Innovation in the Digital Economy: Valuing Investments in Digital Business Models under Uncertainty

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Abstract The Digital Economy has changed the way of how business is done. Since the emergence and growing importance of digital technologies, a new class of digital business models has emerged. These business models have substantially different characteristics from traditional asset-based business models that are built around linear value chains. Today, we can witness increasing success of such digital business models engaged by both tech-newcomers as well as established corporations around the world. When it comes to investment decision-making, managers are facing times of unprecedented pace, unforeseeable trends and ultimately risk. This dissertation aims to help investment decision-makers to face these uncertainties by presenting a set of quantitative frameworks that can identify and evaluate investment opportunities related to digital business models under uncertainty. This dissertation is comprised of three essays that study such investment decisions. In the first essay, we develop a generic framework to value managerial flexibility for investments in digital transformation of business models by using real options analysis. The second essay presents an alternative view on value in digital businesses by applying customer-based corporate valuation techniques to evaluate digital businesses under uncertainty. The third essay shows how input parameters for such investment models can be estimated using quantitative technology forecasting techniques and combines them with technology uncertainty from finance literature. The study concludes with a section that summarizes and discusses findings and describes areas for future research.

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List of Abbreviations

R&D	Research and Development
DTBM	Digital Transformation of Business Models
IoT	Internet of Things
VUCA	Volatility, Uncertainty, Complexity, Ambiguity
DCF	Discounted Cash Flow
NPV	Net Present Value
IS	Information Systems
IT	Information Technology
SIS	Strategic Information Systems
BMI	Business Model Innovation
ROI	Return on Investment
KPI	Key Performance Indicator
IRR	Internal Rate of Return
EVA	Economic Value Added
BCA	Business Case Analysis
PI	Profitability Index
WACC	Weighted Average Cost of Capital
DTA	Decision Tree Analysis
CCA	Contingent Claims Analysis
SDE	Stochastic Differential Equation
EBITDA	Earnings before Interest, Tax, Depreciation and Amortization
EpS	Earnings per Share
BtM	Book to Market Ratio
DR	Debt Ratio
RoA	Return on Assets
MC	Market Capitalization
ARPU	Average Return per User
CAC	Cost of Capital Acquisition
CLV	Customer Lifetime Value
CE	Customer Equity
CBCV	Customer-based Company Valuation
ODE	Ordinary Differential Equation
OTT	Over the Top (Services)
SCI	Science Citation Index
DII	Derwent Innovation Index
OLS	Ordinary Least Squares
MLE	Maximum Likelihood Estimation
CEO	Chief Executive Officer
CAPM	Capital Asset Pricing Model
GBM	Geometric Brownian Motion

Chapter 1

Introduction

1.1. Business Strategy in the Digital Age

We are currently facing times of severe changes triggered by emerging digital technologies. Technological developments are not gradually increasing but skyrocketing exponentially. Living in a world determined by exponential change entails extensive implications for society, politics and the economy. When it comes to aligning businesses, facing these developments is no longer about simply digitizing business processes; it is about transforming business models to maintain sustainable competitive advantage. In short, it is about creating something new, rather than just soliciting a process of adaption. In the near future, industry leaders, even in traditional industries such as automotive or financial services, will increasingly transform into tech companies. Successful innovators such as Amazon, Google, Microsoft, Apple, Netflix and others that have only existed for a few decades are now among the most valuable companies in the world.

Disruptive technologies and exponential technological progress are framing today's business environment across all major industries. For many businesses, expressions such as Big Data, the Internet of Things (IoT), 3D printing, Artificial Intelligence etc., are still only buzzwords that are yet to be implemented into business strategies. On the one hand, this global development opens many opportunity windows for existing businesses as well as new ventures around the world, to achieve strategic competitive advantage, expand business models or enter into entirely new markets. On the other hand, however, these trends are a major threat for established companies, as many of them struggle to keep up with the pace of the developments while mushrooming tech-newcomers are unsettling traditional value chains. In today's digital economy, incumbents have to exploit the potential of digital technologies to innovate their businesses. In other words, they have to proactively invest in the digital transformation of their business models.

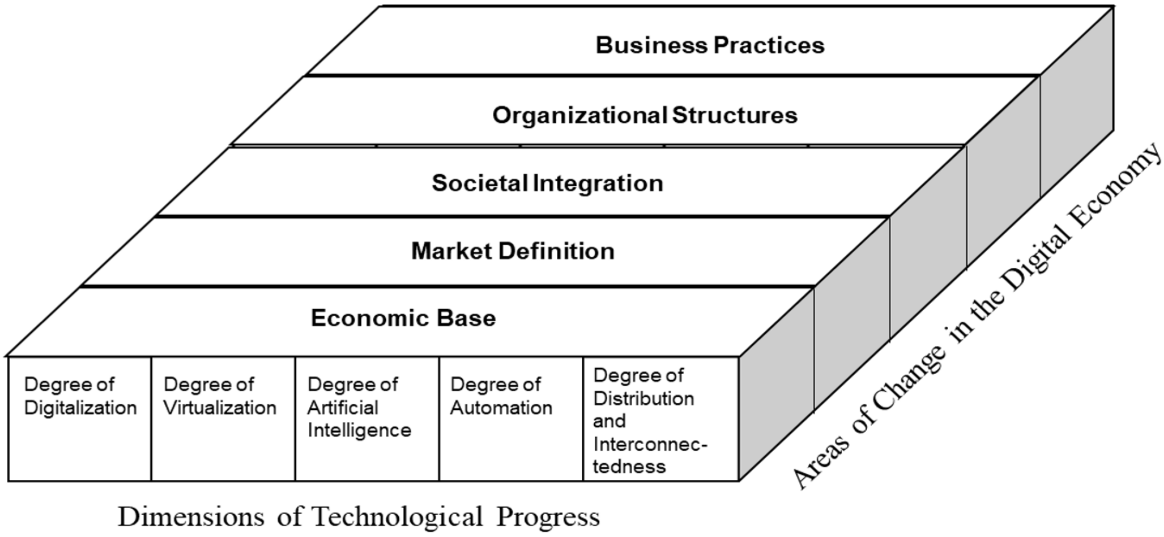


Figure 1.1: Determinants of change in the digital economy; For a detailed explanation of the technological shifts and the determinants of the digital economy, see Leonhard (2016) and Parker (1995)

A prominent example for this development is the automotive industry. Car manufacturers' traditional asset-based business models are built around a linear value chain of producing, selling and distributing vehicles. These companies are facing severe challenges induced by increasingly blurred industry boundaries, changes in regulation and new competitors such as Tesla, Apple and Uber. As a result, incumbents have started to bundle their forces to work on new products and business models by selling mobility services based on digital platforms and self-driving electric vehicles. Recently, rivals BMW and Daimler have merged their car sharing platforms to compete with newcomers on a global scale, while Ford and Volkswagen have entered into a joint venture on electrified physical automobile platforms.

According to a recent study by Murray (2016), 75% of the fortune 500 CEOs said that "*a trio of technologies – cloud computing, mobile computing and the Internet of Things – will be either 'very important' or 'extremely important' to their businesses in the future*" and more than 50% added artificial intelligence and machine learning to the list. Incumbents often lack the core capabilities and resources to exploit technological developments in an effective way. As a consequence, we are facing an era in which the standards of business practice are increasingly set by innovative startups rather than by existing market leaders.

Figure 1.1 summarizes the determinants of paradigmatic change in the digital economy. It illustrates the different dimensions of technological progress and their economic impact flowing together to create a VUCA world[1]. Technological progress can be clustered into five

[1]VUCA, which is an acronym for the words Volatility, Uncertainty, Complexity and Ambiguity, has recently found its way into the business lexicon. It is a concept that describes the unpredictable nature of

dimensions that are expected to have a severe impact on the vectors of the digital economy. These dimensions are highly interdependent unfolding enormous disruptive potential on any layer of our economy. The areas of change described in Figure 1.1 draw a picture about the fast-paced, unpredictable environment surrounding the digital economy and highlight the importance of digital transformation.

1.2. Challenges in Investment Decision-making for Digital Transformation

Digital transformation initiatives have become a necessary tool to avoid disruption and Digital Darwinism[2]. According to a report by IDC (2019), executives of established enterprises have started to realize this phenomenon investing USD 1.18 trillion in digital transformation in 2019, an increase of 17.9% over 2018. However, a recently published study by KPMG (2017) points out that only 41% of companies have an enterprise wide digital strategy, and only 18% of companies rate their use of digital technology as "*very effective*". One reason for this is that most companies focus much on certain technologies rather than the underlying business strategies or long-term customer needs. While new technologies can indeed drive new business models, they are often generic in nature. Where creativity comes into play is in applying them to revolutionize a business. It is the business application and the specific use of the technology which makes the difference (Massa et al., 2017).

As discussed in Gassmann et al. (2014a), decision-making for digital investments thus remains to be a critical task, mainly due to the following reasons: (a) it is hard to think outside traditional industry boundaries, (b) there is a lack of systematic tools that support decision-makers, (c) these investments are highly risky, (d) it is close to impossible to forecast the respective Return on Investment (ROI). This dissertation is aiming to cope with (b), (c) and (d) by developing a number of quantitative frameworks that consider uncertainty, forecast financial performance and derive investment strategies to support decision-makers in the challenging process of digital business model innovation (BMI).

Standard investment decision models in corporate finance theory include the Discounted Cash Flow (DCF) analysis, or Net Present Value (NPV) techniques. According to Copeland and Antikarov (2001), practitioners frequently apply these methods for project valuation and a proxy for decision-making for vast kinds of projects including Information Systems (IS)/ Information Technology (IT) investments. However, these methods do not suffice in coping

the times currently confronted by managers (Bennett and Lemoine, 2014). Especially in the digital economy, it can provide a framework that helps managers to understand how much they know about their situation and how well they can predict the result of their actions by capturing the characteristics of their situation along these four dimensions.

[2] In the rapidly changing digital economy, businesses will digitalize or die – a phenomenon that can already be observed in practice and is recently being referred to as Digital Darwinism (see, for example Kreutzer (2014)).

with high levels of uncertainty, as they do not capture the value of managerial flexibility, neither before nor after an investment is installed. Hence, as suggested by Trigeorgis (1996), these methods systematically undervalue projects in high uncertainty situations. Real options analysis is concerned with valuing this managerial flexibility and finding the right timing or scale of such investment decisions. A broad variety of literature has suggested applying real options reasoning for decision-making for irreversible investments under uncertainty. However, existing research has focused on applying real option analysis to other kinds of projects with crucially different characteristics such as IT investments, energy, mining, oil or Research and Development (R&D) projects.

1.3. Scope and Purpose of this Dissertation

Recent literature has suggested real options reasoning as an approach to strategic thinking and decision-making related to BMI and Digital Transformation of Business Models (DTBM) (McGrath, 2010; Amit and Zott, 2010). Interestingly, however, to the best of our knowledge, no scholars have presented any structured quantitative approach to decision-making for digital transformation initiatives. In this dissertation, we try to close this gap by developing a set of generic frameworks that are able rationally value risky DTBM projects and investments in digital business models under uncertainty.

Our contributions to this interdisciplinary research area are comprised by several studies. First, we discuss recent developments in the digital economy and provide an understanding of digital transformation, BMI and the nature of investments in DTBM. Second, based on these findings, we introduce real options analysis as a viable approach to value these investments and derive investment strategies under uncertainty. A quantitative model is presented that is based on an iterative approach of experimentation and learning to support managers in finding the strategic value of DTBM projects. Third, an alternative perspective on valuation in the digital economy is given by shedding light on the intangible value of users. We introduce customer-based corporate valuation methods as a promising alternative to traditional performance measures and derive business value from a digital company's most valuable asset: It's users. We employ this approach to show how to value a digital business by applying it to real-world business cases including Netflix, Roku and Stitch Fix and present some sensitivity analyses to derive concrete measures for managerial action. Finally, we show how input parameters for some of the presented models can be obtained by integrating finance concepts with quantitative technology forecasting literature and demonstrate its functioning by applying it to the 3D printing technology.

Thus, the overall scope of this dissertation is to provide an understanding of doing business in the digital age, provide deeper understanding of digital business transformation from a financial perspective and improve managerial investment decision-making. The study places its focus on investments in digital business models rather than digitization investments for operational layers of businesses. The presented frameworks shall serve as a guide for decision-makers to evaluate digital transformation opportunities in uncertain environments and increase the efficiency of value-based management in such situations.

1.4. Main Contributions and Research Questions

This dissertation aims to provide an answer to the following major research questions:

1. What is digital business transformation and how does it manifest itself with managerial investment decision-making?
2. How can traditional valuation techniques be improved to cope with the uncertain business environment in the digital economy?
3. What are the major value drivers of digital business models and how can such companies be evaluated?
4. How can we estimate input parameters for investment-decision models in the elusive context of long-term digital investments?

The structure of this study is as follows: In order to facilitate a discussion about business value in the digital economy, we provide a generic definition of the term Digital Business Transformation and DTBM in Chapter 2. In Chapter 3, based on the rapid changes induced by the digital economy, we highlight the challenges of investment decision-making and the differences to traditional environments. These challenges serve as a motivation for the need of more sophisticated valuation techniques, which are introduced in Chapter 4. Chapter 5 provides a generic quantitative framework to value digital transformation initiatives by placing emphasis on managerial flexibility and show how experimentation, learning and expansion decisions can be modelled as real options. We show that these real options can bear substantial value with the potential to shift traditional investment decisions. Chapter 6 then provides an out-of-the-box way of thinking in regards to value in the digital age by introducing an alternative set of performance measures that is more suitable as a basis of assessment for value-based management. These ideas are implemented in Chapter 7 by providing a framework to employ user-based metrics to value digital business models under uncertainty and prove their power by applying the suggested modelling approach to value three digital companies. Chapter 8 provides a guideline of how to estimate input parameter values for technology investments and demonstrate its impact on real options valuation frameworks and their functioning by applying it to the 3D printing technology. Chapter 9 concludes this dissertation by presenting a summary and a future outlook.

Chapter 2

Understanding Digital Business Transformation

Despite the growing importance and an exploding number of academic as well as management articles on the phenomenon of digital business transformation, interestingly, academic literature is yet to provide a generic definition of the term. In the following, we venture to provide such a definition by systematically analyzing the core determinants of the expression. We distinguish different types of digital business transformation initiatives to facilitate further discussion and clarify the scope of investments that are subject to analysis by this dissertation. We further give an overview of the different types of digital business models and their differences to traditional asset-based business models.

2.1. Change

Change is a word used a lot in our everyday language. At first sight, there is nothing scientific about it and if you use it in a conversation, everyone will understand what you mean by it. This is why in science, the definition of change is usually marginalized or ignored. However, as we want to clearly highlight the difference between non-transformational and transformational change, we will present my position on distinguishing these terms. Generally speaking, change can be defined as the *"act or instance of making or becoming different"* (Dictionaries, 2017). Yet, in order to establish a clear line between change and transformation, it is essential to provide a more precise definition of change. The concept of time can help us to do so (for a qualitative definition of time, see Weik (1998)). We can define time as a continuous infinite interval of points in time

$$T = \left]-\infty, \infty\right[.$$

Let us consider an object Ω, which is defined by its attribute space

$$A = \alpha_1, ..., \alpha_n,$$

containing the entire set of attributes of the object. Each of the attributes α_i have a certain set of possible manifestation values M_i defined by

$$M_i = \mu_{i_1}, ..., \mu_{i_2},$$

while the scale of $\mu_1, ..., \mu_n$ can be nominal, ordinal or metric. Now let's regard two random points in time t_n and $t_m \in T$ with $n \neq m$ and an object Ω with an attribute space A and manifestations M. Then, if

$$\Delta(t_n, t_m) = \{\alpha_i \in A | M_i(t_n) \neq M_i(t_m)\} \neq \emptyset,$$

there was a change in manifestations for all $\alpha \in \Delta(t_n, t_m)$ between t_n and t_m and hence a change of object Ω. The change of an object is defined by the change of its attributes' manifestations across time. In other words, the change of every object that is subject to the time order scheme, can be defined as the dissimilarity between the object's attributes' manifestations at two different points in time. This also implies that $|\Delta(t_n, t_m)|$ is the number of changes in object Ω.

As an example, let's consider a newly manufactured automobile. At the time of purchase ($t_0 \in T$) the car's attribute "condition" ($\alpha_1 \in A$) exhibits the manifestation "new" ($\mu_{1_1} \in M_1$). After driving it for some time ($t_1 \in T$), the attribute "condition" (α_1) will change its manifestation to "used" (μ_{1_2}). We get

$$\Delta(t_1, t_2) = \{\alpha_i \in A | M_i(t_1) \neq M_i(t_2)\} = \{\text{condition}\} \neq \emptyset,$$

For the same attribute, the manifestation of the condition of the vehicle has changed. As the car is defined by its attributes and their manifestations it has changed respectively. This represents a generic definition of change that is also valid in the context of transformational change. To differentiate transformational change from other types of change, I will further analyze the term transformation.

2.2. Transformation

Transformation is a commonly used term across various scientific disciplines. In fact, it would be a difficult task to find an area of science in which no kind of transformation process appears. Scientists on mathematics, physics, biology and engineering use the term as do researchers from economic sciences, sociology, anthropology and linguistics. Due to the interdisciplinary nature of transformation it is not that manifest to find a generic definition. It would be obvious to define transformation by the quantity of change processes an object undergoes within a certain period of time, i.e. by $\Delta(t_n, t_m)$. However, in a world that is constantly subject to a countless number of incremental change, it is not practicable to define a quantity X that, if $\Delta(t_n, t_m) \geq X$ then a change is transformational.

While looking for a neutral definition of transformation in a common dictionary, you come across definitions like transformation is *"a marked change in form, nature or appearance"* or *"a thorough or dramatic change in form or appearance"* (Dictionaries, 2017). Most of these definitions have three things in common: (1) there has to be a change (2) that is significant and (3) has an impact on an object's core characteristics such as its shape, type or nature. I have already provided an explanation for (1) in the previous section. By having a closer look at the second and the third components, we can identify the subjective nature of the term transformation. While a change can be significant for one individual, it might not be for another. This implies that transformation depends on individually perceived characteristics. The subjectivity of the term makes general statements about transformation difficult. However, it is still possible to define different types of change by their basic (subjective) determinants. While quantity plays a role, transformation is not only a dependent of the number of changes. Transformation is also and in particular determined by

- the perceived relevance of a change by an individual or a group and
- the perceived degree of change by an individual or a group (Weik, 1998).

Following these dimensions provides us with a stringent logic to subjectively classify change.

In their famous model *"punctuated equilibrium"* for organizational transformation, Tushman and Romanelli (1985) differentiate incremental change vs. transformational change to facilitate a more precise definition of the transformation process. By mapping these two terms to the dimensions of perceived relevance and perceived degree of change as suggested above, we can define incremental change as a change that exhibits both a low perceived degree and low perceived relevance. Correspondently, we can define transformational change (which is a synonym to transformation) as a change with a high perceived degree and a high perceived relevance. In order to get the full picture, we can further define step change, which exhibits a high degree of change but low relevance and fundamental change, which represents a change with high relevance but a low degree. Figure 2.1 summarizes the four types of change and maps them to their deterministic dimensions.

The dimension quantity of change can also be incorporated in this framework. To find out if a set of multiple incremental, step or fundamental changes facilitate a transforma-

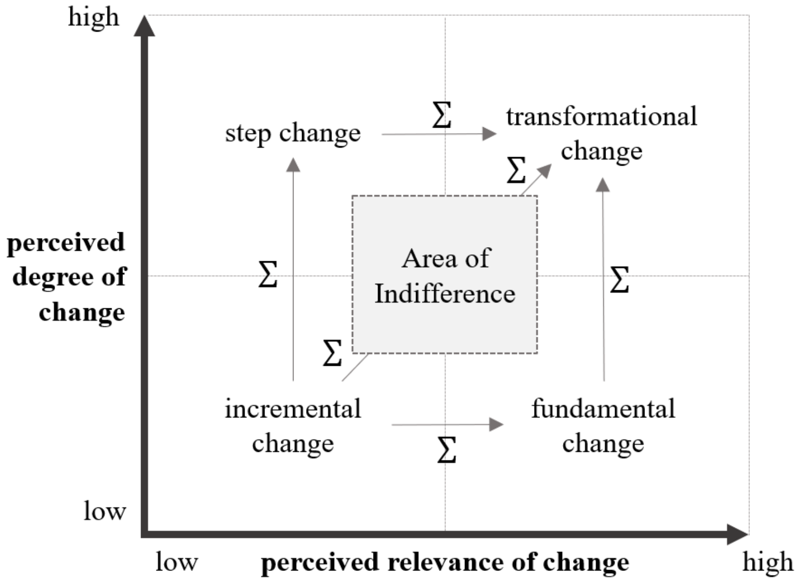


Figure 2.1: The Change Classification Matrix; own illustration based on Weik (1998) and Tushman and Romanelli (1985)

tion/transformational change, we can assess whether the aggregated change reaches a high degree and/or a high relevance respectively. In this way, we can combine any number and types of changes by simply summing up their impact and find out if they constitute a transformation. This simple but holistic framework can help us to draw a line between change and transformation. Due to the subjective nature of the determining dimensions relevance and degree of change, this has to be evaluated individually. This definition of transformation further implies that every transformation is a change, however, not every change is a transformation, which is in line with basic intuition. Additionally, change as well as transformation can be reversible, irreversible, permanent or temporary, which does not influence their identity as change or transformation.

In the next step, in order to get a better understanding of transformation, we have to zoom into the upper right quadrant of the matrix from Figure 2.1. Similar to the existence of different types of change, there is also a variety of different types of transformations, which can be distinguished to analyze the implications for the transformation process. In their work on transformation science, Kollmorgen et al. (2014) analyze the term transformation by considering perspectives from various scientific disciplines. The authors summarize their findings by presenting a taxonomy that characterizes transformation along five dimensions. The first dimension distinguishes between disruptive transformations resulting in a substantial modification and rather reforming transformations. The second dimension concerns the transforming object. It separates transformations affecting single objects from transformations affecting entire systems. By the third dimension, the authors polarize controlled and uncontrolled transformations. Fourth, a transformation can be short-term and

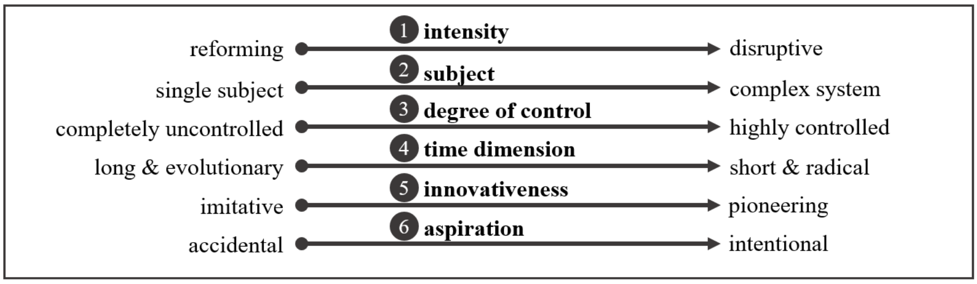


Figure 2.2: The Different Characteristics of Transformation; own illustration based on Kollmorgen et al. (2014)

radical or step-wise and of rather evolutionary nature. Fifth, transformations can exhibit an innovative vs. an imitative character. To incorporate the dimension of aspiration when classifying transformations, we can further classify by distinguishing accidental and intentional transformations. Figure 2.2 illustrates the resulting taxonomy of transformation.

Again, most of these dimensions are of subjective nature, which means that the use of this framework might show different results while being applied by different individuals. Despite the problem of subjectivity, we can use this framework to systematically describe each transformation along six distinct criteria. By assigning indicative values to an examined transformation, we can derive the characteristics of a transformation. In the following, we will have a closer look at transformations in a business and subsequently in a business digitalization context.

2.3. Digital Business Transformation

An insightful perspective on businesses describes the firm's general business architecture. It encompasses the different layers and components that constitute a business. The business architecture serves as a blueprint of the enterprise that provides a common understanding of the organization and is used to align strategic objectives and tactical demands. Irrespective of size and industry, there are certain elements you will find in each and every company. While there are several versions of presenting the components of the business architecture, Figure 2.3 presents them based on the suggestions by Ferstl and Sinz (2013) and Ullrich (2014).

All business components in the business architecture can be (and are frequently) subject to change as well as transformation. A transformation on the infrastructure layer is an infrastructure transformation, on the application systems layer an IT transformation, on the business process layer a process transformation and on the organizational layer an organizational transformation. All types of digital transformations in the business architecture

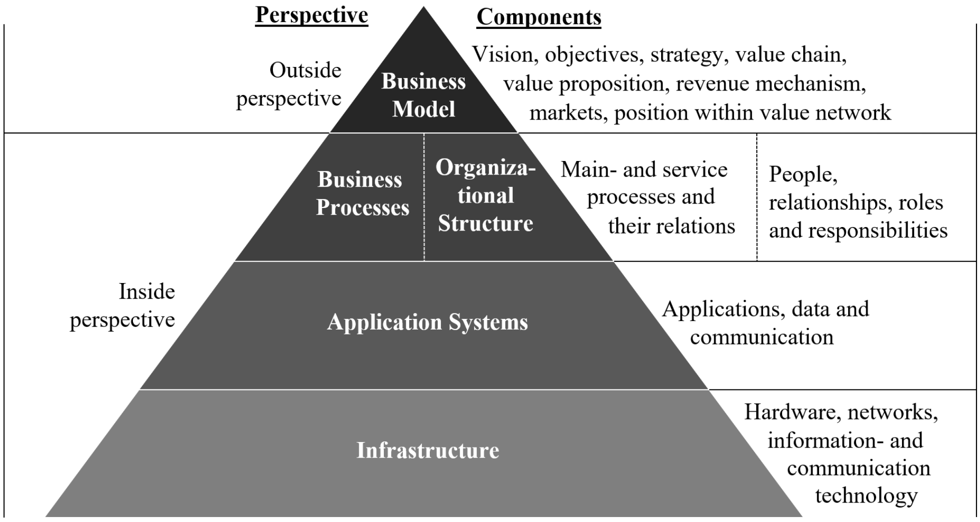


Figure 2.3: The layers of the business architecture; as presented by Ullrich (2014) and Ferstl and Sinz (2013)

can be referred to as digital business transformation. However, as this study is aiming to analyze investments in DTBM, in the following, we place our focus on the business model layer.

The business model represents the highest level of the business architecture. It represents the organization of the company from a strategic perspective. Osterwalder and Pigneur (2010) state it *"describes the rationale of how an organization creates, delivers, and captures value"*. Ferstl and Sinz (2013) argue that it represents the outside view on a business system. It formulates the vision, sets objectives and states the strategy to achieve them. Additionally, it defines the interfaces to the business environment and describes the connections and relationships with external parties. The business model is the determining factor of a company's core characteristics while lower layers in the business architecture are ideally aligned to enable the business model and implement its strategy in an economically viable matter. According to Gassmann et al. (2013) the different components of a business model can be summarized by the four questions *"who?"*, *"what?"*, *"how?"* and *"why?"*. The answers to these questions concretize the business model's customer segment, its value proposition, the value chain and the revenue model. Only a significant change in one or more of the answers to the four questions has the potential to shift a company's core characteristics leading to a business model transformation.

A prominent and promising way to achieve DTBM is BMI. BMI creates new logic regarding how a company creates or captures value by making changes in the components that constitute a firm's business model. Business models subsume a vast scope, multiple interdependencies and side effects (Gassmann et al., 2014b). In contrast to product or process innovation, BMI allows for additional innovation potential based on long-term strategic growth opportunities. However, despite well-known examples such as Apple's iTunes, Netflix's streaming service or Amazon's Kindle e-book reader, radical BMI remains to be elusive and highly risky. Therefore, transforming or innovating a business model remains a complex and challenging task.

Zott and Amit (2008) state that BMI can aim at differentiation or cost advantage, often unguided by principles or theory. It is about achieving strategic competitive advantage by replacing the combined elements of *"who", "what", "why",* and *"how"* involved in providing customers and end users with products and services (Mitchell and Coles, 2003). While product innovations are aiming to rethink what is done, BMI rather focuses on changing how it is done. According to a study by the Economist Intelligence Unit, the majority of CEOs favored new business models over new products and services as a source of future competitive advantage (Borzo, 2005). Moreover, over the period of five years, business model innovators are on average six percent more profitable than pure product and process innovators (Gassmann et al., 2013). BMI is often facilitated by technological innovations, which enable firms to organize and interact in new ways. However, business model innovators do not necessarily need to commit R&D investments to these technologies – it can also be achieved by deploying existing technologies in innovative ways (Amit and Zott, 2010).

We define DTBM as a radical BMI that is driven by digital technologies. It is directed at the company's vision, overall objectives or business strategy and affects a large number of stakeholders inside as well as outside the transforming organization and other entities in the business environment. Ultimately, DTBM can lead to a shift in a firm's core characteristics with the potential to revolutionize or disrupt traditional markets or business practices.

Chapter 3

Investing in Digital Business Transformation

This chapter presents an overview of investments relating to the digital and IT domains. First, we discuss the business value of IT and the business value of digital transformations of business models. Then, we distinguish different types of digital investments and digital business models and explain their differences. The chapter concludes by introducing the main types of risks and uncertainties that surround investments in DTBM, which will serve as the main motivation to present valuation methods that consider uncertainty.

3.1. The Business Value of Information Technology

In order to understand how IS/IT investments should be prioritized and chosen, there is the need for a sound understanding of the benefits of IT and its mechanics when influencing the overall business value of a company. Since the early 80s, loads of research has investigated the business value of IT. Numerous findings, frameworks and models on the influence of IT-based value on the business value have been developed. The most central questions in the discussion about IT business value are where and how IT-based value manifests itself. While some researchers place their focus on certain performance measures to capture IT-based business value (e.g. productivity (Hitt and Brynjolfsson, 1996), market performance (Tam, 1998), accounting performance (Bharadwaj, 2000), intangible benefits (Soh and Markus, 1995), others focus on the different levels on which IT business value reveals itself (e.g. process level (Bartel et al., 2007), firm level (Brynjolfsson and Hitt, 1996), project level, industry/competitive level, macroeconomic level customer surplus (Shih et al., 2007)). Additionally, there is a number of research on the mediating factors between IT and the business value (Davern and Kauffman, 2000; Weill, 1992) and the different types of business value that can be generated by IT (Alshawi et al., 2003).

Kohli and Grover (2008) summarize the most important research findings from this area as follows: (1) IT does create value. Several studies have proven a positive effect of IT investments on business value whether it is financial, intermediate (process-related) or affective (perception-related). (2) IT creates value under certain conditions. IT is simply bundles of hardware and software and cannot create value in isolation. In order to create value, IT has to be part of some business value creating process (which is usually the case when IT is applied in corporations). (3) IT-based value manifests itself in many ways. IT value can be observed at many levels (e.g., individual, group, firm, industry or process). Several frameworks and models exist, to identify the different areas of value manifestation within organizations (see, for example, Barua and Mukhopadhyay (2000), Davenport (1993), and Schryen (2010)). (4) IT-based value is not the same as IT-based competitive advantage. IT-based value has to be differential in order to lead to competitive advantage. (5) IT-based value could be latent. It usually appears with some kind of latency effect (time lag) before it can be observed. (6) Numerous factors mediate IT and value. There are several factors influencing the value of IT-based value before being transformed into business value. Some of them are IS strategy alignment, organizational and process change, process performance, information sharing, and IT usage. (7) Causality for IT value is elusive. Due to points (1) to (6) it is extremely difficult to capture and assign the full picture of the value generated by IT investments. Over the past 30 years, the core question has transformed from *"does IT create value?"* to *"how does IT creates value?"* (Mittal and Nault, 2009). This brings a pervasive difficulty to IS/IT capital budgeting, where it is necessary to find an objective (typically financial) indicator for investment decision-making (e.g. ROI).

The difficulties about IT-based business value can be divided in two sub questions: *"where does IT create value?"* and *"what is the IT value creation process?"*. To answer these questions, several frameworks that can help to understand the mechanics of how IT investments influence the overall business value of a company exist. A simple example is the benefit and value categories of IT investments as presented by Nagel (1991). The author names three distinct categories that can be influenced by investing in new IT solutions: (1) strategic competitive advantage, (2) productivity improvements and (3) cost savings. While cost savings manifest themselves on the operational layer and productivity improvements affect the tactical layer, strategic competitive advantage shows effect on the strategic layer of a company. IT investments are typically targeted at increasing one of these three categories, however, they can also simultaneously influence two or all of them, due to their strong interdependencies. To illustrate these relationships with an example, let's regard an automation technology investment that aims to reduce production downtimes and increase throughput. Successfully implemented, this technology will obviously lead to productivity improvements. If the productivity improvement leads to increased output with underproportionally increasing costs (or same output with decreased costs), the technology will also generate cost savings. Ultimately, if the cost savings are strong enough to enable underpricing of competitors, this will lead to strategic competitive advantage based on cost leadership.

In this context, the most intensively discussed type of value is IT-based strategic competitive advantage. While the impact of productivity improvements and cost savings is calculable, the value of strategic competitive advantage is somewhat harder to determine. Further, a number of researchers argue, that strategic competitive advantage can only be achieved under certain conditions. Zahn (1990) states that competitive advantage can only be achieved in combination with active strategic management. A further criterion for IT-based competitive advantage is the imitability of the applied technologies or the degree to which competitors can benefit from imitation. Brynjolfsson and Hitt (1996) find that, although IS investments do not lead to competitive advantage, they are necessary to maintain competitive parity. More recent research focusing on the resource-based view on IT-based competitive advantage find that its extent is highly dependent on the quality of IT capabilities, managerial skills and dynamic (learning) capabilities (Bhatt et al., 2005).

The most prominent source of IS/IT-based competitive advantage stems from so called Strategic Information Systems (SIS). SIS are information systems that either generate competitive advantage or prevent competitive disadvantage for companies (Krcmar, 1987). They are systems that support or shape a business's competitive strategy (Callon, 1995; Neuman, 1993). The competitive strategy is a broad-based formula for how a business is going to compete, what its goals should be, and what plans and policies will be required to carry out those goals (Porter, 2008). Investments in SIS can influence the competitive strategy in many ways. Typical dimensions are innovative applications, competitive weapons, changes in processes, links with business partners, cost reductions, relationships with suppliers and customers, new products or competitive intelligence (Wetherbe et al., 2007). These dimensions can also be influenced by DTBM investments. In order to create an understanding of the difference between DTBM and SIS investments, the next section further analyzes the relation between IS, corporate strategy and DTBM.

3.2. The Business Value of Digital Transformation of Business Models

SIS investments and DTBM are closely related and have a lot in common. A non-exhaustive list of their shared characteristics is their elusiveness, the existence of influencing factors on their resulting business value, and the variety of its different, sometimes latent, manifestations. Despite these similarities, DTBM and SIS investments must be clearly

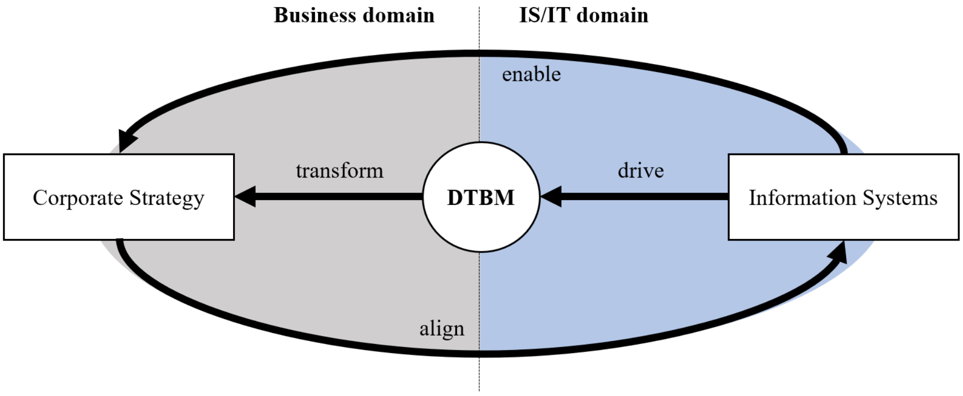


Figure 3.1: DTBM in the Strategic IS/IT Alignment Model; own illustration in extension of Krcmar (2015)

differentiated. DTBM exhibits some special aspects that will change the very nature of the related investment decisions. DTBM consists of SIS investments that have a strategic impact leading to a transformational change in the corporate business model. The two main aspects that should be discussed in this context are the substantial strategic importance of DTBM projects on a corporate level and the extent of risk and uncertainty that is related to these types of investments.

As we have learned, DTBM is directed at the business strategy, i.e. located at the business model layer of the business architecture. Similar to SIS investments, the business value that is generated by DTBM is typically based on strategic competitive advantage. We can say that it is the primary goal of DTBM to transform the existing business model to achieve sustainable strategic competitive advantage. While the category of DTBM-based business value is obvious, the question of how strategic competitive advantage is achieved is somewhat more complex. According to Porter (1979), competitive advantage is based either on cost leadership or on differentiation. Furthermore, in order to be sustainable, the aspect that constitutes the competitive advantage has to be hard to imitate or substitutable. Competitive advantage can lead to an increased market share, a better market position, first mover advantages, a more comprehensive value proposition, improved customer experience and retention, a more efficient value chain and others. Ultimately, these types of benefits will lead to rising revenues and profits. While SIS and DTBM are able to generate these types of benefits, a big difference between SIS-based and DTBM-based competitive advantage remains. This can be illustrated by regarding relation between IS, DTBM and corporate strategy. The strategic alignment model by Krcmar (2015) can help us to do so. A modification of the model is shown in Figure 3.1.

The corporate business strategy and its applied IS are closely related. On the one hand, IS can support the corporate strategy and on the other hand, they can also provide the opportunity for new strategies. IS are aligned to support the corporate strategy. If they present an option to enter into a new strategy, we can speak of enablement. In the digital economy and based on the changing role of IT, the distance between the business domain and the IS/IT domain is becoming increasingly narrow and the boarder blurrier. SIS investments are located on the right side, while DTBM is located at the very center of the enable-alignment cycle. DTBM is influenced by both the technology and the business domain. It is driven by new technologies for IS, and directed to transform the corporate strategy. While SIS investments increase competitive advantage through the new digital technology application, DTBM is based on simultaneous changes in both IS and the business model. Hence, digital business transformation investments must be seen as a hybrid form of IS/IT investment and business model transformation/innovation, which justifies for their transformational strategic impact. As a consequence, the strategic importance of DTBM typically exceeds the strategic importance of SIS investments. DTBM is typically more long-term, more business-driven and more multifaceted than SIS investments. Ultimately, DTBM means exploiting new digital technologies to create new SIS systems that engage transformational business model changes or innovations.

The hybrid nature of DTBM projects indicates that, in addition to the competitive advantage generated by SIS, the business value of DTBM encompasses an additional component: BMI. We can summarize that DTBM projects and SIS investments are different in some respects. DTBMs are interdisciplinary projects that require substantial investments with full impact on both IS and the business model. As DTBM directly (transformational) as well as indirectly (via new SIS) affects corporate strategy, it has a much higher strategic relevance than pure SIS investments. Due to this strategic nature, DTBM is more long-term oriented and has to be assessed over an extended time horizon. As a consequence of its relation to the rapidly changing digital world, its strategic importance and its extended planning period, volatility, risk and uncertainty play an important role in DTBM investments.

3.3. Types of Digital Investments

Investment is defined as the act of incurring an immediate cost in the expectation of future rewards (Dixit and Pindyck, 1994). DTBM projects are unique and can show diverse characteristics. In order to imagine the financing of a DTBM investment, its core characteristics have to be duly considered. Typically, investments in digital technologies lie at the core of each and every DTBM. In order to build a business model based on new technologies, infrastructures have to be built, hardware and software applications systems developed, implemented, tested and configured. The different types of IT investments can be clustered based on several different aspects such as the underlying technology, the investment purpose or the monetary outcome or impact. In their study on strategic IT investments, Ross and Beath (2001) suggest a purpose-based clustering of IT investments: renewal, process improvements, transformation and experiments. They characterize renewal as investments that maintain infrastructure's functionality and keep systems cost-effective. Process improvements are investments in business applications that leverage a firm's infrastructure by delivering short-term profitability based on increasing operational performance. Transformation investments are driven by core infrastructures that are seriously inadequate for the desired business model and therefore have to be aligned with the business strategy. Finally, experiments are IT investments, which test new technologies, new ideas for products or processes or new business models. This terminology does a good job in capturing the spectrum of IT investments. However, it is not in line with today's role of IT as a driver and disruptor of businesses as it does not incorporate highly strategic investments such as DTBM projects. Hence, in order to include IT-driven investments in business transformations, further investment types have to be discussed.

A more comprehensive approach to classifying IT investments is based on their goals: strategic investments with long term goals relating to competitive advantage, informational investments with medium term goals improving managerial decision-making, transactional investments with the goal of cost reduction and threshold investments to stay competitive, even if the ROI of the investment might be negative (Willcocks, 2013). This taxonomy includes strategic IS investments that are aiming at achieving competitive advantage. A similar approach is provided by Quinn (1992), who differentiates between cost-reducing and new product investments, infrastructure investments, and strategic technology investments. As the author summarizes cost-reducing and new product investments into one category, his classification consists of only three investment types. However, he includes strategic IS investments, which he defines as investments that either change the firm's basic position in the marketplace or ensure its very viability, which clearly points in the direction of DTBM investments.

Based on the these classifications, we can summarize three generic types of IS/IT investment as follows:

- ***Operational IS/IT investments:*** This type of investment includes renewal of infrastructure and applications to replace existing technologies to achieve cost reduction or because existing technology is dysfunctional, outdated, or no longer appropriate for the desired business practice;
- ***Tactical IS/IT investments:*** Investments in technologies with mid-term goals typically aiming to increase productivity, lead to improved managerial decision-making or stay competitive. These investments include investments in digitalization projects;
- ***Strategic IS/IT investments:*** Investments in new technologies that enable or

drive the modification of the business strategy of a firm; these investments are aiming to achieve long-term strategic competitive advantage by investments in strategic IS and non-transformational as well as transformational digital change in the business model.

This typology, combines the thoughts of the priors. While operational and tactical investments cover the traditional IT investments on the process, application and infrastructure level, the strategic IS/IT investments also include investments affecting the firm's strategic business layer. This type of investment is closely linked to its business value. It is important to be able to distinguish between the different types of investments as they have entirely different goals and exhibit entirely different characteristics. DTBM is driven by strategic IS/IT investments. However, often there are also tactical or operational IS/IT investments necessary to successfully transform the business. In most cases, when implementing new strategic IS, infrastructures have to be adjusted, processes digitized and operating procedures changed. Additionally, when engaging in DTBM, further non-technology investments will be required. DTBM projects are large-scaled business transformation initiatives with an impact on the entire enterprise. The types and scale of investments are highly dependent on the particular project. However, besides investing to realize the technologies that enable a transformation, investments in R&D, applied personnel, external consultants, marketing and promotion costs, licenses and others to pave the way for successful transformation might be necessary. To decide on a full transformation project, the big picture of all required investments has to be evaluated. For this reason, DTBM cannot be considered pure IS/IT investments when it comes to decision-making and capital budgeting.

3.4. Types of Digital Business Models

After having discussed the investments that are necessary to establish or transform digital business models, in this section, we provide a generic overview of the different business models that can be frequently found in the market. As financial performance measures are highly dependent on monetization strategies, i.e. how a business makes money, we place the focus of our analysis on this dimension.

In accordance with technological developments, new types of business models have emerged as a direct result of the increasingly digitized economy. In contrast to traditional asset-based business models that are built around linear value chains, the class of digital business models is typically based on digital products or services offered, advertised and distributed via digital channels such as online platforms in concurrence with mobile applications. Veit et al. (2014) state that a business model is digital, if changes in digital technologies trigger fundamental changes in the way business is carried out and revenues are generated. Weill and Woerner (2013) define the digital business model as a blueprint that describes how firms engage their customers digitally to create value, via mechanisms such as websites or mobile devices. In recent years, we could witness strong economic success and a global spread of these types of businesses that understood to quickly branch out into all corners of the consumer's life and establish itself there as a new staple. As a consequence, successful innovators such as Amazon, Google, Microsoft, Apple, Uber, Airbnb, eBay or Salesforce that have only existed a few decades, are now among the most valuable, innovative and proliferous companies in the world.

Regarding the different types of digital business models, Moazed and Johnson (2016) distinguish linear digital business models and digital platforms. Linear businesses models describe the standard way of doing business, based on a linear value chain. The company acquires information or material, holds control of it, transforms it into some product and then sells it. Thus, value is added throughout a linear process. In contrast, platform businesses function within their matrix as an intermediary between one or more groups of producers and consumers. Digital platforms are systems that facilitate interaction between different types of users and do not create any of the products or contents that are exchanged on their platforms. In other words, these businesses simply provide the infrastructure to enable efficient matchmaking between producers and consumers while frequency, efficiency and value-add of transactions are at the core of value creation. It is therefore the allegory of the commercialization of multilateral networks linked to digital platforms: The product is the connection of individuals, who then engage in the exchange of classic commodities, information or services.

In brief, linear digital business models are ways to distribute services or products, which are produced or provided by a single producer, who distributes its services or products via digital channels. On digital platforms, products, content or services are produced or provided by a large number of supply-side users, who are independent of the platform provider. It is noteworthy that platform users can represent a homogeneous group, driven by similar purposes and convictions (e.g. social media and dating platforms) or a heterogeneous group of producers and sellers with opposing interests in the facilitated transaction (e.g. drivers and passengers with Uber, landlords and tourists with Airbnb).

Recent literature evidences several attempts at a classification of a variety of different types of digital business models. For example, Bock and Wiener (2017) provide a comprehensive taxonomy of digital business models, analyzing existing models along five distinct dimensions. As our study places its focus on financial aspects and corporate valuation, it is further essential to distinguish digital business models in regard to their approach to monetization. Revenue mechanisms describe how digital businesses earn money. Several

Table 3.1: Overview of Digital Business Models

	Monetization	Description	Typical examples
Linear Digital Businesses	Subscription-based	Products & services are created or acquired by the company and provided to the customer, who pays a fixed subscription fee.	Netflix
	Freemium	Products & services are created or acquired by the company; there are two different versions of the product; a standard product for free users and a superior product for premium users; often these companies include ads to generate additional revenue streams from free users.	Spotify
	Transaction-based	Products & services are created or acquired by the company; the company offers, sells or grants temporary usage of the product for a certain fee.	Software as a Service such as Salesforce, car sharing companies such as ShareNow
Digital Platforms	Free	Contents are not owned by the platform; access to and usage of products and services are free; revenues are generated by secondary revenue streams such as integrated ads, offerings by third parties or commercialization of user data.	Social media platforms such as Facebook and Instagram, Messaging services such as WhatsApp and Line
	Premium	Contents are not owned by the platform; access to and usage of the platform are granted for a fixed subscription fee; often only the producers are charged while consumers can access for free.	WooCommerce, Shopify
	Freemium	Contents are not owned by the platform; a standard product for free users and a superior product for premium users is offered on the platform; often ads are included to generate an additional revenue stream from free users.	LinkedIn, Dropbox, Skype, Tinder
	Transaction-based	Contents are not owned by the platform; many producers offer their products and services to many consumers on the platform; the platform provider typically earns a fee for every successful transaction.	Airbnb, Uber, Amazon, PayPal, eBay, Alibaba

typical approaches can thus be frequently found in business practice. In both, linear as well as platform business models, there are subscription-based, freemium and transaction-based business models. Sometimes, we can also find hybrid monetization mechanisms. Table 3.1 provides a high-level typology of the different types of digital business models with regards to monetization. Understanding the major differences between these models is important to facilitate further discussions about their valuation.

A major difference between linear digital business models and digital platforms is that the value provided by linear digital business models is typically contained in the very object that is sold to consumers. In contrast, the value provided by digital platforms is typically related to direct transactions between users and highly dependent on so-called network effects within the matrix. Network effects describe the phenomenon that a large number of users increases the value to potential new users. It is a self-perpetuating mechanism that explains the rapid, sometimes exponential growth of these platforms, in some cases, such as e.g. Facebook and Amazon, even amounting to almost as much as a social obligation of the user. In other words, an increasing number of producers will attract an increasing number of consumers and vice versa. Furthermore, the very act of consuming will make it more likely that producers join the platform to add additional value. Thus, the more participants are in the system, the more valuable are its products or services for users. This phenomenon describes a ripple-effect, which illustrates the scalability of such business models – we have seen examples of it resulting in an upward spiral that leads to exponential user growth. Network effects can also explain the winner-takes-it-all phenomenon, which is, for example, comprehensively discussed by Moazed and Johnson (2016) and responsible for the global monopolies of successful digital platforms such as Amazon, Google and Facebook.

From a managerial as well as investors' perspective, digital business models have further crucial advantages over traditional asset-based business models:

- ***Almost unlimited scalability:*** Digital businesses sell digital products and services or provide digital infrastructures for frictionless transactions, using technologies such as the internet and the cloud. As a result, growth is not limited by physical boundaries or limited human or material resources and products or services are instantly and infinitely multipliable. Typically, this type of progressive geographic expansion by entering into new markets does not require a significant amount of additional investments.
- ***Extremely low marginal costs:*** Similarly, selling more digital products or increasing the number of users do not result in significant additional costs. A digital business model's cost structure gets more efficient with increasing scale. Especially for digital platforms, cost of goods sold are proportionally much smaller than for traditional businesses. Major cost factors are typically represented by fixed costs including overheads such as general administrative, IT, and marketing expenses. In the case of digital business models, the number of users hardly influences the amount of expenses necessary for the maintenance of the digital infrastructures. As a consequence, large digital companies can invest most of their cash for customer acquisition and R&D to complement network effects and further drive growth.
- ***No physical proximity to customers:*** Digital businesses can simply achieve global reach via digital distribution channels and the internet. Irrespective of location and regional footprint, digital companies can compete on a global scale. Digital products and services can be advertised and distributed globally to any customer online at anytime and anywhere with close-to-zero transactional friction.
- ***High-paced innovations:*** Digital companies can easily test and roll-out new prod-

ucts, product versions or ideas without facing the hurdles of classic business models, which are entangled in a strife to balance costs, resources, staff and other real-life anchors. Congruously, the time to market is extremely short. Typically, innovations follow an iterative lean startup-like innovation cycle that maximizes learning and increases efficiency. Prototypes can be instantly tested with customers and results analyzed and fed back into the system in real-time. Artificial Intelligence helps to process huge amounts of data and to derive appropriate responses to new developments. Additionally, as digital businesses typically collect massive amounts of user-related data, informed managerial decision-making can happen at unprecedented reaction times, capitalizing on the high potential of transparency and automation. Detailed user profiles are created and analyzed and additional revenue streams such as monetizing user data with third parties, introducing targeted and personalized marketing strategies and a huge cross-selling potential are just some decisive advantages of the new data-driven digital company.

- ***Strategic growth options:*** A large part of value of digital businesses stems from their users and the data that are not on the balance sheet. When growing beyond the critical mass, these companies typically face additional data monetization options as their user base snowballs due to the network effects described above, ultimately resulting in a winner-takes-it all scenario. While digital products, services or infrastructures are easy to imitate, sustainable competitive advantage is achieved by a large self-sustaining user base that attracts new users who might, in addition, even become customers of future business opportunities.

Despite some typical advantages of digital business models such as almost unlimited scalability, no physical proximity to customers, extremely low marginal costs and the existence of network effects, there is a threat of overvaluation of these companies, which became palpable for the first time when the dot-com bubble burst in 2000. Today, many finance experts are – again – warning about the high market valuations of these companies, as they typically report razor thin profits and market value is not backed by a reasonable amount of real assets. Thus, most of the equity value of these firms must stem from intangibles such as users, data, network effects and related growth options that are not disclosed with financial statements. This is a strong indicator that managers and investors have started to lose their trust in traditional financial performance measures such as price-earnings ratios, return on assets (ROA) or book-to-market (BtM) values, which often lack explanatory power for shareholder value of digital enterprises. Consequently, some experts demand regulators to impose the disclosure of additional user-based performance measures such as churn rates or purchase behavior, in order to increase transparency and the understanding whether high market valuations are justifiable (e.g., Wiesel et al. (2008), Chakravarty and Grewal (2011), and Bonacchi and Perego (2019)).

Another concern about the value of digital businesses is that these companies are typically subject to high levels of uncertainty, as they are easy to imitate or copy, which makes it difficult to build sustainable competitive advantage. Moreover, even strong network value of digital platforms cannot ensure stability: Once there is a more attractive offering in the market, users will start to flee creating some sort of a downward spiral induced and aggravated by downside network effects. Some key advantages of these new digital business models can therefore also function in reverse, making the industry highly volatile to unforeseeable trends. Thus, business models with strong network effects tend to grow faster but also shrink faster which results in highly volatile stock returns and substantial risk when investing in these companies.[3]

3.5. Uncertainties Surrounding Investments in Digital Transformation of Business Models

DTBM includes both BMI and the creation of new strategic IS. Both approaches can be especially valuable in times of instability. However, according to Boutetière et al. (2018), 84% of digital transformation projects fail. BMI as well as strategic IS creation involve hefty investments, high levels of uncertainty, complexity and, inevitably, risk (Taran et al., 2015). While the potential business value of DTBM can be enormous, these projects are highly risky. Risk relates to the uncertainty of outcome (Chapman and Ward, 2003). It can be seen as a threat to the success of a project leading to the stochastic nature of its financial results. We cluster the major risk factors of DTBM in three groups: (a) business strategy-related risk, (b) technology-related risk, and (c) implementation-related risk, all playing a critical role in the success of DTBM projects.

The business strategy-related risk inherent in DTBM reflects the level of success of the business strategy itself, based on market dynamics, enterprise dynamics and timing. Business strategy risk focuses on the long-term risk surrounding competitive strategy and change in the market environment due to changing supplier-customer relationships, political realignments and demographic or regulatory trends (Parker, 1995). They include several different business aspects. Strategic investment decisions, such as BMIs, affect the entire enterprise. They are long-term oriented and subject to the highly volatile business environment. Long-term investment decisions in a VUCA world are by nature highly risky. Projections of future customer needs and competitive actions have to be conducted in order to assess the potential of BMI in DTBM. Estimating the costs and benefits of business model transformation is ex-

[3]A prominent example for the threats of such developments is the social media platform Myspace. Myspace used to be the leading social network worldwide. However, the eroding quality of its network in conjunction with the market entry of Facebook led to a rapidly decreasing number of active users and the loss of its biggest competitive advantage: its network value.

tremely difficult. Competitors might develop businesses or release solutions that disrupt the desired business model. Moreover, customer needs may change or develop in different patterns than expected. Especially in case of entirely new markets, estimating profitability is extremely challenging, as there are no comparables in the market and no historic data exists. Business strategy risk in DTBM is substantial and due to its exogenous nature, mitigation opportunities are limited. Business strategy risk can result in uncertainty over revenues as well as costs, which are the main determinants of a project's profitability. Sophisticated anticipation of future trends, developments and decision-path flexibility is essential.

Technology-related uncertainty in DTBM refers to choosing and implementing the technologies that should drive the desired business model transformation. The choice of the right technologies is one of the key success factors in DTBM. It comprises the typical dimensions of risk in strategic information system investment decisions. In this context, one of the core considerations will be the solutions and infrastructures that are used to implement a certain technology with the company. In the digital economy, it is difficult to foresee the long-term persistence of certain technologies. Usually, there are several alternative IT-solutions with individual advantages and disadvantages. When investing into emerging technologies such as the IoT or 3D-printing, it is not clear, which of the existing technologies will be the dominant solution in the future. Another technology-related risk is determined by the build-or-buy decision. There is the possibility to self-develop the required technologies with the in-house R&D or IT departments, which typically requires high up-front investments, comprehensive technological capabilities, and further (R&D-related) risks. On the other hand, buying the required technology from third parties might lead to a lock-in effect resulting in increased dependency and long-term inflexibility. Further IT-related risks in DTBM relate to IT scalability, compatibility, security, integrity and availability. IT-based risks are partially exogenous (technological progress) and endogenous (technology deployment). Due to their partially endogenous nature they are easier mitigate than business-related risks. However, a team of experienced IT-experts has to be in place to identify and actively mitigate technology-related DTBM risk.

While business strategy-related risks reflect exogenous risk factors, *implementation-related risks* and uncertainties have an internal enterprise focus. In DTBM, managing business transformation means anticipating and adapting process designs, organizational structures, incentives and rewards, cultural practices, and the skill-set, attitudes and ultimately the work behavior of employees (Gibson, 2004). Implementation-related risks are based on the required change processes within the organization. A recent study has found that most change-related risks do not lie in strategy development but in execution (Half, 2016). 84% of digital transformation programs do not meet their goals, mostly due to people or change management-related issues (Rogers, 2016a). Hence, even in case of a promising business strategy and functioning, cutting-edge technologies, transformation projects have a high probability to fail in the execution stage. To mitigate these risks, effective change programs and enterprise-wide communication must lie at the core of DTBM execution management. Thus, the chance of success of such projects can be best increased by developing a dynamic and innovation-friendly corporate culture that comprises highly skilled human resources that can represent both, technical skills and strong business acumen.

The extent of risks and uncertainties surrounding DTBM, indicates the need of special treatment of related investments. While there exist vast research papers and best practices on idea generation and digital transformation project management, literature is lacking suitable quantitative frameworks to support managers in the investment decision process. However, existing literature indeed provides the different building blocks that are required to construct such frameworks. In the following, we summarize some of these building blocks and subsequently present a generic model that is able to evaluate DTBM projects and help managers to find the right investment decisions in high-uncertainty situations.

Chapter 4

Managerial Investment Decision-making

4.1. Traditional Approaches

Managers regularly evaluate competing actions and strategies with impact on their companies' business value. In the corporate objective function, it is an overarching goal to increase the overall business value. Managing business value is a complex task that brings many dimensions to capital budgeting. The shareholder value approach emphasizes that social welfare is maximized, when all firms in a society maximize their own firm value (Jensen, 2001). This approach is about maximizing the firm's market value, while shareholders are residual claimants. Shareholders are mostly interested in the company's overall performance, i.e. the numbers, which provide a straightforward guideline for managerial decision-making. In theory, investments are only made if they would increase the overall business value of a firm. Investment criteria are usually expressed by so called key performance indicators (KPIs) such as the ROI, the NPV, the Internal Rate of Return (IRR) or Economic Value Added (EVA).

IT investments take a large share in DTBM-related investments. Assessing the business value of existing IT is crucially different from assessing the business value of new IT investments. There are two distinct approaches to measuring the business value of IT: post-investment and pre-investment. In the post-investment situation, measuring the value of IT is basically about assessing the business value of current systems and technologies by observing and determining their performance gain with the company. Measuring the value of existing systems is observable and typically calculable. Additionally, often there is the opportunity to execute before and after comparisons by reviewing past investments to define the value-add of the respective technologies. Unfortunately, this straightforward approach is not applicable in capital budgeting problems, as the investment decision process predates the investment. In contrast to the post-investment perspective, assessing the value of IT pre-investment is more complex. This situation basically requires sophisticated estimates of the expected benefits and the expected expenses associated with a project. Decision makers have to weigh up these numbers across a certain time period and benchmark the results with the respective investment alternatives. As ascertaining the business value-add of the investments is based on expected values, investment decisions are always subject to a certain level of risk and uncertainty.

Often depending on the type of investment, managerial decision-making in capital budgeting is typically made based on value captured by some performance metric. For instance, in IT investment decision-making Business Case Analysis (BCA) is the dominant approach among companies. Ward et al. (2007) found that 96% of European companies use BCA to justify for funding of their IT investments. The authors state that, besides justifying for funding, presenting expected costs and benefits of a potential project in a sound business case has further advantages, that should not be neglected:

- It enables priorities to be set among different investments for funds and resources,
- it identifies how the combination of IT and business changes will deliver each of the benefits identified – resulting in a benefit realization plan,
- it ensures the commitment from the business managers to achieving the desired investment benefits,
- it creates a basis for review of the realization of the proposed business benefits after completion of the investment.

Based on the estimated costs and benefits over the regarded time period (typically three to five years), the net benefits are calculated for every single time period. After the calculation of the net benefits, the key financial metric (or KPI) can be calculated. This metric provides a statement about the profitability of an investment capturing the result in one single standardized number to make it comparable to alternative choices. There are several financial metrics that are frequently applied in investment decision-making, aiming at providing a statement about the profitability of an investment by summarizing their expected profitability in a single metric. In practice, the main methods of valuing such investments are the NPV, the IRR, the ROI and the Profitability Index (PI) (Willcocks, 2013). Bacon (1994) concludes that 75% of companies use some form of DCF or NPV techniques in selecting their large-scalded IS/IT projects. Today, these traditional techniques are still widely applied to value a broad variety business cases and derive investment decisions.

The NPV method is a discounting technique that takes the future expected cash flows and the related expenses back to their value at commencement of a project. It is the most dominant capital budgeting technique in business practice across all major industries. The respective discount rate is typically reflected by the company's weighted average cost of capital (WACC). The WACC is the average of the company's cost of equity and cost of debt weighted by the current equity to debt and debt to equity ratios. The NPV can be calculated as the value of the discounted cash flows minus the value of the discounted investment outlays over the entire lifetime of a project. Normally, in case of several investment alternatives, the project with the highest NPV will be adopted. In case of only a single investment opportunity, the project will be adopted if its NPV exceeds zero.

Additionally, as the cash flows from the business case are estimated, sophisticated models will use probabilistic cash flows (i.e. based on Decision Tree Analysis) combined with scenario and sensitivity analysis to find an investment decision. For standard IT-investments with a moderate level of cash flow and cost uncertainties and a limited life-time of three to five years, this approach seems to present sufficient insights to make the right investment decisions. In regards to DTBM projects, however, the substantial degree of uncertainties over cash flows induces the need of more sophisticated models. Related investments are more long-term, have a higher strategic relevance, a large impact on the entire enterprise and, ultimately, a high degree of risk and uncertainty limiting the applicability of traditional techniques.

4.2. Real Options Analysis

There are several standard investment decision models in corporate finance theory including NPV, IRR, ROI, PI techniques, see Copeland and Antikarov (2001), for example. These methods are very commonly used for technology investments. However, they do not suffice in coping with high levels of uncertainty, as they do not capture managerial flexibility, neither before nor after an investment is made. In general, the higher the uncertainty, the higher the value of managerial flexibility. Hence, traditional methods systematically undervalue projects in situations of high uncertainty (Trigeorgis and Mason, 1987). Especially in the domain of DTBM, applying standard valuation methods may lead to wrong investment decisions, i.e. investments that do not maximize shareholder value.

Managerial flexibility can be expressed as the existence of several different real options related to leeway during or following investment decisions. The term real options was first coined by Myers (1977). Since the 1970s, a large number of papers have addressed the importance of managerial flexibility. Baldwin (1982) examines sequential investment strategies and inter-dependencies with future investment opportunities. Myers (1984) considers strategic investment opportunities as growth options, while Kester (1984) discusses qualitatively strategic and competitive aspects of growth opportunities. Dixit and Pindyck (1994), Trigeorgis and Mason (1987), Trigeorgis (1995), Trigeorgis (1996), and Sick (1989), and many others, discuss a variety of corporate options and provide various expositions of the real options approach to investment.

In IS research, several studies propose the use of real options theory for IS/IT investments, with early adopters being Benaroch and Kauffman (1999), Clemons (1991), and Dos Santos (1991) and Venkatraman et al. (1993). Over the years and with the growing strategic relevance of IT, literature has provided a variety of models and applications to value managerial flexibility in IS/IT investments. For instance, Angelou and Economides (2008) use ROA to prioritize a portfolio of IT projects with interdependencies to follow-up projects of a water supply and sewage company. Balasubramanian et al. (2000) apply the idea of real options with the implementation of a document imaging software in a Canadian mortgage bank. Ekström and Björnsson (2005) value the growth option to extend the purchase of an enterprise resource planning software by additional functionalities in the future, and Li (2009) values the option to defer an investment in new technologies considering organizational learning. On a more strategic level, Hallikainen et al. (2002) use ROA to assess strategic investments in web content management systems and Angelou and Economides (2009) value a compound real option to strategically evaluate different IT-related business paths. While a large number of papers address the phenomenon of managerial flexibility in strategic IS/IT investments, most research is focusing on valuing investments in single technologies to achieve cost efficiency or productivity improvements. However, to our knowledge, few research exists that investigates or applies real options techniques to the interdisciplinary nature of DTBM.

Traditionally, management will decide to invest in the transformation project in case the NPV is positive and reject the project in case it is negative. However, real options theory has shown us that this rule can lead to wrong investment decisions in situations of high uncertainty. Investment decisions typically share three important characteristics in varying degrees: irreversibility, uncertainty, and timing (Dixit and Pindyck, 1994). Investments in DTBM are at least partially, sometimes entirely, irreversible. Timing of these investments is especially important, as the digital economy is characterized by rapid technological developments, changing customer needs and frequent market redefinitions. Additionally, we have shown that DTBM projects are highly strategic, risky, time-intensive and expensive. All these characteristics indicate the value of learning from experimentation associated with these projects is significant, and hence bears the potential to shift traditional NPV-based investment decisions.

There are many similarities between real options and financial options, both granting the right, but not the obligation, to take a pre-defined action at a pre-determined cost (the exercise price) within a certain period of time (the maturity of an option). Therefore, valuation methods for financial options are often applied for valuing real options respectively. Generally, as with financial options, there are five major factors influencing the value of a real option:

- The NPV of the project's cash flows (stock price S),
- the investment expenditure (exercise price X),
- the length of time over which a decision can be deferred (time to expiration T),
- the time-value of money (based on the risk-free rate of return r_f),
- the riskiness of the project's cash flows (its volatility σ) (Luehrman, 1998a).

The motivation of option pricing in capital budgeting arises from its potential to properly quantify the option premium or flexibility component of the project value. Real Option Analysis should not replace static NPV analysis; rather, it should expand the traditional NPV approach to include the strategic component of managerial flexibility into capital budgeting and decision-making. Using the real options approach in capital budgeting will leave us with the following expanded NPV rule (Trigeorgis, 1996).

Expanded (strategic) NPV = Static (passive) NPV + Option Premium

This established, there are several options in the setting of capital budgeting for DTBM. In practice, once an investment is made, managers have the flexibility to expand, contract, abandon a project, or launch follow-on projects. Additionally, there is flexibility with regard to the timing of an investment, i.e. the option to defer an investment. In this section, based on the summary of Trigeorgis (1996), I will name and briefly explain the most important real options in capital budgeting situations. Additionally, I will explain their role in and highlight their importance for decisions about investing in DTBM projects.

Option to defer: When applying standard models such as the NPV for capital budgeting situations, investments are now-or-never decisions. Either the investment is realized now (typically if NPV $>$ 0 or exceeding the alternative investments' NPVs) or it is not realized at all. However, in practice, there is the option to wait, i.e. the option to defer an investment. With an option to defer, management holds a claim on (or an option to buy) certain resources. It can wait x years to observe how technologies, competition and the market develop. Management will invest the outlay I_1 (i.e. exercise its option to invest in DTBM) only if the related technology and business model proves to be successful, otherwise it will not commit to the project. Just before the expiration of the claim, the investment opportunity's value will pay $\max(V - I_1, 0)$ while V is the value of the underlying project. The option to defer is thus analogous to an American call option on the gross present value of the completed project's expected cash flow, with an exercise price equal to the required outlay I_1. Since early investment implies sacrificing the value of the option to wait, this option value loss is like an additional investment opportunity cost, justifying investment only if the value of cash benefits actually exceeds the required outlay by a substantial premium.

In DTBM, the option to wait can be valuable due to the related resolution of technology- and business strategy-related uncertainty over time. This is based on three main factors. First, managers can defer a DTBM project in order to collect more information about the developments in related technologies. Emerging technologies are always risky to some extent, as industry standards are usually non-existent (e.g. IoT) in early phases of new technologies. Hence, with growing maturity of a technology, the related uncertainties will decrease. Second, managers can yield more time to observe competitive actions. Early adopters of technologies or innovative business models are always exposed to higher risks than followers. To defer an investment might provide information about how competitors try to exploit novel technologies or innovate business models with their companies. Third, trends and developments in the market, such as customer needs, will become more evident with time. The uncertainties in anticipating market developments will decrease respectively. However, in today's rapidly changing business world, digital transformation requires speedy decisions. Hence, in DTBM, deferring an investment might come at some cost with a reducing effect on the value of the option to wait.

Time-to-build option: The time-to-build option describes the staging of investment as a series of outlays that create the option to abandon the project if new information received is unfavorable. Each project stage (e.g. infrastructure building) can be viewed as an option on the value of subsequent stages and valued as a compound option (an option on an option). This option is especially valuable in high uncertainty, long-term projects, such as in R&D, for new startup ventures and, similarly, in DTBM. Similar to the option to wait, the value of this option lies in the effect of passing time that resolves uncertainty. The all-or-nothing decision from traditional capital budgeting techniques is abrogated. A simple example in the context of DTBM could be the building of the required technological infrastructure to undergo a DTBM. After this project stage, management can observe the functioning of the technology within their company and may receive additional decision-relevant information about the business environment. If new information is deemed unfavorable, management can default the project at any project stage instead of investing additional outlays to continue an unprofitable project.

Option to alter: If market conditions turn out to be more favorable than expected, the firm can expand the scale of the project or accelerate resource utilization. Conversely, if conditions are less favorable than expected, it can reduce the scale of the project or, in extreme cases, halt and relaunch the project. Due to the strategic nature of DTBM and its dependence on the business environment, market conditions are a critical success factor. The option to adjust the intensity and scale of the project to the development of market conditions can be extremely valuable. This option does not only refer to the investment and implementation phase of the project but also to the degree of operations of the resulting business. The option to alter can be divided into two cases: the option to expand and the option to contract. If market conditions are better than expected, management can accelerate the rate or expand the scale of operations by incurring a follow-on cost (I_E). It resembles a call option to acquire an additional part of the base-scale project, paying I_E as exercise price. The overall project value can then be described as the base-scale case plus the call option to expand investment, i.e. $V + \max(V - I_E, 0)$. The option to expand is especially important in DTBM as it gives management the strategic opportunity to capitalize on future growth opportunities or launch trail projects. Further discussions about and applications of the option to expand will be presented in the next chapter.

If market conditions turn weaker than originally expected, management can operate below capacity or reduce the scale of operations, thereby saving a part of the planned investment outlays (I_c). This is the option to contract that can mitigate loss analogously to a put option on the reduced part of the base-scale project. The exercise price will then be equal to the potential cost savings I_c, giving $\max(I_c - V, 0)$. The extreme case of the option to contract is the option to shut down and restart operations. If market conditions lead to a loss resulting from ongoing operations, it might be sensible to halt operations and restart at a later, more favorable point in time. In this case, operation in each year may be seen as a call option to acquire that year's cash revenues (C) by paying the variable cost of operating (I_V) as exercise price. We get $\max(C - I_V, 0)$. These options can have substantial value in DTBM, because it is related to the introduction of new businesses in highly uncertain immature markets.

Option to abandon: If the project develops in an extremely negative way, management holds the option to abandon a project and sell its capital equipment and other assets to the secondhand market. In practice, it is not necessary to continue unsuccessful projects with negative profit margins. Although most investments are at least partially irreversible, there might be the opportunity to free some cash based on divestments. This option can be valued as an American put option on the project's current value (V) with an exercise price the salvage or best-alternative-use value (A). Management can receive $V + \max(A - V, 0)$ or $\max(V, A)$. This option is especially valuable in investments with high capital expenditures in non-special purpose assets. For DTBM, the value of this option is rather limited, as customized technologies as well as partially built business models usually cannot be divested on secondhand markets.

Option to switch: The option to switch describes the flexibility to change inputs or outputs of a project based on market conditions. For instance, an oil refinery can be designed to use alternative forms of energy, such as fuel oil, gas or electricity. Depending on the prices of input factors, these refineries can switch their input factors. This can lead to investments in more expensive technologies that can provide this built-in flexibility. In both cases the option can be seen as an American put or call option with the value of the cost savings or profit gains from switching inputs or outputs. The resulting switching costs are the exercise price I_c. The project value can be viewed as $V + \max(V_C - I_C, 0)$, while V_C is the adjusted value of the project's cash flows based on the new input or output factors. While there might be substitutable input factors in DTBM, the more relevant option to switch may be related to the project's outputs. If a company develops a business model that might lead to better results applied to different markets than initially planned, there is the opportunity to switch to design products that sell on more profitable markets. For instance, once the infrastructure for 3D printing is built into a company, it has the potential to be applied in other ways (and for other products) than initially planned. This is especially relevant for markets with volatile prices and/or demand. This option is closely related to the category of growth options, describing long-term strategic opportunities.

Growth option: Corporate growth options set the path for future opportunities and are of considerable strategic importance. They can be seen as inter-project compound options (options on options for future projects) that can open up future business opportunity windows including new products, processes, access to markets, strengthening of core capabilities, etc. Growth options lie at the core of strategic investment decisions and of what is intended to be achieved by DTBM. They are extremely valuable in early projects that derive their value not so much from their expected directly measurable cash flows as from the future growth opportunities they may unlock. These options do frequently justify for investment in negative NPV projects, as they generate the infrastructures, experience, potential by-products and ultimately competitive advantage. Without these investments, future business in new markets might not even be feasible. An example suitable for the DTBM setting is the introduction of big data and data analytics software for predictive maintenance in the firm's production sites. These investments are typically cost intensive and do not generate directly measurable cash flows. However, once the infrastructures and know-how on data mining and knowledge discovery is built-up and implemented within the company, the concepts can be applied to other business functions, such as customer relationship management, strategic business forecasts, or built into new high-tech products.

Multiple interacting options: Financial strategy can be regarded as a portfolio of real options (Luehrman, 1998b). In real-life projects, several different options are inherent in investment decisions. Upward-potential enhancing as well as downward-protection options are present in combination. Their combined value may differ from the sum of their separate values; i.e., they interact. For example, the value of the option to switch is zero if the option to abandon has been exercised. In DTBM, most important factors of managerial flexibility are the option to wait, the time-to-build option, growth options and the option to expand. These options can considerably influence a project's value and have the potential to shift investment decisions. In extreme cases, option values can justify for negative NPVs, making the projects that are traditionally evaluated as being unprofitable desirable. The high uncertainties related to DTBM, volatility in demand and the highly strategic nature, make the real options approach inevitable to value DTBM projects. While general statements about the relevance of certain real options in DTBM are possible, their importance highly depends on the particular project setting and has to be assessed for each case individually.

A successful digital transformation strategy is rather driven by strategy than by technology (Kane et al., 2015; Chesbrough, 2007). Real options reasoning can help to build BMI strategies and identify and manage digital transformation initiatives (McGrath, 2010; Gassmann et al., 2016). Many researchers argue that an iterative approach of experimentation is vital to succeed in digital transformation (Rogers, 2016b). Practitioners frequently apply trial projects as a useful tool to learn about a new product or business model and resolve parts of the related uncertainty. It is a common approach to test risky projects on the real market, before deciding on a larger-scale project. Especially in the context of BMI and DTBM, where markets often do not exist and customer segments are still to be defined, experimentation and learning is essential. In the following, after briefly introducing the major real options valuation techniques, I translate these findings into a quantitative model by modeling experimentation as a learning option and a trail project as an expansion option on a digital transformation project's stochastic NPV.

4.3. An Overview of Real Options Valuation Methods

Several valuation methods and analytical techniques for real options have been developed and derived from financial options theory since the discussion about real options has emerged. Research on option pricing had its breakthrough in 1973, when Black, Scholes and Merton published their paper on valuing dividend-protected European-styled options (Black and Scholes, 1973). The authors used a so called "replicating portfolio" – a portfolio that is composed of the underlying asset and risk-free assets that have the same payoff as the option being valued – to derive their continuous-time option pricing formulas. Based on the same logic, Cox et al. (1979) have revolutionized option pricing by introducing a simplified Binomial Lattice Model to value options. Boyle (1977), has first suggested to use numerical Monte Carlo simulation methods for pricing options. With increasing computational power, these simulation methods have been increasingly applied to value financial options. In this context, Longstaff and Schwartz (2001) have developed the Least Squares Monte Carlo method (LSMC), which is still widely applied in Real Option Valuation. Additionally, so called Quasi-Monte Carlo simulation methods, which are an efficient and time-saving alternative to standard Monte Carlo methods, are increasingly being applied in option pricing (Imai and Tan, 2014). Recent research has also started to combine Monte Carlo simulation methods and Lattice models. Moreover, as first noted by Trigeorgis (1993), complex Real Option problems typically embed many options that interact and are strategically interdependent. This is especially important in large-scaled, real-world business projects, such as DTBM, that typically incorporate a portfolio of options which are neither strategically, nor statistically independent from each other.

In the following, I present the basics of the most prominent real options valuation techniques. In general, there are three different groups of models, that can be applied to find the value of the managerial flexibility based on real options. Discrete-time models view time as a discrete number of periods, while managers can make a decision about exercising an option at the beginning of each discrete period. Continuous-time models view time as a continuous flow of points in time. Most of these models are based on the ideas of Black and Scholes (1973) adjusted to the respective capital budgeting problem. These models are based on analytical methods that are aiming to find a closed-form solution for the optimal investment decision. Thirdly, numerical methods can be applied to find option premiums. If there is no analytical closed-form solution, these models can provide approximations to the stochastic process of the underlying patterns.

4.3.1. Discrete-time Models

Discrete-time models to value real options are based on the project value across a discrete number of finite periods (e.g. three six-month periods). Binomial (or trinomial)[4] Lattice models are based on the risk-neutral asset pricing by Black and Scholes (1973), and combines Decision Tree Analysis (DTA) and Contingent Claims Analysis (CCA) (Trigeorgis, 1996). These models have their origin in the work of Cox et al. (1979). A binomial lattice tree is constructed based on the movements of the project value (i.e. the NPV of its cash flows) V_t across time until the final period T is reached. The movements of the time-dependent project value V_t typically follow a stochastic process that is based on probabilities and its volatility σ. The volatility of the project's value development is typically estimated based on numerical methods.

Discrete-time models are a useful and necessary tool to generate a basic understanding of how the value of financial as well as real options is constituted. In contrast to continuous-

[4] Three-dimensional lattice models have been introduced by Boyle (1988).

time and simulation models, they are more intuitive and easy to use. Besides the option to defer, binomial lattice models can be used to value a variety of different options, such as the option to expand, the option to contract, the option to temporarily shut down, or the option to switch. Moreover, this approach can be particularly useful to price American-style options (i.e. options that allow early exercise), which is especially relevant to value managerial flexibility in real-world business projects. However, discrete-time models remain to be a simplified approach that is restricted to analyzing a certain limited number of points in time, lacking one closed-form solution. Furthermore, lattice models cannot handle multiple starting prices at a time and assume that uncertainty at any time can be represented by two alternative states.

With increasing time periods and starting values, the required computational power to compute the model rises rapidly and thus applicability decreases. Despite their limitations, it is sensible to apply discrete-time models for real (non-financial) assets, as they are not traded and their value can thus be observed only at a limited number of points in time. Also, there are a number of extended, more sophisticated lattice models, such as the Log-Normal Binomial Lattice model, which tackle the drawbacks of binomial lattice models by allowing for several stochastic processes including multiple state variables, multiple interacting options and intermediate payoffs (Trigeorgis, 1991).

4.3.2. Continuous-time Models

Continuous-time models view time as an infinite sequence of continuous moments. They are analytical models aiming to find a closed-form optimal solution to capital budgeting problems. Most of the continuous-time models presented by literature are based on the ideas of the Black-Scholes model. The basic process of determining the option value is similar to the approach in discrete-time models. In analytical continuous-time models for option pricing, the movements of the underlying, (e.g. the gross project value $(V_t, t \geq 0)$) is determined by a continuous-time stochastic process. The process is described by Stochastic Differential Equations (SDE). SDEs are differential equations, in which at least one term is a stochastic process. Typically, the stochastic component in an SDE models the random behaviour of the underlying, a geometric Brownian motion (Wiener process). Additionally, more advanced literature has started to incorporate stochastic jump processes into their SDEs. The solution to an SDE is a continuous-time Markov process with almost surely continuous sample paths. Several papers have used SDEs to value different types of real options. McDonald and Siegel (1985) use the following SDE to derive a diffusion process to value the option to defer:

$$dV_t = \mu V_t dt + \sigma V_t dB_t,$$

while $t \geq 0$, $\mu \in \mathbb{R}^+$ is the instantaneous expected return on the project and $\sigma \in \mathbb{R}^+$ its instantaneous standard deviation called volatility and B_t is a standard Brownian motion. Paddock et al. (1988) use a similar, however slightly adjusted, process given via the SDE

$$dV_t = (\mu - \delta)V_t dt + \sigma V_t dB_t,$$

with δ standing for the payout rate for the valuation of off-shore petroleum leases. In general, the construction of the SDE (and the resulting solution) will depend on the type of application (or project) that is to be analyzed. Both papers derive an optimal investment timing rule from their diffusion process. The optimal investment timing is determined as the time until the investment should be deferred. McDonald and Siegel (1985) and Myers and Majd (2001) use a similar SDE approach to value the option to shut-down or abandon a project. Margrabe (1978), analyzes the option to switch between two non-dividend paying risky assets and Geske (1979) first calculates the value of an option on an option (compound option) using similar techniques. Based on this fundamental work, several articles and books have been published that present continuous-time models to value IS/IT-related investments. For instance, Grenadier and Weiss (1997) investigate the option to invest in a current technological innovation at time $t = 0$ or a future technological innovation at a random time $T > t$. The technological progress is modeled using the SDE

$$dX_t = \mu X_t dt + \sigma X_t dz,$$

where μ is the instantaneous conditional expected percentage change in X per unit time, σ is the instantaneous conditional standard deviation per unit time and dz is the increment of a standard Wiener process. More recent research has also started to model two stochastic input factors allowing for individual consideration of, for instance, cost and revenue uncertainties of a project. A famous example for models that use multiple stochastic input factors are the Schwartz & Moon model (Schwartz, 2000; Schwartz and Moon, 2000). It is heavily applied in R&D as well as Venture Capital investments, as in both cases costs as well as future cash flows are subject to uncertainty.

The presented models are especially important for finding optimal investment decision rules based on stochastic movements of the underlying (and its influencing factors). Much work in that area was characterized by these analytical solutions that offer a closed-form solution to simplified problems that seldom reflect reality (Schulmerich, 2010). All of these models are simplifications of real-life scenarios that only work under certain circumstances (e.g. only if there are no intermediate project payouts). Moreover, there are two major downsides of these analytical continuous-time models. First, in order to find a viable solution, the capital budgeting problem has to be traceable, i.e. the SDE describing the behaviour of the underlying has to be known. This is almost never the case in practice, which indicates highly limited applicability to real-world business projects. Moreover, in practice, managers are typically confronted with a collection of real options, i.e. a portfolio of real options. Finding a solution when there are interactions between the several options in the portfolio is extremely difficult (mostly impossible) by using the analytical continuous-time models (Schulmerich, 2010). Hence, the presented analytic techniques may not be viable for capital budgeting problems, if competitive entry, compoundness within or between projects, or other strategic interactions are important (Trigeorgis, 1996). Finally, as these models are based on the Black-Scholes model, which has originally been developed to value financial options on traded assets, some of the underlying assumptions should be critically considered when applying analytical continuous-time models to real-life capital budgeting techniques. Hence, this approach is especially valuable if the value of the underlying is based on traded assets with mature futures markets, such as, for instance in oil, gas, gold, energy etc. projects.

4.3.3. Numerical Models

In a lot of real-life business scenarios, such as those involving multiple interacting real options, analytical closed-form solutions may not exist, and one may not be able to write down a set of partial differential equations describing the underlying stochastic process (Trigeorgis, 1996). Numerical Models can be applied to overcome these problems by approximation. They can be divided in three groups: (i) finite difference and lattice models, (ii) numerical simulation models and (iii) formulas, approximations and other specialized methods. The first includes the explicit and implicit finite difference methods that aim at approximating the partial differential equation as well as lattice models as briefly explained in Section 4.3.1. The second is based on Monte Carlo and similar simulation methods. Instead of approximating the differential equation, these models estimate the underlying stochastic process (Schulmerich, 2010). The third includes transform and asymptotic expansion techniques and other specialized methods. Two of the most prominent numerical methods are briefly described below.

Finite-difference models: Finite-difference models try to approximate the differential equation of the underlying by a set of partial differential equations. The partial differential equations are solved recursively to find the approximate differential equation of the underlying. Finite-difference models discretize the stochastic movements of the underlying resulting in a movement grid. They can also handle multiple state variables resulting in a multidimensional grid. There are three types of finite-difference models: implicit, explicit and hybrid models; which differ in the way the grid is solved (Schulmerich, 2010). Finite-difference models require less intuition than lattice models, however, they are mechanically more challenging. All finite-difference models are able to value American as well as European-type options. They can be used in complex option pricing problems, where a closed-form solution does not exist. However, a prerequisite to this approach is the ability to determine the partial differential equations for the underlying capital budgeting problem. For two pertinent research examples that use finite-difference models for (real) option pricing, see Brennan and Schwartz (1978) and Majd and Pindyck (1987).

Numerical simulation models: Numerical simulation models use Monte Carlo simulation to approximate the stochastic process of the underlying. In the context of option pricing, they were first introduced by Boyle (1977). Originally, these models were only applicable for European-style options. However, more recent research has improved standard Monte Carlo methods making them suitable for valuing American-style options respectively (Barraquand and Martineau, 1995; Broadie and Glasserman, 1997; Broadie et al., 1997). The Monte Carlo approach approximates the movements of the underlying based on the simulation of one or multiple input factors. The starting point of a standard Monte Carlo simulation is the stochastic differential equation that describes the underlying for $t \geq 0$. For instance, the underlying $S_t(t) \geq 0$ can be described via

$$dS_t = \alpha S_t dt + \sigma S_t dB_t,$$

where α is the instantaneous return of the underlying, σ its instantaneous standard deviation and dB_t is a normally distributed random variable with variance dt. A discretization of the stochastic differential equation allows the simulation of a path of the underlying with a computer simulation program. In order to get a significant result, these path values should be simulated a large number (e.g. 10,000) of times. The basic idea is to divide the time interval $[0, T], T > 0$, in $N \in \mathbb{N}$ subintervals with equal length $\Delta s := \frac{T}{N}$. Δs is called step size of the simulation. The goal is to simulate a path value $S_i := S(\tau_i)$ for each of the time points $\tau_i := i\Delta_s, i = 0, 1, ..., N$. The different path values S_i will then be iteratively calculated based on the given start value S_0. For European call options with strike price X, S_T and X will be compared at the time of maturity. Let $P_j := \max(S_T - X, 0)$ be the option price of the j^{th} simulated path at maturity T. The mean of all path option prices discounted by the risk-free rate will then be the resulting option value at $t = 0$ (Schulmerich, 2010).

Numerical simulation methods are especially valuable, in complex but realistic, real-life projects including several options, multiple input factors, multiple start values, or intermediate (dividend-style) payout, where no known analytical solution exists. The simulations can be drawn from a lognormal distribution, a Poisson distribution, or a combination of both. Thus, they can be directly used for different types of stochastic processes including pure diffusion, pure jump, or jump-diffusion valuation models. Simulation methods are a sim-

Table 4.1: Real Options Valuation Techniques – An Overview; own illustration based on the summarizing reviews of Schulmerich (2010), Schwartz (2004) and Trigeorgis (1996)

	Multiple starting points	**Multiple stochastic processes**	**Multiple state variables**	**Multiple (interacting) options**	**American-style options**	**Dividend payments**	**Continuous closed-form solution**
Binomial lattice	no	yes	no	no	yes	yes	no
Log-transformed binomial lattice	no	yes	yes	yes	yes	yes	no
Analytical methods	yes	no	yes	no	no	no	yes
Finit-difference	yes	yes	yes	yes	yes	yes	no
Monte Carlo simulation	yes	yes	yes	yes	no	no	no
Extended simulation techniques	yes	yes	yes	yes	yes	yes	no

ple forward induction procedure that is more intuitive than backward induction techniques such as finite-difference models or binomial lattice models. Due to their forward induction approach, standard Monte Carlo techniques are especially suitable to value European-style options. However, as mentioned, more recent literature has developed extended models for valuing American-style options (see, for example, Cortazar (2001) and Longstaff and Schwartz (2001)).

4.3.4. Summary

Research on Real Option valuation has existed for more than 30 years. In these years, loads of different models and model extensions standing for individual advantages and disadvantages have been developed. In general, the decision about the applied model has to depend on the type of option as well as on the individual underlying project characteristics. Most real-life capital budgeting scenarios are complex and lack an analytical solution. In these situations, numerical approximations such as lattice models, finite-difference methods or simulation techniques have to be applied. Additionally, when applying real options valuation techniques, the underlying assumptions should always be critically questioned against the project circumstances. Table 4.1 provides a basic summary of the core characteristics of the different standard methods. Most applications to IT investments use the Black-Scholes model to find an analytical solution for capital budgeting problems by assuming the cost of the underlying project is known. However, these models are subject to strong assumptions (for instance, the underlying is traded, replicating portfolios can be built), which, in fact, renders them non-applicable for such investment decisions.

In the following, I translate the discussions about real options and DTBM into a quantitative framework that develops a continuous-time model for valuing investments in DTBM by including several sources of uncertainty and two types of real options. To solve the model, I use discretization and simulate the underlying's sample paths using Monte Carlo and LSMC techniques.

Chapter 5

Valuing Investments in Digital Transformation of Business Models

This chapter summarizes our findings around DTBM and Real Options analysis and tries to bring them together to form a reference model that can be used to value digital transformation projects under uncertainty. We show a generic scenario and apply the model to a fictional business case to demonstrate its practical functioning.

5.1. Real Options in Digital Transformation of Business Models

As mentioned in the previous chapter, there are several real options that can play an important role in DTBM capital budgeting decisions. The relevance and value of these options highly depends on the project's characteristics. In every case, the strategic circumstances, inherent uncertainties and risks, markets and competition have to be analyzed in order to evaluate the significance of different real options. The option to wait can generally be incorporated with all investment decisions, however, it might come at some cost with DTBM, as delayed investments may eliminate first mover advantages associated with the BMI. Thus, when modeling the option to wait in DTBM, the cost of waiting has to be modeled as a function against time, which leads to a reduced option value respectively (an exemplary model that enables modeling of cost uncertainties is provided by Schwartz and Moon (2000)). Similarly, there is the generic option to abandon a project, if the situation turns out to exhibit unfavorable market conditions or project dynamics. In DTBM, the option to abandon an unsuccessful project certainly has some value, however, it does not play a special role in DTBM as this option is strategically not interesting. As the related investments are typically irreversible, the option to abandon should be exercised very carefully as this would lead to the realization of sunk costs. The option to switch might play a role in specific DTBM projects, however, it is only relevant if substitutes for the project's input or output factors exist and if the transaction costs of switching are low.

In the DTBM setting, there are several strategic options that are of more interest and typically more valuable than the generic real options mentioned above. The time-to-build option can be especially interesting in DTBM projects that consist of several subsequent and interdependent project stages. It comprises compound options that can be seen as a multi-stage option to expand (or abandon), exercisable at the end of predefined project stages. As DTBM is typically realized by large-scaled and complex project structures with several phases and work streams, practitioners should be aware of the inherent value of this option. Similarly, the strategic growth option can be of great value in DTBM, especially if the transformation enables new market entry or increased market penetration, which typically comes with a high degree of strategic, long-term growth potential. Due to the compound nature of time-to-build as well as strategic growth options, their valuation is mathematically rather complex. In most cases, an analytical solution cannot be found and numerical methods have to be applied to approximate the value of the compound option.

Another option that is of special interest in the DTBM context is the multifaceted option to alter. This option includes the option to expand, reduce or shut-down (and restart). It is of high strategic value in projects with a high degree of payoff uncertainty such as R&D, new venture investments and innovative technology adoption. Similarly, as DTBM has a lot of shared characteristics with the named types of projects, the option to expand is of special importance. For instance, the option to expand can be set up as the option to launch a large-scaled follow-on project after the completion of a smaller-scaled pilot project. This will facilitate the full investment decision to be based on a broader and more reliable information base, an approach that is common practice in projects with high uncertainties. In contrast to the valuation of time-to-build options, the valuation of the option to expand is somewhat simpler, as it expresses itself as a single call option on the project value of the larger follow-on project.

Digital business transformation projects are risky, time-intensive and expensive. In practice, before management decides to undergo such a project, it will require reliable information indicating a high success potential. The standard approach to receiving this information is testing. Hence, before a new business model is implemented, the reaction of the market and the underlying technologies will be duly tested. This approach can reduce business-strategy-related as well as technology-related risks and uncertainties. Typically, this is achieved by small test projects or prototypes that enable management to gather more information about the potential of the transformation in one or more real-world business scenarios.

In the following, we will first develop a simple Real Option pricing model that is able to value the option to expand in the DTBM setting. Theoretically, there are many ways to incorporate the option to expand in a DTBM capital budgeting problem. In practice, it is a common approach to launch a pilot project to test the potential of the new business model before management will decide on the full-scaled digital transformation project. Thus, the presented model views the option to expand as the opportunity to execute a large-scaled digital business transformation project after an initial pilot project has been completed.

5.2. Model Development

The model consists of two parts. The first part of the model uses Monte Carlo DCF methods to find the NPV distribution of a potential DTBM under four sources of uncertainty. The second part of the model includes the value of managerial flexibility, namely a learning option and an expansion option. Based on a numerical demonstration, we will show that these options have a significant value and the potential to shift solely NPV-based investment strategies.

We first present a generic approach to finding the NPV for risky DTBM projects under four sources of uncertainty. In contrast to building a static and discrete business case over the expected economic lifetime of a DTBM project, we use a variety of stochastic processes to forecast future values and explicitly include uncertainty to estimate the resulting NPV distribution. This is a more elegant way to determine the NPV, as we only need to input initial values at t_0 to receive all state values across time until the end of the project's economic lifetime T. This DCF model is partly based on the work of Schwartz and Moon (2000) and Schwartz and Moon (2001), who have proposed a sophisticated model to value high-growth internet companies such as Ebay and Amazon after the burst of the dot-com bubble in 2000. Based on their model, we apply several simplifications as well as extensions to adapt the model to the DTBM setting. The presented model implements the value-add of the new (transformed) business model by modelling the isolated cash-flows generated by the transformation project. The model is first developed in continuous time. In the application section of this chapter, solutions are approximated by discretization and simulation of the model.

Consider a company that has a new business idea to extend its existing business model based on some emerging technology or technology bundle. We model project revenues following a time-inhomogeneous jump-diffusion process including three sources of uncertainty. The first uncertainty is about the changes in revenues, the second is uncertainty about the expected rate of growth in revenues and the third is related to technological progress induced by the underlying technologies that are critical to succeed in the transformation of the business model. Accordingly, the instantaneous rate of revenues at any time t is given by R_t following the stochastic differential equation:

$$\frac{dR_t}{R_{t_-}} = \mu_t dt + \sigma dW_1 + dJ_t, \tag{5.1}$$

where R_{t_-} is the left-hand limit of R_t, μ_t is the expected rate of growth in revenues assumed to follow a mean-reversion process with a long-term average $\bar{\mu}$, σ is the volatility in the rate of revenue growth, dW_1 is the Wiener increment, and dJ_t a time-inhomogeneous compound Poisson jump process.

The growth rate of project revenues evolves stochastically over time following the mean-reverting stochastic differential equation:

$$d\mu_t = \kappa(\bar{\mu} - \mu_t)dt + \eta dW_2, \tag{5.2}$$

where κ is the mean-reversion coefficient describing the speed of convergence to the long-term average of revenue growth; η is the volatility of expected rates of growth in revenues and dW_2 is the Wiener increment, which we assume to be uncorrelated with dW_1. $\frac{\ln(2)}{\kappa}$ can be interpreted as the time at which any deviation μ_t is expected to be halved.

Jumps reflect the revenue impact of technological progress based on innovation arrivals or breakthroughs in complementary as well as substituting technologies. Jumps are given by

$$J_t = \sum_{j=1}^{N(t)} Y_j, N(t) \sim Poisson[\Lambda(t)], \tag{5.3}$$

where $N(t)$ follows a Poisson process with an accumulated intensity $\Lambda(t)$, that is given by

$$\Lambda(t) = \int_0^t \lambda(u)du, \tag{5.4}$$

and Y_j represents Gaussian random jump size, i.e.,

$$Y_j \sim N(\psi, \delta^2).$$

The respective logistic[6] jump frequency function is given by

$$\lambda(t) = \frac{K}{1 + e^{-\alpha t - \beta}}, \tag{5.5}$$

[6]Logistic S-curve models are frequently applied and have shown broad empirical evidence in technology forecasting, see for example Kucharavy and De Guio (2011) and Trappey et al. (2011). Technology forecasting research suggests estimating the required parameters using curve-fitting techniques to historical data that is able to indicate technological progress of the underlying technologies, for example by using patent data or bibliometrics (Daim et al., 2006; Daim and Suntharasaj, 2009).

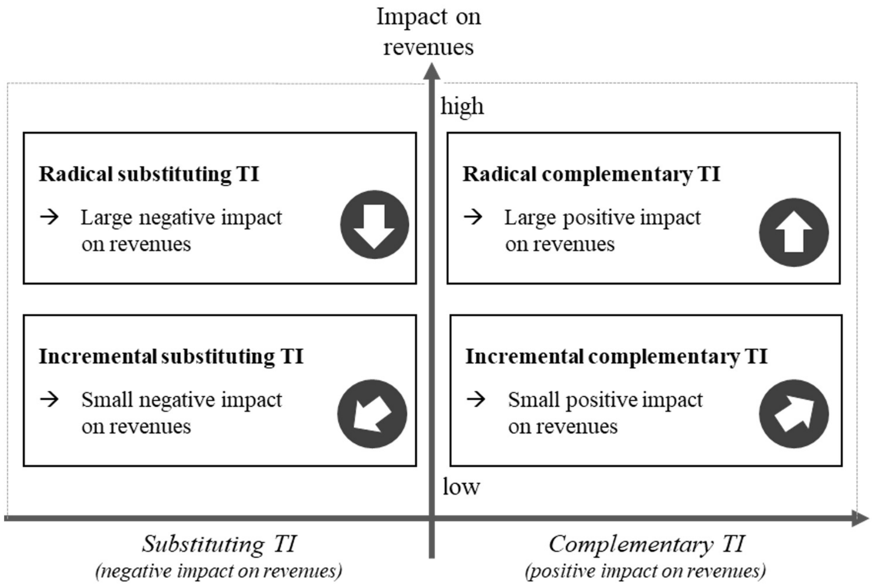


Figure 5.1: Types of technological innovation and their impact on model revenues

with $\alpha > 0, \beta > 0$, $K > 0$, reflecting an increasing frequency of innovations in the relevant technology markets.

We use this jump-diffusion process to extend the revenue process as introduced by the Schwartz & Moon model by explicitly including technology uncertainty, as the success of DTBM projects typically strongly depends on the underlying technologies' performance. Parameters ψ and δ can then be used to determine the average direction and magnitude of impact of technological innovations. Small-size jumps can be interpreted as incremental innovations, while larger jumps can be viewed as radical innovations. The well known Innovator's Dilemma in Christensen (2013) can also be reproduced by the suggested jump process. While complementary innovations result in an improved performance of the underlying technologies, substituting innovations reflect an improved performance of competing technologies, which might be utilized by competitors or have the potential to disrupt the technologies driving the regarded DTBM project. Due to the logistic S-curve that determines the expected movement of jump frequencies across time, expected innovation behavior can be modeled by scaling the parameters α, β, K. Note that K describes the asymptotic maximum of the number of relevant expected annual innovations, α is the respective rate of change of growth while β is the inflection point or mid-point of the curve, describing the time at which half of the growth is reached. The possible effects of technology uncertainty are summarized in Figure 5.1.

Following Schwartz & Moon's extension of their original model (Schwartz and Moon, 2001), total operating cost at any time t, denoted by C_t, have two components; a variable part $\gamma_t R_t$, which is assumed to evolve stochastically but proportionally to revenues R_t, and a fixed part F resulting in the total cost function, that is,

$$C_t = \gamma_t R_t + F. \tag{5.6}$$

The variable cost parameter γ_t at time t can be interpreted as a stochastic variable cost margin that adds another source of uncertainty. Its dynamics are given by the stochastic differential equation

$$d\gamma_t = \nu\gamma_t dt + \varphi\gamma_t dW_3, \tag{5.7}$$

where ν is the expected growth rate of variable costs, φ its volatility and dW_3 the Wiener increment uncorrelated with dW_1 and dW_2.

The marginal free cash flows of the project at time t are given by revenues minus cost deducted by the investing company's corporate tax rate τ as follows:

$$\mathrm{FCF}_t = (R_t - C_t)(1 - \tau). \tag{5.8}$$

We can then calculate the NPV by accumulating the free cash flows from time $t_0 = 0$ to the expected economic lifetime of the project T discounted by the investing company's risk-adjusted discount rate r resulting in

$$\mathrm{NPV}_0 = \int_0^T e^{-rt}\mathrm{FCF}_t dt. \tag{5.9}$$

Several assumptions have to be installed in order to arrive at the suggested model dynamics. First, changes in working capital related to the project are assumed to be constant or within standard errors. Second, capital expenditures and depreciation are assumed to compensate for each other in the long run and are hence neglected by the model. Third, loss carry-forward is assumed to be non-existent, as the investing company is assumed to be sufficiently profitable to compensate for losses generated by the transformation project. Hence, the tax effects of a negative cash flow immediately show effect and do not have to be deducted from potential profits in the following years. Fourth, for the same reason, bankruptcy is not considered. Therefore, we assume that even in case of negative cash flows, the company can still hold on to the project and wait for more profitable time periods to come. Finally, we further assume constant interest rates and volatilities. Note, however, that the overall volatility of revenues and the resulting NPV is time-changed as the jump frequency in revenues evolves along the logistic frequency function λ_t as described in equation (5.5).

We have identified a generic decision path management typically faces in the context of DTBM illustrated in figure 5.2. Let us now consider an established company with an existing business model. Assume that management comes up with some idea to transform

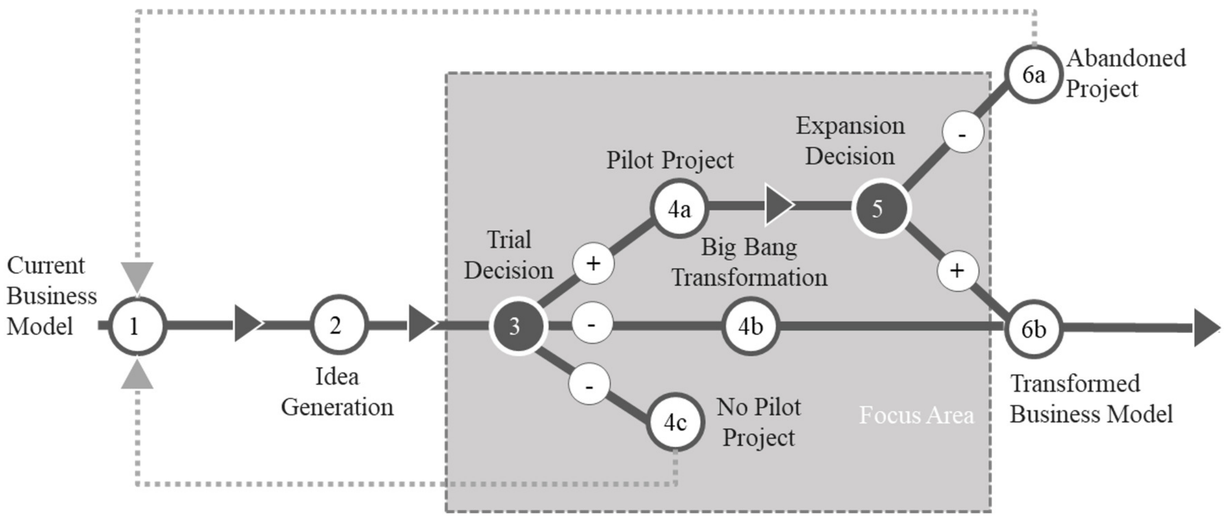


Figure 5.2: A generic DTBM investment decision process including two types of real options

its current business model based on emerging technologies or mature technologies being deployed in a new way. Management could decide to invest in a big bang transformation without testing, which represents the traditional now-or-never decision based on the NPV rule. At the same time, however, management also holds the option to launch a trial project to test its idea. Once the trial project is launched, management can observe the performance of the pilot project and update its expectations regarding the potential profitability of the transformation project. As no comparable business model exists in the market, we assume that management cannot learn about the project's potential if it does not invest in the trial project. Thus, the option to invest a fixed amount I_P to install the pilot project represents a learning option. If this option is exercised, management can update its expectations of the NPV dynamics of the transformation project and decide whether or not to expand. Accordingly, by investing into the trial project, management obtains the option to expand. In case new information turns in favor of the transformation project's expected NPV, management will exercise this option. In case the learning from the pilot project suggests negative profits from the transformation, management will walk away from the project realizing a loss associated with the cost of testing I_P. Hence, this decision model includes two options, while the expansion option is obtained by exercising the learning option with exercise price I_P.

The options' underlying is the transformation project's NPV. As no comparable securities are traded on the market, we cannot build a replicating portfolio to find the option price. To solve this problem, we apply the Market Asset Disclaimer approach as proposed in Copeland and Antikarov (2001). The authors make the widely accepted assumption that in absence of a twin security, the present value of the cash flows of the project without flexibility is the best unbiased estimate of the market value of the project were it a traded asset.

We assume that the dynamics of accumulated revenues, costs and thus cash flows follow the same uncertainty pattern as the marginal values described in equations (5.1)-(5.9). The only difference is that we replace the initial state variables with the respective sum of present values resulting from the DCF model. Thus, in order to find the option values, we first have to recalculate the initial state variables R_0, γ_0 and F by computing the present value of marginal value sums so that $R_0^{\mathrm{PV}} = \int_0^T R_t e^{-rt} dt$, $C_0^{\mathrm{PV}} = \int_0^T C_t e^{-rt} dt$, $\bar{F} = \int_0^T F e^{-rt}$ and $\bar{\gamma} = \frac{C_0 - \bar{F}}{R_0}$.
The gross NPV at any time t is then given by

$$\mathrm{NPV}_t = (R_t^{\mathrm{PV}} - C_t^{\mathrm{PV}})(1 - \tau), \tag{5.10}$$

resulting in the immediate payoff at time t

$$\Pi_t = \mathrm{NPV}_t - I_E$$

and the claim value of the expansion option at t_0

$$V_t^E = \max_{t^* \in \mathcal{T}(t, T^E)} \left\{0, \mathrm{E}_t^P[e^{-r(t^* - t)} \Pi_{t^*}]\right\},$$

where I_E is the immediate cost of expansion, $\mathcal{T}(t, T^E)$ the set of stopping times in $[t, T^E]$ with regards to V_t^E and $\mathrm{E}_t^P[\cdot]$ is the expectation with respect to the physical measure P, conditional on the information available at t. The value of the compound option to learn can then be determined as a function of the price of the option to expand. We model it as a now or never decision, which implies that there is no timing flexibility relating to the trial project. The value of the learning option depends on the value of the expansion option and the costs associated with the trial project. Hence, the value of the option to learn at t_0 can then be calculated by

$$V^L = \max\left\{0, \mathrm{E}_t^P[V_0^E - I_P]\right\},$$

which is simply the expected maximum between zero and the value of the option to expand minus the losses that are associated with launching and operating the trial project. We solve this model in a dynamic programming fashion. First, we need to find the value of the expansion option and then calculate the value of the learning option. At time t_0, if $V^E > I_P$, management will launch the pilot project, learn about the success potential and subsequently decide to expand if new information is in favor of the transformation project.

5.3. Discretization

We assume an underlying complete probability space $(\Omega, \mathcal{F}, P)$ and finite time horizon $[0, T]$, where the state space Ω is the set of all possible realizations of the stochastic economy between time 0 and T and has typical elements ω representing a sample path. $\mathcal{F}$ is the sigma field of distinguishable events at time T, and P is a probability measure defined on the elements of $\mathcal{F}$. We define $\mathcal{F} = \mathcal{F}_t; t \in [0, T]$ to be the augmented filtration generated by the relevant price processes for the project, and assume that $\mathcal{F}_T = \mathcal{F}$.

We use Monte Carlo simulation to approximate the continuous-time model by choosing an integer m so that the time span $[0, T]$ is divided into m intervals whose length is $\Delta t = \frac{T}{m}$. We choose T and m in a way to discretize the continuous-time model to generate periodic (e.g. quarterly, annual) state variables and compute the present value of the sum of all periods $\{[t_n, t_n + \Delta t] \in [1, T]\}$. The state variables are simulated by generating N sample paths for values of $R_t(\omega), C_t(\omega), \mathrm{FCF}_t(\omega), \omega \in [1, 2, \cdots, N]$ restricted to the discrete set of dates $\{t_1 = \Delta t, t_2 = 2\Delta t, \ldots, T = m\Delta t\}$.
Discretization of equations (5.1), (5.2), (5.5), (5.7) are respectively given by

$$R(t + \Delta t) = R(t) e^{\left[\mu(t) \frac{\sigma^2}{2}\right] \Delta t + \sigma \sqrt{\Delta t} \epsilon_1 + \sum_{j=1}^{\Delta N_t} Y_j},$$

$$N_{t+\Delta t} - N_t \sim P\left(\int_t^{t+\Delta t} \lambda(u) du\right),$$

$$Y_j = \begin{cases} 0, & N_{t+\Delta t} - N_t = 0, \\ q, & N_{t+\Delta t} - N_t \neq 0, \end{cases}$$

$$q \sim N(\psi, \delta^2),$$

$$\mu(t + \Delta t) = \gamma(t) e^{\left\{\left[\theta - \frac{\upsilon^2}{2}\right] \Delta t + \upsilon \sqrt{\Delta t} \epsilon_3\right\}}.$$

We can simulate N sample paths directly from these expressions and calculate periodic costs by computing

$$C_t(\omega) = \gamma_t(\omega) R_t(\omega) + F$$

and periodic cash flows by computing

$$\mathrm{FCF}_t = [R_t(\omega) - C_t(\omega)](1 - \tau).$$

The NPV expectation can then be calculated by averaging the discounted sum of cash flows over all sample paths

$$\mathrm{E}[R_{\mathrm{PV}}] = \frac{1}{N} \sum_{\omega=1}^{N} \sum_{t=1}^{m} e^{-rt} R_t(\omega),$$

the present value of total costs

$$\mathrm{E}[C_{\mathrm{PV}}] = \frac{1}{N} \sum_{\omega=1}^{N} \sum_{t=1}^{m} e^{-rt} C_t(\omega),$$

the average share of variable costs over the lifetime of the project

$$\mathrm{E}[\bar{\gamma}] = \frac{E[C_{\mathrm{PV}}] - \bar{F}}{E[R_{\mathrm{PV}}]},$$

and the present value of accumulated fixed cost

$$\bar{F} = \sum_{t=\Delta t}^{T} e^{-rt} F.$$

Next, we set $R_0 = \mathrm{E}[R_{\mathrm{PV}}]$, $\gamma_0 = \mathrm{E}[\bar{\gamma}]$ and $F = \bar{F}$ as our new initial state variables and re-run the simulation as in (5.1) – (5.9) to receive the total NPV at any time t until time of maturity of the expansion option T^E. In this setting, the value process of a contingent claim on NPV_t, with maturity T^E and payoff Π, can be computed using the LSMC method as introduced in Longstaff and Schwartz (2001). We choose this method as it is sufficiently flexible regarding the underlying stochastic processes and easy to integrate with the Monte Carlo techniques presented under section 3.1. At each point in time t and all sample paths ω, we compute the continuation value ϕ by regression and compare it with the discounted immediate payoff. Like in any American option valuation procedure, the optimal exercise decision at any point in time is obtained as the maximum between the immediate exercise value and the expected continuation value. Given that the expected continuation value depends on future outcomes, the procedure must work its way backwards, starting from the end of the option's time horizon T^E. For details on the implementation of the LSMC method refer to Appendix A.1.

5.4. Numerical Application

This section presents a numerical example of the described model, to illustrate some results and provide an idea about how to obtain the required input variables. We implement an annual discretization for a digital transformation project with an economic lifetime of 15 years and simulate 30,000 sample paths to approximate the respective NPV and re-run the simulation 30,000 times to approximate the values of the Bermudan expansion option as well as the compound learning option. Table 5.1 lists the input variables we used for the base case of this example. The presented parametrization implies that the transformation project is expected to generate USD 100 million over the first year with initial variable

Table 5.1: Illustrative parametrization of base case

Parameter	**Label**	**Input value**
Revenues in the first year	R_1	100
Revenue growth in the first year	μ_1	30%
Revenue volatility	σ	20%
Long term revenue growth	$\bar{\mu}$	2%
Mean reversion coefficient	κ	0.0924
Drift volatility	η	5%
Share of variable costs in the first year	γ_1	100%
Variable cost drift	ν	-1%
Variable cost volatility	φ	5%
Fix costs	F	80
Corporate tax rate	τ	30%
Risk-adjusted interest rate	r	10%
Lifetime of transformation project	T	15 years
Lifetime of expansion option	T^E	5 years
Speed of tech progress	α	0.5
Half time growth of tech progress	β	7.5 years
Asymptotic maximum of innovations	K	100
Mean of Gaussian jumps	δ	1
Standard deviation of Gaussian jumps	ψ	2%
Cost of expansion	I_E	500
Cost to launch pilot project	I_P	200

costs of USD 100 million and constant annual fix costs amounting USD 80 million. Hence, management expects negative cash flows in the early phase of the project. However, the initial annual growth in revenues amounts 30% and is expected to approach its long-term average growth rate of 2% p.a.. The mean reversion coefficient equals 0.0924, which implies that the growth rate of revenues has reached its half time after 7.5 years. The share of variable costs in revenues is expected to decrease by 1% annually. We assume a constant risk-adjusted interest rate of 10% and a corporate effective tax rate of 30% p.a..

There are four sources of uncertainty represented by the model. The first is the volatility in revenues amounting 20% p.a., the second and third are the volatility of revenue growth and the volatility in variable costs both amounting 5% p.a. and the fourth is represented by the jumps in revenues determined by the time-changed jump frequency and the standard deviation of Gaussian jumps. The logistic frequency function is defined by its slope of $\alpha = 0.5$, the inflection point, which is set to $\beta = 7.5$ years and the asymptotic maximum of annual innovations amounting $K = 50$ innovations p.a.. The mean of the multiplicative Gaussian jumps is set to 1 and its standard deviation to 0.02. We assume a lifetime of the option to expand of 5 years. This can be interpreted as an internal deadline, until which management wants to decide whether to expand or not. In other words, if the project does not seem profitable after this time, management will decide to abandon the project, in which case management will be confronted with a loss of USD $I_P = 200$ million. The cost of expansion I_E is expected to amount USD 500 million.

Table 5.2: Summary of simulation results

	Results	**Std. error**
NPV	-23.25	
Option to expand	371.03	1.90262
Learning option	171.03	
Expansion probability	76.21%	
Expected expansion timing	After 4.24 years	
Investment decision	**Launch pilot project**	

The simulation results of the described parametrization are summarized in table 5.2. The NPV of the simulation is negative amounting USD -23.25 million. Thus, following the traditional NPV rule, the project would be regarded as unprofitable and management would decide to refuse the transformation project in a now-or-never decision. However, if we include the value of managerial flexibility, i.e. the value of learning and conditional exercising, the overall transformation project value increases to a positive amount of USD 371.03 million. As management would be required to launch a trial project to obtain the expansion option and receive the information required for the expansion decision, the value of the compound learning option amounts USD 171.03 million. Thus, in this example, the real options approach suggests launching the trial project and subsequently decide to expand in case new information from the trial project is in favor of the transformation. Learning from the trial project can be regarded as a hedge against the downside potential of negative returns from the transformation project without limiting its upside potential, which results in large option values.

The probability of expansion and the expected expansion timing provides us with further insights regarding optimal investment strategies. While the expected payoff of expansion amounts USD 371.03 million, only for 76.21% of simulated trajectories an expansion results in a positive payoff. Thus, in 23.79% of cases, management would decide to abandon the project after 5 years leading to a negative return of USD 200 million. The average optimal expansion timing over all expansion-favoring scenarios is 4.24 years after launching the trial project. This value is very close to the time of maturity, as the initial payoff expectations are significantly negative resulting in a long time period until expected growth leads to positive profit expectations.

Table 5.3: Sensitivity of base case results to varying input parameters

Parameter	**Label**	**Input**	**NPV**	**Option to expand**	**Learning option**	**Expansion probability**	**Expansion timing**	**Investment decision**
Mean reversion coefficient	κ							
(after 1/4 of the project's lifetime)		0.185	-158.3931	125.7696	0	44%	4.55	Do not launch trial project
(after 3/4 of the project's lifetime)		0.0616	76.37959	542.2672	342.2972	86%	3.96	Launch trial project
Variable cost drift	ν							
		-2%	125.591	582.7813	382.7813	94%	3.78	Launch trial project
		0%	-180.9173	156.2052	0	40%	4.51	Do not launch trial project
Revenue volatility	σ							
		30%	-24.2599	383.0444	183.0444	66%	4.12	Launch trial project
		0%	-21.19318	292.4973	92.4973	87%	4.30	Launch trial project
Drift volatility	ν							
		10%	-17.95691	383.3183	183.3183	77%	4.22	Launch trial project
		0%	-26.97746	370.5783	170.5783	76%	4.23	Launch trial project
Variable cost volatility	φ							
		10%	-23.30408	431.4268	231.4268	69%	3.90	Launch trial project
		0%	-21.63441	373.0016	173.0016	88%	4.42	Launch trial project
Std. dev. of Gaussian jumps	ψ							
		0.015	-20.0603	377.587	177.587	77%	4.22	Launch trial project
		0.025	-23.2441	374.5819	174.5819	76%	4.23	Launch trial project
Speed of tech progress	α							
		0.8	-15.71356	388.9325	188.9325	77%	4.22	Launch trial project
		0.2	-25.53169	372.754	172.754	75%	4.23	Launch trial project
Half time growth of tech progress	β							
(after 1/4 of the project's lifetime)		3.75	-23.01621	367.8448	176.8448	75%	4.23	Launch trial project
(after 3/4 of the project's lifetime)		11.25	-18.03165	384.2928	184.2928	78%	4.22	Launch trial project
Asymptotic maximum of innovations	K							
		100	-20.85118	378.5316	178.5316	76%	4.21	Launch trial project
		0	-75.2928	262.3053	62.3053	67%	4.41	Launch trial project

5.5. Sensitivity Analysis

In this section, we analyze the impact of a variety of input variables by applying sensitivity analyses. We start at the base case presented in section 4 and vary the value of input variables, to identify the most critical parameters. We also come up with an economic interpretation of the results and generic implications for managerial decision-making in regards to the DTBM setting. The results of the sensitivity analysis are summarized in Table 5.3. The mean reversion coefficient κ determines the speed of conversion from the initial revenue growth rate μ_1 to its long-term average $\bar{\mu}$. This variable is most crucial to define the expected revenue growth over the entire project lifetime. In our case, where μ_1 is significantly higher than $\bar{\mu}$, increasing κ leads to a decrease in overall revenues and thus to smaller NPV and option values, while a decrease leads to increasing overall revenues and larger NPV as well as option values. A small change in this variable has a relatively large impact on the results, which is in line with the findings of Schwartz and Moon (2000) and Schwartz and Moon (2001).

The drift of variable costs describes the expected growth of γ_t. In our example, we assume this to be negative, which can be explained by expected efficiency gains. Furthermore, digital business models typically have decreasing marginal costs per user. By reducing this value from -1% to -2% the resulting NPV significantly increases to a positive value of USD 125.59 million. As this number is positive, even the traditional NPV rule would suggest a profitable big bang transformation. However, as the value of the learning option is significantly higher than the NPV, even in this case, launching a trial project is favorable. Setting the expected growth of γ_t to zero, results in a negative NPV of USD -180.92 million and an option value of zero. Thus, in this scenario, the profit potential does not compensate for the costs of launching a trial project, and management would decide not to invest at all. Similar to the mean reversion coefficient, a relatively small level of variation in variable costs has a large impact on the results as it drives the overall cost over the lifetime of the project.

Volatility parameters do not have a significant impact on the project's NPV, as they do not affect expected (i.e. mean) values. However, by increasing the uncertainty parameters, option values increase as the value of managerial flexibility is positively correlated with uncertainty. This is, increased volatilities have a large effect on the upside potential of project cash flows, whereas the downside potential is hedged by not exercising the expansion option. By comparing the results between revenue volatility, drift volatility and variable cost volatility, we find that the latter has the largest impact on option values. This can be explained by that fact that changes in costs show full impact on pre-tax cash flows, while the effect of variation in revenues is reduced by the proportional co-movement of variable costs.

Regarding the variables that determine the size and frequency of jumps, i.e. innovations that directly affect revenues, provides us with some further insights that are typically not covered by existing real options literature. A small change of the standard deviation of jump sizes ψ only shows little impact on option values. Note, however, that unless ψ is equal to 1, a change of intensity directly affects the mean of the process. Parameters α, which defines the steepness of the logistic S-curve and β, describing the mid-point of the curve, do not have a significant effect on the results. Among the variables that define the jump-frequency function, variations in the total maximum of annual innovations K show the largest impact. It defines the deterministic maximum of annual innovations at the end of the project's lifetime, while parameters α and β only define the shape of the curve between t_0 and T. Increasing K boosts the total number of jumps resulting in a higher level of uncertainty, NPVs and option values. For instance, doubling this number from a maximum of 50 to 100 annual innovations, slightly increases the option value to USD 378.53 million. However, reducing this number to zero, which represents the case without technology uncertainty (or jumps), leads to a significant decrease in NPVs and option values. The asymmetric effects of variations in K on the results might seem surprising but can be explained by the following phenomenon: including jumps leads to an expected change in the NPV of zero. However, as revenues can never become negative while there is no upper boundary, the upside potential of jumps is significantly larger than its downside potential, leading to non-linear effects on expected values. Thus, when rapidly developing technologies play a crucial role in a project's revenue expectations and costs remain unaffected, uncertainty increases alongside upside profit potential. Regarding option values, jumps have a positive effect, due to two reasons. First, jumps increase the NPV expectation, which is used as the underlying of the analyzed real options and second, an increased volatility always results in an increased value of managerial flexibility, which is in line with existing real options literature.

The expansion probabilities after launching a trial project vary between 44% and 94%. These values describe the share of simulated cases that turn in favor of expansion before reaching the time of maturity of the expansion option. Hence, in the majority of cases, the learning from the trial project turns in favor of the transformation and results in expansion. Optimal expansion timings lie between 3.9 years and 4.55 years. Only in a very limited number of cases, expansion after 1, 2 and 3 years are optimal, while most trajectories result in an expansion between year 4 and the option's maturity. Thus, if management sets itself an early deadline for making an expansion decision, investment timing might not be optimal if the value of further uncertainty resolution exceeds the immediate payoff. Note, however, that in practice, waiting often comes at some cost, as sustaining the trial project might result in additional expenses and competitors could enter into the market and secure the majority of market shares.

Except the examples of decreasing the mean reversion coefficient of revenue growth and increasing the drift of variable costs from -1% to 0, management would always decide to launch the trial project to learn about the transformation's profit potential. Even in cases with positive NPVs it is always favorable to launch the trial project and learn before deciding upon expansion. Thus, the hedge against downside potential, i.e. the decision whether to expand or abandon bears significant value. In this case, after investing the cost of the trial project of USD 200 million, management can update its expectations annually and decide whether or not to spend another USD 500 million to transform their business model. In case the trial project indicates negative returns, management will decide not to invest, leading to a loss of USD 200 million. The high option values are a result of the high level of uncertainty that is typical for DTBM projects. The results clearly suggest that investing in DTBM should be based on a trial and error, rather than a now-or-never investment approach, which is in line with the findings of pertinent qualitative BMI and digital transformation literature.

Despite the use of fictional data, the presented example can serve as an illustration of how experimentation can be valued in highly uncertain environments. It gives an understanding about the most critical parameters and shows that the value of expansion and learning can be approximated in different scenarios. The example is based on valuing a single DTBM project. However, the model could be further extended to value a portfolio of business model transformation ideas to further mitigate risks by diversification. The higher the surrounding uncertainty, the larger the value of uncertainty resolution by learning. Only if the expected costs of experimentation and expansion exceeds the upside potential of a transformation project, management should reject the investment opportunity.

5.6. Summary and Discussion

The presented framework opens a new chapter of research at the interface between strategic management, IS research and real options analysis. It applies a set of existing quantitative models to DTBM and tries to increase the understanding of decision-making in the digital economy. We have presented a first approach to include experimentation as a type of managerial flexibility in DTBM projects, which represents a common approach applied by practitioners and is in line with major findings of related academic literature. This chapter applied existing real options valuation models and adapts them to a generic DTBM investment process. It showed how traditional NPV methods can be extended to include the value of testing, learning and expansion. We found that these options have the potential to change strategic investment decisions for risky DTBM projects. The resulting option values are particularly large, as DTBM projects typically have a long time-horizon surrounded by high levels of uncertainty. The results from sensitivity analyses underlined the importance of modifying traditional capital budgeting techniques for DTBM investment decisions. However, as it is the case with most real options research, careful parameter estimation is critical to generate meaningful results.

We can expect that the area of DTBM will grow in importance as emergent technologies mature and the economy further digitalizes. New methods should be developed, which will require comprehensive cross-functional skills and experts on digital transformation as well as ROA. The presented study serves as an introduction to ROA in the context of digital business transformation. It highlights the importance of the intersection of these two areas and lays the foundations for future research. Future research could engage in extending the presented model, by analyzing different types of real options or a portfolio of trial projects. Another interesting extension could be to include metrics other than revenues and costs to analyze the profit potential of DTBM. Finally, scholars could focus more on parameter estimation than model development, as this remains to be a challenging task for real options valuation, especially in the rapidly changing and unpredictable context of the digital economy.

Chapter 6

An Alternative Perspective on Value for Digital Business Models

In this chapter, we introduce an alternative perspective on value and performance measures in the context of ascertaining value of digital business models. While, in the previous chapter, traditional financial metrics such as cash flows and NPVs were used as an underlying to value investments in digital business models, in this section we introduce a user-based view to value for such companies.

6.1. Empirical Value-drivers of Digital Business Models

The distinctively different characteristics of digital business models, the threat of overvaluation of such companies and the strong value of intangibles such as user data and network effects lead to an important question. Whether traditional accounting-based valuation methods are still suitable to rationally determine the real value of digital businesses has become a controversy amongst experts in the global business community. In the following, the considerations, therefore, are as follows: first, we present an empirical study that analyzes the most important financial performance measures for the value of traditional as well as digital firms. We will see that, while these measures perform reasonably well for traditional asset-based firms, they lack in explanatory power for value of digital businesses. Second, we introduce a user-based valuation model that shows how user-related data can be applied to value subscription-based digital business models and prove relevance and accuracy by applying it to a real-world business case.

The structure of the following two chapters compliments these considerations. First, a brief empirical study about the most important value drivers of digital and traditional businesses lays the foundation for the enclosed examination. Second, we summarize existing literature on customer-based company valuation and postulate it as a viable alternative for valuing digital businesses. Third, we develop a simple model that employs user base diffusion as a stochastic logistic growth curve and is able to estimate the customer lifetime values as well as customer equity of any contractual digital business under uncertainty. We then apply the model to evaluate the customer equity of Netflix based on publicly disclosed data and link it to its market capitalization. We also provide some sensitivity analysis over input parameters and derive some economic insights. Finally, we summarize the findings and provide some ideas for future research.

The qualitative differences between digital versus traditional businesses have been discussed in section 3.4. In this section, we focus on the quantitative differences by presenting a brief empirical study. More precisely, we want to find out if there is a difference in financial value drivers for the two types of companies. For this purpose, we have collected two data sets, one representing what we have defined as digital companies and the other representing companies with traditional business models. The digital business sample is comprised of 71 public mid- and large-cap companies. All these firms are generating substantial revenues from a modern digital business model, including linear models as well as platforms. The traditional business sample includes all 1360 non-digital large-cap companies worldwide with a market capitalization of more than USD 10 billion as of November 2019. In a second step, we collected a large variety of quarterly financial data for both data sets including important performance measures such as profits, cash, leverage, profitability and others for the last 15 quarters from Q4 2015 to Q2 2019. The resulting data sets include 22,050 data points for digital companies and 428,400 data points for traditional companies. All data was retrieved via the Microsoft Excel plug-in by S&P's Capital IQ. Table A.1 in Appendix A.2 summarizes the descriptive statistics for both collected data sets.

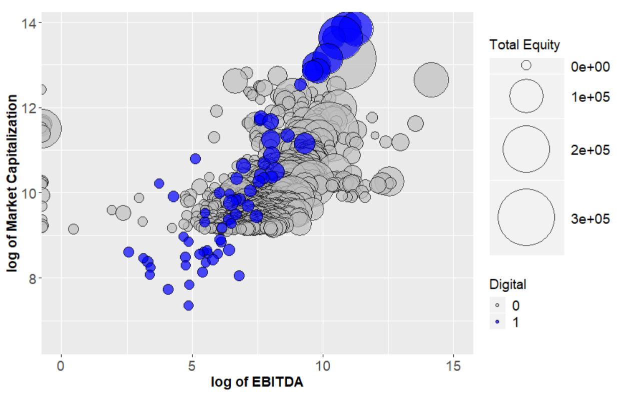


Figure 6.1: Example Value Drivers

		Revenue Multiple	EBITDA Multiple
Mean	*Trad.*	4.0x	14.9x
	Dig.	7.2x	34.9x
Median	*Trad.*	2.6x	12.1x
	Dig.	5.9x	22.1x
Two-sample	t-value	19.817	15.238
t-test	prob.	$<$0.001	$<$0.001

Table 6.1: Trading Multiple Analysis

Note: *Trad.* refers to the 1360 traditional businesses and *Dig.* refers to the 71 digital companies that comprise our sample.

In order to find potential patterns in the data sets, we ran several analyses. Figure 6.1 provides a first impression of the relation between some fundamental financial metrics and market capitalization. The x-axis describes the natural log of 2019 earnings before taxes, depreciation and amortization (EBITDA) and the y-axis indicates the natural log of the respective companies' market capitalization. Bubble sizes indicate total book equity, while blue bubbles represent digital and gray bubbles traditional businesses. The graph suggests that digital businesses can achieve a substantially higher market valuation with the same level of profits. Additionally, despite similar market valuation, digital companies tend to have a book equity that is much lower. A similar conclusion can be drawn from Table 6.1, which shows that revenue and EBITDA multiples are on average almost twice as high for digital companies.

In order to further analyze the importance of traditional financial performance measures for firm value, we aim to find an answer to the following two questions: (a) Can market value of digital companies be explained by traditional financial metrics? (b) Which are the most important financial metrics for the two types of businesses? For the purpose of this analysis, spot stock prices serve as the proxy for firm value. In order to limit the effect of extreme values, the natural log of the stock price is used as the dependent variable in our regression analysis. Concerning independent variables, we chose the following financial performance measures that are often used to analyze company performance and value by analysts and investors alike:

- ***EBITDA*** is used as an indicator of profits of the regarded company. As this measure does not include depreciation, interests and taxes, it is a suitable profit measure when comparing companies across various regions and industries.
- ***Earnings per share*** (EpS) is used to describe relative profits on a per share basis. It describes how much profit the company generated for each outstanding share. This measure is often used by analysts as an indicator to identify whether a company is under- or overvalued by the market. Following a common approach, we calculate EpS by computing the net income divided by the number of shares outstanding.
- ***BtM ratio*** compares the book value of equity from the balance sheet with the market value of equity of the respective company. The ratio is calculated by dividing the common shareholder's equity by the market capitalization. If the BtM is larger than one, i.e. the book value is larger than the market value, the company is considered undervalued and vice versa. Thus, high BtM ratios can be interpreted as the market valuing the company's equity cheaply compared to its book value. Low BtMs can be an indicator of overvaluation. However, this ratio is often used to analyze the value of

intangibles that are not accounted for in financial statements, yet considered valuable assets by investors.

- ***ROA*** is included in our analysis to include a measure of profitability. In contrast to EBITDA, this ratio benchmarks profits as a fraction of the total assets used by the company. RoA thus expresses how efficiently a company's assets were used to generate profits. It is calculated by dividing the company's net income by its average total assets in the respective period.
- ***Debt ratio*** (DR) is used as a proxy for leverage. This measure is defined as the ratio of a company's total debt to its total assets. It describes the fraction of a company's assets that are financed by debt. While debt is typically cheaper than equity, a high debt ratio indicates that the company may be putting itself at a risk of default on its loans if interest rates were to rise. However, additional debt may also be an indicator for additional growth, if cash is invested effectively and assets harnessed efficiently.
- ***Market capitalization*** (MC) is used as a control variable and a proxy for company size. We include this variable to ensure that there is no bias in regard to the scale of the underlying companies.

The correlation matrices for both data sets can be found in Table A.2 in Appendix A.2. With the exception of the control variable (MC), for both data sets, there are no significant correlations between the chosen independent variables that are larger than 0.2. Thus, we proceed the following analysis assuming that there exists no significant multicollinearity. For both samples, we ran a panel random effects model using the following linear equation:

$$\ln(S_{i,t+1}) = \beta_1 + \beta_2\mathrm{EBITDA}_{i,t} + \beta_3\mathrm{EpS}_{i,t} + \beta_4\mathrm{BtM}_{i,t} + \beta_5\mathrm{RoA}_{i,t} + \beta_6\mathrm{DR}_{i,t} + \beta_7\mathrm{MC}_{i,t},$$

where $S_{i,t+1}$ is the spot price of the following quarter. Subscripts i and t represent cross-section i and time t. We installed a time lag for the dependent variable of one quarter to ensure that financial ratios are known by market participants (i.e. investors).

The regression results are summarized in Tables 6.2 and 6.3. The outcome suggests the following five major findings: First, while the coefficients for EBITDA are relatively small for both samples, this is of low significance for digital companies, however, considerably more significant for traditional companies. The levels of profits thus do not influence the value of digital companies, which is a phenomenon that can be observed with companies such as Spotify and Dropbox, which have a history of extremely high market valuations despite reporting constant losses in consecutive fiscal years. In contrast, for traditional companies, EBITDA is somewhat significant and short-term profits can thus be regarded as important value driver for these companies.

Second, EpS are insignificant for the value of digital firms, while they are highly sig-

Table 6.2: Panel Regression Results for Digital Businesses; Method: Panel Least Squares (Random Effects), Sample: Q4 2015 to Q2 2019 (15 periods included), Cross-sections included: 68 companies, Total panel: 808 unbalanced observations.

Variable	Coefficient	Std. Error	z-value	Prob.
(Intercept)	1.1246e-01	9.8282e-02	36.7263	<0.001 ***
EBITDA	1.2113e-05	1.0676e-05	-1.2548	>0.1
EpS	4.3702e-03	5.8397e-03	0.7484	>0.1
BtM	-8.3363e-01	6.8142e-02	-12.2337	<0.001 ***
RoA	2.5630e-01	2.6720e-03	2.1687	<0.05 *
DR	5.3961e-01	1.4006e-01	1.8299	<0.1 .
MC	2.3428e-06	2.0015e-07	11.7054	<0.001 ***
R-Squared	0.35364			
Adj. R-Squared	0.3488			
Chisq.	438.149 on 6 DF			
p-value	<0.001 ***			

Table 6.3: Panel Regression Results for Traditional Businesses; Method: Panel Least Squares (Random Effects), Sample: Q4 2015 to Q2 2019 (15 periods included), Cross-sections included: 1114 companies, Total panel: 14787 unbalanced observations.

Variable	Coefficient	Std. Error	z-value	Prob.
(Intercept)	3.2361e+00	4.6868e-02	69.0479	<0.001 ***
EBITDA	5.4601e-06	22.0001-06	1.2548	<0.05 *
EpS	-2.5848e-05	-3.7583e-06	0.7484	<0.001 ***
BtM	-4.7524e-01	9.8892e-03	-48.0565	<0.001 ***
RoA	6.9770e-04	14.0667-04	2.1687	<0.001 ***
DR	-1.2060e-01	2.6434e-02	-4.5623	<0.001 ***
MC	1.2586e-05	1.6950e-07	74.2539	<0.001 ***
R-Squared	0.43414			
Adj. R-Squared	0.43391			
Chisq.	11338.5 on 6 DF			
p-value	<0.001 ***			

nificant for the value of traditional firms. As EpS represent the level of net income on a per share basis, it is not surprising that there are no significant effects on firm value for digital companies. Interestingly, however, there is a significant negative effect of EpS on log spot prices for traditional enterprises, which might be a consequence of dilution through increases in capital stock (i.e. an increase in shares outstanding).

Third, RoA has a significant positive effect on both samples. We can conclude that profitability has a positive effect on firm value for both types of businesses. However, the confidence level for traditional businesses is much higher, indicating that profitability is less significant for the value of digital firms.

Fourth, DR exhibits a significant but rather low confidence level for digital businesses. In contrast, it is highly significant for the value of traditional corporations. Additionally, the effect shows opposing signs for the two groups, which suggests that investors regard increasing leverage as rather negative for traditional firms while it is perceived as positive news for digital firms. A possible interpretation could be that additional cash through debt is expected to be more efficiently invested with digital firms, as there is typically no need to finance fixed assets and cash can directly be used to drive growth, for instance via investments in R&D or business development projects. As expected, the control variable MC is significant for both samples, although, coefficients are relatively small.

Finally, BtM, which defines the difference between book value and market value of equity, exhibits a large significant negative effect on both types of businesses. Furthermore, it can be emphasized that the effect for digital businesses is almost twice as high. According to our results, BtM is the most important variable for explaining stock prices of digital companies. The negative effect of BtM indicates that stock prices decrease when the BtM increases. That is, in case the book equity is smaller than the market equity, an increasing difference between these values describes an increase in intangibles, which positively affects stock prices - even more so for digital businesses. The BtM is often used to describe the value of intangible assets that are not on the balance sheet. The ratio is forward-looking as it reflects intangibles that are yet to be monetized. It thus represents future earnings potential as expected by investors. The high sensitivity of stock prices of digital companies to BtMs thus shows that a large part of value of digital companies must stem from future profit expectations from intangibles rather than performance that is derivable from financial statements. Hence, the extreme excess of market equity over book equity for digital companies (as indicated by their low BtMs, see the descriptive statistics in Table A.1 in Appendix A.2 must be a consequence of intangibles such as users, data or network effects. Note that, in general, as the value of intangible assets is more volatile than the value of tangible assets, the high value digital business models is associated with high levels of uncertainty and therefore, ultimately, risk.

Despite the large difference in sample sizes, regarding R-squared, we can conclude that the explanatory power of the model is slightly higher for traditional businesses, which further suggests that the chosen financial performance measures are more meaningful in explaining value for traditional companies. In summary, our results indicate that traditional financial metrics are not sufficient in explaining firm value of digital businesses. The most important metric, the BtM, considers future growth and profitability generated by intangibles that are not observable in financial statements. In contrast, standard financial performance measures that are reported such as profits, short-term profitability, leverage or equity are no significant factors in explaining a digital enterprise's market value. Traditional company valuation techniques such as the enterprise DCF or multiple methods are based on these metrics. We can thus expect these methods to have difficulties in valuing corporations that engage digital business models. While financial statements can serve as a tool for understanding a digital company's historic performance, our findings show that we should be doubtful whether they represent a suitable proxy, assessing the value of a digital business. Accordingly, there is the need of an alternative and more appropriate valuation approach that is flexible and forward-looking enough to include and consider the massive value of intangibles held by digital corporations. In the next section we thus introduce a different perspective on performance measures and company valuation that play a more important role analyzing the value of digital business models.

6.2. User-based Corporate Valuation

A digital company's customers are its users. User behavior drives, makes and breaks the profitability of a digital business model. Since the global deployment of the internet and the associated emergence of digital business models, a large number of new performance measures have been introduced in academic literature and managerial practice alike. While these metrics are derived from traditional performance measures such as revenues, net income or the return on assets, mapping them to users is a helpful tool for understanding a digital business's revenue mechanisms, increase transparency in regards to value-based management and to optimize financial planning and analyses. While different approaches to monetizing users have been found, all digital business models produce user-based metrics that can be employed to track performance.

In this context, a frequently applied metric is the *average revenue per user* (ARPU). It shows how much revenue a single user generates on average and, thus, the incremental revenue of acquiring new or losing existing users. A firm's gross margin multiplied by the ARPU then reflects the gross profit per user. Another important metric is the *cost of customer acquisition* (CAC). It shows us how much the company has to spend on marketing and sales to acquire one new user. Typically, these costs take a large part in a digital firm's cost structure unfolding substantial impact on profitability. In order to be profitable, the company's CAC should be significantly lower than its ARPU. Regarding future performance, the net growth rate of the user base is important. The net growth of users in a certain period is the sum of all newly acquired users minus the users who have churned. In order to have positive net growth, the number of churning users has to be smaller than the number of user acquisitions.

With the growing importance of digital business models and the increasing popularity of customer-centric management, the *Customer Lifetime Value* (CLV) has gained in popularity. It is a concept that has originated from marketing and has grown into an important metric for monitoring and management of digital businesses. The customer lifetime value is the sum of all discounted net cash flows of a user or a cohort of users. Additionally, *Customer Equity* (CE) is used to express the total value of all existing and new users in a single monetary number. It is typically calculated as the sum of all CLVs of existing and future users.

Osterwalder and Pigneur (2004) state that maximizing CE must be one of the main goals of any company. Further studies have reinforced the link between marketing performance and financial metrics (e.g. Mintz and Currim, 2013) as well as firm value (e.g. Srinivasan and Hanssens, 2009; Edeling and Fischer, 2016) and therefore postulate the essential role of marketing metrics in value-based management (Verhoef and Lemon, 2013). Hence, marketers need to measure and manage this value of the customer to the firm and have to incorporate this aspect into management decisions (**kumar2016**).

In marketing literature, several approaches exist that link CLV and CE to company valuation. Srivastava et al. (1998) were the first marketing academics to recognize the potential for using some of the models of customer behavior to generate key insights for estimating cash flows. Gupta et al. (2004) labeled these valuation approaches as the family of *Customer-based Company Valuation* (CBCV). CBCV describes the process of valuing a firm by forecasting current and future customer behavior using customer data in conjunction with traditional financial metrics. For many firms, CE represents a major share in shareholder value enabling the link between user behavior and enterprise valuation (McCarthy and Fader, 2018). A vast number of scholars have published articles that further analyze this link (Bauer et al., 2003; Bauer and Hammerschmidt, 2005; Gupta, 2009; McCarthy et al., 2017). Most of these articles focus on contractual (i.e. subscription-based) monetization examples, as user-behavior can be modeled by fixed revenue streams and easy to observe retention rates (McCarthy et al., 2017). However, more recent studies have also started to value non-contractual businesses by applying CLV techniques. For example, Kumar and Shah (2009) use probabilities of a customer to purchase in a certain time period to calculate the CE and link it to a firm's market capitalization.

A number of articles apply their CLV models to digital companies such as the online streaming platform Netflix (e.g. Gupta and Zeithaml, 2006; Pfeifer, 2011; Zhang, 2016) or the social network xing.com (e.g. Gneiser et al., 2009). Digital business models are especially suitable for CBCV, as user bases are typically large, exhibit high growth rates and easily observable purchase behavior. Thus, users are a digital company's most valuable asset and the main value driver for enterprise value. Shapiro et al. (1998) show that the number of customers in prosperous new technology companies, especially in internet-based companies, increases exponentially in the first few years of the company's existence. After a while, growth rates start to decrease gradually until an upper asymptotic limit of the total potential user base is reached. This phenomenon can be often observed in natural growth dynamics such as biological population growth (Sakanoue, 2007; Tsoularis and Wallace, 2002), technological progress (Daim et al., 2006; Daim and Suntharasaj, 2009; Easingwood et al., 1981; Young, 1993), new product deployment (Mahajan et al., 1993) or dynamics in production volumes (Clark et al., 2011). Logistic growth curves are often applied to forecast these dynamics based on historical data. Accordingly, several scholars use logistic growth curves to model customer growth across time. For example, Cauwels and Sornette (2011) use a logistic model to forecast the growth of Facebook users. Similarly, Gupta et al. (2004) use logistic user growth to link the CE of one traditional company (Capital One) and four internet firms (Amazon, Ameritrade, eBay and E*Trade) to their market capitalization. The author's results show that estimates of customer value are reasonably close to current market valuation.

In spite of the overwhelming evidence on the strong link between marketing metrics and financial performance and a growing body of research on CE and CLV, the finance community is yet to acknowledge the increasingly well established marketing metrics and, in fact, few companies have adopted them (Persson and Ryals, 2010). One reason might be that existing CBCV research mostly uses rather inflexible logistic growth curves to model deterministic user dynamics. Growth curves are typically applied to be fitted to historical data by non-linear least squares or maximum likelihood techniques to forecast future developments of user growth. While this approach is easy to implement and its interpretation straightforward, it has some critical limitations as it explicitly assumes that future user growth is known and can be directly derived from historical data. This fairly unrealistic assumption can be relaxed by modeling state variables as stochastic processes to include uncertainty and thus allow for time-changed parameters and deviations from deterministic prediction results.

There are several ways to include uncertainty with logistic growth models: add uncertainty about the total number of users, add uncertainty about user growth rates or add uncertainty about the asymptotic limit of total users. The difference between these approaches is basically a modeling issue, as all three relate to uncertainty about the number of users across time. Finance literature provides several stochastic approaches to company valuation. Most are related to the real options approach, that is able to value managerial flexibility in investments under uncertainty. For example, Schwartz (2000) and Schwartz and Moon (2001) value high-growth internet companies by modeling discounted cash flows as a growth option under three sources of uncertainty. Similarly, Perotti and Rossetto (2000) value internet portals as a portfolio of real options. Both studies argue that internet companies have call-option characteristics, since they have a large upside with limited downside potential (i.e. bankruptcy). However, most finance articles use traditional financial metrics to model cash flows and NPVs of such to estimate firm value.

From a CBCV perspective, we only know of a single article that is based on stochastic logistic growth dynamics. Tallau (2006) includes several sources of uncertainty relating to the number of customers, the ARPU and the variable costs of a company. The author further assumes that the number of users evolves based on the Bass (1969) model, which is a famous mixed-influence model for logistic growth that distinguishes two groups of new adopters, namely innovators and imitators. However, due to the model's complexity, it requires estimation of 32 different input variables, which are mostly not observable limiting its relevance for practical application.

This study extends existing CBCV techniques by combining them with some basic concepts from quantitative finance literature. That is, rather than modeling future user growth based on a deterministic fitted growth curve, we use stochastic processes for user acquisition and churn to model user base diffusion, which increases flexibility by allowing for time-changed growth patterns and random deviations from the underlying deterministic user growth dynamics. In the next section, we develop a simple stochastic CE estimation model for subscription-based digital business models including uncertainty in user growth. After developing the model, we apply it to the examples of Netflix, Roku and Stitch Fix and show how the required input parameters can be obtained.

Chapter 7

User-Based Valuation of Digital Subscription Business Models

7.1. Introduction

The distinctively different characteristics of digital business models, the threat of overvaluation of such companies and the substantial value of intangibles all lead to the same question. Whether traditional accounting-based valuation methods are still suitable to rationally determine the real value of digital businesses has become a controversy amongst experts in the global business community. This chapter, therefore, aims to contribute to this debate by introducing a user-based valuation model that is able to employ user-related data to value subscription-based digital businesses under uncertainty. Additionally, in order to highlight the relevance and accuracy of the suggested model, we further apply it to the real-world business case of Netflix and investigates the sensitivity of results to identify the most critical user-based metrics.

The proposed model has several advantages over existing CBCV. First, in contrast to previous models, the model allows us to observe how different user-based metrics influence estimation results across time. Additionally, due to the high flexibility of the model, it enables us to analyze how this impact evolves for different combinations of user metrics and derive suggestions optimize user value from a managerial perspective. Therefore, model results can be used to extract concrete measures for value-based management that increase customer equity and thus shareholder value by improving the effectiveness of managerial action. The model further allows for deviations from deterministic growth curves by including uncertainty in user growth, which is a valuable tool for scenario-based planning and analysis. Finally, due to the high flexibility of the Monte Carlo methods that are used to simulate the model, it can be easily extended and tailored to other types of user monetization mechanisms. The incorporated uncertainty also allows for including the value of managerial flexibility that can be modeled as real options, which are especially valuable in high uncertainty situations.

The structure of this chapter is as follows: first, we develop a simple CE valuation model that employs user base diffusion as a stochastic logistic growth curve for any contractual digital business. Second, we apply the model to evaluate the customer equity of Netflix based on publicly disclosed data and link it to its current as well as historic market capitalization. We then present a comprehensive sensitivity analysis to deepen the understanding of the model's mechanics and derive some general managerial recommendations for value-based management. Finally, we summarize the findings and provide some ideas for future research.

7.2. Model Development

Consider an existing company with a subscription-based digital business model. The revenue mechanics of such a company are driven by the number of subscribing users and the ARPU. The number of future users depends on three variables: The number of existing users, the number of newly acquired and the number of churning users. We consider a company with an existing and self-sustaining user base. The churn rate is equal to one minus the retention rate and the number of newly acquired users is the net growth of the user base plus the number of churned users in the same time period. Thus, we can model user growth based on a birth-death population growth model, which can be often found in mathematical biology (see, for example Brauer and Castillo-Chavez, 2001). In a business context, birth can then be interpreted as acquiring a new user and death as a churning user. The growth dynamics are logistic, as the user base cannot grow infinitely large. The upper limit of the total number of subscribing users can be interpreted as the total number of all potential users across all relevant markets (e.g. all households with internet access). Previous studies have found that the predicted number of acquired customers exerts the strongest influence on shareholder value (e.g. Schulze et al., 2012), which is why the proposed model places its focus predicting user growth under uncertain acquisition as well as churn rates.

7.2.1. Continuous-time Model

We assume that the total number of paying users at time t, denoted by U_t, follows a simple differential logistic growth equation:

$$dU_t = (a_t - c_t)U_t \left(\frac{1 - U_t}{K} \right) dt, \tag{7.1}$$

where a_t is the instantaneous acquisition rate (or birth rate) relative to the user base U_t, c_t its instantaneous user churn rate (or death rate) and K the theoretical asymptotic limit (or carrying capacity) of total users at the end of the regarded time horizon T. We choose this model for user growth as the proposed setting is nothing but an analogy to population growth. In case that a_t and c_t are constant, equation (7.1) becomes an ordinal differential equation (ODE) which has the closed-form solution

$$U_t = \frac{K}{1 + be^{-(a-c)t}},$$

where $U_0 > 1$ and $b > 0$ is a constant. That is, the solution to equation (7.1) becomes the standard logistic growth function, where the constant $a - c$ defines the pace of the growth between U_0 and K. This model can often be found to describe natural growth dynamics in the fields of mathematical biology and epidemiology but also in business-related applications including new product adoption, technological diffusion and others.

However, the assumption that growth coefficients a_t and c_t are constant across time is not reasonable for our setting. We relax this assumption by including two sources of uncertainty into our model. The first is uncertainty regarding a_t, the rate of newly acquired users, that is represented by the stochastic acquisition rate

$$da_t = \mu^a a_t dt + a_t \sigma^a dW_t^a, \tag{7.2}$$

where μ^a is the expected change in a_t, σ^a its volatility and dW_t^a the Wiener increment. The second is uncertainty regarding c_t, the rate of users who cancel their subscription, which is modelled by the stochastic churn rate

$$dc_t = \mu^c c_t dt + c_t \sigma^c dW_t^c, \tag{7.3}$$

where μ^c is the expected change in c_t, σ^c its volatility and dW_t^c the Wiener increment. We therefore assume that both acquisition rates and churn rates evolve as geometric Brownian motions (GBM).[7]

We further assume that the diffusion terms of a_t and c_t are correlated, that is,

$$dW^a dW^c = \rho dt,$$

[7]GBMs have the implicit assumption that the state variable can never be negative. While the net user growth rate can be negative, that is, in case the churn rate is higher than the acquisition rate, positive acquisition and churn rates are a desirable assumption. GBMs are a widely applied concept in finance, for example when modelling stock price diffusion, which is why we refrain from further explaining this concept at this point. We choose the GBM to model uncertainty as it is simple and fulfils the reasonable behaviour of growth rates.

where ρ is the correlation coefficient between the two Wiener increments dW^a and dW^c. Thus, if $\rho \neq 0$, variations in acquisition rates will likely result in variations in churn rates and vice versa.

It is noteworthy that, even in case of constant values for a_t and c_t, the effective net user growth is time-changed, i.e. follows a bell-shaped curve as given by the derivative of the solution to equation (7.1). Thus, effective growth rates are expected to first increase and then decrease after half-time growth of users is reached and the user base approaches the asymptotic maximum of users K. In general, in early growth stages, effective growth increases for constant nominal growth rates until the inflection point of the number of users is reached. After this point, effective growth decreases for constant nominal growth rates. However, negative changes in a_t and c_t indeed result in negative deviations from the bell-shaped growth curve and vice versa, while the magnitude of their impact strongly depends on U_0, K and t.

The discounted after-tax operating profit across the entire user base at any time t can be calculated by

$$P_t = e^{-rt}(\pi \text{ARPU} U_t - \text{CAC} a_t U_t - F)(1 - \tau), \tag{7.4}$$

where π is the company's gross margin, F is the company's fix costs, τ the corporate tax rate and r the company's risk-adjusted discount rate. The total CE at the time of valuation $t = 0$ can then be determined by computing

$$\text{CE} = \int_0^T P_t dt + \frac{P_T(1 + g)}{r - g},$$

where g is the terminal growth rate of P beyond T. The last term of this equation is a perpetuity, which is commonly applied in calculating terminal values for company and project valuation. Thus, the CE is the NPV sum of all cash flows created by existing and future users. It describes the net worth of a company's current and future user base. Note that this way of computing the CE of a company is different from most existing CBCV models, as we do not use individual CLVs, but instead, base our calculations on instantaneous profits of the entire user-base.

In order to link the resulting CE estimates to firm value, we need to further include non-operating assets and total debt. Some of existing studies ignore this link and argue that changes in CE result in proportional changes of shareholder value. However, Schulze et al. (2012) have found that this assumption might lead to a bias in shareholder value estimations. Therefore, the shareholder value should be calculated as in Bauer and Hammerschmidt

(2005) and Schulze et al. (2012). That is

$$\text{SHV} = \text{CE} + \text{NOA} - D,$$

where NOA is the company's non-operating assets and D its total liabilities.

7.2.2. Discretization

We assume an underlying complete probability space $(\Omega, \mathcal{F}, P)$ and a finite time horizon $[0, T]$, where the state space Ω is the set of all possible realizations of the stochastic economy between time 0 and T and has typical elements ω representing a sample path. $\mathcal{F}$ is the sigma field of distinguishable events at time T, and P is a probability measure defined on the elements of $\mathcal{F}$. We define $\mathcal{F} = \mathcal{F}_t; t \in [0, T]$ to be the augmented filtration generated by the relevant value processes for the CE, and assume that $\mathcal{F}_T = \mathcal{F}$.

We use the Monte Carlo method to approximate the continuous-time model by discretization. Let m denote an integer so that the time span $[0, T]$ is divided into m intervals whose length is $\Delta t = \frac{T}{m}$. We choose T and m in a way to discretize the continuous-time model to generate periodic (e.g. monthly, quarterly, annual) state variables and compute the present value of the sum of all periods. To be concrete, let t_i be the i-th period, i.e., $t_i = i\Delta t, i = 0, 1, \ldots, m$.

The state variables are simulated by generating N sample paths for values of $a_{t_i}(\omega_j)$, $c_{t_i}(\omega_j)$, $U_{t_i}(\omega_j)$ and $P_{t_i}(\omega_j)$, where ω_j stands for the j-th sample path with $j = 1, \ldots, N$. We simulate the user base diffusion based on the solution of the differential equation in (7.1) such that

$$U(t_i) = \frac{U_{t_0} K}{U_{t_0} + (K - U_{t_0}) e^{\left(-(a_{t_i} - c_{t_i}) t_i\right)}},$$

where U_{t_0} is the initial value of the user base at time $t_i = 0$.

The discrete-time approximation of equations (7.2) and (7.3) are given as

$$a(t_i + \Delta t) = a_0 e^{(\mu^a - \frac{\sigma^{a^2}}{2}) dt + \sigma^a \sqrt{\Delta t} \mathcal{E}^a)}$$

and

$$c(t_i + \Delta t) = c_0 e^{(\mu^c - \frac{\sigma^{c^2}}{2}) dt + \sigma^c \sqrt{\Delta t} \mathcal{E}^c)},$$

where $\mathcal{E}^a$ and $\mathcal{E}^c$ are standard correlated normal variates.

We can simulate directly from these expressions and then compute $P_{t_i}(\omega_j)$ as in equation (7.4) for each sample path ω. The total CE expectation can then be calculated by averaging the discounted sum of the N sample paths for P such that

$$E[\text{CE}] = \frac{1}{N}\sum_{j=1}^{N}\sum_{i=0}^{m} P_{t_i}(\omega_j) + \frac{P_T(\omega_j)(1+g)}{r-g}.$$

As with any Monte Carlo simulation, the accuracy of resulting estimates of $E[\text{CE}]$ is dependent on the number of simulations N and the distance between the time steps Δt. In the following, we apply the suggested model to a number of business cases to demonstrate its functioning and evaluate how our CE estimates compare to the market value of three digital businesses.

7.3. Numerical Applications

In order to find out how well the presented CE model tracks the value of digital subscription-based companies, we applied the model to evaluate the CE of three public subscription-based corporations. We computed the suggested model for Netflix, Roku and Stitch fix and compared the resulting CE estimates with their respective market capitalizations. Netflix is the leading provider of subscription streaming entertainment. It offers TV series, documentaries, and feature films across various genres and languages. Roku provides a subscription-based TV streaming platform to its users. The company operates in two segments, Platform and Player. Its platform allows users to discover and access various movies and TV episodes, as well as live sports, music, news, and others. Stitch Fix offers a subscription service that sells a range of apparel, shoes and accessories through its website and mobile app in the United States.

All three companies represent suitable examples for our model, as they are subscription-based providers of digital contents and consumer goods that exhibit significant market value despite relatively low profits. All three companies are listed on the NASDAQ stock exchange, which makes most input parameters directly observable or calculable from publicly disclosed data. As financial results are disclosed quarterly, we discretize the continuous-time model on a quarterly basis and use the company's 10-Q filings to estimate the respective input parameters.

7.3.1. Parameter Estimation

In this section, we present how to obtain the input parameters from publicly available data published by the companies. This section provides detailed explanations about how the parameter values were obtained. For Netflix and Roku, we have included the last ten available quarterly results in our analysis. For the case of Stitch Fix, since the company had its initial public offering in 2018, only seven quarterly results could be obtained. Table 7.1 lists all input parameters for the simulation of the most recent quarter at the time of our analysis. Table A.3 in Appendix A.3 lists the input variables for all simulations for previous quarters. In the following, we explain how the parameters can be obtained in more detail using the example of Netflix. The data for Roku and Stitch Fix was obtained in exactly the same fashion. Netflix's input values for Q2 2020 were obtained as follows:

- ***Number of subscribed users:*** this parameter is publicly available and can be directly extracted from Netflix's quarterly report.
- ***Acquisition and churn rates:*** unfortunately, Netflix has stopped disclosing its churn rates in 2010. However, the net growth rate of the user base is observable. According to our definition in equation (7.1), the net growth rate is equal to the acquisition rate subtracted by the churn rate. Thus, in order to estimate the current acquisition rate, we needed to find a proxy for its current churn rate. The average churn rate of over-the-top (OTT) media service companies amounts to 35%, which is the churn rate we assumed to be true for Roku. However, our research has shown that Netflix is among the companies with the lowest churn rates, which business press and media frequently estimated to amount to roughly 10%. That established, we calculated acquisition rates as the sum of the annual net growth rate and the churn rate in the same quarter. In order to find a more stable estimate for acquisition rates, we used the mean of a one-year rolling window of acquisition rates to calculate the current value. From Q3 2019 to Q2 2020, the average annual acquisition rate of Netflix amounted to 38.02%.

  The drifts of the respective Brownian motions are assumed to be zero, i.e. there are no expected deviations in growth rates from the dynamics determined by the underlying S-curve. The combined annual volatility of acquisition and churn rates is assumed to be constant and equal to the volatility of historic annual net growth rates. Computing this value for user growth between 2013 and 2020 results in an annual volatility of 0.14166. We can apply the general fact that $\text{Var}(X - Y) = \text{Var}(X) + \text{Var}(Y) - 2\text{Cov}(X, Y)$. Assuming that the volatilities of a_t and c_t are equal and their correlation coefficient is -0.6, we arrive at an estimation for σ^a and σ^c of around 0.06421.
- ***Gross margin:*** the gross margin is directly observable from the income statement. It is calculated by taking the share of gross profits in total revenues. We used the mean value of a one-year rolling window to estimate the current gross margin.
- ***Average revenue per user:*** this can be easily calculated by dividing total (quarterly) revenues by the total number of users. The total number of users over one period is calculated by averaging the number of users at the beginning and end of the respective time period. Again, we used the mean value of a one-year rolling window

to estimate the current ARPU.

- ***Cost of customer acquisition:*** this metric is calculated by dividing the periodic marketing expenses by the number of users in the previous quarter multiplied with the current acquisition rate. As we found this number to be highly volatile based on significant changes in both user growth rates and marketing expenses, we used the median of all CAC values between 2013 and the respective current CAC value.
- ***Fixed costs:*** this is the sum of all non-operating expenses directly observable from Netflix's income statements.
- ***Asymptotic limit of total users until T:*** In order to obtain an unbiased value for this critical input parameter, we ran a non-least squares curve fitting model to find the logistic growth curve that best fits the historic user base diffusion. Feeding the model with the number of users between 2013 and 2020, the model suggested a K-value of 1.06 billion users.
- ***Coefficient of correlation between acquisition and churn rates:*** as acquisition rates and churn rates are not separately disclosed, we have to install an assumption about this value. It is intuitive that, when acquisition rates go down, churn rates go up. This could for instance, be a result of a decreasing perceived attractiveness of the product or increasing popularity of competitive products (e.g. Amazon Prime Video, Disney+). On the other hand, a decreasing churn rate suggests high user satisfaction, which will also attract more new users (e.g. word of mouth effect). The value of ρ can also be calibrated to account for network effects. A high correlation between acquisition and churn rates suggests that more acquisitions lead to less churns which lead to more acquisitions and so on. Thus, we expect a strong negative correlation between variations in these two metrics. In our simulation, we assume the coefficient of correlation to amount to -0.6. Note that this variable does not have a significant effect on the resulting CE estimation, as it only influences the magnitude of uncertainty in user growth, which has only a small influence on expected (mean) values.[8]
- ***Weighted average cost of capital:*** we use the WACC as the discount rate for customer lifetime values. The WACC represents a common approach to discount cash flows and is typically calculated by applying the capital asset pricing model (CAPM). It is the weighted average of a company's cost of equity and cost of debt, while the cost of equity is calculated based on the company's beta. Our research has shown that Netflix's historic WACC values have fluctuated between 9% and 11%. Thus, we assumed a constant WACC of 10%.

[8]Typically, increasing uncertainty has no effect on expected values and thus CE estimates. However, due to the deterministic upper limit of total users K that can never be exceeded, effects of uncertainty are asymmetric. This phenomenon is also observable in Figure 7.1 showing that no sample path exceeds K and Figure 7.2 showing that the resulting CE distribution is left-skewed (i.e. downside risk is larger than upside potential). This effect is further investigated in section 7.3.3.

- ***Effective tax rate:*** Calculating Netflix's effective tax rate between 2013 and 2020 results in an overall mean value of roughly 23%.
- ***Terminal growth rate:*** we assume that the CE cohorts will grow at an annual rate of 3% after the forecast horizon T. Depending on the terminal CE and the company's discount rate, this parameter can show large effects on model results, which is why it has to be chosen carefully. Small positive growth rates can be justified by growth of served markets induced by population growth or increasing deployment of internet connections, but also by increasing user revenues or decreasing costs.
- ***Length of the forecast period:*** we choose a relatively long time-horizon of 15 years for our forecast. While this explicitly assumes that our metrics follow the presented equations over the next 15 years, the inherent uncertainty increases across time allowing for a broad spectrum of different realizations.

Table 7.1: Parametrization of input variables estimated based on the companies' latest publicly disclosed quarterly results

Label	Description	Netflix (Q2 2020)	Roku (Q1 2020)	Stitch Fix (Q1 2020)	Estimation method
U_0	User base Q2 2020	192,950,000	39,800,000	3,418,000	Disclosed number of subscriptions
a_0	Annual acquisition rate	38.01%	71.82%	85.5%	Net growth of user base plus churn rate
c_0	Annual churn rate	10%	35%	70%	Assumption based on online research
π	Gross margin	38.96%	43.6%	43.7%	Gross profit divided by total revenues
ARPU	Quarterly average revenue per user	$ 33.28	$ 9.24	$ 127.19	Total revenues divided by number of users
CAC	Cost of customer acquisition per user	$ 38.84	$ 6.66	$ 57.83	Rolling median of Marketing & Sales expenses divided by the number of new users
F	Quarterly fixed costs	$ 712,281,000	$ 128,000,000	159,866,000	All other expenses from the income statement (e.g. R&D)
K	Asymptotic maximum of potential users at time T	1,060,000,000	174,200,000	5,810,000	Estimated from non-least squares curve-fitting based on historical user data
ρ	Coefficient of correlation between deviations in acquisition and churn rates	-0.6	-0.6	-0.6	Assumption
σ_a, σ_c	Annual volatility of acquisition/churn rates	0.06421412	0.0236929	0.0244	Calculated from the volatility of historic growth rates
μ_a, μ_c	Expected annual growth of acquisition/churn rates	0	0	0	Assumption, as there are no expected deviations from the chosen logistic user base diffusion
r	Company WACC	10%	9%	11.5%	CAPM calculation
τ	Corporate effective tax rate	23%	0%	35%	Calculated from historical data (quarterly reports)
g	Annual growth rate of CE cohorts after T	3%	3%	3%	Assumption
NOA	Non-operating Assets	$ 7,153,248,000	$ 515,500,000	$ 241,584,000	Cash and equivalents from balance sheet
D	Total Debt	$ 17,708,159,000	$ 499,700,000	$ 165,634,000	Total debt from balance sheet

7.3.2. Results

The sample path realizations of user diffusion for Netflix based on Q2 2020 data for 1,000 sample paths are illustrated in Figure 7.1. Figure 7.2 illustrates the respective distribution of the resulting simulated total CE realizations. The graphs show that the user base is expected to further increase with first increasing and then decreasing effective growth rates. Most realizations result in a terminal user base between 800 million to 1 billion users. Given the presented growth dynamics, it is highly unlikely, however, not impossible that Netflix's user base in 15 years is going to be smaller than today's user base. Regarding Figure 7.2, we can observe that the inherent uncertainty results in a significantly left-skewed CE distribution, as the upper limit K prevents the user base from growing beyond the total market size. Note that the total CE can become negative if the sum of all CE cohorts is expected to be negative.

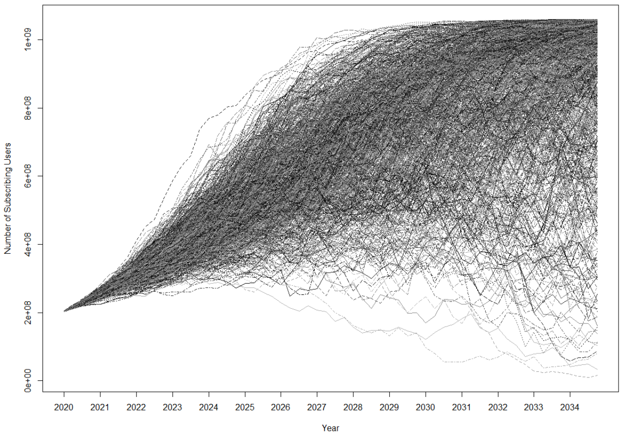


Figure 7.1: Sample paths of Netflix's projected user base diffusion for Q2 2020. $T = 15$ years, $n = 1,000$, quarterly discretization

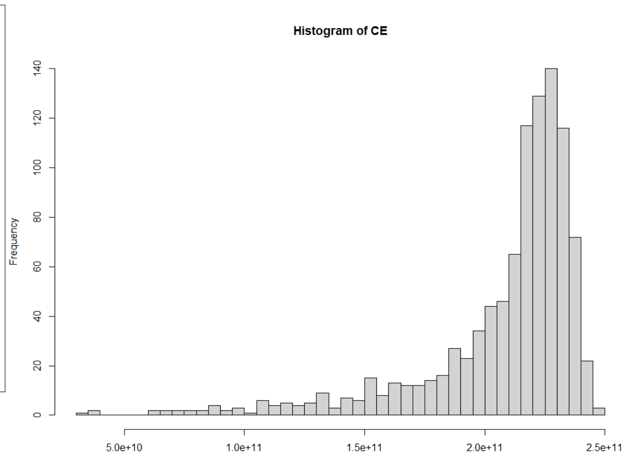
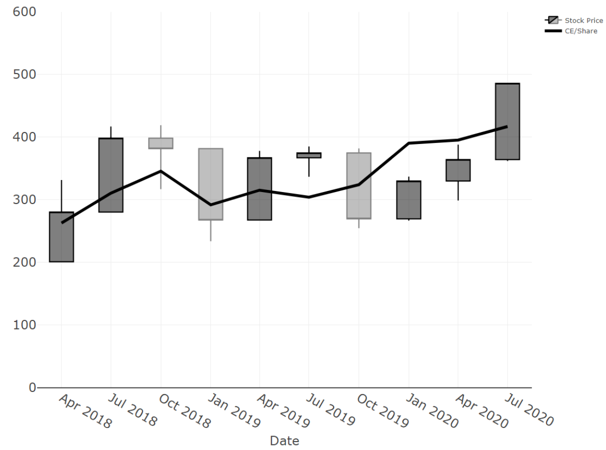


Figure 7.2: Simulated CE distribution for Q2 2020. $T = 15$ years, $N = 1,000$, quarterly discretization

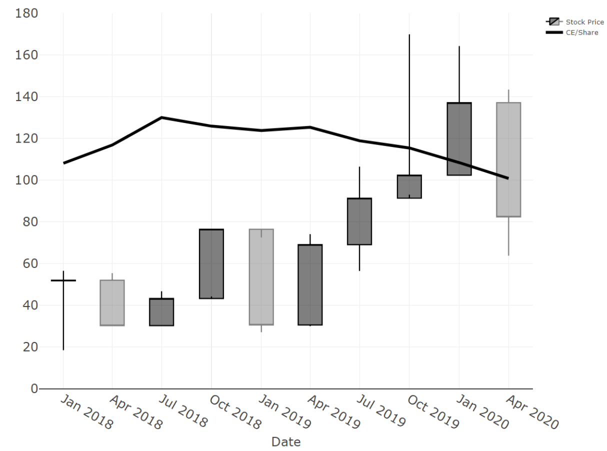
After having estimated all input parameters for each company and quarter, we fed the model with the data, forecasted the companies' CE developments and estimated the resulting total CE per share. For each quarter, we ran 100,000 simulations to find the companies' total CE for all available quarters between Q1 2018 and Q2 2020 for Netflix, from Q4 2017 to Q1 2020 for Roku and from Q3 2018 to Q1 2020 for Stitch Fix. We arrived at a total of 27 CE estimates for the three different businesses. This helped us to draw some conclusions about accuracy and reliability of our model cross section and across time. In order to do so, we compared the resulting CE estimates with the respective market capitalizations and the CEs per share with the share price developments within the same quarter.

For Netflix's Q2 2020, we arrive at a total CE of roughly USD 183 billion. Netflix's average market capitalization during the same quarter was around USD 188 billion. Accordingly, the CE per share of USD 415.14 is only about USD 12 lower than the respective average share price of USD 427.55. Thus, the CE was reasonably close to the actual values that are perceived in the market. As no sample path in our simulation hits zero, the probability of extinction (i.e. the case Netflix's user base drops to zero within the next 15 years) is smaller than 0.0001%. Increasing the volatility in the simulation will result in an increasing extinction probability and decreasing CE estimates. Regarding Roku, for Q1 2020, the simulated CE per share was USD 13.24 lower than the respective mean share price and for Stitch fix, the difference between these two numbers amounted to USD 11.81. The probabilities that the number of subscribing users at time T is smaller than U_0 equal 0.84% for Netflix, 0.3% for Roku and 17.63% for Stitch Fix.

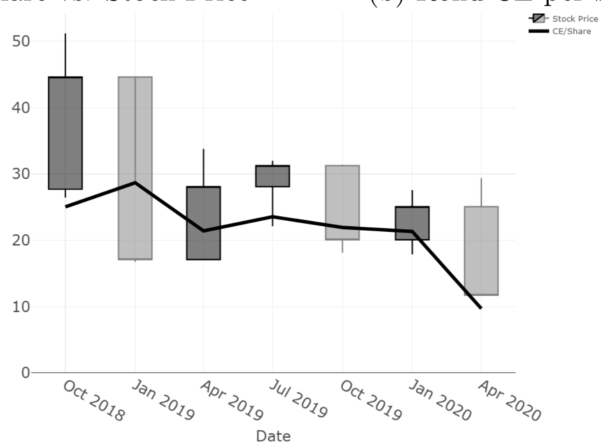
Figure 7.3 summarizes the performance of the model for all analysed quarters of the three companies. The candlesticks illustrate the open, close, min and max values of stock prices within the respective quarter and the black lines describe the CE per share simulations as performed by our model. For Netflix and Stitch Fix, in most cases, our estimates were within the stock price movements of the respective quarter. Almost all CE estimates were reasonably close to stock prices. Additionally, magnitude and direction of change in value show extremely similar patterns. For Roku, however, model results showed CE estimates that were much higher than the respective market capitalization. Only the last three to four quarters show results that are reasonably close to the market value. Thus, our model results suggest that Roku used to be undervalued until the stock price significantly increased during 2019. Tables A.6 to A.8 in Appendix A.4 list the results for all investigated quarters that are illustrated in Figure 7.3. Regarding the overall performance of our model, we can conclude that, despite its simplicity, CE estimates track market capitalization remarkably well and produce realistic results.



(a) Netflix CE per Share vs. Stock Price



(b) Roku CE per Share vs. Stock Price



(c) Stitch Fix CE per Share vs. Stock Price

Figure 7.3: Model Performance of the three example companies: simulation vs. real market data. The candles illustrate the stock movements (high, low, open, close) stock prices of the respective quarter. Dark grey candles indicate an increase while light grey candles indicate a decrease in stock prices. The line describes the simulated CE per share estimates by our model. The respective input data for the entire time horizon is listed in Table A.3 in Appendix A.3.

In summary, the user perspective seems to provide us with some valuable insights about a digital subscription model's valuation. The underlying user-based performance measures should thus play a vital role in managerial decision-making and corporate valuation for digital businesses. Furthermore, our results show that there is a strong link between user data and financial performance and the need to emphasize the importance of aligning user-centric and value-based management for digital corporations.

7.3.3. Sensitivity Analysis

In this section, we use the example of Netflix to provide some sensitivity analyses of our numerical example. We aim to demonstrate how changes in input parameters affect our estimation results and to identify the most critical parameters in our model. As we had to make some assumptions about some of the required input parameter values such as churn rates and correlation, we place our focus on these variables. We proceed the analysis using our estimation results for Q2 2020 and input parameters as described in Table 7.1 as our base case. We first provide sensitivity analyses over acquisition rates, churn rates, growth in these values and the carrying capacity without uncertainty. In a second step we present the effects of adding uncertainty to the model and show how volatility of acquisition and churn rates affect our results.

Deterministic model

Sensitivity over a_0 and c_0: Netflix's average annual net user growth of 38.01% was estimated based on historic data. However, as acquisition and churn rates are not separately disclosed, we assumed a constant churn rate of 10% and calculated the acquisition rate as the sum of net user growth and churn rates. In order to investigate how much deviations in these numbers affect our results, we varied the values of a_0 and c_0 between 0% and 50%. The effects on the number of users at time T are illustrated in Figure 7.4 and on CE per share in Figure 7.5. We can observe that higher acquisition rates and lower churn rates result in a larger number of users, ceteris paribus. The incremental value-add of increased net growth rates first increases and then decreases. Hence, larger values of a_0 and smaller values of c_0 show less effect the smaller the distance between the current user base its asymptotic limit. In all scenarios that represent higher churn than acquisition rates, $U(T)$ is smaller than the initial number of users U_0, as these combinations represent negative net growth dynamics. We can further observe that, in absence of uncertainty, any combination of a and c that results in the same net growth leads to the same number of total users after the end of the simulation lifetime T. In our simulation, the largest user base is thus reached with an acquisition rate of 50% and a churn rate of 0%. It is further noteworthy that, within a time window of 15 years, the carrying capacity K of 1.06 billion users is only approximately reached for very high net growth rates.

Regarding the CE simulation results, the graph draws a similar picture. We can observe that the CE always increases when larger net user growth is induced by decreasing churn rates. In contrast, an increased net user growth induced by higher acquisition rates does not necessarily result in higher CE values, despite an increasing number of total users. That is, until a certain effective growth rate is reached, higher acquisition rates have a positive effect on CE estimates. However, acquisition rates beyond this point result in decreasing CE estimates, ceteris paribus. Moreover, the higher initial churn rates, the higher acquisition rates can grow without decreasing CE values. Thus, despite the larger number of total users for higher acquisition rates, the maximum value of CE estimates amounting to USD 560.50

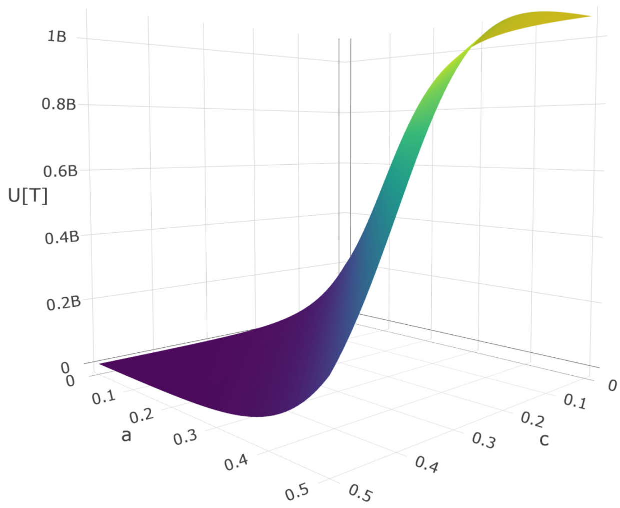


Figure 7.4: Sensitivity of user base to user acquisition and churn rates

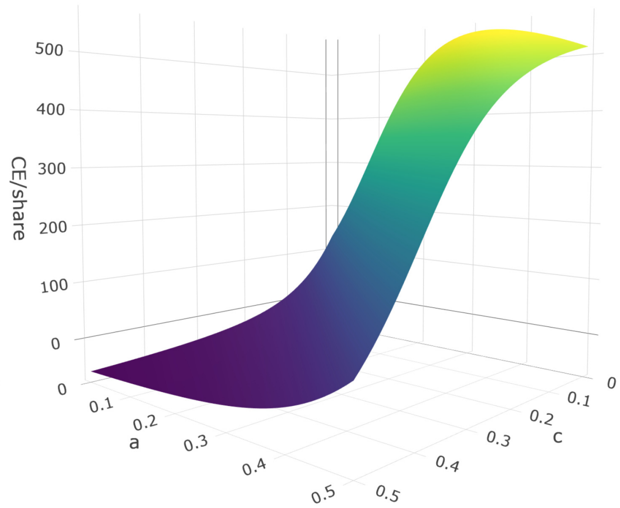


Figure 7.5: Sensitivity of CE to user acquisition and churn rates

is reached at a churn rate of 0% and an acquisition rate of 33%. For the example without uncertainty and a constant nominal churn rate of 10%, the optimal nominal acquisition rate amounts to 42% resulting in a CE/share of USD 496.68.

This result might seem counter-intuitive, however, it can be explained by having a closer look at equation (7.2). Customer lifetime values are a function of user profits and marketing expenses. It would be intuitive to believe that, under the assumption of constant values for CAC, π and ARPU, both values increase proportionally with a growing number of users. In this case, it would always be profitable to add new users as long as costs of customer acquisition are smaller than profits per user. However, as our proposed model is logistic, when approaching the asymptotic limit of total users, despite constant nominal acquisition rates, effective user growth decreases and thus effective CAC increase, ceteris paribus. While marketing expenses are a function of nominal growth, user profits are a function of effective growth, which, due to the logistic user evolvement, decreases when approaching K. Thus, for a large number of existing users, paying $a_t U_t$CAC results in an effective acquisition rate that is smaller than the nominal acquisition rate a_t resulting in negative marginal CE values and ultimately losses for adding new users.

From a managerial perspective this result can be justified by the following phenomenon: The less users are left to acquire in the total population of potential users, the less effective becomes an additional dollar of marketing expenses. That is, users that have waited longer to subscribe are less likely to become customers at all, as they are typically less susceptible to marketing campaigns and thus harder to acquire than early users. This is also the reason why this effect shows more impact for scenarios with lower churn rates. The lower the churn rate the quicker K is reached. In summary, adding new users adds value to the firm's CE as

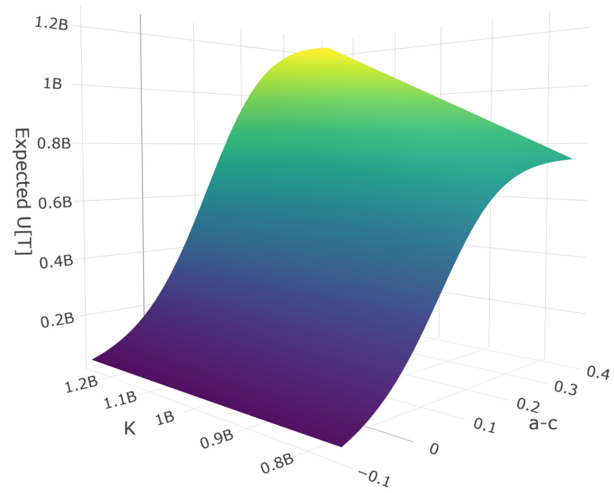


Figure 7.6: Sensitivity of user base to carrying capacity and net user growth

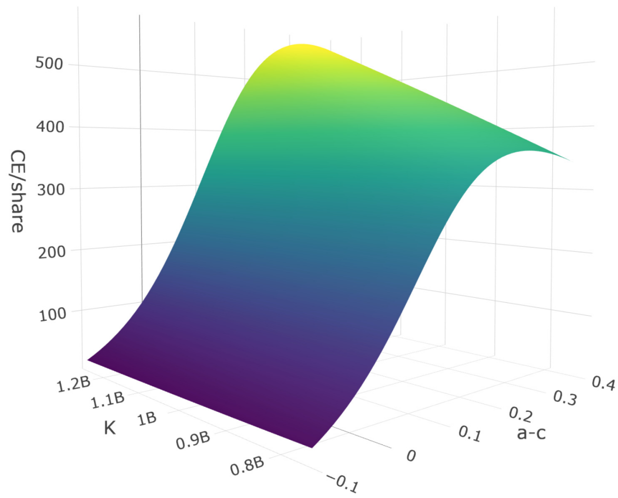


Figure 7.7: Sensitivity of CE to carrying capacity and net user growth

long as profits per user calculated by U_tARPUπ are larger than the CAC times the nominal acquisition rate a_t. In any case, the optimum is thus reached when profits per user are equal to the effective costs of acquiring a new user.

Sensitivity over K***:*** We have further analysed how changes in the carrying capacity of the total number of potential users in the market affects user base and CE dynamics. To do so, we varied K between 750 million and 1.25 billion users. Additionally, to investigate how combinations of different values of K and net nominal growth rates $(a_t - c_t)$ affect our results, we have further varied a_0 to arrive at net user growth rates between -10% and 40% p.a.[9] The resulting sensitivities for the user base are presented in Figure 7.6 and for CE estimates in Figure 7.7. Regarding the resulting user base at time T, it is not surprising that the largest value is reached for the highest K and the largest net growth rate. Note that, for small growth rates, the value of K does not show any influence, as the inflection point of growth is not reached in the regarded time horizon of 15 years. However, for large growth rates lower carrying capacities lead to significantly lower user bases, as K can never be exceeded.

CE simulations draw a similar picture as the results presented in Figure 7.4 and 7.5. However, we can additionally observe that increasing K allows for higher growth rates as this pushes the point at which effective CAC exceeds per user profits further into the future. The higher K, the longer high effective user acquisition rates can be sustained leading to higher CE estimates. We can conclude that higher K values always lead to higher CE estimates, however, the magnitude of the effect is highly dependent on the respective growth rates as well as the specific combination of a and c. For our base case of 1.06 billion total

[9]In this example, c was set to 0.1 and a was varied between 0 and 0.5.

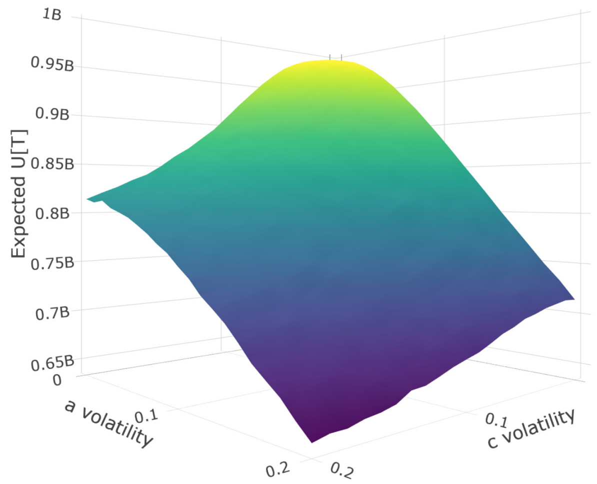


Figure 7.8: Sensitivity of user base to uncertainty in user acquisition and churn rates

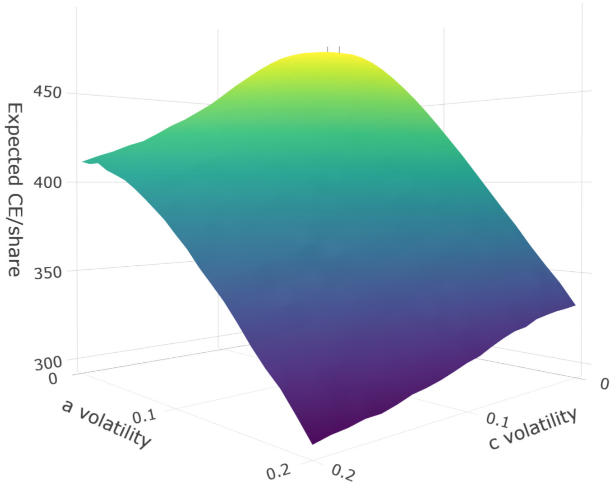


Figure 7.9: Sensitivity of CE to uncertainty in user acquisition and churn rates

potential users and a churn rate of 10%, the optimal net growth rate equals roughly 32%, while for a K of 1.25 billion users it equals roughly 33% resulting in a CE/share estimate of USD 577.01.

Stochastic model

Sensitivity over σ^a and σ^c: In this section, we present our results regarding the effects of introducing uncertainty to the model. All simulations were performed with $n = 100,000$ sample paths. In our base case, volatilities of a_t and c_t were assumed to be equal and ρ was set to -0.6, which resulted in an estimate of σ^a and σ^c of 0.0642. In order to analyse potentially different combinations of volatility values, we have varied σ^a and σ^c between zero and 20%. The results of our user base estimates are displayed in Figure 7.8 and for CE estimates in Figure 7.9. We can observe that the higher the uncertainty, the lower the resulting expected number of users and CE estimates. The highest numbers of users and CE estimates are thus reached when σ^a and σ^c are equal to zero, which represents the case without uncertainty. This might seem surprising, as expected values of GBMs are typically unaffected by the magnitude of uncertainty. In our model, however, as there exists an asymptotic limit of the total number of users, upside potential of effective user growth is limited by the carrying capacity K. Thus, for large user bases, the total upside potential of uncertainty in U_t becomes smaller than its downside potential. This phenomenon is also the reason for the slightly left-skewed CE distribution presented in Figure 7.2. Hence, in the absence of hedging mechanisms such as managerial flexibility, increasing uncertainty decreases our CE estimates as K gets closer. Consequently, this effect is stronger for lower K values.

The effect of adding uncertainty to the model is surprisingly high. For instance, the case with $\sigma^a = \sigma^c = 20\%$ results in an expected number of 645.72 million users and a CE/share of USD 298.67 , while the case without uncertainty yields 993 million users and USD 492.97. The coefficient of correlation ρ, that describes the co-movement of noise in a_t and c_t also takes a part in explaining the magnitude of the influence on simulation results. That is, negative ρ-values increase the overall user growth uncertainty, which results in slightly lower CE estimates. In general, a ρ-value of 1 does only eliminate the effect of uncertainty on net user growth, but not on CE estimates, as combinations with different a_t-values show different impact on CE estimates. If $\rho = 1$ and $\sigma^a = \sigma^c$, noise in a_t always results in equal noise in c_t, which always leads to the same net growth rate. A ρ-value of 0 describes a scenario in which noise in acquisition and churn rates is independent from each other and a ρ-value of -1 the case in which noise in c_t evolves perfectly mirror-inverted to noise in a_t resulting in a larger magnitude of uncertainty. The total impact of ρ on our simulation results, however, is rather small and decreases with decreasing volatilities and larger distances of the current user base to the asymptotic limit. For our example, varying ρ between -1 and 1 results in varying CE estimates between USD 449.07 and USD 477.67.

Note that, the effect of uncertainty on the expected number of users and CE does not only depend on the values for σ^a, σ^c and ρ, but also on the specific combinations of parameters K, a_t, c_t and U_0. For instance, as the user base can never be smaller than zero, for a small number of existing users, uncertainty has a positive effect on value of model results. In general, when the distance of the user base to K is larger than the distance of the user base to zero, CE distributions are right-skewed and thus expected values increase. In contrast, when the distance of the user base to K is smaller than the distance of the user base to zero, CE distributions are left-skewed and thus expected values decrease. Hence, the direction and magnitude of impact of uncertainty depends on the specific combination of many different input parameters.

7.3.4. Discussion and Strategic Considerations

From our sensitivity analysis results, we can conclude that marketing-induced user growth can result in negative effects on a firm's CE when the number of existing users approaches the total number of potential users in the market. That is, the smaller the remainder of potential users in the market, the more acquisition costs are necessary to acquire a new user. We can further conclude that for different market sizes, different acquisition rates are optimal. In general, the optimal amount of marketing and sales expenses is reached when the effective CAC becomes equal to per user profits. Thus, the optimal nominal growth rate also depends on effective user growth, the ARPU and their gross margin. Furthermore, it is always more profitable to decrease churn rates rather than increasing acquisition rates, as, in contrast to user acquisition, user retention does not induce additional costs.

For our Netflix example, and in absence of managerial flexibility, uncertainty in user growth negatively affects the total number of subscribing users and thus CE estimates. However, this is not a generic finding, as uncertainty can have positive impact on model results in case the distance of the number of users to K is larger than its distance to zero. Negative correlation between uncertainty in acquisition and churn rates further increases effects, however, the impact of correlation is rather small. Introducing uncertainty becomes more critical the smaller the distance between the current user base and the total number of potential users in the market. Thus, for seed and growth companies, where boosting marketing costs still results in an exponential growth of users, adding users is always profitable as long as per user profits are smaller than CAC.

Our findings suggest that it is not always advisable to further boost marketing expenses to increase user engagement and acquisition. In our model, such initiatives only make sense until the optimal level of a sustainable nominal acquisition rate is reached. As Netflix's user base is still in its growth stage and yet to reach the inflection point of user growth, increasing acquisition rates still has a positive marginal effect on CE. In any setting, decreasing churn rates and increasing market size represent the most promising managerial measures to increase the company's CE. The first could be achieved, for instance, by introducing a reward system for loyal existing users or optimization of content offerings. The latter could be accomplished by entering into new markets, either geographically or by product or BMI that expands the number of potential customers. In presence of uncertainty, managerial investment decisions can be modelled as real options, which can further add value to the firm's CE.

7.4. Summary and Discussion

This chapter extended existing literature on customer-based company valuation by using a logistic birth-death-rate process, including an adjustment for uncertainty about growth rates. We have discussed that traditional financial performance measures often fall short in explaining, tracking and predicting the value of digital business models. We have explained why traditional company valuation techniques have difficulties to justify the high market capitalization of successful digital companies. This study suggests user-based company valuation techniques as a reasonable alternative that is derived from user-base diffusion based on customer acquisition and retention mechanics. Building on existing literature that uses deterministic growth curves to forecast user base diffusion, we have developed a stochastic logistic company valuation model that presents a simple framework to integrate CBCV models with core finance concepts and include uncertainty around the most important metrics for value-based management of user-driven businesses.

We have also proven accuracy of our considerations by applying the model to estimate the CE of three subscription-based digital companies. We have demonstrated how to estimate the required input parameters to compute CE estimates based on publicly available data. We compared our results with stock prices across time and concluded that the model results track the investigated companies' market capitalizations remarkably well. Despite the simplicity of the model, user forecasting and CE calculation seem to be sufficiently accurate and thus might perform better at explaining business value in the digital economy. We do also recognize the limitations of our model: The presented model is only suitable for valuing subscription-based businesses. As it assumes a fixed and known revenue stream for every user, it does not apply to scenarios, where the users meet a more flexible mode of participation, which breaks up the regularity which lies at the base of our calculations. Furthermore, despite consideration of uncertainty, the model does not explicitly value potential real options that relate to additional future growth opportunities, which are especially valuable in situations of high uncertainty. Future research could extend the model to freemium business models, for instance by modelling two different revenue streams by user types and a stochastic conversion rate, which describes the probability of a 'free user' becoming a 'premium user'. The model could further be extended to be applicable to platform businesses by including random purchase volume and timing and the explicit value of network effects. Finally, the model could also be extended to allow for valuing managerial flexibility for digital companies, which would represent an interesting option for future research.

Chapter 8

On Estimating Parameters of Digital Investments: An Application to 3D Printing

In the digital economy technology and information have transformed into one of the core resources of businesses around the world. However, the increasingly important role and rapid developments in technology markets represent a major challenge for managers when it comes to investment decision-making. Real options literature provides a large number of sophisticated models for managerial decision-making concerned with technology investments under uncertainty. However, practical application with businesses is still very limited, one major reason being the problem of estimating input variables.

8.1. Literature Review

One of the fastest growing branch of research on real options and technology is concerned with IT investments. For instance, Ekström and Björnsson (2005) and Wu et al. (2008) value a growth option using DTA to model the decision to purchase a new enterprise resource planning system. Angelou and Economides (2008) and Angelou and Economides (2009) provide a decision analysis framework for prioritizing a portfolio of information and communication systems infrastructure projects by valuing a growth option and Bardhan et al. (2004) value an IT project portfolio for an energy provider modeling projects as nested option with interdependencies.

Another important branch of research that is based on technology diffusion is concerned with investments in R&D or new product development. While a large number of these models are based on Dixit and Pindyck (1994)'s stochastic cost-to-completion model, several extensions as well as applications have been developed. For example, Schwartz (2004) values patents and R&D as real options modeling random time to completion as well as cash flow uncertainty as risk factors. A portfolio approach is provided by Van Bekkum et al. (2009), who use basket options to model R&D portfolio diversification applying portfolio theory based on correlation and normal distributions. Not many studies exist that integrate R&D real options models with technology forecasting techniques, an exception being Wang et al. (2015), who develop a new methodology that integrates real options analysis with the Bass technology diffusion model.

A more generic trajectory of real options research on technology investments is given by articles on technology adoption investments. Grenadier and Weiss (1997) provide a quantitative framework for investments in technological innovations, modeling migration strategies under uncertainty based on stochastic technology arrivals. Doraszelski (2004) provides an extension of this model by distinguishing between innovations and improvements and determine the optimal adoption timing of new technologies. Regarding the risk of technological substitution, Schwartz and Zozaya-Gorostiza (2002) provide a framework to value disruptive innovations by modeling stochastic cost-to-completion and stochastic cash flow over three development stages.

While vast research on technology investments exists, most scholars use generic stochastic processes such as GBMs or Poisson jump processes to model the underlying stochastic technology diffusion. These processes are widely applied and can result in neat analytical solutions to derive general findings and investment strategies, however, they are subject to strong assumptions such as constant growth and no upper limit and thus have their limitations when it comes to practical implication. Furthermore, the majority of research in this area feeds their models with fictional numerical examples to demonstrate their results, while ignoring the process of input parameter estimations for real-world application. However, this remains to be one of the major challenges with investment decision models, as the input values of, for instance, drift, volatility or jump frequency and magnitude parameters, significantly affect model results and thus the efficiency of investment strategies.

In this chapter, we try to solve the problem of parameter estimation for technology investments by showing how technology forecasting literature can help to estimate the required parameters for technology diffusion under uncertainty. Technology forecasting is a broad field of research comprised by vast number of different approaches. Porter et al. (1991) summarize that the main motivation of technology forecasting is to assess the impacts of implementing a new technology on both the firm and its external environment. Then, it can help to identify the magnitude of impact technology induces in the market. Martino (1993) highlights the importance of technology forecasting and provides details about the reason why people try to predict the change of technology. In summary, he argues the main reasons are as follows:

- to maximize gain from future events,
- to minimize loss associated with future uncontrollable events,
- to forecast demand for facilities, capital planning, etc.,
- to develop plans or policy for an organization or individual.

Thus, the main reason for the importance of forecasting technological progress is mainly to maximize benefits or minimize losses. In other words, technology forecasting can help to mitigate risks and enable improved decision-making.

Martino (1980) reports that there are two methods, trend extrapolation and Delphi, which were mainly used for practical research in the 1970s. Delphi is a qualitative approach using expert opinions and questionnaires. Trend extrapolation is an quantitative method using easy analytical techniques, however, forecasting performance is poor for emerging technologies. Yoon and Park (2007) state that these methods have easiness to carry out, but they also argue that more powerful methods have been introduced in more recent years with the ease of database availability. Today, growth curves have become the most prominent technique for technology forecasting. These models use logistic S-curves to estimate technology diffusion by applying curve fitting techniques to bibliometric data such as patents, scientific publications or news related to the technology or technology bundle under consideration. In this article, we show how to apply growth curves as a quantitative forecasting technique to estimate technology diffusion and demonstrate the diffusion of 3D printing as a numerical example. More precisely, we use the Bass (1969) model to describe the diffusion, as it has proven solid results and is easy to integrate with investment decision models.

Accordingly, Massiani and Gohs (2015) try to estimate coefficients and market potential for forecasting the development of the market for electric vehicles. Turk and Trkman (2012) estimate broadband diffusion in European countries by using the Bass diffusion model. For the estimation of their parameters, a nonlinear least squares curve fitting model is used. They include 20 European countries and find that parameters differ between countries. Tunstall (2015) tries to estimate the Eagle Ford Shale oil and gas development in south Texas. The author's approach uses non-linear least squares techniques to fit the curve to the data and estimate diffusion parameters.

While various data sources are applied for curve fitting, in this chapter, we use bibliometric data about patents, scientific publications as well as news articles, as it includes ample information for forecasting emerging technologies. A large amount of patents or publications indicates that there is an optimistic view in terms of economy and technological development as R&D is costly and time intensive (Daim et al., 2006). Campbell (1983) highlights the importance of using patent data for technology forecasting as patent data exhibits typical growth patterns for technology markets such as emerging, maturing or declining. Ernst (1997) reinforces the usefulness of patent analysis by using Japanese and German patenting activity for forecasting CNC-technologies in the machine tool industry. Similarly, Altuntas et al. (2015) summarize the historical development of technology forecasting methods using patent data. Rotolo et al. (2015) define emerging technologies and find that they exhibit uncertainty and ambiguity in their practical usage and possible impacts on the market. The authors argue that, in addition to patents, publications in academic journals can help to forecast emerging technologies whose fundamental or applied research is still ongoing. For example, Watts and Porter (1997) use data from the science citation index and the engineering index as technology life cycle indicators for technologies in the basic research phase. Similarly, Daim et al. (2006) use a combination of patents and academic publications to forecast laser diode and fuel cell technologies.

As 3D printing is still a relatively young technology and application areas, markets and business models are yet to be defined, forecasting technological progress is an important task when it comes to deciding where and when to invest in this technology. In the following, we present a simple quantitative framework about how technology diffusion can be predicted based on publicly available data. The structure of this chapter is as follows. First, we demonstrate how the required historical data for the input of the forecasting model can be obtained. Second, we apply existing technology forecasting methods to this data on patents and other bibliometrics and come up with an estimate of future technology diffusion for 3D printing products and services. Third, we discuss different estimation methods and provide some sensitivity analysis about the carrying capacity, i.e. the asymptotic maximum of future patents/publications. Fourth, we introduce a stochastic version of logistic S-curve models for technology diffusion, estimate the volatility of 3D printing diffusion and link the estimation results to the diffusion of the global 3D printing market. Finally, we use our parameter estimation results to demonstrate a numerical example that compares the value and exercise strategies of a timing option between the chosen model and a standard GBM model.

8.2. Data Collection

It is necessary to obtain an understanding of the different 3D printing technologies and their advancement as well as the spread of related services to forecast the 3D printing market. We have identified ten major types of 3D printing technologies in 2019. Table

8.1 lists these ten technologies. We thought of them as basic technologies for 3D printers and used the number of research papers, patents and news articles on these technologies to determine current technological state and future progress. We further collected the same bibliometrics for the keywords *'3D printing'* and *'additive manufacturing'*, as they typically include information on not only certain technologies, but also about services and applications that facilitate or are frequently used in conjunction with 3D printing. By using this data, we aimed to identify patterns that tell us about the stage of development of 3D printing technologies including research as well as practical application.

Table 8.1: Most prominent types of 3D printing technologies in 2019

Fused Deposition Modeling (FDM)	Selective Laser Melting (SLM)
Stereolithography (SLA)	Electron Beam Melting (EBM)
Digital Light Processing (DLP)	Material Jetting(MJ)
Selective Laser Sintering(SLS)	Drop on Demand(DOD)
Direct Metal Laser Sintering (DMLS)	Sand/Metal Binder Jetting (SBJ/MBJ)

In order to retrieve the described data, we have accessed several databases. First, in order to collect the number of published research papers, we used the *Science Citation Index* (SCI) by Web of Science and the academic database *Scopus*. Web of Science was launched in 1961 and includes about 12,000 journals. This database focuses on academic journals in the fields of science and social science. Scopus was launched in 2004 and includes about 20,000 journals. This database places its focus on academic journals in the fields of science, technology and medicine. As can be seen in the number of journals recorded, Scopus is considered to have slightly less restrictive acceptance standards than Web of Science, however, both databases stand for the highest quality of academic research.

Second, to obtain the number of news articles that are related to 3D printing, we collected data from Dow Jones's news database *Factiva*. Factiva includes more than 32,000 data sources across 200 countries focusing on business information. It incorporates not only newspapers, but also online business articles and magazines and is thus a good indicator for breakthroughs in science with regard to business applications.

Third, to get the number of patents related to 3D printing technologies, we used the *Derwent Innovation Index* (DII). Despite the existence of many patent databases containing citation information, the DII is often used for economic analysis of technological changes (Tomizawa, 2007). It represents an integration of two databases, namely the *'Derwent World Patents Index'* and the *'Derwent Patents Citation Index'*. The first includes data of the patent family and the latter is a database that focuses on citation information.

We have accessed the described databases to search for the annual number of patents, scientific publications and news articles for each of the ten major technologies as well as our two keywords. Data was gathered for the time interval from 1990 to 2018. We choose this time period, as there were almost no publications on 3D printing before 1990 and, at the time of our analysis, there was still a large amount of articles and patents missing for 2019. In order to ensure that all search results were strongly related to 3D printing, we have entered the keywords into the search engines in a way that it includes titles, abstracts and keywords. In Appendix A.5, we provide a brief description of the resulting data sets.

8.3. Estimation Method and Results

The mixed-influence model for our 3D printing example can be expressed using equation

$$\frac{dN(t)}{dt} = \left(p + \frac{q}{m}N(t)\right)(m - N(t)), \tag{8.1}$$

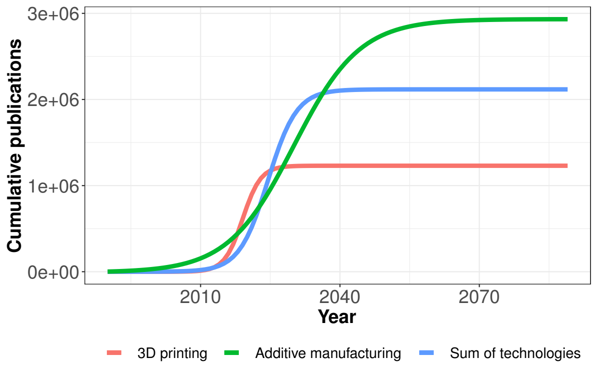
where $N(t)$ is the cumulative number of technology adopters at time t, m is the ultimate ceiling (i.e. upper limit) of all potential adopters, p is the coefficient of innovation and q is the coefficient of imitation. According to equation (8.1) the cumulative number of adopters $N(t)$ thus follows a S-shaped curve that converges to the total number of adopters m when the technology matures.

There are several methods for estimating the parameters of innovation diffusion models. The Ordinary Least Squares (OLS) method is one of the earliest methods for estimating the parameters as suggested by Bass (1969). This method estimates the parameters by discretizing the differential equation and estimates regression coefficients to come up with values for p, q and m. However, for our 3D printing data, the OLS method performed very poorly and was not able to show meaningful results. That is, most forecasts did not exhibit smooth logistic S-curves as they are expected when applying the Bass model. In fact, some of the estimates resulting from SCI, Scopus and Factiva data even became negative. Contrarily, the estimated number of future patents showed a sudden jump to infinity in 2029. The main reason for these unrealistic results is the lack of data points, which leads to unstable estimates, as explained in Mahajan and Schmittlein (1982). Due to the novelty of 3D printing, the data on research papers and patents in each year is not sufficient for the OLS method, which is why we refrain from presenting our OLS results in more detail.

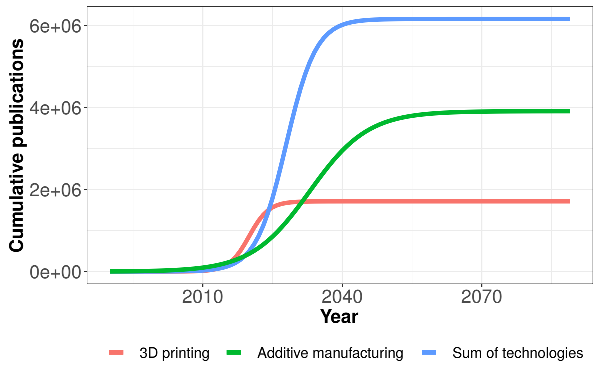
Maximum Likelihood Estimation (MLE) fitting is a prominent alternative for the Bass model that has been first proposed by Mahajan and Schmittlein (1982) for estimating an innovation diffusion model of new product acceptance as originally considered by Bass (1969). For details on the implementation of the MLE methods we have employed in our analysis, refer to Appendix A.6.

8.3.1. Results

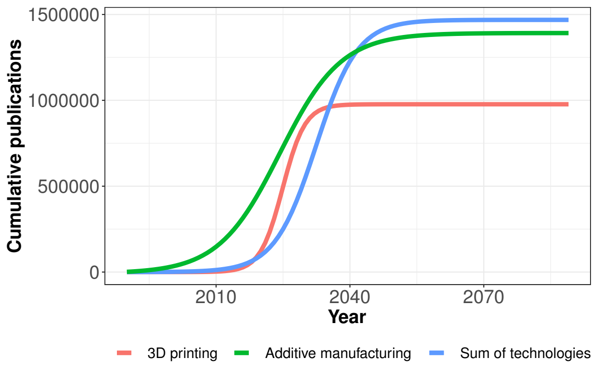
In this section we apply the described MLE curve fitting technique to our 3D printing example. More precisely, we fit the Bass model to the collected bibliometric as well as patent data to estimate growth curves for 3D printing diffusion. The results of the MLE forecasts are illustrated in Figure 8.1.



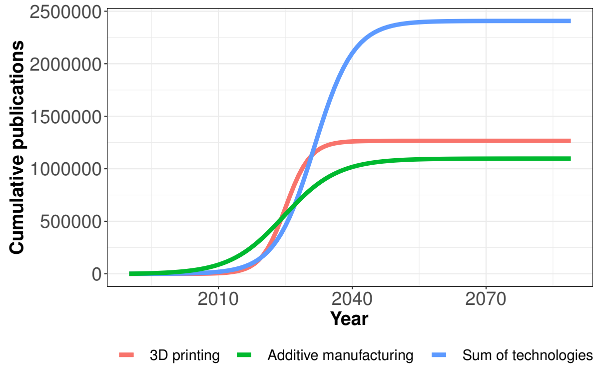
(a) SCI + Patents + Factiva



(b) Scopus + Patents + Factiva



(c) SCI + Patents



(d) Scopus + Patent

Figure 8.1: Estimation results by MLE method - M was set to 100 times the respective cumulative number of hits in 2018

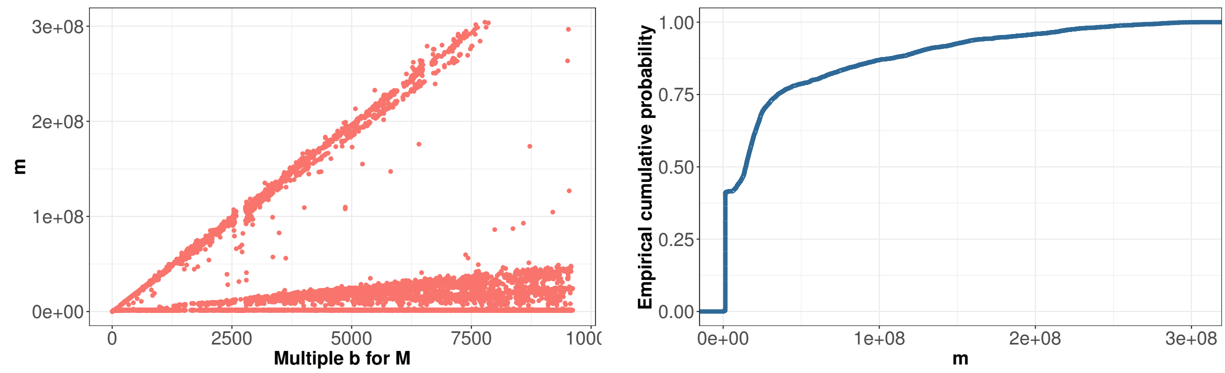
We receive effective estimates that result in realistic logistic S-curves. Figure 8.1a shows our forecast using the sum of SCI, DII and Factiva data, 8.1b the sum of Scopus, DII and Factiva data, 8.1c the sum of SCI and DII without Factiva data and 8.1c the sum of Scopus and DII without Factiva data. The graphs show that the forecasts including news articles lead to higher ceilings and faster growth. This is not surprising as Figure A.2 in Appendix A.5 shows that there was a drastic increase in news articles especially for '3D printing' from 2010. For the same reason, however, these forecasts suggest that 3D printing is going transition into its maturity stage before 2030, which seems somewhat unrealistic. According to the graphs in Figure 8.1, 3D printing will enter its maturity stage before 2030, additive manufacturing around 2040 and the sum of technologies around 2035. It is further noteworthy that, while the curves for additive manufacturing and 3D printing differ strongly between data sources, the forecasts for the sum of technologies seems to be more stable. These curves show similar shapes in all four graphs. Finally, regarding Figure 8.1c, we can observe that all three curves are relatively close to each other indicating that SCI + Patents exhibits the smallest keyword bias. Thus, in the next section we proceed our analysis using the results from forecasting the sum of technologies based on the sum of SCI and patent data as illustrated by the blue curve in Figure 8.1c.

8.3.2. Sensitivity Analysis

Building on the estimates obtained in the previous section, in the following, we introduce some analytical methods that provide a better understanding of the results and their stability. It is the purpose of this study to introduce a framework to find an answer to questions surrounding technology investments as they are frequently faced by managers. Two questions are particularly in focus of this study. First, how far are the 3D printing technology and related business applications going to spread in the future? Second, in which phase of the technology life-cycle is 3D printing currently positioned, i.e. is it an emerging, growth or maturing technology?

In order to find an answer to these questions, we applied the Bass model to publicly available data on 3D printing and performed an estimate for 3D printing technology diffusion. In the Bass model, m denotes the asymptotic growth ceiling and thus determines how important the 3D printing technology will ultimately become. Estimating this parameter is both difficult and important, as it shows the most crucial effect on our results. As 3D printing is still a relatively young technology, we had to estimate m based on a small data set. Typically, small data sets result in unstable estimates of m. Thus, in order to investigate the stability of our results, in the following, we present some sensitivity analyses about this critical parameter.

In order to estimate the Bass model parameters using the MLE method it is initially necessary to manually set a value for M. In contrast to m, which describes the actual number of ultimate adopters, M describes the total population of all specimens that have the possibility to adopt. As can be seen from equation (A.2), m is a subset of M and thus has an influence on estimates of m. In the following, we provide our results of performing sensitivity analysis over M for the described data set. We can assume that M is larger than the collected cumulative number of patents or publications in 2018. Therefore, in our sensitivity analysis, we assigned values to M such that it is between 1 and $10,000$ times larger than the cumulative number of patents and publications in 2018. To determine the possible range of m, for each value of M, we re-estimated the parameters of the Bass model by applying the MLE method as described in Appendix A.6. Figure 8.2 shows the results of estimating m for these different values of M.



(a) Sensitivity analysis for M - m either increases linearly or falls into a relatively narrow range

(b) Empirical cumulative function of m - The steepness of the curve suggests that m falls into a certain range with a high likelihood

Figure 8.2: Sensitivity analysis results for m

The vertical axis of Figure 8.2a describes the value of m and the horizontal axis represents the value of the multiple b of M such that $M = bN_{t=2018}$. We can observe that, for some cases, the value of m increases approximately linearly when b is increased. However, in most cases, m seems to fall into a certain range that does not exceed 1.5 million. In order to clarify the likelihood of m not exceeding this range, we further computed the empirical cumulative distribution function of m, as illustrated in Figure 8.2b. The vertical axis in Figure 8.2b indicates the cumulative probability and the horizontal axis describes the value of m. Until a cumulative probability of around 0.4, the curve is very steep, which means that m has a high likelihood of taking a value within a small range. When exceeding a cumulative probability of 75%, however, the curve flattens out. The cumulative probability of 0.9 is exceeded when m equals around 200 million. We can conclude that, when estimating m by MLE, changing M causes fluctuations in estimates of m. While there is a tendency of m falling into a small range of values for large differences in M, for our 3D printing example, the effect of changes in M on m are rather large.

Table 8.2: Example percentile of m for different values of M

percentile	2.5	25	50	75	97.5
m	$1,389,068$	$1,396,142$	$1,5304,117$	$45,390,869$	$346,679,981$

Table 8.2 highlights the range of realistic values of m when varying b between 1 and $10,000$. The table summarizes representative quantiles with respect to Figure 8.2b. Accordingly, the 95% confidence interval for m is $[1,389,068; 346,979,981]$. Thus, despite the initial steepness of the CDF shown in Figure 8.2b, the range of m on this confidence level is extremely large. In other words, there is a high degree of uncertainty regarding the estimates

of m for our 3D printing example. In order to investigate the effects of this uncertainty, we further analyzed how changes in M affect the location and shape of the S-curve and parameters p and q.

First, we analysed the sensitivity of the inflection point of the S-curve towards different values of M. This is an important measure, as it defines the point at which half time growth of the technological progress is reached. It also describes the point in time at which growth rates start to decrease. The mid point can be calculated by substituting the estimated parameters p and q into the following equation:

$$T^{*} = -\frac{1}{p+q} \ln\left(\frac{p}{q}\right), \tag{8.2}$$

where T^{*} is inflection point.

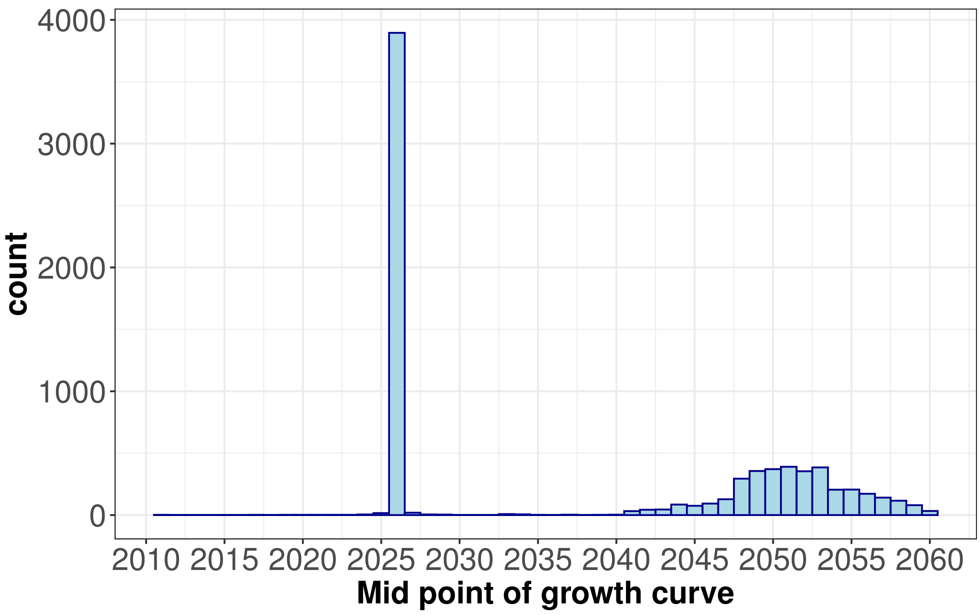
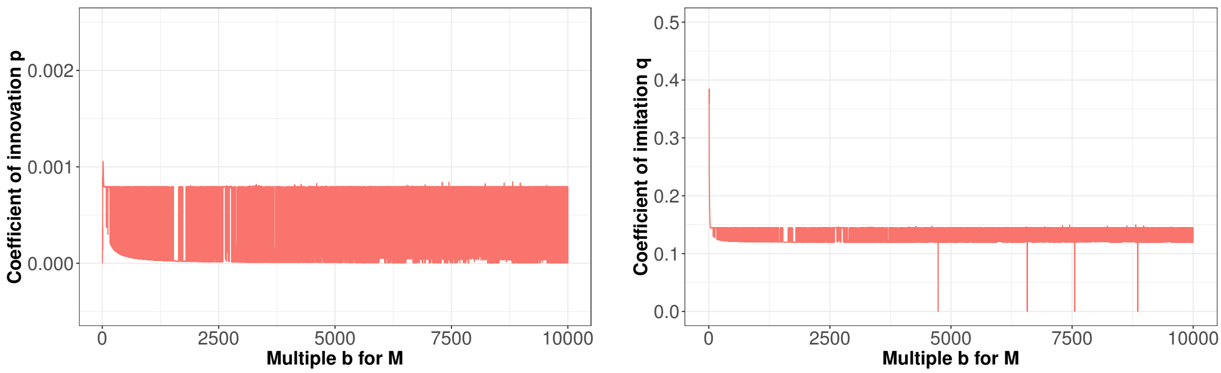


Figure 8.3: Mid point simulation for 10,000 different values of M

Again, we simulate the value for the 10,000 different values of M. The simulation results can be found in Figure 8.3. The horizontal axis describes the year and the vertical axis describes the resulting frequency of inflection points as performed by our simulation. The graph suggests that for most values of M, the inflection point is estimated to be reached in 2026. Almost 4,000 out of the 10,000 simulated curves have their mid point in 2026 and almost no curve has its mid point in neighboring years. Thus, the mid point simulation shows very stable results indicating that the inflection point of 3D printing progress is reached in 2026 regardless of the value of M. That is, the annual number of new SCI publications and DII patents on 3D printing is going to grow until 2026 before growth rates start to decrease.



(a) Result of parameter p simulation, $n = 10000$

(b) Result of parameter q simulation, $n = 10000$

Figure 8.4: Sensitivities of p and q towards m

Next, to further investigate the reason for the independence between M and the inflection point, we have analyzed sensitivities of parameters p and q towards M. The results are summarized in Figure 8.4. Again, we varied the value of b to find out how changes in M affect our results. Figure 8.4a indicates that the value of parameter p fluctuates between 0 and 0.001 and thus hardly changes with any variation in M. Similarly, Figure 8.4b shows that the value of parameter q stays between 0.1 and 0.2 and thus hardly changes with changes in M. Therefore, the independence of the inflection point and the value of M is a result of the negligibly small sensitivities of p and q towards M.

In addition to the inflection point that describes the time at which half of technological progress is reached, it is further important to determine the current and future technological stages of the technology. In order to conduct this analysis, we defined the periods when the cumulative probability of the S-curve reaches from the 0% to 30% as emerging stage, 30% to 70% as growth stage and from the 70% to 100% as the maturing stage. Accordingly, technological stage periods were calculated for each of the selected S-curves.

Table 8.3: Distribution of innovation phases; frequency of transition points between technological stages of 3D printing

	Maturing stage from 2031	Maturing stage from 2032
Emerging stage until 2021	29	0
Emerging stage until 2022	1507	20

Table 8.3 shows the frequency of transition points from emerging to growth and from growth to maturity stages. The table shows that for any of the 3913 different values of M that resulted in a mid point in 2026, the timing of the transition from the emerging to the growth stage and from the growth to the maturing stage are roughly the same. That

is, 1507 of the curves show their emerging stage until 2023 and their maturing stage from 2031, while none of the curves had their emerging stage until 2022 with a maturing stage from 2032. Therefore, we can underline the result that p, q and the technological stage are insensitive to M. Following the logic of these results, technological stages of 3D printing are as shown in Table 8.4. We can conclude that, with high certainty, 3D printing can still be declared an emerging technology that is going to transition into its growth period from 2023 and start to mature from 2031.

Table 8.4: Most likely technological stage periods of 3D printing

	Emerging	Growth	Maturing
Period	1990-2022	2023-2030	2031-2064

Finally, in order to analyze the most likely dynamics of innovators and imitators as given by the Bass model, we had a closer look at parameters p and q. The numbers of innovators and imitators at each point in time are calculated by the following expression provided by the Bass model's analytical solution:

$$N_1(t) = m\frac{p}{q}\ln\left[\frac{1+\frac{q}{p}}{1+\frac{q}{p}\mathrm{e}^{-(p+q)t}}\right], \tag{8.3}$$

where, $N_1(t)$ is the number of innovators each year,

$$N_2(t) = N(t) - N_1(t), \tag{8.4}$$

where $N_2(t)$ is the number of imitators each year and

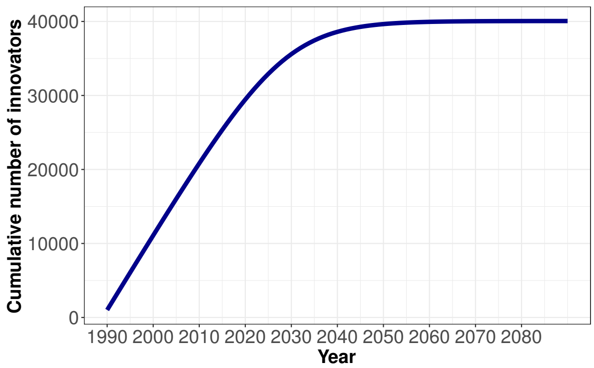
$$n(t) = m\left[\frac{p(p+q)^2\mathrm{e}^{-(p+q)t}}{(p+q\mathrm{e}^{-(p+q)t})^2}\right], \tag{8.5}$$

where, n(t) is the number of total publications / patents on 3D printing each year.

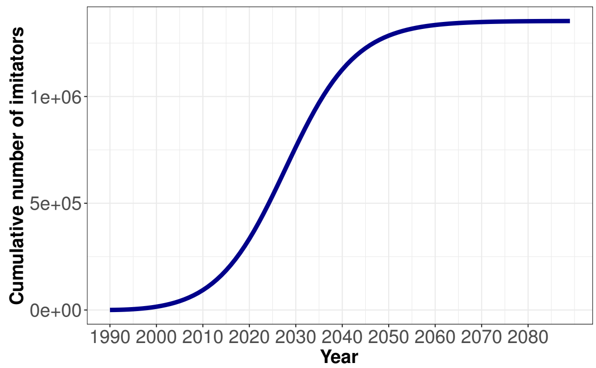
Using these equations, the most likely numbers of innovators N_1 and imitators N_2 are calculated. For that purpose, it is necessary to specify parameters m, p and q. Sensitivity analysis on the inflection point showed that the position of the inflection is independent of changes in M. Table 8.3 showed that the technology phase is roughly the same for any S-curve chosen by this criterion. Therefore, a model with a growth stage from 2023 to 2030 and an inflection point in 2026 was selected to calculate the variables. One combination of the respective parameters p, q and m that describes these dynamics for our 3D printing example is listed in Table 8.5.

Table 8.5: Bass model parameters of the selected model

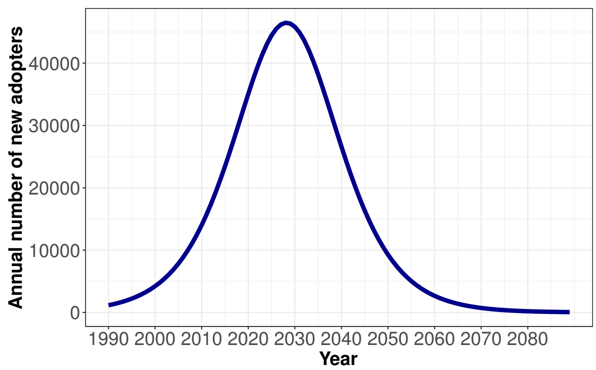
	p	q	m
Value	0.0007279	0.1318882	$1,394,527$



(a) Cumulative number of innovators



(b) Cumulative number of imitators



(c) Annual number of adopters

Figure 8.5: Summary of the Bass model results applied to 3D printing technologies

Figures 8.5a and 8.5b show the resulting cumulative number of innovators and imitators. The figures show that the number of innovators started to increase in 1990, while the number of imitators has started to grow significantly from around 2010. Additionally, we can see that innovators are going to start to mature around 2030, while the number of imitators continue to increase until around 2050. Figure 8.5c describes the annual number of new adopters of 3D printing. We can see that the growth rate peaks in 2026. Thus, we can expect that the technological progress of 3D printing is further going to pick up speed generating most progress within the next couple of years. Despite the decrease in growth from 2026, the model suggests that there will still be new adopters of 3D printing until around 2070, which represents important insights when it comes to investment decision-making.

8.4. Stochastic Logistic Growth Models

8.4.1. Stochastic extensions of deterministic models

Most technology forecasting models use deterministic functions to estimate technology diffusion. While these models can provide an idea about the expected development of the analysed technology, they do not allow for uncertainty, which makes scenario analysis and planning difficult. Thus, in order to find out about the distribution of technology states across time, we have to include uncertainty. This enables us to measure the risk of technology-related investments (e.g. by calculating relevant risk measures) or value potential real options, which are especially interesting in the context of managerial decision-making. More precisely, stochastic technology growth models can be a valuable tool for optimizing:

- technology adoption strategies,
- R&D investment strategies,
- IS or IT investment strategies,
- venture capital investment strategies,
- (tech-)company valuation techniques,
- technology-based trading strategies.

There are several ways to make deterministic logistic growth models such as the Bass model probabilistic. The most common approach is to add noise to the differential equation, that then describes the expected development of a technology. Existing literature presents three different ways to do so. The first method is to add noise to the accumulated number of published articles and patents as in Giovanis and Skiadas (1999) such that

$$dN(t) = \left(p + \frac{q}{m}N(t)\right)(m - N(t))\,dt + \sigma N(t)dW(t), \tag{8.6}$$

where p is the coefficient of innovation, q is the coefficient of imitation, m is the carrying capacity, σ the instantaneous volatility of $N(t)$ and $W(t)$ is the standard Wiener process.

A second possibility to include uncertainty into the mixed-influence model is to add noise to the growth rate $g(t)$, see, for example, Eliashberg et al. (1983) and Lungu and Øksendal (1997). Applied to the mixed-influence model $N(t)$ could evolve such that

$$\frac{dN(t)}{dt} = \left(p(t) + \frac{q(t)}{m}N(t)\right)(m - N(t))\,, \tag{8.7}$$

with stochastic coefficients of innovation and imitation following GBMs such that

$$\begin{aligned} dp(t) &= \mu^p p(t) + \sigma^p p(t) dW^p(t), \\ dq(t) &= \mu^q q(t) + \sigma^q q(t) dW^q(t), \end{aligned} \tag{8.8}$$

while μ^p and μ^q describes the expected changes in $p(t)$ and $q(t)$ and σ^p and σ^q their instantaneous volatilities.

The third and less common option that can be found in literature is including noise in the asymptotic ceiling or carrying capacity $m(t)$ as in Anderson et al. (2016). In conjunction with the mixed-influence model, we can express the diffusion of $N(t)$ such that

$$\frac{dN(t)}{dt} = \left(p + \frac{q}{m(t)} N(t)\right)(m(t) - N(t)), \tag{8.9}$$

with a stochastic carrying capacity $m(t)$ that follows a GBM. That is,

$$dm(t) = \mu^m m(t) + \sigma^m m(t) dW^m(t), \tag{8.10}$$

while μ^m describes the expected changes in $m(t)$ and σ^m its instantaneous volatility. For a graphical illustration of the three different diffusion models, see Appendix A.7.

All three presented approaches show some noise in $N(t)$. However, we can observe some important differences between the different realizations. First, (8.7)-(8.8) (Figures A.3c and A.3d) make the implicit assumption that, despite noise in growth rates, the ceiling m can never be exceeded. This assumption is the reason for the extremely skewed distribution of the histogram in Figure A.3d. However, as discussed in section 8.3.2, there exists high uncertainty concerning the value of m, which has the potential to significantly influence our estimation results. An example for the simulation of equations (8.9)-(8.10) is illustrated in Figures A.3e and A.3f. This model includes uncertainty about the value of the ceiling m into our estimates. We can observe that different realizations of m lead to compression or stretching of the curve that unfolds the largest effect at the end of our simulation horizon. Interestingly, earlier points in time are hardly affected by including uncertainty in this way. This is in line with our findings from Section 8.3.2 indicating that slope and inflection point hardly change with varying values of m. However, it might not be realistic to assume such a high certainty about slope and mid-point of the underlying technological diffusion. Thus, equation (8.6) with sample realizations illustrated in Figures A.3a and A.3b represent the most realistic uncertainty pattern for our application example. In contrast to the model with uncertainty about p and q, this model allows for exceeding m. Furthermore, the normally distributed noise evolves symmetrically across time, which represents the desired setting. Thus, we proceeded our analysis choosing the model from equation (8.6) as the best fit for our desired setting.

8.4.2. Volatility Estimation

The stochastic model we choose for our application is the SDE as presented in equation (8.6). It can be written as the general form

$$df_t = \mu_t f_f dt + c_t f_t dw_t, \tag{8.11}$$

where μ_t is the drift and c_t is called volatility coefficient. Existing literature provides us with a systematic approach to estimate c_t. That is, suppose the values of μ_t are already known, then c_t can be estimated using Ito's lemma.[10]

Based on the assumption that the external and internal influence on the diffusion process is independent of the whole system's noise, the estimation for a constant value c on a set of real data of length T, is

$$\hat{c} = \frac{1}{T-1} \sum_{t=2}^{T} \left| \frac{f_t - f_{t-1}}{\sqrt{f_t f_{t-1}}} \right|, \tag{8.12}$$

while f_t describes the the number of observations at time t.

The presented estimation method is applied by a vast number of researchers. Skiadas and Giovanis (1997) and Giovanis and Skiadas (1999) use stochastic Bass models to study the innovation diffusion in the electricity consumption in Greece and the United States. The authors use MLE methods to estimate the drift and equation (8.12) for estimating future volatility from historic data. Similarly, Gutiérrez et al. (2005) use a stochastic Gompertz model to forecast the natural-gas consumption in Spain, using a similar version of equation (8.12) to come up with a volatility estimation. The authors use their estimation of c to calculate confidence intervals and show that between 1973 and 2003, the observed real data is well within the limits of the resulting confidence interval. In the following section we apply their approach to the estimation of the volatility coefficient for our 3D printing data.

8.4.3. Application to 3D Printing

We have presented several approaches to estimating the parameters for the deterministic Bass model based on the collected data for 3D printing technologies. In this section, we extend this estimation by adding a probabilistic diffusion term to the deterministic model

[10]For derivation of the estimation for a non-linear SDE, see Katsamaki and Skiadas (1995).

as in equation (8.6) and estimate the volatility coefficient as in equation (8.12). As in accordance with existing research, we use some results from the prior sections that have been estimated by applying MLE techniques. Thus, the combination of p, q and m as provided in Table 8.5 defines our expected technology development, while the volatility coefficient c is to be estimated as described in equation (8.12). Some simulation results for our 3D printing example based on SCI and DII data are illustrated in Figure 8.6.

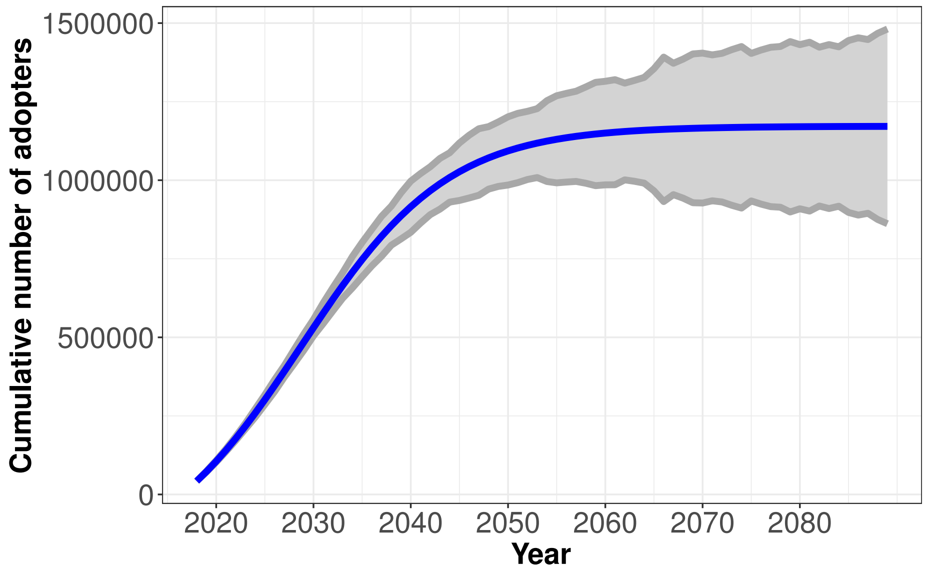


Figure 8.6: Simulation results for SCI + DII MLE estimation including uncertainty - $p = 0.0007279$, $q = 0.1318882$, $m = 1,394,527$, $c = 0.162278$, 100 simulations, annual discretization

The figure shows the expected progress of 3D printing technologies as described in Section 8.3 and the 95% confidence interval of our simulation that includes noise in $N(t)$. In our example, the estimated annual volatility amounts to 0.162278. We can observe that the added volatility coefficient results in sample path trajectories that fluctuate around the expected diffusion, resulting in a broad spectrum of potential realizations. However, as the modeled uncertainty increases over time, it unfolds rather small effects on the steepness and shape of the curve in earlier years. Most of the uncertainty is associated with the ultimate upper limit of technological development, which is in line with the findings from our sensitivity analysis. Thus, when applying this logic to technology investments we can expect that investment timing is less critical than investment scale and that short-term investments into 3D printing are not subject to high levels of uncertainty. However, regarding long-term investments such as newly entering into the 3D printing market or future growth opportunities that are related to this technology, uncertainty can play a crucial role.

8.4.4. Linking the Results to Technology Performance

Most existing research concerned with technology forecasting solely focuses on finding trajectories of the cumulative number of patents or publications for the respective technologies. For example, Daim et al. (2006) forecast the number of patents and publications for emerging technologies to find the timing of substitution by applying the Fisher-Pry model. Similarly, Trappey et al. (2011) feed a simple logistic S-curve model with data on China's RFID patents to estimate upper limits, time of maturity and technological stages and Chen et al. (2011) forecast the number of future patents on hydrogen energy and fuel cell technologies focusing on growth periods, mid-point of the logistic S-curve and technology stages.

As presented in Section 8.3, these models can provide us with important insights regarding the relative importance of certain technologies as well as growth stages and substitution timing of mature technologies. However, when it comes to investment strategies, the number of publications might not suffice as a performance indicator relating to economic value. Thus, the projected cumulative number of patents and publications should be translated into monetary performance measures that can serve as a proxy for managerial decision-making.

While vast research on technology forecasting exists, it tells us little about how to link bibliometric data to technological performance measures. Lee et al. (2010) provide a study on the relationship between technology diffusion and product adoption by comparing patent citation data with mobile phone adoption data and find that technology diffusion can explain demand quite well. Kim and Bae (2017) analyze patent forward citations, triadic patent families and independent claims to assess whether technology clusters are promising and forecast their diffusion. Depending on the way how a new technology is planned to be deployed, different performance measures are crucial.

For instance, consider a company that wants to enter into the 3D printing market, by offering products or services that are used with 3D printers. The success of such a business model will then highly depend on the future size of the 3D printing market and the expected market share of the investing company. In contrast, if a business wants to invest in 3D printing technologies for product manufacturing or to optimize its existing supply chain by printing spare parts on site, printing cost and efficiency play a more critical role in assessing investment opportunities. Typically demand, adoption and efficiency increase while costs decrease when the underlying technology matures. However, in order to make informed investment decisions, we need to estimate the trajectories of these numbers. We have learned that patents and bibliometrics can help us to describe and forecast technological diffusion. Thus, we can expect that these numbers also highly correlate with more relevant measures that indicate how technology markets or performance evolve.

As a concluding discussion, in the following, we briefly present a simple approach to link the presented bibliometric forecasting results to demand. In our example, global demand for 3D printing products and services is represented by the global 3D printing market size. We choose this measure, as market size is a crucial economic measure and various studies on the global 3D printing market exist that determine and predict historical as well as future market sizes. Market size estimates from these studies are often freely accessible online. We included 11 data sources provided by well-known market research institutions resulting in 42 point estimates of the global 3D printing market size between 2003 and 2027. According to these estimates, the global 3D printing market size was 530 million US Dollars in 2003 and has increased to an average of 14.15 billion US Dollars in 2019. The market is further expected to reach 55.8 billion US Dollars by 2027. The average compound annual growth rate in this period is estimated to amount roughly 20%.

In order to analytically obtain the trajectory of the total market size, we run a linear regression model using market size as the dependent variable and the sum of the cumulative numbers of annual SCI publications and DII patents as the independent variable. The regression results can be summarized as follows. The coefficient that defines the slope of the regression curve amounts to USD $83,560$ per publication/patent and is highly significant with a p-value of $< 2.2e - 16$. The model has a extremely high explanatory power with an adjusted R-squared of 0.8786. Thus, we can conclude that there is a strong linear relationship between the annual number of cumulative patents and publications and total market size. We predict the market curve by using this linear regression model based on the estimated cumulative number of publications and patents obtained by MLE curve fitting as explained in Section 8.3. The resulting curve as well as the collected point estimates are illustrated in Figure 8.7.

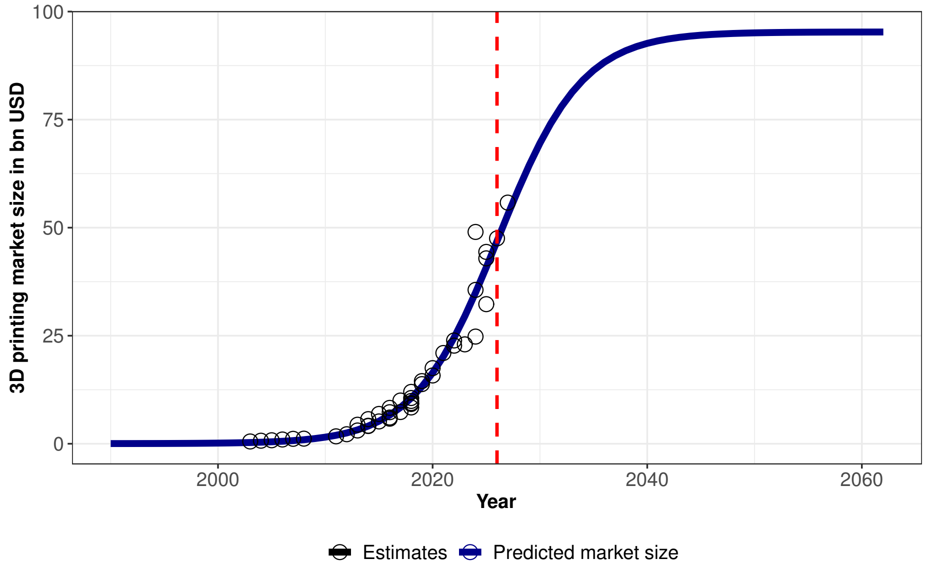


Figure 8.7: 3D printing market prediction. Point estimates of provided by: Statista, Wholers, Allied Market Research, Markets and Markets, Mordor Intelligence, Transparency Market Research, Smitherspira, International Data Corporation, BCC Research, IMARC Group and Verified Market Research

The S-curve describes the market prediction based on the regression model while the circles illustrate the collected market estimates. The dashed vertical line highlights the mid point of the curve in 2026. The results suggest that, the chosen data on publications and patents track the market growth of 3D printing remarkably well. Despite the high growth rate in 2019, only a small fraction of the total market size is reached. The curve further suggests that the market will grow to a total size of almost USD 100 billion reaching its maturity around 2040, which is in line with the results from Section 8.3. Thus, as 3D printing is currently approaching its transition point from an emerging technology to a growth technology, the market will face exponential growth within the next few years and investments into this market can still unfold a huge potential.

8.4.5. Comparison of the Geometric Brownian motion model with the Stochastic Bass Model

In order to examine the effect of employing the Bass model, we consider a standard capital budgeting problem with managerial flexibility about investment timing. We demonstrate how the proposed model affects the value of an investment project by comparing it to that under a standard GBM setting.

Let us consider a company that can invest an initial amount X to enter into the 3D printing market. The value of the project is described by its NPV. It can be calculated by discounting all future net cash flows to the company after entering the market. As shown in the previous section, the total 3D Printing market size is dependent on the future number of cumulative patents and publications $N(t)$, which is subject to uncertainty. The company uses two different models to estimate the diffusion of $N(t)$. The first model is the stochastic Bass model as introduced in equation (8.6). The second is a GBM, which is the standard approach to option pricing in Real Options literature. It can be described by the stochastic differential equation

$$dN(t) = \mu N(t)dt + \sigma N(t)dW(t),$$

where μ is the expected rate of growth in $N(t)$, σ the volatility and $dW(t)$ is the Wiener increment.

As shown in the previous section, the expected market size at any time t can be estimated by

$$M(t) = gN(t), \tag{8.13}$$

where g stands for the rate at which the market grows for each new patent or publication. Let us assume that the NPV can be calculated by applying a predefined revenue multiple R to the expected market size $M(t)$. Then, the NPV of the project at any time t can be calculated by computing

$$\mathrm{NPV}(t) = RM(t)s, \tag{8.14}$$

where s is the expected market share of the investing company.

Let us further assume that the company holds the option to choose the investment timing. Expected future values of $\mathrm{NPV}(t)$ will be dependent on market size diffusions. The option to defer can be modelled as an American-style call option on the project's NPV with strike price X. Thus, the immediate payoff at time t is given by

$$\Pi(t) = \mathrm{NPV}(t) - X, \tag{8.15}$$

resulting in the claim value of the timing option at t_0 of

$$V(t_0) = \max_{t^* \in \mathcal{T}(t_0,T)} \left\{0, \mathrm{E}^P(t_0)[e^{-r(t^*-t_0)}\Pi(t^*)]\right\}, \tag{8.16}$$

where $\mathcal{T}(t_0, T)$ is the set of stopping times in $[t_0, T]$ and $\mathrm{E}^P(t_0)[\cdot]$ is the expectation with respect to the physical measure P, conditional on the information available at t.

We consider the typical optimal investment problem based on the usual complete probability space with finite time horizon T. Option values considered in this subsection are evaluated under the physical probability measure. The validity of the risk-neutral probability measure is discussed in Borison (2005).

Table 8.6: Input parameters for both models

Parameter	**GBM**	**Bass**	**Estimation method**
N_0	42,455	42,455	Cumulative number of SCI publications and patents in 2018
p	-	0.0007278993	MLE estimation
q	-	0.1318882	MLE estimation
m	-	1,394,527	MLE estimation and sensitivity analysis (best fit)
σ	0.142937322	0.162278	Estimated from historical data*
μ	0.096379829	-	Estimated from historical data*
r	10%	10%	Assumption
X	USD 10 billion	USD 10 billion	Assumption
T	1 - 35 years	1 - 35 years	Assumption
g	USD 83,560	USD 83,560	Estimated by linear regression
S	3%	3%	Assumption
R	10x	10x	Assumption

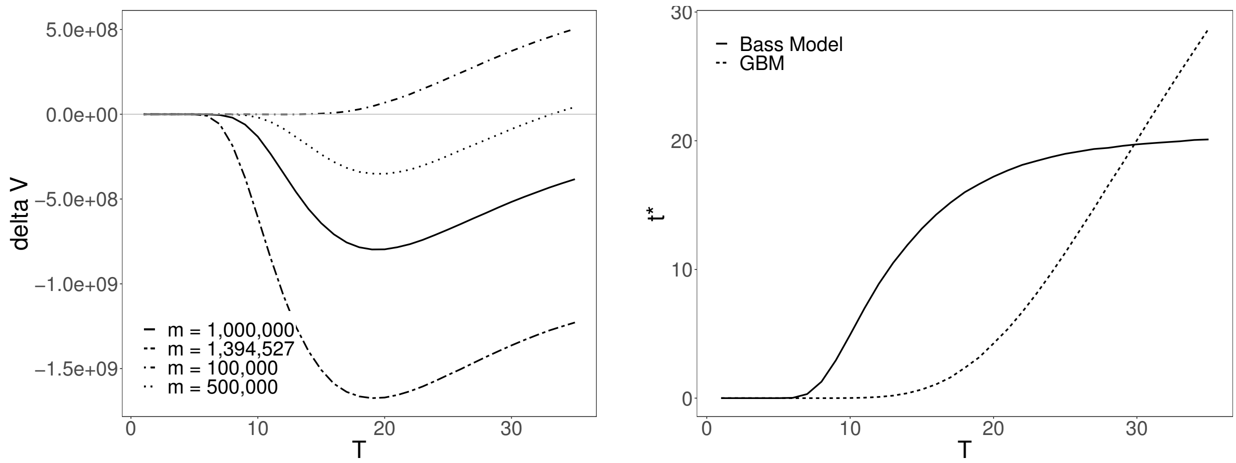
*Estimation of σ for the Bass model was estimated according to equation (8.12). For the GBM, σ and μ were calculated from the same data set of the historical numbers of cumulative SCI publications and patents from 1990 to 2018. σ is estimated as a sample standard deviation of log returns and $\mu - \frac{1}{2}\sigma^2$ is estimated as a sample mean.

For both models, we use Monte Carlo simulation to approximate the continuous-time model by choosing an integer l so that the time span $[t_0, T]$ is divided into l intervals whose length is $\Delta t = \frac{T}{l}$. The value process of a contingent claim on NPV(t), with maturity T and payoff $\Pi(t)$, can be computed using the Least Squares Monte Carlo (LSMC) method as introduced by Longstaff and Schwartz (2001). We choose this method as the LSMC can be applicable to both stochastic Bass and GBM in the same framework. It is valid to compare the real option value under the two different stochastic processes. We generate 40,000 sample paths for both models under annual discretization. At each point in time t and for all sample paths ω, we compute the continuation value by regression and compare it with the discounted immediate payoff. Like in any American option valuation procedure, the optimal exercise decision at any point in time is obtained as the maximum between the immediate exercise value and the expected continuation value. Given that the expected continuation value depends on future outcomes, the procedure must work its way backwards, starting from the end of the option's time horizon T.

Plugging in the previously estimated input parameters as listed in Table 8.6, according to equation (8.14), the value of the project without managerial flexibility at $t = 0$ equals roughly USD 1.064 billion at an initial investment outlay of USD 10 billion. Thus, without the option to wait, the project would yield a highly negative NPV and would thus be rejected.

Table 8.7: Simulation results

Value of the investment project including the timing option (in million USD)							
	$T = 5$	$T = 10$	$T = 15$	$T = 20$	$T = 25$	$T = 30$	$T = 35$
GBM	0	0.6	26.4	144.4	331.7	512.9	649.4
Bass	0	488.7	1,436.2	1,726.0	1,780.7	1,790.0	1,792.0
Exercise probability							
	$T = 5$	$T = 10$	$T = 15$	$T = 20$	$T = 25$	$T = 30$	$T = 35$
GBM	0%	0.1%	4.3%	21.1%	45.6%	67.4%	82.2%
Bass	0%	50.4 %	89.9%	95.7%	96.1%	96.2%	96.3%



(a) Difference between option prices of the two models for different option maturities and carrying capacities m. Delta V denotes the difference between option values of the two models. As it is defined as $V(t_0)^{\text{GBM}} - V(t_0)^{\text{Bass}}$ negative Delta V values suggest that the option value of the Bass model is higher than the option value based on the standard GBM model and vice versa. Delta V values of zero suggest that option prices of both models are equal.

(b) Approximated optimal exercise timing for the two models for varying option maturities. t^* denotes the expected optimal exercise timing of the respective timing option with maturity time T. Note that values of $t^* = 0$ suggest that the option will never be exercised and that the project should be rejected despite the existence of a timing option.

Figure 8.8: Real Options Analysis Results - Comparison between the stochastic Bass model and the GBM

Computing the value of the timing option $V(t_0)$ yields different results for the two different models. Table 8.7 lists the resulting option values as well as approximated exercise probabilities for both models under different option maturities T. The table shows that there are significant differences in option values between the two models. That is, the Bass model yields much higher option values and exercise probabilities than the GBM for all regarded values of T except for the case of $T = 5$. The relative difference of these values first increases substantially for early variations of maturity times and then decreases when the underlying starts to approach the asymptotic limit of the Bass model m. To further investigate this result, Figure 8.8a illustrates the absolute difference in option prices between both models for different option maturities and different values of m. Delta V is defined as $V(t_0)^{\text{GBM}} - V(t_0)^{\text{Bass}}$. Thus, negative values of delta V suggest that option values of the Bass model are higher than of those of the GBM model. We can observe that for lower values of m the difference in results of the Bass model and the GBM become smaller. An m-value of 100,000 results in larger option prices for the GBM, while for an m-value of $500,000$, the option value of the GBM only approximately exceeds the option price of the Bass model with long maturity times of more than 30 years.

Figure 8.8b illustrates the expected optimal investment timings t^* for both models under different option maturities T. The figure shows that the Bass model suggests much earlier optimal exercise timings, leading to strong differences in optimal investment strategies. Note that, we omit an analysis of the differences in optimal exercise boundaries, as is not straightforward to derive when using the LSMC method. In addition, comparing the boundaries does not lead to major implications for investment decision-makers, as the resulting option values and exercise probabilities are much more relevant when deciding if and when a technology investment becomes profitable.

We can conclude that, in our 3D printing example, option values resulting from our Bass model simulations are significantly higher than for the GBM-based calculations. That is, despite the significant positive drift of the GBM model, the Bass model curve grows much faster in early time periods, leading to larger market sizes and thus larger NPVs and option values. However, if the state variable in the Bass model was sufficiently close to its carrying capacity m, the GBM model would yield larger option prices. Thus, the difference in the results between both models is highly dependent on the different combinations of input variables.

We can expect that the GBM with μ and σ estimated from historical data, highly undervalues investment opportunities for emerging and growth technologies, while it might overvalue them, in the case of an underlying maturing technology. Our numerical examples imply that a naive choice of a standard GBM model often misrecognizes rapid growth patterns of innovative technologies and tends to postpone the investment, which could mislead the adaption to new technology environments. These examples clearly show that the firm could suffer from huge economic losses due to the misrecognition of the underlying technology development. In most cases of technology diffusion, the GBM is thus not a reasonable stochastic process to model innovation. That is, when estimating drift and volatility from historical data, the GBM model leads to unrealistic results and ultimately suboptimal investment decisions.

8.5. Summary and Discussion

This chapter explained the importance of technology forecasting for technology investments and demonstrated how to apply common techniques to 3D printing technologies. We have shown which data can be used to come up with estimations for future technological developments and estimated Bass model parameters fitted to our collected data set of 3D printing-related publications and patents. While estimation of the parameters is often flawed, mostly due to small or highly volatile samples, we could provide some interesting insights about the current technological state of 3D printing and its diffusion in the future. We have also included technological uncertainty into the deterministic model by adding stochastic noise to our forecast. We could see that probabilistic models have some advantages, as they enable us to model different probabilistic scenarios, which can represent a helpful tool in decision-making under uncertainty. We have also shown a simple method of how to link publications and patents to monetary performance measures and applied it to the global 3D printing market size. Finally, we have shown that standard real option analysis models based on the GBM are not suitable for technology investments, as technology diffusion typically does not evolve geometrically. For our 3D printing example and input parameters estimated from historical data, the GBM can result in significant under- as well as overvaluation of investment opportunities when there is a timing option. However, the direction and magnitude of this difference is dependent on the technological state and thus the particular combination of input variables for the underlying stochastic process. Future research could try to make better estimates for the model parameter values, for example by expanding sample sizes, applying different estimation techniques or increase the number of time-steps. It would also be interesting to compare the presented stochastic logistic growth model with other existing real options models concerned with technology investments such as processes that include jumps or mean reversion and investigate differences for technologies in different growth stages.

Chapter 9

Conclusions and Outlook

9.1. Conclusion

New challenges require new measures. The combination of real options, user-based performance measures and technology forecasting can improve strategic reasoning and investment decision-making for investments in digital business models. All of the presented models are highly flexible and can thus be tailored to specific company needs and a large variety of investment decision-making scenarios. Technology forecasting and logistic growth modelling represent important building blocks for financial as well as technological forecasting for digital business model investments. Big data and business analytics have the potential to further boost efficiency of models while the economy further digitalizes, companies become more customer-centric and decision-making is increasingly based on data. Despite the importance of this interdisciplinary field, this research area is still young and should be further developed in academia as well as practical business application.

9.2. Outlook

We acknowledge the limitations of the presented models that are yet to be overcome. This dissertation places its focus on investment decision-making under uncertainty for single, fairly isolated digital transformation projects. The main goal of this dissertation is to highlight the importance of the field, provide the building blocks for future research and an easy to understand and easy to implement logic for practitioners. Future research could build on the presented frameworks to come up with portfolio approaches that are able to capture and prioritize several investment projects, evaluate synergies and derive efficient portfolio construction and project selection. In addition, the application to different types of digital business models such as freemium models and transactional monetization models represent a desirable extension to the presented frameworks. This will include the consideration of alternative revenue mechanisms and the valuation of further digital intangibles such as network effects. As no theory can be seen as valid without careful practical application, the application and use of the presented and extended models to a larger number of real-world business examples will be required to prove accuracy and reliability of such models. We can also expect see more work around the integration of technology forecasting techniques, marketing measures, valuation of intangibles and strategic management by leveraging proceedings in big data and machine learning.

Appendix

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A.1. Least Squares Monte Carlo Implementation

The path-wise optimal exercise time $t^*(\omega)$ is given by the path-wise maximum value of the difference between immediate payoff and continuation value. We can then estimate the total option value by computing the average over all sample paths ω when playing the path-wise optimal exercise strategy. The conditional optimal decision is made by comparing the payoff $\Pi(t_n, \mathrm{NPV}_{t_n}(\omega))$ with the value function $V^E(t, \mathrm{NPV}_t(\omega))$. Thus, if $V^E(t, \mathrm{NPV}_t(\omega)) = \Pi(t_n, \mathrm{NPV}_{t_n}(\omega))$, the optimal stopping time along the ω-th path is updated, $t^*(\omega) = t_n$, otherwise, it is left unchanged. Since $V^E(t, \mathrm{NPV}_t)$ is not available at this step, a way around this is offered by the Bellman equation of the optimal stopping problem in discrete time:

$$V^E(t_n, \mathrm{NPV}_{t_n}) = \max\left\{\Pi(t_n, \mathrm{NPV}_{t_n}), e^{r(t_{t+1}-t_n)}\mathrm{E}^P_{t_n}[V^E(t_{n+1}, \mathrm{NPV}_{t_n+1})]\right\}$$

By denoting the continuation value

$$\Phi(t_n, \mathrm{NPV}_{t_n}) = e^{r(t_{t+1}-t_n)}\mathrm{E}^P_{t_n}[V^E(t_{n+1}, \mathrm{NPV}_{t_n+1})], \Phi(T^E, \mathrm{NPV}_T) = 0,$$

we can determine the path-wise optimal policy by comparing Φ with the payoff Π. So, if

$$\Phi(t_n, \mathrm{NPV}_{t_n}(\omega)) \leq \Pi(t_n, \mathrm{NPV}_{t_n}(\omega)), \quad \text{then } t^*(\omega) = t_n. \tag{A.1}$$

The optimal stopping time is found by recursive application of the above decision rule, proceeding backward from T^E. At some previous step of this procedure, if we have already determined $t^*(\omega) > t_n$, and the condition above holds at the current step t_n, then the stopping time is updated: $t^*(\omega) = t_n$. At $t_n = 0$, when the optimal stopping times along all paths are determined, the value of the American option is estimated by averaging the path-wise values

$$V^E(0,\mathrm{NPV}) = \frac{1}{K}\sum_{\omega=1}^{K} e^{rt^*(\omega)}\Pi(t^*(\omega),\mathrm{NPV}_{t^*(\omega)}(\omega)).$$

Let $\Pi(t,s,t^*,\omega)$ be the (not necessarily positive) ω-th path payoff from optimally exercising the contingent claim at time s with respect to the stopping time $t^*(\omega)$, assuming that it has not been exercised yet. Hence,

$$\Pi(t,s,t^*,\omega) = \begin{cases} \Pi(s,\mathrm{NPV}_s(\omega)), & t^*(\omega) = s, \\ 0, & t^*(\omega) \neq s. \end{cases}$$

The continuation value at t_n is

$$\Phi(t_n,\mathrm{NPV}_{t_n}) = \mathrm{E}^P_{t_n}\left[\sum_{i=n+1}^{N} e^{-r(t_i-t_n)}\Pi(t_n,t_i,t^*,\cdot)\right].$$

Since Φ is an element of a linear vector space, the continuation value can be represented as $\Phi(t,\mathrm{NPV}_t) = \sum_{j=1}^{\infty}\phi_j(t)L_j(t,\mathrm{NPV_t})$ with respect to the basis $\{L_j\}$. If $J<\infty$ basis elements are used to determine Φ, we obtain an approximation of the continuation value $\Phi^J(t,\mathrm{NPV_t}) = \sum_{j=1}^{J}\phi_j(t)L_j(t,\mathrm{NPV}_t)$ and $\phi_j(t)$ can be estimated by least squares regression of $\Phi^J(t,\mathrm{NPV}_t)$ onto the basis $\{L_j(t,\mathrm{NPV}_t)\}$ by computing

$$\left\{\widehat{\Phi_J}(t_n)\right\}_{j=1}^{J} = \arg\min_{\{\phi_j\}_{j=1}^{J}}\left\|\sum_{j=1}^{J}\phi_j(t_n)L_j(t_n,\mathrm{NPV}_{t_n}) - \sum_{i=n+1}^{N} e^{-r(t_i-t_n)}\Pi(t,t_i,t^*,\cdot)\right\|^2.$$

The estimated continuation value,

$$\widehat{\phi_J}(t_n,\mathrm{NPV}_{t_n}) = \sum_{j=1}^{J}\widehat{\phi_J}(t_n)L_j(t,\mathrm{NPV}_{t_n}),$$

is then used to apply the decision rule recursively in (A.1).

Accuracy of the American option value depends on the number of time steps, N, the number of simulated paths, K, and the number of basis functions J. By increasing these numbers, it has been proven that the estimate converges to the actual value of the corresponding Bermudan option value with N dates (Moreno and Navas, 2003). The value of the expansion option at t_0 drives the decision whether to invest in the trial project. If the costs of launching the trial project I_P is smaller than the present value of the option to expand, management will decide to launch the trial project and follow the optimal expansion policy.

A.2. Descriptive Statistics of Traditional vs. Digital Businesses

Table A.1: Descriptive Statistics of the two data sets

	Market Capitalization		**Spot Price**		**EBITDA**		**Net Income**	
	Trad.	*Dig.*	*Trad.*	*Dig.*	*Trad.*	*Dig.*	*Trad.*	*Dig.*
Min	0.20	370.20	0.00	2.28	-25,403	-329.77	-25,392	-6,302
1st Qu.	11,748	4,794	9.00	32.99	222.40	24.61	99.01	-1.33
Median	18,571	11,024	36.40	61.10	483.80	84.32	239.38	45.72
Mean	32,304	70,098	347.80	128.11	961.70	917.21	486.91	559.58
3rd Qu.	34,282	39,172	82.30	121.69	1,051	459.23	554.00	266.03
Max.	527,451	1,090,308	320,000	2,080	30,887	29,019	32,551	20,065
Missing	616	4	1,595	19	3,319	32	671	3

	Free Cash Flow		**Book Equity**		**Debt Ratio**		**Earnings per Share**	
	Trad.	*Dig.*	*Trad.*	*Dig.*	*Trad.*	*Dig.*	*Trad.*	*Dig.*
Min	-151,886	-4,889	-23,726	-605.40	0.00	0.00	-15,486	-11.50
1st Qu.	-2.38	9.64	3,444	757.90	0.14	0.87	-2.38	-0.01
Median	167.89	66.06	8,427	1,946	0.25	0.21	167.89	0.28
Mean	163.59	755.72	17,790	9,852	0.27	0.22	163.59	0.69
3rd Qu.	523.52	409.84	18,355	6,453	0.37	0.32	523.52	0.83
Max.	272,780	25,483	386,391	140,199	3.95	0.75	272,780	38.14
Missing	3,426	147	627	1	1,764	190	3,426	7

	Price Earnings Ratio		**Book to Market Ratio**		**Return on Assets**	
	Trad.	*Dig.*	*Trad.*	*Dig.*	*Trad.*	*Dig.*
Min	-1,451,304	-57,351	-11.63	-0.17	-108.37	-28.08
1st Qu.	41.00	-30.14	0.21	0.10	1.78	0.38
Median	71.00	99.51	0.43	0.19	4.22	3.79
Mean	169.00	157.97	0.57	0.24	5.35	6.75
3rd Qu.	113.00	194.80	0.78	0.32	7.53	8.27
Max.	3,180,175	101,333	30.47	2.71	753.80	196.89
Missing	1,987	22	895	5	1,592	10

Table A.2: Correlation matrices of independent variables

	EBITDA	**EpS**	**RoA**	**BtM**	**DR**	**MC**
EBITDA	1	0.185***	0.054 .	-0.09**	0.083*	0.868***
EpS	0.251***	1	0.077*	-0.04	0.050	0.174***
RoA	0.015**	0.006	1	-0.17	0.007	0.038
BtM	0.189***	0.003	-0.23***	1	-0.11**	-0.18***
DR	0.02**	-0.01	0.086***	-0.14***	1	0.107**
MC	0.743***	0.151***	0.021**	-0.02**	-0.02***	1

Traditional business models

Digital Business Models

A.3. Company Input Data

Table A.3: Input variables for Netflix - Q1 2018 - Q2 2020

Time	U_0	a_0	c_0	π	**ARPU**	**CAC**	F	r	μ^c	μ^a	K	ρ	**#shares**	σ^a	σ^c	**NOA**	**D**
Q1 2018	118,902,000	0.347	0.1	0.323	30.27	33.59	416,922,000	0.1	0	0	1.06E+09	-0.6	433,589,249	0.0452	0.0452	2,822,800,000	6,499,400,000
Q2 2018	124,354,000	0.352	0.1	0.348	31.10	34.99	450,619,000	0.1	0	0	1.06E+09	-0.6	434,551,388	0.0438	0.0438	2,593,700,000	6,542,400,000
Q3 2018	130,422,000	0.353	0.1	0.364	31.59	35.30	477,248,000	0.1	0	0	1.06E+09	-0.6	435,323,943	0.0427	0.0427	3,906,400,000	8,342,100,000
Q4 2018	118,902,000	0.311	0.1	0.377	31.36	35.61	507,319,000	0.1	0	0	1.06E+09	-0.6	435,955,513	0.0633	0.0633	3,067,500,000	8,336,600,000
Q1 2019	148,863,000	0.309	0.1	0.374	31.74	37.22	574,716,000	0.1	0	0	1.06E+09	-0.6	435,955,513	0.0612	0.0612	3,794,500,000	10,388,100,000
Q2 2019	151,562,000	0.300	0.1	0.375	31.91	38.84	607,890,000	0.1	0	0	1.06E+09	-0.6	437,200,000	0.0606	0.0606	3,348,600,000	11,192,500,000
Q3 2019	158,334,000	0.290	0.1	0.386	32.52	38.84	612,950,000	0.1	0	0	1.06E+09	-0.6	438,300,000	0.0601	0.0601	5,004,200,000	13,678,100,000
Q4 2019	167,090,000	0.373	0.1	0.383	33.50	38.84	663,962,000	0.1	0	0	1.06E+09	-0.6	438,800,000	0.0654	0.0654	4,435,000,000	13,539,400,000
Q1 2020	182,860,000	0.367	0.1	0.385	33.30	38.84	705,904,000	0.1	0	0	1.06E+09	-0.6	439,800,000	0.0642	0.0642	5,151,900,000	16,265,500,000
Q2 2020	192,950,000	0.380	0.1	0.390	33.28	38.84	712,281,000	0.1	0	0	1.06E+09	-0.6	441,015,443	0.0642	0.0642	7,153,248,000	17,708,159,000

Table A.4: Input variables for Roku - Q4 2017 - Q1 2020

Time	U_0	a_0	c_0	π	**ARPU**	**CAC**	F	r	μ^c	μ^a	K	ρ	**#shares**	σ^a	σ^c	**NOA**	**D**
Q4 2017	19,300,000	0.809	0.35	0.390	8.09	5.49	44,800,000	0.09	0	0	1.74E+08	-0.6	97,800,000	0.0090	0.0090	66,900,000	0
Q1 2018	20,800,000	0.811	0.35	0.408	7.98	5.18	49,700,000	0.09	0	0	1.74E+08	-0.6	99,600,000	0.0047	0.0047	177,300,000	0
Q2 2018	22,000,000	0.801	0.35	0.437	8.11	5.25	55,600,000	0.09	0	0	1.74E+08	-0.6	1.02E+08	0.0032	0.0032	160,800,000	0
Q3 2018	23,800,000	0.797	0.35	0.451	8.04	5.31	65,200,000	0.09	0	0	1.74E+08	-0.6	1.06E+08	0.0055	0.0055	174,200,000	0
Q4 2018	27,100,000	0.788	0.35	0.455	8.14	5.55	72,200,000	0.09	0	0	1.74E+08	-0.6	1.09E+08	0.0091	0.0091	179,700,000	0
Q1 2019	29,100,000	0.771	0.35	0.462	8.27	5.79	77,800,000	0.09	0	0	1.74E+08	-0.6	1.1E+08	0.0117	0.0117	197,700,000	74,200,000
Q2 2019	30,500,000	0.754	0.35	0.452	8.54	5.90	88,000,000	0.09	0	0	1.74E+08	-0.6	1.13E+08	0.0144	0.0144	263,900,000	121,500,000
Q3 2019	32,300,000	0.737	0.35	0.452	8.72	6.01	98,400,000	0.09	0	0	1.74E+08	-0.6	1.16E+08	0.0205	0.0205	386,500,000	158,700,000
Q4 2019	36,900,000	0.726	0.35	0.448	8.99	6.33	117,200,000	0.09	0	0	1.74E+08	-0.6	1.18E+08	0.0231	0.0231	387,500,000	419,200,000
Q1 2020	39,800,000	0.718	0.35	0.436	9.24	6.66	128,000,000	0.09	0	0	1.74E+08	-0.6	1.2E+08	0.0237	0.0237	515,500,000	499,700,000

Table A.5: Input variables for Stitch Fix - Q3 2018 - Q1 2020

Time	U_0	a_0	c_0	π	**ARPU**	**CAC**	F	r	μ^c	μ^a	K	ρ	**#shares**	σ^a	σ^c	**NOA**	**D**
Q3 2018	2,900,000	0.908	0.7	0.441	122.71	63.21	115,371,000	0.115	0	0	5.81E+06	-0.6	99,537,988	0.0046	0.0046	258,326,000	0
Q4 2018	3,000,000	0.904	0.7	0.443	123.89	49.92	123,838,000	0.115	0	0	5.81E+06	-0.6	99,969,863	0.0043	0.0043	276,859,000	0
Q1 2019	3,133,000	0.890	0.7	0.447	126.77	63.21	138,615,000	0.115	0	0	5.81E+06	-0.6	100,882,811	0.0123	0.0123	291,608,000	0
Q2 2019	3,236,000	0.891	0.7	0.446	131.28	60.52	148,110,000	0.115	0	0	5.81E+06	-0.6	101,646,601	0.0093	0.0093	314,208,000	0
Q3 2019	3,416,000	0.883	0.7	0.446	132.08	63.21	150,442,000	0.115	0	0	5.81E+06	-0.6	101,726,682	0.0085	0.0085	297,283,000	154,736,000
Q4 2019	3,465,000	0.872	0.7	0.448	133.52	60.52	158,089,000	0.115	0	0	5.81E+06	-0.6	102,476,609	0.0101	0.0101	300,581,000	149,400,000
Q1 2020	3,418,000	0.855	0.7	0.437	127.19	57.83	159,866,000	0.115	0	0	5.81E+06	-0.6	102,587,524	0.0244	0.0244	241,584,000	165,634,000

A.4. Simulation Results

Table A.6: Simulation Results for Q1 2018 to Q2 2020 - Netflix's Estimated CE vs. Market Value

Dates	Simulated Total CE	Average Market Cap.	Simulated CE/Share	Average Share Price
01/04/2018	1.13935E+11	1.18E+11	262.77	272.22
01/07/2018	1.34296E+11	1.48E+11	309.05	340.90
01/10/2018	1.50629E+11	1.58E+11	346.02	362.95
01/01/2019	1.27253E+11	1.30E+11	291.90	299.26
01/04/2019	1.37392E+11	1.51E+11	315.15	346.67
01/07/2019	1.33517E+11	1.58E+11	305.39	360.78
01/10/2019	1.41698E+11	1.37E+11	323.29	312.89
01/01/2020	1.70903E+11	1.30E+11	389.48	297.42
01/04/2020	1.74189E+11	1.55E+11	396.07	354.33
01/07/2020	1.83084E+11	1.88E+11	415.14	427.55

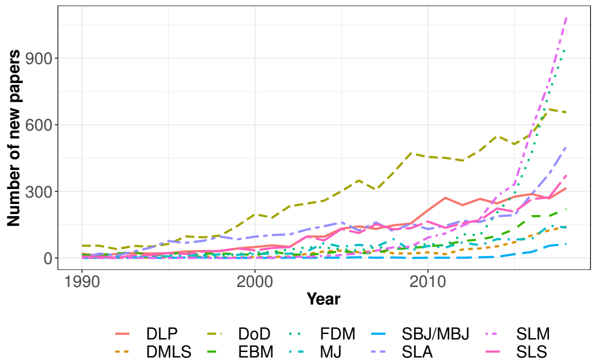
Table A.7: Simulation Results for Q4 2017 to Q1 2020 - Roku's Estimated CE vs. Market Value

Dates	Simulated Total CE	Average Market Cap.	Simulated CE/Share	Average Share Price
01/01/2018	10,573,084,443	3,397,944,987	108.11	34.89
01/04/2018	11,635,769,473	4,013,878,101	116.82	40.80
01/07/2018	13,209,933,029	3,701,803,189	130.02	36.68
01/10/2018	13,357,531,596	6,039,213,581	125.90	57.80
01/01/2019	13,516,414,800	4,985,514,157	123.78	46.40
01/04/2019	13,783,745,200	5,861,165,746	125.31	53.51
01/07/2019	13,483,501,453	9,100,798,182	118.90	80.50
01/10/2019	13,391,192,798	14,111,130,149	115.24	122.47
01/01/2020	12,750,000,828	16,246,775,263	108.51	138.45
01/04/2020	12,119,340,849	13,551,657,511	100.99	114.23

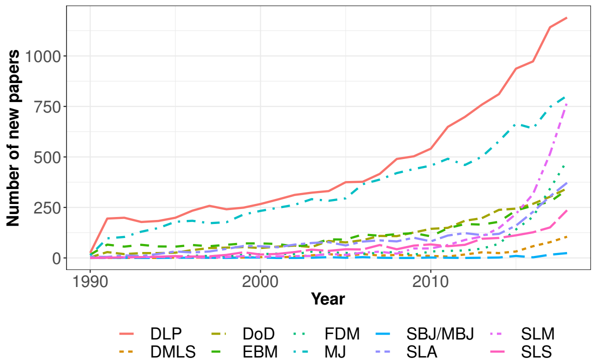
Table A.8: Simulation Results for Q3 2018 to Q1 2020 - Stitch Fix's Estimated CE vs. Market Value

Dates	Simulated Total CE	Average Market Cap.	Simulated CE/Share	Average Share Price
01/10/2018	2,493,615,786	3,593,107,514	25.05	36.71
01/01/2019	2,865,020,541	2,413,651,507	28.66	24.31
01/04/2019	2,163,757,980	2,477,582,138	21.45	24.86
01/07/2019	2,393,109,948	2,686,350,955	23.54	26.80
01/10/2019	2,234,543,765	2,331,034,916	21.97	23.11
01/01/2020	2,185,310,676	2,375,795,256	21.32	23.36
01/04/2020	991,951,348	2,187,669,672	9.67	21.48

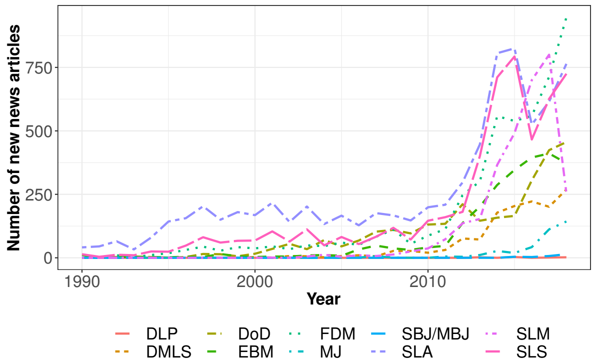
A.5. Data collection results



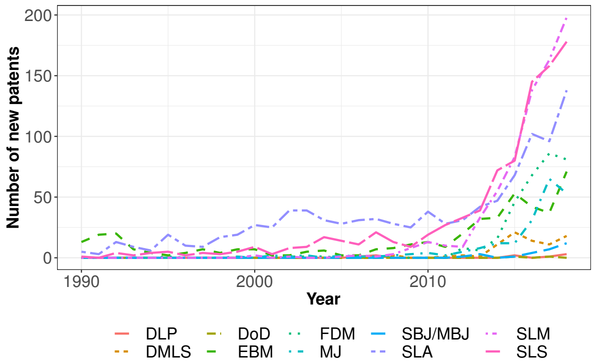
(a) Number of academic papers as retrieved via Scopus



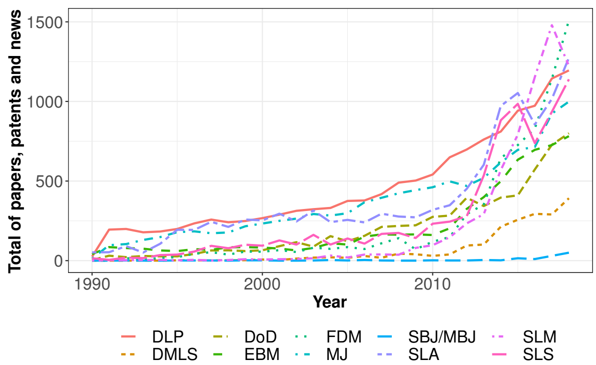
(b) Number of academic papers as retrieved via SCI



(c) Number of news articles as retrieved via Factiva



(d) Number of patents as retrieved via Derwent Innovation Index



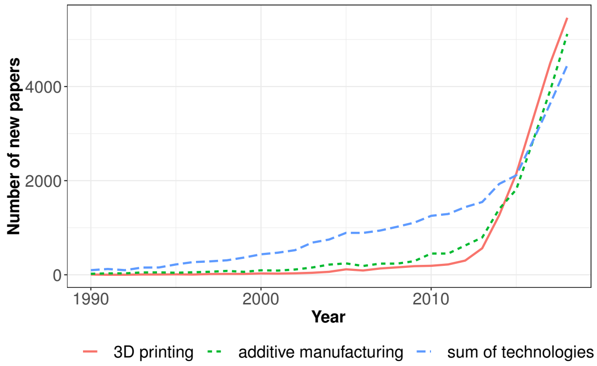
(e) Sum of SCI, patents and Factiva hits

Figure A.1: Data collection overview - ten different 3D printing technologies.

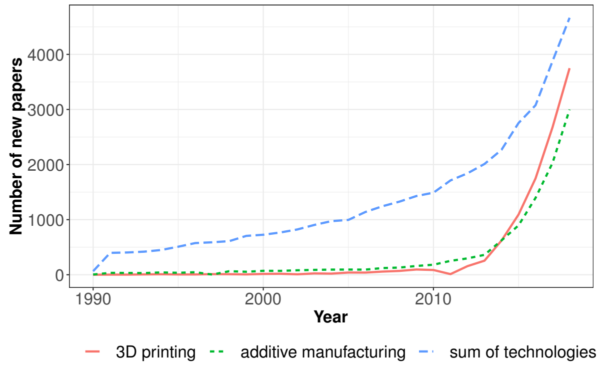
Figure A.1 illustrates the annual number of academic papers, news articles and patents on each of the identified 3D printing technologies retrieved via the four different databases. Respectively, Figure A.2 shows the number of academic papers, news articles and patents referring to the keywords *'3D printing'* and *'Additive Manufacturing'* as well as the sum of hits related to the ten different technologies from Figure A.1. The data in Figures A.1a and A.2a has been retrieved via Scopus and the data in Figures A.1b and A.2b via SCI. These graphs refer to academic publications and thus represent how much technologies related to 3D printing have been developed as a research topic. In contrast, the data presented in Figures A.1c and A.2c has been retrieved via Factiva. As news articles typically have an application focus, the data presented in these graphs indicate how much attention 3D printing has gained in the context of practical application. Similarly, Figures A.1d and A.2d present the number of patents and thus show how much the technology was subject to commercial development. Figures A.1e and A.2e consolidate the data of three of the four databases, namely SCI, Factiva and DII. Note that we did not include Scopus at this point to avoid duplicates, as papers that are included with SCI might also included with Scopus.

In regard to the prominence of the different technologies that are used to enable 3D printing, we can have a closer look at Figure A.1. Scopus data suggests that SLM and FDM represent the most researched 3D printing technologies, while SCI data highlights DLP and MJ. However, similarly to Scopus, SCI data ranks SML and FDM as third and fourth most researched technologies with much higher growth rates. Thus, it can be expected that FDM and SLM are going to exceed DLP and MJ within upcoming years. Regarding Figure A.1c, we can see that there is a similar amount of news articles to academic publications, however, the fluctuation in annual news is much higher. Factiva also favors SLM and FDM as dominant technologies, however, in 2018 newly published news on SLM have dropped significantly. Regarding the number of annual patent grants, SLM again represents the leading technology. However, there are less patents on FDM than on SLS and SLA technologies in recent years. Adding up the data from SCI, Factiv and DII as illustrated in Figure A.1e, we can conclude that SLM and FDA have attracted most attention and thus represent the two most prominent 3D printing technologies followed by SLA, DLP and SLS. SLM uses powder of materials and the object can be created by stacking melted powder for each layer according to the design. This technology has practically no restriction on the geometry to make objects and also allows us to produce objects made out of metal. In contrast, FDM is a process based on the extrusion of feed-stock plastic filaments through a nozzle tip to deposit layers onto a platform to build parts layer by layer directly from a computer-aided design (CAD) model (Masood, 2014). FDM printers allow us to produce many types of materials because the range of filaments which this process uses is extensive and the costs of the filaments are relative low. These processes are especially known for their high degree of versatility, which is why they have started to become the dominant technologies recently.

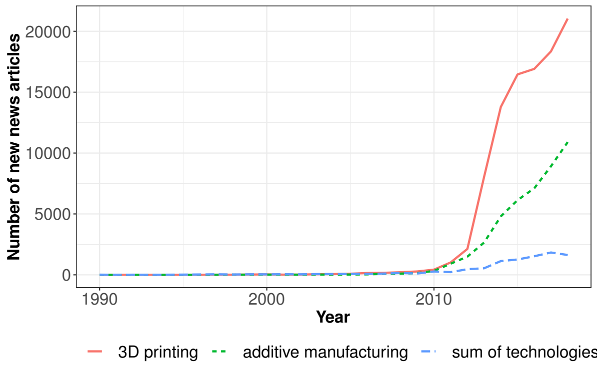
Figure A.2 provides a more consolidated picture of the developments in publications about 3D printing. Scopus and SCI both show steadily increasing growth in tech-based publications since 1990. The numbers of publications on 3D printing, additive manufacturing and the underlying ten technologies in both graphs are reasonably close to each other. In contrast, regarding Figure A.2c, Factiva draws an entirely different picture. Here, almost no articles have been published until 2010. In 2010 we could observe a skyrocketing number of news on 3D printing, less on additive manufacturing and only a few on the ten underlying technologies. The number of new patents as illustrated in Figure A.2d shows a similar pattern to Factiva data, however, the relative importance of tech-based patents is much higher than it is for news.



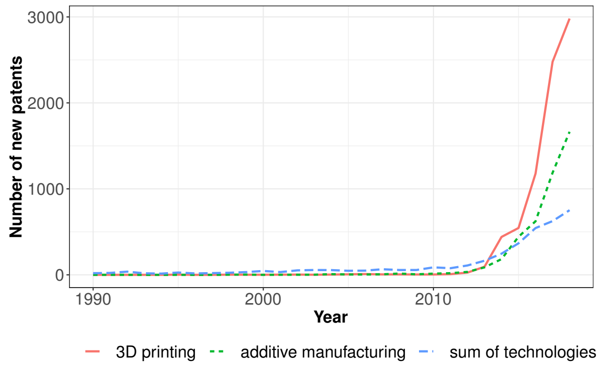
(a) Number of academic papers as retrieved via Scopus



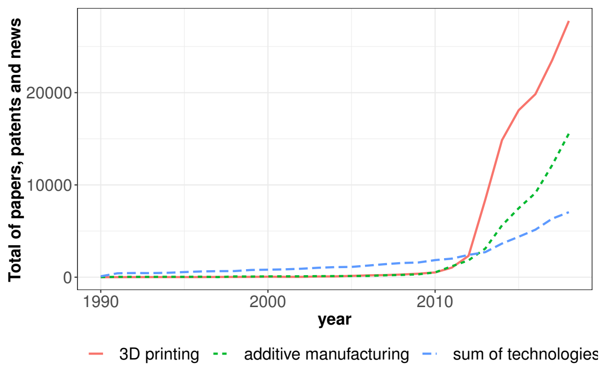
(b) Number of academic papers as retrieved via SCI



(c) Number of news articles as retrieved via Factiva



(d) Number of patents as retrieved via Derwent Innovations Index



(e) Sum of SCI, patents and Factiva hits

Figure A.2: Data collection overview - keywords *'3D Printing', 'Additive Manufacturing'* and sum of technologies.

To summarize, Figure A.2 shows a typical pattern of technological progress. Despite some publication of academic papers about 3D printing and additive manufacturing in the early 1990s, there were almost no news or patents on until 2010. Similarly, academic publications were focusing on certain 3D printing technologies rather than their application (i.e. 3D printing and additive manufacturing) in the early stage, while there was exponential growth in these more application-oriented research fields in more recent years. Interestingly, news and patents seem to show very similar patterns, as both are typically related to later stages of the technology life-cycle. These findings are in line with Table A.9 that illustrates the general phenomenon that different R&D stages lead to hits in different databases. Following this logic, we can thus conclude that 3D printing has started to transition into its applied research or development phase in 2010[11].

Table A.9: Sources for technology life cycle data from Martino (2003)

R&D stage	Typical source
Basic research	Science Citation Index
Applied research	Engineering Index
Development	US patents
Application	Newspaper Abstracts Daily
Social impacts	Business and Popular Press

The patterns revealed by our collected raw data from all databases are similar to patterns that have been discovered by existing studies on technology forecasting. By comparing our results with the findings by Trappey et al. (2011), who presents his forecasting results about RFID technologies by using patent data, we can conclude that our results have a similar increasing trend with early stage RFID technologies. At the same time, the bibliometric data collected in Daim et al. (2006) also represents the typical patterns of emerging and growth technologies that can be observed with our 3D printing results.

A.6. MLE Estimation Methods for the Bass Model

Bass (1969) states that the likelihood for eventual adopters of the purchase at time t given that no purchase has yet been made can be written as follows:

$$\frac{f(t)}{1-F(t)} = p + qF(t), \tag{A.2}$$

[11] Note that the differences between news and patents on tech-based versus 3D printing keyword might be a result of the hype that has been undergone by 3D printing in recent years. Since 2010, *'3D printing'* and *'additive manufacturing'* have somewhat transformed into buzzwords resulting in extreme growth rates of related news articles and patents. While it makes sense that there are more hits when using broader keywords, the extreme difference between hits for the sum of technologies and these buzzwords might seem unreasonable. Thus, the mushrooming number of patents and publications surrounding these keywords and the large gap to publications about enabling technologies might lead to a bias and thus overestimation when using this data for the related technological progress.

where $f(t)$ is the likelihood of purchase at t and

$$F(t) = \int_0^t f(t)\,dt.$$

From equation (A.2), $f(t)$ can be expressed as

$$f(t) = (p + qF(t))(1 - F(t)).$$

Setting the initial value of $F(t)$ as $F(0) = 0$, the integration of the above equation can be expressed as

$$F(t) = \frac{1 - \exp(-bt)}{1 + a\exp(-bt)},$$

where $a \equiv \frac{q}{p}$, $b \equiv p + q$, since this equation is only appropriate for eventual adopters and the probabilities are conditional. Thus, in a system where the probability of eventually adopting is c, the unconditional probabilities for adoption times can be given by

$$F(t) = \frac{c(1 - \exp(-bt))}{1 + a\exp(-bt)}. \tag{A.3}$$

The relations between p, q, m and a, b, c are easily obtained as

$$\begin{aligned} \hat{q} &= \frac{\hat{a}\hat{b}}{\hat{a}+1}, \\ \hat{p} &= \frac{\hat{b}}{\hat{a}+1}, \\ \hat{m} &= \hat{c}M. \end{aligned} \tag{A.4}$$

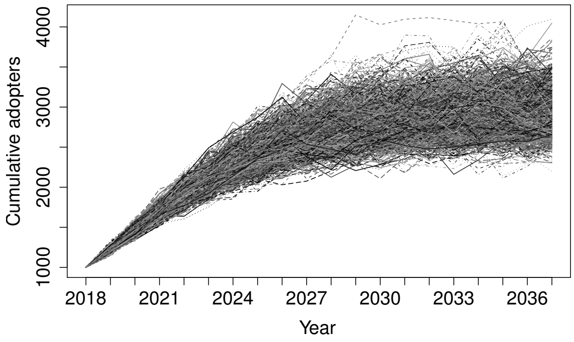
We can proceed our analyses using equation (A.3) and assuming x_i to be the number of academic publications, news or patents in year $i, i = 1990, 1991, ...T$, the likelihood function can be expressed as

$$L(a, b, c, x_i) = (1 - F(t_{T-1}))^{x_T} \prod_{i=1990}^{T-1} (F(t_i) - F(t_{t-1}))^{x_i}, \tag{A.5}$$

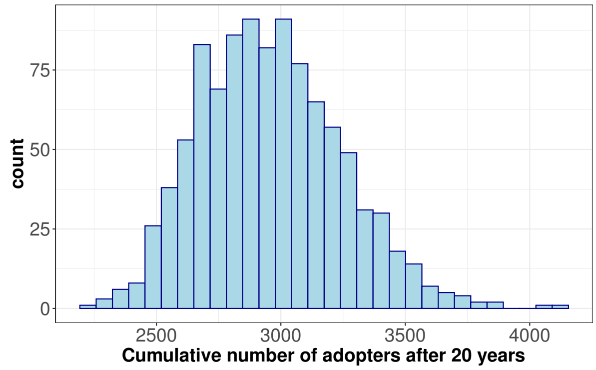
and the logarithm of the likelihood function is then given by

$$\begin{aligned} l(a, b, c, x_i) = & \sum_{i=1990}^{T-1} x_i \left(\ln c + \ln \left(\frac{1 - \exp(-bt_i)}{1 + a\exp(-bt_i)} - \frac{1 - \exp(-bt_{i-1})}{1 + a\exp(-bt_{i-1})} \right) \right) \\ & + x_T \ln \left(1 - \frac{1 - \exp(-bt_{T-1})}{1 - a\exp(-bt_{T-1})} \right). \end{aligned} \tag{A.6}$$

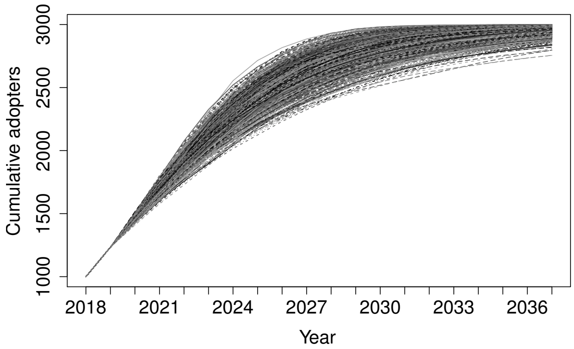
A.7. Stochastic Logistic Growth Models Overview



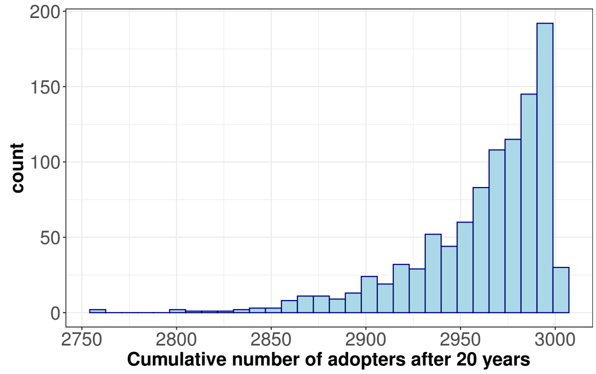
(a) Sample paths with noise in $N(t)$



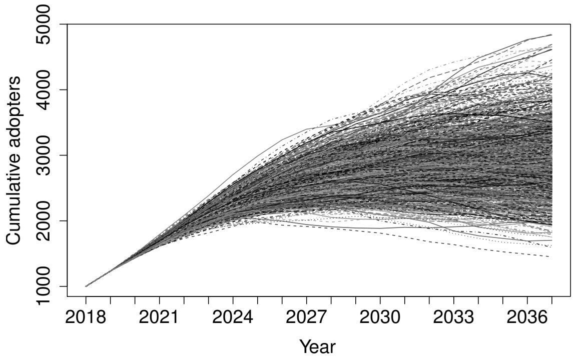
(b) Histogram of $N(T)$ with noise in $N(t)$, mean = 2,960.91, standard deviation = 274.37, skewness = 0.587



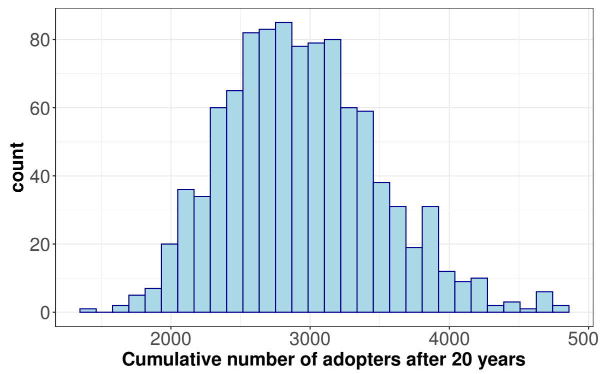
(c) Sample paths with noise in $g(t)$



(d) Histogram of $N(T)$ with noise in $g(t)$, mean = 2,961.53, standard deviation = 38.30, skewness = -1.958



(e) Sample paths with noise in $m(t)$



(f) Histogram of $N(T)$ with noise in $m(t)$, mean = 2,974.39, standard deviation = 556.58, skewness = 0.591

Figure A.3: Simulation of the three stochastic models presented in Section 8.4.1 based on a generic numerical example - $T = 20, n = 1000, m = 3000, p = 0.05, q = 0.2, N_0 = 1000, \sigma = \sigma^m = 0.05, \sigma^q = \sigma^p = 0.1, \mu^p = \mu^q = \mu^m = 0, \mu^m = 5,000$, annual discretization

Bibliography

Alshawi, S., Z. Irani, and L. Baldwin (2003). “Benchmarking information technology investment and benefits extraction”. In: *Benchmarking: An International Journal* 10.4, pp. 414–423.

Altuntas, S., T. Dereli, and A. Kusiak (2015). “Forecasting technology success based on patent data”. In: *Technological Forecasting and Social Change* 96, pp. 202–214.

Amit, R. and C. Zott (2010). “Business model innovation: Creating value in times of change”. In: *IESE Business School Working Paper No. 870.*

Anderson, C. et al. (2016). “Logistic equation is a simple stochastic carrying capacity”. In: *ANZIAM Journal* 56, pp. 431–445.

Angelou, G. N. and A. A. Economides (2008). “A decision analysis framework for prioritizing a portfolio of ICT infrastructure projects”. In: *IEEE Transactions on Engineering Management* 55.3, pp. 479–495.

— (2009). “A compound real option and AHP methodology for evaluating ICT business alternatives”. In: *Telematics and Informatics* 26.4, pp. 353–374.

Bacon, C. J. (1994). “Why companies invest in information technology”. In: *Information management.* Springer, pp. 31–47.

Balasubramanian, P, N. Kulatilaka, and J. Storck (2000). “Managing information technology investments using a real-options approach”. In: *The Journal of Strategic Information Systems* 9.1, pp. 39–62.

Baldwin, C. Y. (1982). “Optimal sequential investment when capital is not readily reversible”. In: *The Journal of Finance* 37.3, pp. 763–782.

Bardhan, I., R. Sougstad, and R. Sougstad (2004). “Prioritizing a portfolio of information technology investment projects”. In: *Journal of Management Information Systems* 21.2, pp. 33–60.

Barraquand, J. and D. Martineau (1995). “Numerical valuation of high dimensional multivariate American securities”. In: *Journal of Financial and Quantitative Analysis* 30.3, pp. 383–405.

Bartel, A., C. Ichniowski, and K. Shaw (2007). “How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement, and worker skills”. In: *The Quarterly Journal of Economics* 122.4, pp. 1721–1758.

Barua, A. and T. Mukhopadhyay (2000). “Information technology and business performance: Past, present, and future”. In: *Framing the Domains of IT Management: Projecting the Future Through the Past*, pp. 65–84.

Bass, F. M. (1969). “A new product growth for model consumer durables”. In: *Management Science* 15.5, pp. 215–227.

Bauer, H. H. and M. Hammerschmidt (2005). “Customer-based corporate valuation: Integrating the concepts of customer equity and shareholder value”. In: *Management Decision* 43.3, pp. 331–348.

Bauer, H. H., M. Hammerschmidt, and M. Braehler (2003). “The customer lifetime value concept and its contribution to corporate valuation”. In: *Yearbook of Marketing and Consumer Research* 1.1, pp. 47–67.

Benaroch, M. and R. J. Kauffman (1999). “A case for using real options pricing analysis to evaluate information technology project investments”. In: *Information Systems Research* 10.1, pp. 70–86.

Bennett, N. and G. J. Lemoine (2014). “What a difference a word makes: Understanding threats to performance in a VUCA world”. In: *Business Horizons* 57.3, pp. 311–317.

Bharadwaj, A. S. (2000). “A resource-based perspective on information technology capability and firm performance: an empirical investigation”. In: *MIS Quarterly*, pp. 169–196.

Bhatt, G. D., V. Grover, and V. GROVER (2005). “Types of information technology capabilities and their role in competitive advantage: An empirical study”. In: *Journal of Management Information Systems* 22.2, pp. 253–277.

Black, F. and M. Scholes (1973). “The pricing of options and corporate liabilities”. In: *Journal of Political Economy* 81.3, pp. 637–654.

Bock, M. and M. Wiener (2017). “Towards a Taxonomy of Digital Business Models-Conceptual Dimensions and Empirical Illustrations”. In: *ICIS*.

Bonacchi, M. and P. Perego (2019). “Customer Equity for External Reporting and Valuation”. In: *Customer Accounting*. Springer, pp. 67–82.

Borison, A. (2005). “Real options analysis: Where are the emperor’s clothes?” In: *Journal of Applied Corporate Finance* 17.2, 17–31.

Borzo, J. (2005). “Business 2010-Embracing the challenge of change”. In: *Report from the Economist Intelligence Unit sponsored by SAP, London.*

Boutetière, H. De la, A. Montagner, and A. Reich (2018). *Unlocking success in digital transformations*. Web Page. URL: `https://mck.co/2AzwomG`.

Boyle, P. P. (1977). “Options: A monte carlo approach”. In: *Journal of Financial Economics* 4.3, pp. 323–338.

— (1988). “A lattice framework for option pricing with two state variables”. In: *Journal of Financial and Quantitative Analysis* 23.1, pp. 1–12.

Brauer, F. and C. Castillo-Chavez (2001). *Mathematical models in population biology and epidemiology*. Vol. 40. Springer.

Brennan, M. J. and E. S. Schwartz (1978). "Finite difference methods and jump processes arising in the pricing of contingent claims: A synthesis". In: *Journal of Financial and Quantitative Analysis* 13.3, pp. 461–474.

Broadie, M. and P. Glasserman (1997). "Pricing American-style securities using simulation". In: *Journal of Economic Dynamics and Control* 21.8, pp. 1323–1352.

Broadie, M., P. Glasserman, and G. Jain (1997). "Enhanced Monte Carlo estimates for American option prices". In: *The Journal of Derivatives* 5.1, pp. 25–44.

Brynjolfsson, E. and L. Hitt (1996). "Paradox lost? Firm-level evidence on the returns to information systems spending". In: *Management Science* 42.4, pp. 541–558.

Callon, J. D. (1995). *Competitive advantage through information technology*. McGraw-Hill Higher Education.

Campbell, R. S. (1983). "Patent trends as a technological forecasting tool". In: *World Patent Information* 5.3, pp. 137–143.

Cauwels, P. and D. Sornette (2011). "Quis pendit ipsa pretia: Facebook valuation and diagnostic of a bubble based on nonlinear demographic dynamics". In: *ArXiv preprint arXiv:1110.1319*.

Chakravarty, A. and R. Grewal (2011). "The stock market in the driver's seat! Implications for R&D and marketing". In: *Management Science* 57.9, pp. 1594–1609.

Chapman, C. and S. Ward (2003). *Project risk management: processes, techniques, and insights*. Wiley.

Chen, Y.-H., C.-Y. Chen, and S.-C. Lee (2011). "Technology forecasting and patent strategy of hydrogen energy and fuel cell technologies". In: *International Journal of Hydrogen Energy* 36.12, pp. 6957–6969.

Chesbrough, H. (2007). "Business model innovation: it's not just about technology anymore". In: *Strategy & Leadership* 35.6, pp. 12–17.

Christensen, C. (2013). *The innovator's dilemma: when new technologies cause great firms to fail*. Harvard Business Review Press.

Clark, A. J., L. W. Lake, and T. W. Patzek (2011). "Production forecasting with logistic growth models". In: *SPE annual technical conference and exhibition*. Society of Petroleum Engineers.

Clemons, E. K. (1991). "Evaluation of strategic investments in information technology". In: *Communications of the ACM* 34.1, pp. 22–36.

Copeland, T. and V. Antikarov (2001). *Real options: A practitioner's guide*. New York: Texere.

Cortazar, G. (2001). "Simulation and numerical methods in real options valuation". In: *EFMA 2000 Athens*.

Cox, J. C., S. A. Ross, and M. Rubinstein (1979). “Option pricing: A simplified approach”. In: *Journal of Financial Economics* 7.3, pp. 229–263.

Daim, T. and P. Suntharasaj (2009). “Technology diffusion: forecasting with bibliometric analysis and Bass model”. In: *Foresight* 11.3, pp. 45–55.

Daim, T. U. et al. (2006). “Forecasting emerging technologies: Use of bibliometrics and patent analysis”. In: *Technological Forecasting and Social Change* 73.8, pp. 981–1012.

Davenport, T. H. (1993). *Process innovation: reengineering work through information technology*. Harvard Business Press.

Davern, M. J. and R. J. Kauffman (2000). “Discovering potential and realizing value from information technology investments”. In: *Journal of Management Information Systems* 16.4, pp. 121–143.

Dictionaries, O. (2017). *Definition of change in English*. Web Page. URL: `https://en.oxforddictionaries.com/definition/us/change`.

Dixit, A. K. and R. S. Pindyck (1994). *Investment under uncertainty*. Princeton university press.

Doraszelski, U. (2004). “Innovations, improvements, and the optimal adoption of new technologies”. In: *Journal of Economic Dynamics and Control* 28.7, pp. 1461–1480.

Dos Santos, B. L. (1991). “Justifying investments in new information technologies”. In: *Journal of Management Information Systems* 7.4, pp. 71–89.

Easingwood, C., V. Mahajan, and E. Muller (1981). “A nonsymmetric responding logistic model for forecasting technological substitution”. In: *Technological Forecasting and Social change* 20.3, pp. 199–213.

Edeling, A. and M. Fischer (2016). “Marketing’s impact on firm value: Generalizations from a meta-analysis”. In: *Journal of Marketing Research* 53.4, pp. 515–534.

Ekström, M. A. and H. C. Björnsson (2005). “Valuing flexibility in architecture, engineering, and construction information technology investments”. In: *Journal of Construction Engineering and Management* 131.4, pp. 431–438.

Eliashberg, J., C. S. Tapiero, and J. Y. Wind (1983). “Diffusion of new products in heterogeneous populations: incorporating stochastic coefficients”. In.

Ernst, H. (1997). “The use of patent data for technological forecasting: the diffusion of CNC-technology in the machine tool industry”. In: *Small Business Economics* 9.4, pp. 361–381.

Ferstl, O. K. and E. J. Sinz (2013). *Grundlagen der Wirtschaftsinformatik*. Walter de Gruyter GmbH & Co KG.

Gassmann, O., K. Frankenberger, and M. Csik (2013). “Geschäftsmodelle aktiv innovieren”. In: *Das unternehmerische Unternehmen*. Springer, pp. 23–41.

— (2014a). *Business Model Navigator*. Pearson Education Limited Harlow.

Gassmann, O., K. Frankenberger, and M. Csik (2014b). *The business model navigator: 55 models that will revolutionise your business*. Pearson UK.

Gassmann, O., K. Frankenberger, and R. Sauer (2016). *Exploring the field of business model innovation: New theoretical perspectives*. Springer.

Geske, R. (1979). "The valuation of compound options". In: *Journal of Financial Economics* 7.1, pp. 63–81.

Gibson, C. F. (2004). "IT-enabled business change: an approach to understanding and managing risk". In.

Giovanis, A. and C. Skiadas (1999). "A stochastic logistic innovation diffusion model studying the electricity consumption in Greece and the United States". In: *Technological Forecasting and Social Change* 61.3, pp. 235–246.

Gneiser, M. et al. (2009). "Valuation of online social networks-an economic model and its application using the case of xing. com". In.

Grenadier, S. R. and A. M. Weiss (1997). "Investment in technological innovations: An option pricing approach". In: *Journal of Financial Economics* 44.3, pp. 397–416.

Gupta, S. (2009). "Customer-based valuation". In: *Journal of Interactive Marketing* 23.2, pp. 169–178.

Gupta, S., D. R. Lehmann, and J. A. Stuart (2004). "Valuing customers". In: *Journal of Marketing Research* 41.1, pp. 7–18.

Gupta, S. and V. Zeithaml (2006). "Customer metrics and their impact on financial performance". In: *Marketing Science* 25.6, pp. 718–739.

Gutiérrez, R, A Nafidi, and R. G. Sánchez (2005). "Forecasting total natural-gas consumption in Spain by using the stochastic Gompertz innovation diffusion model". In: *Applied Energy* 80.2, pp. 115–124.

Half, R. (2016). *Where Change Management Fails*. Web Page. URL: `http://www.prnewswire.com/news-releases/where-change-management-fails-300214278.html`.

Hallikainen, P., H. Kivijarvi, and K. Nurmimaki (2002). "Evaluating strategic IT investments: an assessment of investment alternatives for a web content management system". In: *System Sciences, 2002. HICSS. Proceedings of the 35th Annual Hawaii International Conference on*. IEEE. ISBN: 0769514359.

Hitt, L. M. and E. Brynjolfsson (1996). "Productivity, business profitability, and consumer surplus: three different measures of information technology value". In: *MIS Quarterly*, pp. 121–142.

IDC (2019). *Worldwide semiannual digital transformation spending guide*. Web Page. URL: `https://www.idc.com/`.

Imai, J. and K. S. Tan (2014). "Pricing Derivative Securities Using Integrated Quasi–Monte Carlo Methods with Dimension Reduction and Discontinuity Realignment". In: *SIAM Journal on Scientific Computing* 36.5, A2101–A2121.

Jensen, M. C. (2001). “Value maximization, stakeholder theory, and the corporate objective function”. In: *Journal of Applied Corporate Finance* 14.3, pp. 8–21.

Kane, G. C. et al. (2015). “Strategy, not technology, drives digital transformation”. In: *MIT Sloan Management Review and Deloitte University Press* 14, pp. 1–25.

Katsamaki, A and C. Skiadas (1995). “Analytic solution and estimation of parameters on a stochastic exponential model for a technological diffusion process”. In: *Applied Stochastic Models and Data Analysis* 11.1, pp. 59–75.

Kester, W. C. (1984). *Turning growth options into real assets.* Division of Research, Graduate School of Business Administration, Harvard University.

Kim, G. and J. Bae (2017). “A novel approach to forecast promising technology through patent analysis”. In: *Technological Forecasting and Social Change* 117, pp. 228–237.

Kohli, R. and V. Grover (2008). “Business value of IT: An essay on expanding research directions to keep up with the times”. In: *Journal of the Association for Information Systems* 9.1, p. 23.

Kollmorgen, R., W. Merkel, and H.-J. Wagener (2014). *Handbuch Transformationsforschung.* Springer-Verlag.

KPMG Nash, H. (2017). “KPMG CIO Survey 2017”. In.

Krcmar, H. (2015). “Informationsmanagement”. In: *Informationsmanagement.* Springer, pp. 85–111.

Krcmar, H. A. (1987). “Innovationen durch strategische Informationssysteme”. In: *Innovation und Wettbewerbsfähigkeit.* Springer, pp. 227–246.

Kreutzer, R. T. (2014). “Digital Darwinism and the Need for a Digital Transformation”. In: *International Conference on Business Strategy and Organizational Behaviour (BizStrategy). Proceedings.* Global Science and Technology Forum, p. 38.

Kucharavy, D. and R. De Guio (2011). “Logistic substitution model and technological forecasting”. In: *Procedia Engineering* 9, pp. 402–416.

Kumar, V. and D. Shah (2009). “Expanding the role of marketing: from customer equity to market capitalization”. In: *Journal of Marketing* 73.6, pp. 119–136.

Lee, M., K. Kim, and Y. Cho (2010). “A study on the relationship between technology diffusion and new product diffusion”. In: *Technological Forecasting and Social Change* 77.5, pp. 796–802.

Leonhard, G. (2016). *Technology vs Humanity.* Fast Future Publishing London.

Li, X. (2009). “Preemptive learning, competency traps, and information technology adoption: a real options analysis”. In: *IEEE Transactions on Engineering Management* 56.4, pp. 650–662.

Longstaff, F. A. and E. S. Schwartz (2001). “Valuing American options by simulation: a simple least-squares approach”. In: *The Review of Financial Studies* 14.1, pp. 113–147.

Luehrman, T. A. (1998a). “Investment opportunities as real options: Getting started on the numbers”. In: *Harvard Business Review* 76, pp. 51–66.

— (1998b). “Strategy as a portfolio of real options”. In: *Harvard Business Review* 76, pp. 89–101.

Lungu, E. M. and B. Øksendal (1997). “Optimal harvesting from a population in a stochastic crowded environment”. In: *Mathematical Biosciences* 145.1, 47–75.

Mahajan, V. and D. C. Schmittlein (1982). “Maximum Likelihood Estimation for an Innovation Diffusion Model of New Product Acceptance”. In: *Marketing Science* 1.1, 57–78.

Mahajan, V., E. Muller, and F. M. Bass (1993). “New-product diffusion models”. In: *Handbooks in Operations Research and Management Science* 5, pp. 349–408.

Majd, S. and R. S. Pindyck (1987). “Time to build, option value, and investment decisions”. In: *Journal of Financial Economics* 18.1, pp. 7–27.

Margrabe, W. (1978). “The value of an option to exchange one asset for another”. In: *The Journal of Finance* 33.1, pp. 177–186.

Martino, J. P. (1980). “Technological forecasting—an overview”. In: *Management Science* 26.1, pp. 28–33.

— (1993). *Technological forecasting for decision making*. McGraw-Hill, Inc.

— (2003). “A review of selected recent advances in technological forecasting”. In: *Technological Forecasting and Social Change* 70.8, pp. 719–733.

Masood, S. H. (2014). “Advances in Fused Deposition Modeling”. In: *Comprehensive Materials Processing*. Ed. by S. Hashmi. Philadelphia: Elsevier, pp. 69–91.

Massa, L., C. L. Tucci, and A. Afuah (2017). “A critical assessment of business model research”. In: *Academy of Management Annals* 11.1, pp. 73–104.

Massiani, J. and A. Gohs (2015). “The choice of Bass model coefficients to forecast diffusion for innovative products: An empirical investigation for new automotive technologies”. In: *Research in Transportation Economics* 50, pp. 17–28.

McCarthy, D. M. and P. S. Fader (2018). “Customer-Based Corporate Valuation for Publicly Traded Noncontractual Firms”. In: *Journal of Marketing Research* 55.5, pp. 617–635.

McCarthy, D. M., P. S. Fader, and B. G. Hardie (2017). “Valuing subscription-based businesses using publicly disclosed customer data”. In: *Journal of Marketing* 81.1, pp. 17–35.

McDonald, R. L. and D. R. Siegel (1985). “Investment and the valuation of firms when there is an option to shut down”. In: *International Economic Review*, pp. 331–349.

McGrath, R. G. (2010). “Business models: A discovery driven approach”. In: *Long Range Planning* 43.2-3, pp. 247–261.

Mintz, O. and I. S. Currim (2013). “What drives managerial use of marketing and financial metrics and does metric use affect performance of marketing-mix activities?” In: *Journal of Marketing* 77.2, pp. 17–40.

Mitchell, D. and C. Coles (2003). “The ultimate competitive advantage of continuing business model innovation”. In: *Journal of Business Strategy* 24.5, pp. 15–21.

Mittal, N. and B. R. Nault (2009). “Research note—Investments in information technology: Indirect effects and information technology intensity”. In: *Information Systems Research* 20.1, pp. 140–154.

Moazed, A. and N. L. Johnson (2016). *Modern monopolies: what it takes to dominate the 21st century economy*. St. Martin’s Press.

Moreno, M. and J. F. Navas (2003). “On the robustness of least-squares Monte Carlo (LSM) for pricing American derivatives”. In: *Review of Derivatives Research* 6.2, pp. 107–128.

Murray, A. (June 2016). *Every Company is a Technology Company*. Web Page. URL: `http://fortune.com/2016/06/10/henry-schein-ge-digital-revolution/?iid=sr-link1`.

Myers, S. C. (1977). “Determinants of corporate borrowing”. In: *Journal of Financial Economics* 5.2, pp. 147–175.

Myers, S. C. (1984). “Finance theory and financial strategy”. In: *Interfaces* 14.1, pp. 126–137.

Myers, S. C. and S. Majd (2001). “Abandonment value and project life”. In: *Real Options and Investment under Uncertainty: Classical Readings and Recent Contributions. Cambridge*, pp. 295–312.

Nagel, S. S. (1991). *Decision-aiding software: Skills, obstacles and applications*. Springer.

Neuman, S. (1993). *Strategic information systems: Competition through information technologies*. Prentice Hall PTR.

Osterwalder, A. and Y. Pigneur (2004). “An ontology for e-business models”. In: *Value Creation from E-business Models* 1, pp. 65–97.

— (2010). *Business model generation: a handbook for visionaries, game changers, and challengers*. John Wiley & Sons.

Paddock, J. L., D. R. Siegel, and J. L. Smith (1988). “Option valuation of claims on real assets: The case of offshore petroleum leases”. In: *The Quarterly Journal of Economics* 103.3, pp. 479–508.

Parker, M. M. (1995). *Strategic transformation and information technology: paradigms for performing while transforming*. Prentice Hall Press.

Perotti, E. and S. Rossetto (2000). *Internet portals as portfolios of entry options*. Report. Tinbergen Institute Discussion Paper.

Persson, A. and L. Ryals (2010). “Customer assets and customer equity: Management and measurement issues”. In: *Marketing Theory* 10.4, pp. 417–436.

Pfeifer, P. E. (2011). “On estimating current-customer equity using company summary data”. In: *Journal of Interactive Marketing* 25.1, pp. 1–14.

Porter, A. L. et al. (1991). *Forecasting and management of technology*. Vol. 18. John Wiley & Sons.

Porter, M. E. (1979). "How competitive forces shape strategy". In: *Harvard Business Review*.

— (2008). *Competitive advantage: Creating and sustaining superior performance*. Simon and Schuster.

Quinn, J. B. (1992). *Intelligent Enterprise: A Knowledge and Service Based Paradigm for Industry*. Simon and Schuster.

Rogers, B. (Jan. 2016a). *Why 84% Of Companies Fail At Digital Transformation*. Web Page. URL: https://www.forbes.com/sites/brucerogers/2016/01/07/why-84-of-companies-fail-at-digital-transformation/#5f126eb1397b.

Rogers, D. L. (2016b). *The digital transformation playbook: Rethink your business for the digital age*. Columbia University Press.

Ross, J. W. and C. Beath (2001). "Beyond the business case: Strategic IT investment". In: *MIT Sloan Working Paper No. 4351-01*.

Rotolo, D., D. Hicks, and B. R. Martin (2015). "What is an emerging technology?" In: *Research Policy* 44.10, pp. 1827–1843.

Sakanoue, S. (2007). "Extended logistic model for growth of single-species populations". In: *Ecological Modelling* 205.1-2, pp. 159–168.

Schryen, G. (2010). "Preserving knowledge on IS business value". In: *Business & Information Systems Engineering* 2.4, pp. 233–244.

Schulmerich, M. (2010). *Real options valuation: the importance of interest rate modelling in theory and practice*. Springer Science & Business Media.

Schulze, C., B. Skiera, and T. Wiesel (2012). "Linking customer and financial metrics to shareholder value: The leverage effect in customer-based valuation". In: *Journal of Marketing* 76.2, pp. 17–32.

Schwartz, E. S. (2000). "Evaluating research and development investments". In: *Project Flexibility, Agency, and Competition: New Development in the Theory and Application of Real Options*.

— (2004). "Patents and R&D as real options". In: *Economic Notes* 33.1, pp. 23–54.

Schwartz, E. S. and M. Moon (2000). "Rational pricing of internet companies". In: *Financial Analysts Journal* 56.3, pp. 62–75.

— (2001). "Rational pricing of internet companies revisited". In: *Financial Review* 36.4, pp. 7–26.

Schwartz, E. S. and C. Zozaya-Gorostiza (2002). "Evaluating investments in disruptive technologies". In: *Mathematical Finance—Bachelier Congress 2000*. Springer, pp. 463–486.

Shapiro, C., S. Carl, and H. R. Varian (1998). *Information rules: a strategic guide to the network economy*. Harvard Business Press.

Shih, E., K. L. Kraemer, and J. Dedrick (2007). “Research Note—Determinants of Country-Level Investment in Information Technology”. In: *Management Science* 53.3, pp. 521–528.

Sick, G. (1989). *Capital budgeting with real options.* Salomon Brothers Center for the Study of Financial Institutions, Leonard N. Stern School of Business, New York University.

Skiadas, C. H. and A. N. Giovanis (1997). “A stochastic Bass innovation diffusion model for studying the growth of electricity consumption in Greece”. In: *Applied Stochastic Models and Data Analysis* 13.2, pp. 85–101.

Soh, C. and M. L. Markus (1995). “How IT creates business value: a process theory synthesis”. In: *ICIS 1995 Proceedings*, p. 4.

Srinivasan, S. and D. M. Hanssens (2009). “Marketing and firm value: Metrics, methods, findings, and future directions”. In: *Journal of Marketing research* 46.3, pp. 293–312.

Srivastava, R. K., T. A. Shervani, and L. Fahey (1998). “Market-based assets and shareholder value: A framework for analysis”. In: *Journal of Marketing* 62.1, pp. 2–18.

Tallau, C. (2006). “A customer-based stochastic valuation approach for growth companies”. In: *Available at SSRN 924155.*

Tam, K. Y. (1998). “The impact of information technology investments on firm performance and evaluation: evidence from newly industrialized economies”. In: *Information Systems Research* 9.1, pp. 85–98.

Taran, Y., R. Chester Goduscheit, and H. Boer (2015). “Managing business model innovation risks-lessons for theory and practice”. In: *16th International CINet Conference on Pursuing Innovation Leadership*, pp. 919–929.

Tomizawa, H. (2007). “Patent Data Applications for Science and Technology Indicators: Recent Trend in the World”. In: *Journal of Intellectual Property Association of Japan* 3.3, pp. 4–16.

Trappey, C. V. et al. (2011). “Using patent data for technology forecasting: China RFID patent analysis”. In: *Advanced Engineering Informatics* 25.1, pp. 53–64.

Trigeorgis, L. (1991). “A log-transformed binomial numerical analysis method for valuing complex multi-option investments”. In: *Journal of Financial and Quantitative Analysis* 26.3, pp. 309–326.

— (1993). “The nature of option interactions and the valuation of investments with multiple real options”. In: *Journal of Financial and Quantitative Analysis* 28.1, pp. 1–20.

— (1995). *Real options in capital investment: Models, strategies, and applications.* Greenwood Publishing Group.

— (1996). *Real options: Managerial flexibility and strategy in resource allocation.* MIT press.

Trigeorgis, L. and S. P. Mason (1987). “Valuing managerial flexibility”. In: *Midland Corporate Finance Journal* 5.1, pp. 14–21.

Tsoularis, A. and J. Wallace (2002). “Analysis of logistic growth models”. In: *Mathematical Biosciences* 179.1, pp. 21–55.

Tunstall, T. (2015). “Iterative Bass Model forecasts for unconventional oil production in the Eagle Ford Shale”. In: *Energy* 93, pp. 580–588.

Turk, T. and P. Trkman (2012). “Bass model estimates for broadband diffusion in European countries”. In: *Technological Forecasting and Social Change* 79.1, pp. 85–96.

Tushman, M. L. and E. Romanelli (1985). “Organizational metamorphosis: A punctuated equilibrium model of organizational evolution”. In: *Research in Organizational Behavior* 7.3, pp. 171–222.

Ullrich, C. (2014). “Bewertung von Handlungsflexibilität bei Prozess-und IT-Investitionen”. In: *Dissertation, Universität Augsburg, Wirtschaftswissenschaftliche Fakultät*.

Van Bekkum, S., E. Pennings, and H. Smit (2009). “A real options perspective on R&D portfolio diversification”. In: *Research Policy* 38.7, pp. 1150–1158.

Veit, D. et al. (2014). “Business Models: An Information Systems Research Agenda”. In: *Business & Information Systems Engineering (BISE)* 6.1, pp. 45–53.

Venkatraman, N., J. C. Henderson, and S. Oldach (1993). “Continuous strategic alignment: Exploiting information technology capabilities for competitive success”. In: *European Management Journal* 11.2, pp. 139–149.

Verhoef, P. C. and K. N. Lemon (2013). “Successful customer value management: Key lessons and emerging trends”. In: *European Management Journal* 31.1, pp. 1–15.

Wang, J., C. Y. Wang, and C. Y. Wu (2015). “A real options framework for R&D planning in technology-based firms”. In: *Journal of Engineering and Technology Management* 35, pp. 93–114.

Ward, J, E Daniel, and J Peppard (2007). “Building Better Business Cases for It Investments.” In: *The Open University*.

Watts, R. J. and A. L. Porter (1997). “Innovation forecasting”. In: *Technological Forecasting and Social Change* 56.1, pp. 25–47.

Weik, E. (1998). *Zeit, Wandel und Transformation. Elemente einer postmodernen Theorie der Transformation*. Rainer Hampp Verlag.

Weill, P. (1992). “The relationship between investment in information technology and firm performance: A study of the valve manufacturing sector”. In: *Information Systems Research* 3.4, pp. 307–333.

Weill, P. and S. L. Woerner (2013). “Optimizing your digital business model”. In: *MIT Sloan Management Review* 54.3, p. 71.

Wetherbe, J. C. et al. (2007). *Information technology for management: Transforming organizations in the digital economy*. New York: Wiley.

Wiesel, T., B. Skiera, and J. Villanueva (2008). “Customer equity: an integral part of financial reporting”. In: *Journal of Marketing* 72.2, pp. 1–14.

Willcocks, L. (2013). *Information management: the evaluation of information systems investments*. Springer.

Wu, L.-C., C.-S. Ong, and Y.-W. Hsu (2008). "Active ERP implementation management: A Real Options perspective". In: *Journal of Systems and Software* 81.6, pp. 1039–1050.

Yoon, B. and Y. Park (2007). "Development of new technology forecasting algorithm: Hybrid approach for morphology analysis and conjoint analysis of patent information". In: *IEEE Transactions on Engineering Management* 54.3, pp. 588–599.

Young, P. (1993). "Technological growth curves: a competition of forecasting models". In: *Technological forecasting and social change* 44.4, pp. 375–389.

Zahn, E. (1990). "Informationstechnologie als Wettbewerbsfaktor". In: *Wirtschafts Informatik* 32.6, pp. 493–502.

Zhang, S. T. (2016). "Firm valuation from customer equity: When does it work and when does it fail?" In: *International Journal of Research in Marketing* 33.4, pp. 966–970.

Zott, C. and R. Amit (2008). "The fit between product market strategy and business model: implications for firm performance". In: *Strategic Management Journal* 29.1, pp. 1–26.