisitions	0.234 ***	(0.074)
Wald χ^2 (df)	23.12 (10)**	
Log Likelihood	-109.373	
Observations (groups)	255 (41)	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

All significance tests are two-tailed. The values in parentheses are standard errors.

These differences further support our theoretical arguments about the influence of our chosen explanatory variables on the number of acquisitions of patenting targets as we get the most significant effects with our initial dependent variable.

Apart from the discussion about our chosen dependent variable, the design of this study is subject to some more general limitations. As we only focus on acquisitions, we do not control for any previous financial or organizational commitments like joint ventures or minority stake investments. Although we acknowledge the general importance of these activities, the interpretation should be different. While acquisitions are a very clear long-term commitment, more limited investments and venture funding serve different purposes and can be interpreted as a form of purchase of future options or means of control during very early stages of a business. An analysis of sequential patterns of hierarchical arrangements in this high-tech industry environment is certainly intriguing but is not a goal of this study.

In addition, our data do not allow the tracking of acquisition activities among privately held firms. While this could definitely be a very interesting field of study, obtaining this information appears to be prohibitively difficult. Further, there are fundamental differences in the institutional settings between private and public firms. As a result, it can be very difficult to derive assumptions and hypotheses that are universally valid for both groups.

4.8. Conclusion and future research

The empirical analysis in this chapter aims to generate more knowledge in a very specific and yet a very essential field of management research studies. Against the background that patents are a widely used and accepted means to indicate the innovation-related activities and traits of firms, one has to pose the question of the method’s applicability within industries in which patent portfolios seem to be largely disconnected from actual capabilities or activities, and treated more often as a strategic resource. In a scenario, where patents do not accurately mirror firm-specific characteristics and outputs, the basic principle of absorptive capacity can still hold true but should be measured differently. In the case of corporate takeovers, patents may not only under- or over-represent a firm's innovative output and therefore its capabilities to identify, evaluate and absorb new IP: their existence or absence can also lead to false evaluations of potential acquisition targets. This issue becomes even more relevant the easier it is to implement alternative forms of IP protection; an aspect especially important to consider in the case of software industries, where third parties can very easily be excluded from product technology through encryption, secrecy or remote services.

This has direct and indirect implications for technology-driven acquisition behavior. The first direct effect leads to our first hypothesis based on the fact that the relative costs of patenting decrease with the size of the patenting firm. All things being equal, we can confirm at least in Model 1 that the average size of all acquired targets has a significant positive effect on the number of acquired patenting targets with patents per acquiring company and year. A second direct result of the fuzzy indication for software patenting is embedded in our second hypothesis about the limited explanatory power of patent-measured absorptive capacity to explain acquisition behavior.

Statements about the idiosyncrasies of patenting in high-tech (software) industries alone are clearly not satisfactory since we can still assert genuine patent activity within these industries (not only patent accumulation through acquisition). Therefore, we also offer a solution by relating detailed product information and evaluation to different appropriability regimes within a single-industry setting. In turn, our acknowledgement of a situational rationale of patenting led to the integration of product specific dyadic variables, which combine characteristics of acquirers and targets. Incorporating specific product information enables us to investigate very specific contingent questions and test them empirically. Our specific model tests for the product categories in which the acquired and patenting firms are active. At the same time, part of the acquired product portfolio has to be new to the acquiring firm and has to be retained in the upcoming years. Through this modeling, we can be sure that the acquired firm has valuable competencies that are at least in part new to the acquiring party. Further, we show that the existence of patents in software industries hinges on the types of products that are being produced and sold. This seems to be valid at least for firms that are successful enough to be targets for acquisition.

Utilizing product information as an indicator for innovative performance especially in the context of acquisitions, is an accepted approach. The work by Stern and Henderson (2004) very clearly showed the importance of within-industry diversification for the survival of firms. In another study, Puranam, Singh, and Zollo (2006) used new product releases as their dependent variable to measure the impact of acquisitions on innovative performances. It is worth mentioning that both analyses adopted a very narrow industry focus, which we think is necessary to test fine-grained hypotheses. As our work also represents a single-industry, we clearly see the necessity of doing similar research in more high-tech and software industries to verify our methodology of industry specific dyadic contingency factors in order to unravel the role of patenting in modern sectors.

We see this as a rather exploratory study to approach the apparent disruptive relationship between patent systems and firm behavior in high-tech industries. Understanding the role of patents within these relatively new sectors can help to evaluate the effectiveness of today's IP legislation. Furthermore, it can also contribute normative statements for practitioners to support decision making within the respective fast-paced environments relating to the utilization or evaluation of IP protection.

In addition to tackling the issues of patent policies in high-tech industries, our analysis also points toward the need for M&A research to adopt new ways to operationalize absorptive capacity and to relativize the role of patents as indicators of innovativeness in general. Although we are aware of the long-lasting and controversial discussion about patents in empirical management research, we feel the need to revitalize a critical view on the often inconsiderate use of patent measures. The ever-increasing importance of digital goods-based industries makes it impossible to overstate the importance of this topic with regard to the relevance of empirical studies. Recalling the two general implications suggested at the beginning of this chapter, the acknowledgement of the disconnect between patenting and technological knowledge has to culminate in new methodologies in empirical research, which also implies a separate analysis of software industries in multi-industry samples.

This work tries to empirically acknowledge these implications and represents a first step toward a proposal for a more pragmatic approach to M&A research.

5. AN INTEGRATED EMPIRICAL VIEW

The three main analyses in this thesis have a common goal of understanding acquisition behavior in high-tech industries with a special emphasis on the EDA industry. Although the main chapters follow a conceptual logic, each tackles very different aspects of the acquisition phenomenon. With the knowledge of all empirical results, it seems appropriate to test an integrated approach as another logical step towards a more complete understanding of firm behavior.

From a conceptual point of view, Chapter 2 and 3 are very closely related. Taken together, these first two empirical settings can be regarded as a two-stage concept, where at the first stage the fundamental assumption about the critical role of technology- and product-related motives behind acquisitions is tested and verified. The second analysis builds on these results, introduces further contingency factors, and derives assumptions about certain types of acquisitions that happen at certain times. Although it builds thematically on the ambiguous picture of the influence of patent-based measures in the first two analyses, the fourth chapter is more conceptually separated from the first two-thirds of the thesis,[41] and will not be included in this complementary integrated analysis.

Therefore, the integration of the models of Chapters 2 and 3 is made starting from the final specification of Chapter 3 with the more strict selection criteria for the included firms. Only considering core EDA firms serves as a common denominator as opposed to applying the explanatory variables of Chapter 3 to the larger and less restrictive sample of Chapter 2. Table 13 shows the estimation results after the subsequent addition of the two explanatory variables of Chapter 2.

[41] This is also mirrored by a different dependent variable.

Table 13: Integrated negative binomial panel regression analyses on the number of annual acquisitions

Variable	full model from chapter 3		Integrated model 1		Integrated model 2		Fully integrated model	
Product diversification			0.769 ***	(0.254)			0.743 ***	(0.253)
Product portfolio breadth					0.591	(0.528)	0.460	(0.534)
new 90 nm technology	-0.408	(0.640)	-0.475	(0.640)	-0.435	(0.528)	-0.486	(0.638)
(firm w/) ESL products	1.418 **	(0.564)	0.987 *	(0.573)	-0.228	(1.583)	-0.277	(1.582)
(firm w/) only non-ESL Products	-0.211	(0.616)	-0.215	(0.608)	-1.042	(0.971)	-0.841	(0.955)
90 nm techn. * ESL products	0.350	(0.678)	0.525	(0.682)	0.390	(0.677)	0.549	(0.681)
90 nm techn. * only non-ESL products	1.912 **	(0.865)	1.670 *	(0.863)	1.813 **	(0.859)	1.567 *	(0.864)
R&D intensity	0.295	(1.154)	0.351	(1.186)	0.211	(1.257)	0.252	(1.283)
R&D output	0.595	(0.498)	0.703	(0.470)	0.711	(0.496)	0.797 *	(0.475)
Firm size	0.318 *	(0.165)	0.360 **	(0.162)	0.285 *	(0.164)	0.333 **	(0.163)
Growth	0.585 ***	(0.190)	0.442 **	(0.192)	0.547 ***	(0.190)	0.423 **	(0.191)
Profitability	1.176	(0.758)	0.828	(0.750)	1.185	(0.762)	0.852	(0.756)
Liquidity	-0.109	(0.136)	-0.160	(0.143)	-0.091	(0.134)	-0.145	(0.142)
Industry's annual acquisitions	0.082 ***	(0.020)	0.077 ***	(0.020)	0.081 ***	(0.020)	0.076 ***	(0.021)
Likelihood ratio test for nested full model from chapter 3			6.97 ***		1.28		7.94 **	
Wald χ^2 (df)	52.40 (12) ***		62.77(13) ***		55.02(13) ***		64.74(14) ***	
Log Likelihood	-131.9792		-127.4034		-131.3406		-127.0254	
Observations (Groups)	178 (36)		178 (36)		178 (36)		178 (36)	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

All significance tests are two-tailed. The values in parentheses are standard errors.

The results of Table 13 clearly show that integration is only partly feasible. Apparently, the addition of the *product diversification* variable (integrated Model 1) can lend the model more explanatory power, as it shows a clear significant effect, while the rest of the results show no qualitative change. The results of integrated Model 2 are less consistent. The added *product portfolio breadth* variable shows no significant effect (in contrast to the models in Chapter 2) and the coefficient of *ESL products* becomes insignificant as well. This effect also remains in the fully integrated model with both explanatory variables from Chapter 2. The detrimental effects of including the *product portfolio breadth* variable become apparent in the likelihood ratio test results, too.

When we examine the combined variables from Chapters 2 and 3 more closely, the above results are no surprise. The *product diversification* variable essentially measures the change in the product portfolio from year t-1 to t. There is little interpretational overlap compared to the explanatory variables of the 'base model' from Chapter 3. The results of the integrated Model 1 reflect that. The picture apparently changes when integrating the *product portfolio breadth* variable in integrated Model 2. The interpretational overlap of this added variable and the explanatory variables from Chapter 3 is very high, which can be empirically shown through the correlation factors between those regressors. Descriptive statistics and the correlation matrix for the integrated models above are shown in Tables 14 and 15.

Table 14: Descriptive statistics

	Variable	Mean	S.D.	Min.	Max.
1	Number of acquisitions	0.573	1.158	0.000	7.000
2	Product diversification	0.185	0.390	0.000	1.000
3	Product portfolio breadth	1.410	1.152	0.000	3.000
4	new 90 nm technology	0.427	0.496	0.000	1.000
5	(firm w/) ESL products	0.309	0.463	0.000	1.000
6	(firm w/) only non-ESL Products	0.404	0.492	0.000	1.000
7	90 nm techn. * ESL products	0.169	0.375	0.000	1.000
8	90 nm techn. * only non-ESL products	0.112	0.317	0.000	1.000
9	R&D intensity	0.274	0.195	0.032	1.993
10	R&D output	0.335	0.456	0.000	3.319
11	Size	5.494	1.715	1.703	9.036
12	Growth	0.249	0.696	-0.645	6.462
13	Profitability	0.143	0.292	-1.490	0.783
14	Liquidity	2.912	1.940	0.314	14.812
15	Industry's annual acquisitions	12.652	5.650	4.000	22.000

Table 15: Correlation matrix

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Number of acquisitions	1.00														
2	Product diversification	0.44 **	1.00													
3	Product portfolio breadth	0.41 **	0.35 **	1.00												
4	new 90 nm technology	-0.05	0.06	0.04	1.00											
5	(firm w/) ESL products	0.45 **	0.28 **	0.81 **	0.16 **	1.00										
6	(firm w/) only non-ESL Products	-0.27 **	-0.07	0.05	-0.25 **	-0.55 **	1.00									
7	90 nm techn. * ESL products	0.15 **	0.09	0.53 **	0.52 **	0.67 **	-0.37 **	1.00								
8	90 nm techn. * only non-ESL products	-0.07	0.01	0.00	0.41 **	-0.24 **	0.43 **	-0.16 **	1.00							
9	R&D intensity	-0.04	0.11	0.07	-0.03	-0.01	0.20 **	0.00	0.06	1.00						
10	R&D output	-0.12	-0.17 **	-0.23 **	0.20 **	-0.04	-0.13	0.05	0.05	0.25 **	1.00					
11	Firm size	0.22 **	-0.09	0.02	0.14	0.17 **	-0.44 **	0.14	-0.20 **	-0.52 **	-0.31 **	1.00				
12	Growth	0.07	0.17 **	-0.02	-0.21 **	-0.09	0.10	-0.11	-0.08	0.37 **	0.12	-0.32 **	1.00			
13	Profitability	0.34 **	-0.06	0.07	0.03	0.13	-0.27 **	0.07	-0.09	-0.50 **	-0.38 **	0.62 **	-0.19 **	1.00		
14	Liquidity	-0.17 **	-0.10	0.29 **	-0.07	-0.29 **	0.19 **	-0.24 **	0.08	0.17 **	0.26 **	-0.27 **	0.10	-0.12	1.00	
15	Industry's annual acquisitions	0.22 **	0.12	-0.01	0.35 **	-0.11	0.17 **	-0.21 **	0.07	-0.03	-0.11	0.06	-0.04	-0.02	0.02	1.00

** $p < 0.05$

The variable *product portfolio breadth* is highly correlated with the *(firm w/) ESL products* variable, meaning that firms with a broader product portfolio also tend to have ESL products (see Table 15). This high correlation also explains the insignificance of the likelihood ratio test for integrated Model 2. The very similar behavior of these two variables shows that it does not necessarily make sense to combine the first two main analyses of this thesis and that it does not inevitably lead to a more complete picture. Admittedly, the focal research goal of both studies is very similar. However, although these two analyses are built on the same data and the same dependent variable, they focus on different potential reasons behind acquisition behavior. Two of the variables from the first two main chapters, namely *product portfolio breadth* and *(firm w/) ESL products*, are meant to measure different things but they behave very similarly. The limitations of available indicators for empirical models certainly show their effect here, too. Another noteworthy factor is the less than optimal balance between the number of independent variables and the total number of observations when integrating the two analyses.

This complementary analysis suggests, that it is only partly feasible to integrate the single empirical models. However, there certainly should be a sensibility check in this regard similar to this one to test for the possibility of employing more appropriate indicators as explanatory variables or controls in future analysis.

6. SUMMARY

This section starts with an overview of the results of the three empirical studies of this thesis. This is followed by concluding thoughts on the contribution of this work and implications for future research.

6.1. Overall results and contribution

Each of the studies constituting this thesis represents a self-contained effort to contribute to the understanding of corporate acquisitions in high-tech industries. However, these empirical analyses can also be regarded as interrelated building blocks for a more complete and consistent picture about acquisition behavior in general and that of EDA firms in particular.

Technically speaking, the empirical model in Chapter 2 forms the groundwork for the other two studies. It shows the general feasibility of utilizing a mix of qualitative and quantitative product information and market knowledge to characterize strategic positions of firms within a single industry. Moreover, it makes the theoretical argument, that product portfolios not only reflect a current competitive position but are also an appropriate indicator of the knowledge base of a whole organization. While these concepts are not new, they seem to be largely ignored in M&A literature especially in conjunction with single-industry analyses as a new approach to meet the needs for more consistent results (e.g., Schulz, 2008). The subsequent Chapters 3 and 4 fully embrace and leverage this methodological groundwork.

Apart from the method-related contributions (which will be discussed again in Section 6.3.) the interpretation of the concrete results of the three studies also shows the conceptual interdependence and coherence of the individual chapters of this work. Thus, the analysis of the second chapter forms the basis from that perspective, too. Here, two different acquisition motives can be empirically identified. Within the field of technology-induced acquisitions[42] these are ‘expansive’ and ‘defensive’ acquisitions. Using changes and characteristics in the product portfolios as proxies, these two indirectly-measured motives show highly significant effects on the frequency of mergers within the EDA industry. Given the immense pressure to innovate in this exemplary industry, this result is no surprise. In order to adapt to the ongoing (technological) progress and changes, corporate acquisitions can be seen as an ideal managerial instrument to assist with survival within such dynamic environments.

The empirically verified identification of major motives behind acquisitions is an appropriate starting point for the more contingent analyses in Chapter 3. Following on from the general results of the first study, one of the immediate questions that come to mind relates to under which circumstances which firms acquire which target firms. Therefore, the transition towards a smaller manufacturing scale (90 nm) was identified as a major trend with significant ramifications for the EDA industry. Alongside a general increase in complexity and the corresponding requirements for all EDA software tools, this led to an increased demand for a certain type of product category, namely ESL. The results show that the trend itself did not have any significant influence on the frequency of acquisitions. This can be explained by the fact that we can observe a constant high level of acquisition activities within such a dynamic environment (which is also why this industry is very attractive for scientific research on acquisitions). Thus, one trend continuously replaces the other leading to a continuous need for the latest technologies and therefore most probably leads to the insignificance of the identified trend in the study of the third paper. However, by differentiating EDA firms according to their

[42] The technology and product induced characteristic of the deals in the EDA industry was ensured through the strict manual filtering and the exclusion of deals involving non-EDA firms. This was even better accomplished by qualitative triangulation in trade journals and online magazines.

ESL offerings, more fine-grained dynamics can be revealed. Firms with ESL products do contribute significantly to the number of acquisitions over the whole period analyzed in the sample. As these firms are also usually active in the other main product categories, this strongly suggests defensive acquisitions among products in categories already offered.[43] Even more interesting, a significant contribution to the number of annual acquisitions comes from firms without ESL products during the time of the 90 nm trend. Closer scrutiny of the deal information shows that none of these firms acquires ESL products. Instead, they still focus on product categories they already offered; hence, they also follow the logic of defensive acquisitions. This result is remarkable since it implies that existing businesses are prioritized over promising new products even within a single-industry setting. Within the extreme conditions of these high-tech industries, firms that are not fully diversified apparently prefer to rely on existing knowledge instead of acquiring more unrelated products and technology. Thus, a certain degree of conservatism seems to be part of survival strategies even in industries as progressive as EDA.

The fourth chapter investigates the role of patents in acquisition behavior within the EDA industry as part of a survival strategy of innovating firms. From the acquirer's point of view, patents can decrease uncertainty about the value of the target's technological competence and capabilities. From the target's perspective, patents can legally exclude others from a particular technology and further function as a signal of competence for potential buyers. To integrate these two perspectives, the employed model features dyadic variables with information about both, the acquirer and the target. The results suggest that the number of acquired targets with patents can partially be explained by the type of products these acquired

[43] The high correlation between the qualitative breadth of the product portfolio and the firms with ESL products in the integrated analysis in Chapter 5 can be seen as another confirmation.

firms bring into the merger. In particular, the analysis looks into cases, where the type of the acquired product is new to the acquiring firm, thus the information asymmetry is quite high. This implies that the investing party should have every interest in decreasing the risk associated with the acquisition with a new product line, which will be continued after the merger. The results suggest that this interest can be implied for rather non-technical new products. However, the argument of the non-feasibility of patent applications for very technical products could not be fully validated in the employed models. Better evidence exists for the apparent non-feasibility for rather small firms to make many patent applications. Based on arguments of efficiency and effectiveness, alternative means of IP protection like secrecy or encryption appear to offer clear advantages in software industries such as EDA.

6.2. Concluding thoughts on the contribution and implications for future research

All major contributions of this work can ultimately be linked to the pragmatic observation of firm behavior, which culminated in a research design that tries to address and account for the realities of competitive high-tech industries. Although almost every contributive aspect has already been mentioned in the respective chapters, this final section aims to accentuate some arguments and round off this thesis.

From a methodological point of view, the single-industry approach is one of the most noteworthy and important contributions of this research. Although it seems obvious to analyze the immediate core business of a respective firm in order to understand its behavior, very little work has been done with this particular empirical scope. The relative strategic position undeniably influences firm behavior in a very meaningful way, especially in terms of the results of complex decision-making processes like acquisitions.

Regarding the differentiation and contribution in terms of the subject matter of research, it is necessary to point out that post-acquisition performance can only be appropriately measured and evaluated when there is knowledge of the reasons for a particular merger. This statement is very intuitive, logical and hard to dispute. However, based on the current research, this fact has not been registered often enough, especially in the case of quantitative empirical analyses. Rather, there has been an emphasis on post-acquisition performance in the literature, which provides more or less inconsistent and ambiguous results. The common symptom of this unsatisfactory situation has been identified in the limited explanatory value of the independent variables, which are found to be used ubiquitously and routinely in studies in that field (King *et al.*, 2004). Apart from the need for more apt explanatory variables, it was also found that *'main conclusion points'* from often large-scale multi-industry studies "*cannot be supported with sufficient scientific rigor*," which consequently must result in more *"in depth studies of specific industries"* (Schulz, 2008, p. 19). This thesis addresses these concerns through an emphasis on the identification of relevant measures of acquisition informing conditions and the implied motives behind those conditional factors within a single-industry setting.

An integral part of the single-industry approach adopted in this thesis is the detailed knowledge about the nature of the business, which is essential in order to design product portfolio structures and to interpret them. Within this industry-focused setting, product information is a very powerful proxy for the technology that is embodied in it, as it implies that the respective resources are of sufficient quality to permit a firm to compete for market share. The reliance on marketed products is not a new approach and has been successfully applied in empirical research before (e.g., Stern and Henderson, 2004). However, a large body of literature in that field relies on patent information as the support for innovation-related measures.

Accordingly, another important contribution of this work is the theoretical and empirical assessment of the fact that patent-based measures are becoming increasingly problematic in today's high-tech industries. A root cause of this issue is the proliferation of non-physical products (software) in combination with product life cycles that have become so short that they almost constitute continuous product improvements.[44] The introduction of digital technology in communication and value creation has led to drastic economic changes with immense ramifications for IP creation and protection strategies. Cost benefit analyses for patent applications in digital (software) industries are subject to very different terms and conditions compared to those in the traditional industrial sectors. This not only leads to less patenting in favor of alternative ways to protect new IP, but the complexities of high-tech products make it necessary to preempt potential accusations over patent infringements by purchasing new patents as a means of protection. Logically, future research should acknowledge these changes in IP protection strategies by either excluding the affected industries from cross-industry samples or including variables that can mirror technological competence in a more appropriate way. The current research undertook the often-simultaneous utilization of established patent-based measures and product-based variables with the intention of empirically validating these logical but theoretical arguments.

At this point, it must be acknowledged that the empirical results in this work are based on a single-industry sample. Therefore, this is also a suggestion for future research to utilize, refine, and further test some arguments from this work. Applying this to other high-tech

[44] For software products these improvements can be made through online software updates.

industries is one of the most obvious potential extensions of the general approach of this thesis. Only through additional empirical testing can both the methodological and the interpretational results of this research be further validated and more appropriately valued.

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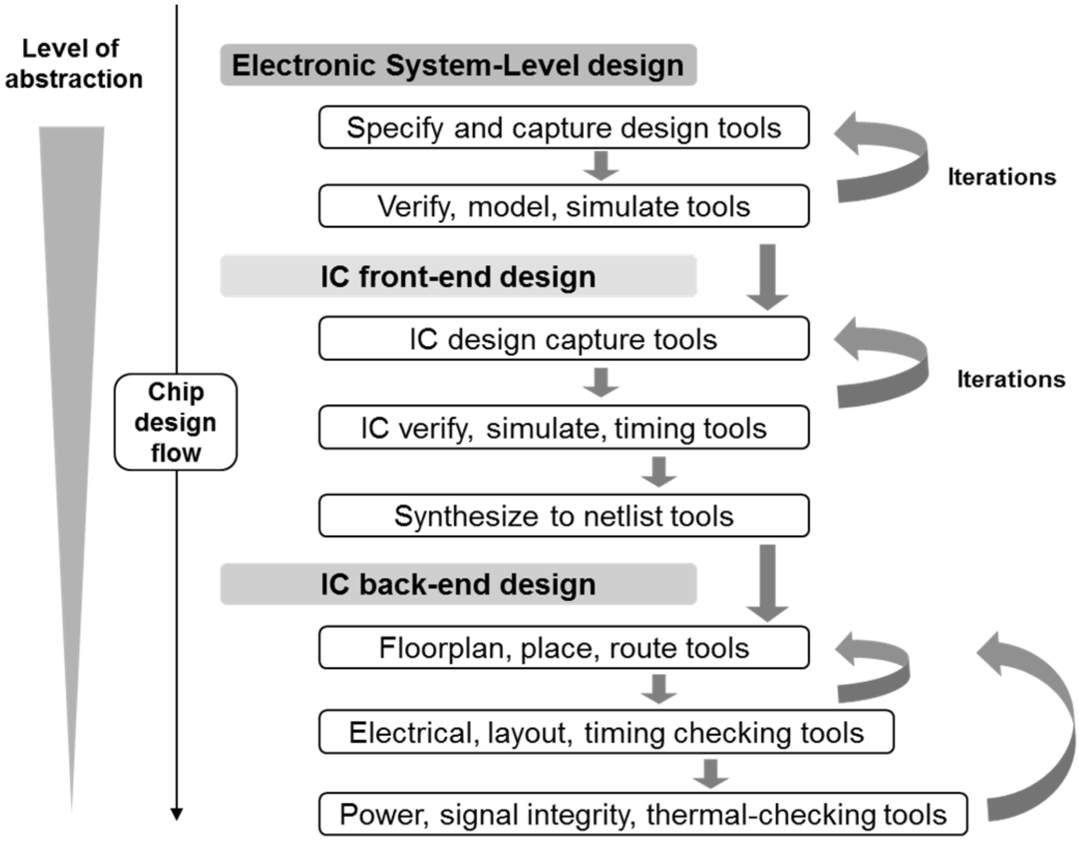
8. APPENDIX

Figure G: A schematic overview of the chip design process and involved EDA tools



Source: Own illustration with reference to Birnbaum (2003, p. 66).

Table 16: Number of (acquiring) firms - per number of IC back-end (BE) tools and analyzed year in analysis of Chapter 2

	No. of IC back-end (BE) tools																						
year	0	1	2	3	5	6	7	8	9	10	11	12	14	15	16	17	18	19	20	21	22	23	total
1998	13	4	1	1	1									1			2		1				24
1999	12	1	2						1						1	1				2			20
2000	9	3	2	1					1					1			1			1		1	20
2001	12	1	2	2			1			1			1		1			1	1				23
2002	8	2	3	3					1								1			1	1		20
2003	9	1	3	1		1					1						1			1	1		19
2004	10	2	3	1				1				1					1					2	21
2005	10	2	2	2							1	1						1			2		21
2006	9	1	2	2							1	1					1				1	1	19

Table 17: Number of (acquiring) firms - per number of IC front-end (FE) tools and analyzed year in analysis for Chapter 2

	No. of IC front-end (FE) tools																					
year	0	1	2	3	4	5	6	7	8	9	11	12	13	14	16	17	18	19	20	21	23	total
1998	7	8	1		2	1	1							1		1			1	1		24
1999	8	6		1					1				1					1	1	1		20
2000	9	4	1	1					1				2					1	1			20
2001	9	7	1	1					1		1	1					1		1			23
2002	9	4	1	1	1					1					1				1	1		20
2003	8	3		1	1	2				1					1				1	1		19
2004	10	3		1	1	1	1	1									1			1	1	21
2005	11	3			1	2		1									1				2	21
2006	9	3				3		1									1				2	19

Table 18: Number of (acquiring) firms - per number of electronic system level (ESL) tools and analyzed year in analysis for Chapter 2

	No. of Electronic System Level (ESL) tools								
year	0	1	2	3	4	5	6	7	8	total
1998	18	3			2	1				24
1999	16		1	1			1	1		20
2000	16		2			2				20
2001	17	2	1	1		2				23
2002	14	2		2		1		1		20
2003	10	5	1	1		1		1		19
2004	12	5		2		1	1			21
2005	14	3	1	2			1			21
2006	13	2	1		2				1	19

Table 19: Number of (acquiring) firms - per product (portfolio) complexity level and analyzed year in analysis for Chapter 2

	Product (portfolio) complexity				
year	0	1	2	3	total
1998	4	12	2	6	24
1999	6	8	2	4	20
2000	5	8	3	4	20
2001	5	9	5	4	23
2002	5	5	6	4	20
2003	6	3	3	7	19
2004	7	4	3	7	21
2005	7	6	2	6	21
2006	7	4	2	6	19