UNIVERSITÄT REGENSBURG

Fakultät für Wirtschaftswissenschaften

The Impact of Digital Platforms and Networks on Companies and Markets: Empirical Analysis of the Financial Services Sector

Dissertation zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaft

eingereicht an der Fakultät für Wirtschaftswissenschaften der Universität Regensburg

Vorgelegt von: Laura Stiller, M.Sc.

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Prof. Dr. Hans-Gert Penzel

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Prof. Dr. Michael Dowling
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Tag der Disputation: 16. Juli 2021

For my parents, Heike and Bernd

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List of Acronyms

AI	Artificial Intelligence
API	Application Programming Interface
App	Application Software
B2B	Business-to-Business
B2C	Business-to-Consumer
BaFin	Bundesanstalt für Finanzdienstleistungsaufsicht
C2C	Consumer-to-Consumer
CEO	Chief Executive Officer
Co.	Compagnie
Cor. R^2	Pearson correlation coefficient
COVID-19	Coronavirus Disease 2019
e.g.	For Example (exempli gratia)
ERGM	Exponential Random Graph Models
et al.	And Others (et alii)
etc.	And so Forth (et cetera)
EU	European Union
GDPR	General Data Protection Regulation
GOF	Goodness of Fit
H	Hypothesis
i.e.	That is (id est)
IS	Information Systems
MCMCML	Markov Chain Monte Carlo Maximum Likelihood
P	Proposition
p.	Page
pp.	Pages
P2P	Peer-to-Peer
PF	Platform
PSD2	Payment Service Directive 2
R^2	Coefficient of Determination
R&D	Research and Development
RQ	Research Question
Sig	Significant
US	United States
VHB	Verband der Hochschullehrer für Betriebswirtschaft e.V.
VIF	Variance Inflation Factor
vs.	Versus
Web	World Wide Web

1. Introduction

Today, digital platforms are transforming many industries and markets and have become an important field of research not only in the information systems literature, but also in the fields of economics, technology management, and strategy (Tiwana, Konsynski, & Bush, 2010; Gawer, 2011; de Reuver, Sørensen, & Basole, 2018). Digital platforms are changing established competition and market structures in industries at the macroeconomic level and business models of companies at the microeconomic level (Katz & Shapiro, 1985; Rochet & Tirole, 2003; Armstrong, 2006; Evans & Schmalensee, 2010; Cennamo, 2019). The best known platforms are consumer-oriented platforms like social media platforms provided by Facebook, platforms in the sharing economy organized by Airbnb and Uber, or operating system platforms developed by Apple or Microsoft (de Reuver et al., 2018). In the COVID-19 pandemic, the use of digital platforms has continued to rise in various areas of life, including financial markets. As part of social distancing, customers are encouraged to make contactless payments and use online banking, rather than visiting bank branches, which has further increased the use of digital platforms in financial markets (Bundesbank, 2021). The most prominent example of a platform provider from the financial sector is PayPal. The entry of platform providers into financial markets shows that even strictly regulated markets are attractive markets for platform providers. Financial markets worldwide are being strongly affected by the changes brought about by digital platforms. The ecosystems and networks in platform markets are becoming increasingly complex, so financial service providers operating a platform need to consider more than just network effects in their platform strategies and therefore require a deeper understanding of platform-based business models (Teece, 2010; Parker & Van Alstyne, 2014).

To date, there has been little research examining digital platforms in financial markets. Previous research related to payment platforms focused for example on payment platform design (Kazan & Damsgaard, 2014), technological aspects (Dahlberg, Mallat, Ondrus, & Zmijewska, 2008), market entry (Kazan & Damsgaard, 2016), competition (Kazan, Tan, Lim, Sørensen, & Damsgaard, 2018) consumer preferences (Choi, Park, Kim, & Jung, 2020; Dahlberg, Mallat, & Öörni, 2003), and investigated the impact of openness on the market potential of multisided platforms by studying payment platforms (Ondrus, Gannamaneni, & Lyytinen, 2015). Recent calls for research encourage empirical investigation of current theoretical considerations and concepts on platform characteristics, platform strategies and competition in platform markets (Cennamo, 2019). Motivated by this research call and the gap in the literature, the first research question of my dissertation aims to address these shortcomings:

Research Question 1: *How can platform providers in financial markets improve the strategic alignment of their platform to strengthen their market position?*

Platform providers deliberately build partner networks in order to strengthen the platform ecosystem. This phenomenon is referred to in the literature as "coopetition" (Dowling, Roering, Carlin, & Wisnieski, 1996; Bengtsson & Kock, 2000; Bouncken, Gast, Kraus, & Bogers, 2015; Gnyawali & Charleton, 2018; Dowling, 2020). Coopetition is not only important for companies to exploit synergy effects for sustainable competitive advantages, but also to ensure the survival of companies under rapidly changing conditions, such as the digital transformation (Bengtsson & Raza-Ullah, 2016). With the market entry of digital platforms in financial markets, it can increasingly be observed that direct competitors in financial markets are starting to cooperate with each other on platforms or in platform ecosystems. In neither literature on coopetition nor on digital platforms has the influence of digital platforms and platform ecosystems on coopetition or the emergence of network structures been studied. As a result, the second research question of my dissertation addresses these research gaps and aims to examine the influence of digital platforms on coopetition and network formation:

Research Question 2: *Do platforms have an impact on coopetition in highly regulated markets, such as the financial market, and how do platforms impact network formation in these industries?*

The central chapters of my dissertation include three different papers on digital platforms. The first paper, a single author paper, examines the impact of platform size on payment platform value using a qualitative research method. The second paper, co-authored by Dr. Dr. Stefanie Steinhauser, uses a quantitative research method to analyze the influence of platforms on coopetition in financial markets as well as on the factors that influence network development in financial markets. The third paper, co-authored by Dr. Dr. Stefanie Steinhauser, Erich Renz, and Alexander Zanon, uses a quantitative research approach to examine the individual factors of business models in terms of their influence on the success of digital platforms.

Financial markets serve as the empirical setting of my dissertation. I chose the financial sector for my research as it is a highly regulated market and thus insights can be gained on the impact of digital platforms on regulated markets. In addition, financial markets worldwide are currently affected by the transformation through digital platforms, which provides an ideal environment to investigate what impact digital platforms have on market and competition structures.

My dissertation is structured as follows. In Sections 1.1, 1.2, and 1.3 in this chapter, I introduce digital platforms, coopetition, and business model research. In Section 1.4, I give an overview of the theoretical foundation, structure, and content as well as the methodology of my three papers. The subsequent chapters form the core of my dissertation. Chapter 2 contains Paper 1, Chapter 3 contains Paper 2, and Chapter 4 contains Paper 3. In Chapter 5, I summarize the main findings of the three papers and provide answers to my overarching research questions. I conclude with the theoretical and practical implications of my dissertation, as well as its limitations.

1.1 Conceptual Background

In this section, I will introduce the main theoretical concepts on which I have built my thesis. First, I will discuss digital platforms and introduce the main core concepts of digital platforms and platform ecosystems. Further, I will focus on coopetition theory before discussing concepts from business model research.

1.1.1 Digital Platforms

Digital platforms are broadly defined as an interactive ecosystem in which two or more platform users can exchange goods, services, or social currency (Hagiu & Wright, 2015a; Parker, Van Alstyne, & Choudary, 2016). The increasing influence of platforms is also having an impact on the economic order in our society. Today, a wide range of technological products and services are built on or around a digital platform (Gawer & Henderson, 2007; Ondrus et al., 2015). The exchange or trade of digital as well as non-digital products and services between buyers and sellers is increasingly taking place in various industries via platforms (Ghazawneh & Henfridsson, 2015). Even highly regulated markets such as the financial or healthcare sectors are taking advantage of digital platforms. Payment platform systems provided by Apple, PayPal, or the start-up Revolut are transforming financial markets worldwide. Digital platforms are no longer unique to the consumer, retail, or entertainment sectors, but are penetrating nearly all industries, playing a key role in expanding and driving innovation, and strongly influencing the business models of established companies (Gawer, 2011). In today's competition, it is often no longer about how to build and control a value chain, but more about attracting generative activities linked to a platform (de Reuver et al., 2018).

The markets in which platforms dominate are based on the market mechanisms of *two-sided markets*. As early as the 1980s, Nobel Prize winner Tirole and his colleague Rochet began studying two-sided markets, long before the first digital platforms, as we know them today, existed (Rochet & Tirole, 2003; Rochet & Tirole, 2006). Two-sided markets bring together two distinct groups, such as buyers and sellers. The value to one group in a two-sided market increases as the number of participants from the other group increases (Evans, 2003; Eisenmann, Parker, & van Alstyne, 2006a). In the literature on information systems (IS) and economics, this is referred to by the term two-sided or multisided markets. The difference between a two-sided and a multisided market is that in a multisided market, instead of two groups, arrangements are made between multiple groups (Rochet & Tirole, 2003; Boudreau & Hagiu, 2009; Evans & Schmalensee, 2013). A platform that links different groups of participants is typically called a multisided platform (Boudreau & Hagiu, 2009; Hagiu & Wright, 2015b).

As platforms bring together multiple user groups and create an interactive ecosystem, they create the so-called *network effects*. These effects describe the phenomenon that a technology's usefulness increases as its installed base of users increases (Katz & Shapiro, 1985; Shapiro & Varian, 1998). In the context of platforms, network effects describe the relationship between the number of users and the value of the platform for the individual user. Further, network effects are divided into direct and indirect network effects. With direct network effects, the platform value increases proportionally to the number of users in the same user group, as the platform becomes more valuable if more users join the platform (Shapiro & Varian, 1998). In the case of indirect network effects, on the other hand, the value of the platform increases when the number of users in another user group increases (de Reuver et al., 2018). However, the challenge for multi-sided platforms is to get both user groups on the platform, as the two user groups need to grow proportionally to each other in order to successfully scale a network (Caillaud & Jullien, 2003; Rochet & Tirole, 2003).

On digital platforms, networks are created between individual platform participants. In general, a network is defined as a collection of interconnected nodes. In this context, the nodes represent the interfaces of the edges and as such exist and function only within the network (Castells, 2004). The networks that emerge on and around platforms are not physical networks but virtual networks where, unlike real networks, the connections between nodes are not primarily physical but immaterial (Amit & Zott, 2001).

1.1.1.1 Research on Digital Platforms

Over the last decade, platforms have established themselves as an important field of research in the literature on IS and economics. A variety of research activities on digital platforms has covered multisided platforms (de Reuver et al., 2018; McIntyre, Srinivasan, Afuah, Gawer, & Kretschmer, 2020), types of platforms (Gawer, 2020), platform ecosystems (Iansiti & Levien, 2004b, 2004a; Tiwana, 2013; Gawer & Cusumano, 2014; Evans & Basole, 2016; Jacobides et al., 2018; Helfat & Raubitschek, 2018; Cennamo & Santaló, 2019), platform openness (Benlian, Hilkert, & Hess, 2015; Ondrus et al., 2015; Broekhuizen, Emrich, Gijsenberg, Broekhuis, Donkers, & Sloot, 2021), platform governance (Darking, Whitley, & Dini, 2008; Tilson, Lyytinen, & Sørensen, 2010; Wareham, Fox, & Cano Giner, 2014; Parker, Petropoulos, & Van Alstyne, 2020), platform envelopment (Eisenmann, Parker, & van Alstyne, 2011), platform resources (Henfridsson & Bygstad, 2013; Ghazawneh & Henfridsson, 2013; Eaton, Elaluf-Calderwood, Sorensen, & Yoo, 2015), platform competition (Rochet & Tirole, 2003; Noe & Parker, 2005; Armstrong, 2006; Eisenmann et al., 2006; Cennamo & Santalo, 2013; Kazan, Tan, Lim, Sørensen, & Damsgaard, 2018; Cennamo, 2019), as well as platform innovation and leadership (Gawer & Cusumano, 2002; Boudreau, 2012; Cusumano, Yoffie, & Gawer, 2020). An overview of the definitions of core concepts on digital platforms is provided in Table 1. In my thesis, I focus in particular on platform ecosystems as well as on platform characteristics, such as platform openness and platform competition in multisided markets.

Concept	Definition
Multisided platform	Mediating different groups of users, such as buyers and sellers.
Multisided markets	Bringing together distinct groups, whereby the value for one group increases as the number of participants from the other group increases.
Digital platform (technical view)	An extensible codebase to which complementary third-party modules can be added.
Digital platform (sociotechnical view)	Technical elements (of software and hardware) and associated organizational processes and standards.
Ecosystem (technical view)	A collection of complements (apps) to the core technical platform, mostly supplied by third parties.
Ecosystem (organizational view)	Collection of firms interacting, contributing thereby to the complements.
Platform openness	The extent to which platform boundary resources support complements.
Applications	Executable pieces of software that are offered as apps, services, or systems to end-users.
Boundary resources	Software tools and regulations facilitating the arms' length relationships between the involved parties.

Table 1: Definitions of Core Concepts on Digital Platforms[1]

1.1.1.2 Platform Ecosystem

The term ecosystem originates from biology and has been increasingly used in IS and economics literature, especially in recent years (Moore, Rao, Whinston, Nam, & Raghu, 1997; Gawer & Cusumano, 2002; Iansiti & Levien, 2004a, 2004b; Gawer & Cusumano, 2014; Shipilov & Gawer, 2019). The term ecosystem describes a group of interacting firms that depend on each other's activities. Jacobides et al. (2018) reviewed the literature related to ecosystems and found that scholars emphasized different aspects of an ecosystem depending on the unit of analysis. They were able to identify three broad

[1] Own representation based on de Reuver, M., Sørensen, C., & Basole, R. C. (2018).

groups of research streams; *business* ecosystems, *innovation* ecosystems, and *platform* ecosystems (see Table 2).

Concept	Authors & Year	Definitions
Ecosystem	Jacobides et al. (2018)	"An ecosystem is a set of actors with varying degrees of multilateral, nongeneric complementarities that are not fully hierarchically controlled." (p. 2264)
	Shipilov and Gawer (2019)	"Ecosystems emerge from the participants' actions in managing nongeneric complementarities." (p. 95)
Business Ecosystem	Moore (1993)	"In a business ecosystem, companies co-evolve capabilities around a new innovation: they work cooperatively and competitively to support new products, satisfy customer needs, and eventually incorporate the next round of innovations." (p. 76)
	Teece (2007)	"… the community of organizations, institutions, and individuals that impact the enterprise and the enterprise's customers and supplies." (p. 1325)
Innovation Ecosystem	Adner (2006)	"… the collaborative arrangements through which firms combine their individual offerings into a coherent, customer-facing solution." (p. 2)
	Kapoor (2018)	"… a set of actors that contribute to the focal offer's user value proposition." (p. 2)
Platform Ecosystem	Tiwana et al. (2010)	"The collection of the platform and the modules specific to it." (p. 676)
	Altman and Tushman (2017)	"Ecosystems organize and leverage external entities, which are frequently complementors and have interdependencies between them …." (p. 7)
	Constantinides, Henfridsson, and Parker (2018)	"In this regard, the notion of a platform ecosystem rests firmly on the idea of modularity … making a distinction between the platform core—consisting of tightly coupled components—and loosely coupled peripheral components …." (p. 2)
	Kretschmer, Leiponen, Schilling, and Vasudeva (2020)	"This makes platform ecosystems an organizational form on its own (a "meta-organization"), neither possessing the hierarchical instruments of a firm, nor the largely uncoordinated decision-making of markets." (p. 2)

Table 2: Summary of Selected Definitions of "Ecosystem"

In the *business* ecosystem stream, authors focus on a company and its environment. In the *innovation* ecosystem stream, papers concentrate on a particular innovation or new value proposition and the constellation of actors that support it. The *platform* ecosystem stream, on the other hand, examines how different actors organize around a platform. Here, everything revolves around the technology of digital platforms and the interplay between platform sponsors and their complementors (Jacobides et al., 2018). Baldwin and Woodard (2009) describe a platform as a system consisting of a stable core component and a peripheral component. The platform is linked to an array of peripheral firms via shared or open-source technologies or technical standards. By connecting to the platform, complementors can not only generate complementary innovations, but also gain direct or indirect access to the platform's customers, enabling transactions between different user groups and creating multisided markets (Cennamo & Santalo, 2013; Jacobides et al., 2018). In platform ecosystems, the mechanisms for coordinating the different participants are usually organized flexibly and openly, and there are few coordination mechanisms for hierarchically organized control (Hagiu & Wright, 2015b; Shipilov & Gawer, 2019). In the context of my thesis, I focus on *platform* ecosystems.

1.1.2 Coopetition

Definition and Theoretical Background

The continuous process of change, strongly driven by globalization and the digital transformation, creates uncertainty and volatility in markets and influences entrepreneurial actions related to collaboration between companies (Powell, Koput, & Smith-Doerr, 1996; Dagnino & Padula, 2002; Bengtsson, Wilson, Bengtsson, Eriksson, & Wincent, 2010; Bouncken et al., 2015). Collaboration between companies not only acts as a source of sustainable competitive advantage by leveraging emerging synergies, but also ensures the survivability of companies under rapidly changing conditions. Even competing companies are increasingly recognizing the need to share resources and capabilities in order to strengthen their competitive position (Carlin et al., 1994; Brandenburger & Nalebuff, 1996; Dowling et al., 1996; Bengtsson & Kock, 2000;

Gnyawali & Park, 2009; Dorn, Schweiger, & Albers, 2016). This form of collaboration between companies that cooperate and compete with each other at the same time is referred to as coopetition, a term composed of “cooperation” and “competition” (Dowling et al., 1996; Dowling & Lechner, 1998; Bengtsson & Kock, 2000; Dagnino & Padula, 2002; Bengtsson & Kock, 2014; Bouncken et al., 2015; Gnyawali & Ryan Charleton, 2018; Dowling, 2020). Blohm (1980) defines a business cooperation as a collaboration based on a tacit or contractual agreement between legally independent companies that are not economically dependent on each other in the areas not affected by the cooperation. Definitions of competition in the literature, on the other hand, describe the rivalry between actors and the emphasis on common resources as well as conflicting activities, goals, and interests (Porter, 1997; Bengtsson & Kock, 2000; Porter, 2011; Hoffmann, Lavie, Reuer, & Shipilov, 2018). Prior to the emergence of the term coopetition, business relationships were viewed in terms of either cooperation or competition (Gast, Filser, Gundolf, & Kraus, 2015). In the literature so far, no universal definition of the phenomenon of coopetition exists (see Table 3). What all definitions have in common, however, is that in coopetition there are simultaneously two conflicting logics of interaction between the parties, namely cooperation and competition.

Authors & Year	Definitions
Dowling et al. (1996)	"… examines a growing form of interorganizational "multifaceted" relationship under "coopetition", where a buyer, supplier, and/or partner is also a competitor." (p. 155)
Bengtsson and Kock (2000, 2014)	"… the cooperative and competitive parts of the relationship are separated between different business units. Competitors cooperate in some markets or product areas whereas they compete in others." (p. 420) and "… coopetition is a paradoxical relationship between two or more actors simultaneously involved in cooperative and competitive interactions, regardless of whether their relationship is horizontal or vertical." (p. 182)
Bengtsson, Hinttu, and Kock (2003)	"… as firms interact in accordance with two different logics of interaction, cooperation and competition." (p. 4)
Dagnino and Padula (2002)	"… a kind of interfirm strategy which consents the competing firms involved to manage a partially convergent interest and goal structure and to create value by means of coopetitive advantage." (p. 13)
Luo, Slotegraaf, and Pan (2006)	"… joint occurrence of cooperation and competition across functional areas within a firm." (p. 67)
Zhang and Frazier (2011)	"… a supply chain partnership between competing firms with different competencies through a contractual agreement to meet each other's strategic objectives such as expanding market share, enhancing efficiency, entry to a new channel, etc." (p. 853)
Bouncken et al. (2015)	"Coopetition is a strategic and dynamic process in which economic actors jointly create value through cooperative interaction, while they simultaneously compete to capture part of that value." (p. 592)
Gnyawali and Charleton (2018)	"… coopetition refers to simultaneous competition and cooperation among firms with value creation intent." (p. 2513)

Table 3: Summary of Selected Definitions of the Term "Coopetition"

The origin of the term coopetition is not fully known, but most researchers attribute the term to Raymond John Noorda, founder and CEO of Novell, who is said to have first used it in the 1980s (Dowling et al., 1996; Nalebuff & Brandenburger, 1997; Gast et al., 2015; Dowling 2020). Dowling et al. (1996) then developed a theoretical approach to explain coopetition based on the resource dependence approach of the transaction cost theory of Williamson (1975) and Pfeffer and Salancik (1978). Brandenburger and Nalebuff (1996) developed another theoretical approach using game theory by simulating business life as a game. Here they describe which strategies and decisions are strategically valuable for companies and how companies create win-win situations by generating value and using coopetition strategies (Nalebuff & Brandenburger, 1997; Bengtsson & Kock, 2000; Walley, 2007). Both are traditional theories that describe factors in the external and internal environments of firms that could drive them into multi-layered relationships such as coopetition (Gast et al., 2015). Moreover, the network theory is applied to show how participating firms gain information about other actors and their partners as well as access to resources and knowledge through coopetition (Bengtsson & Kock, 2014; Bengtsson, Kock, Lundgren-Henriksson, & Näsholm, 2016; Gnyawali & Park, 2009).

Factors Influencing Coopetition

In the platform economy, it can be observed that competitors start cooperating with each other in certain business areas. But what actually causes fierce competitors to suddenly start cooperating with each other? In addition to the different basic theories of coopetition, the literature has also identified different factors that may have an influence on the emergence of coopetition in different industries (Dowling et al., 1996; Padula & Dagnino, 2007; Luo, 2007; Bengtsson & Raza-Ullah, 2016; Gnyawali & Ryan Charleton, 2018; Dowling 2020). These factors are referred to as drivers of coopetition and can push companies to enter into collaborations with competitors (Bengtsson & Raza-Ullah, 2016). Table 4 provides an overview of the different factors identified as important drivers for coopetition in my research.

Authors & Year	Factors that drive Coopetition
Dowling et al. (1996)	Internal environment-related influencing factors: Resource importance, asset specificity, and supplier opportunism. External environment-related influencing factors: Industry concentration, generosity, interconnectedness.
Padula and Dagnino (2007)	Change of environmental factors and knowledge structure of companies.
Bengtsson and Kock (2000)	Internally available resources and capabilities to generate competitive advantages.
Dorn et al. (2016)	The length of product life cycles, R&D costs, regulatory bodies or laws, technological capabilities, or resource complementarity.
Bengtsson and Raza-Ullah (2016)	External factors: environmental conditions, technological requirements, growth level, industry uncertainty, stakeholder influence, government tactics, regulatory constraints. Relational factors: resources, capabilities, general characteristics of partners, structures, perceived trust. Internal factors: own motives, resources, strategies, capabilities, vulnerabilities, reputation, past experience.

Table 4: Overview of Selected Factors that Drive Coopetition

1.1.3 Business Model Research

Similar to platforms, the term business model is omnipresent in practice as well as in theory. Business models and platforms are often related to each other, as platforms often have or are part of a business model. In the literature, there are different definitions for the term business model (see Table 5).

Authors & Year	Definitions
Amit and Zott (2001) Zott and Amit (2010)	"A business model depicts the content, structure, and governance of transactions designed so as to create value through the exploitation of business opportunities." (p. 511) "… business model as a system of interdependent activities that transcends the focal firm and spans its boundaries." (p. 216)
Chesbrough and Rosenbloom (2002)	"The business model provides a coherent framework that takes technological characteristics and potentials as inputs, and converts them through customers and markets into economic outputs." (p. 532)
Magretta (2002)	"They are, at heart, stories—stories that explain how enterprises work. A good business model answers Peter Drucker's age old questions: Who is the customer? And what does the customer value? It also answers the fundamental questions every manager must ask: How do we make money in this business? What is the underlying economic logic that explains how we can deliver value to customers at an appropriate cost?" (p. 4).
Osterwalder and Pigneur (2010)	"A business model describes the rationale of how an organization creates, delivers, and captures value." (p. 14)
Teece (2010)	"A business model articulates the logic, the data and other evidence that support a value proposition for the customer, and a viable structure of revenues and costs for the enterprise delivering that value." (p. 179)
Upward and Jones (2016)	"… a description of how a business defines and achieves success over time …." (p. 10)
Wells (2016)	"… business model can be defined as having three constituting elements: the value network and product/service offering that defines how the business is articulated with other businesses and internally (i.e. how value is created); the value proposition that defines how products and/or services are presented to consumers in exchange for money (i.e. how value is captured); and the context of regulations, incentives, prices, government policy and so on (i.e. how value is situated within the wider socioeconomic framework)." (p. 37)

Table 5: Selected Definitions of the Term "Business Model"

Common to the different definitions is that value generation and value mediation are a central component of business models. In my work, I predominantly follow the definition of Osterwalder and Pigneur (2010), who describe a business model as the basic principle of how an organization creates, delivers and captures value. Although there is no general agreement on the definition and the number and types of business model dimensions, Hartmann, Zaki, Feldmann, and Neely (2016) were able to identify the following six key dimensions from different authors: customer segment, value proposition, revenue streams, key resources, key activities, and cost structure. However, these dimensions can only be applied to platforms to a limited extent. Platforms bring additional operational and strategic challenges to the analysis of the business model as platforms only provide the infrastructure for platform users and users interact directly with each other without an intermediary (Hagiu & Wright, 2015a).

1.2 Overview of the Dissertation

1.2.1 Theoretical Foundation

My dissertation investigates how platform providers in financial markets can improve their strategic alignment of their platform to strengthen their market position and how platforms influence coopetition and network formation, especially in strictly regulated markets such as financial markets. To answer my overarching research questions, this dissertation primarily builds on insights from platform and platform ecosystem theory as well as on coopetition theory and business models research. The structure of my dissertation is depicted in Figure 1, which visually represents how my three papers relate to each other. In my thesis, I investigate the impact of digital platforms on market and competition structures from a microeconomic as well as from a macroeconomic perspective. I addressed Research Question 1 (RQ 1) in Paper 1 and Paper 3, while I focused on Research Question 2 (RQ 2) in Paper 2.

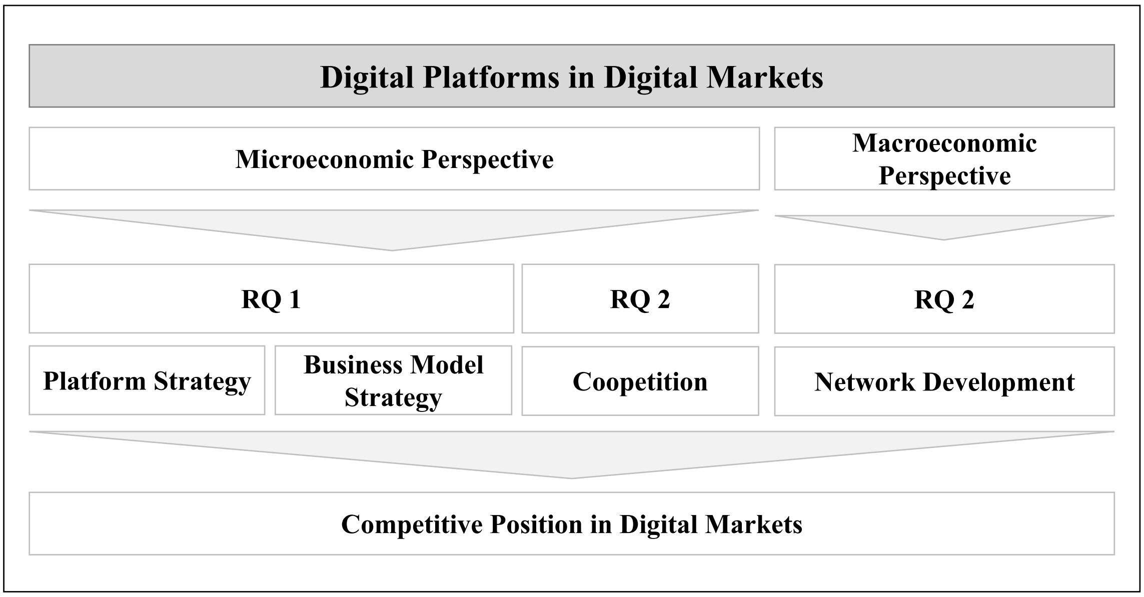


Figure 1: Theoretical Foundation of my Dissertation

Digital platforms serve as the overarching research object that all three papers have in common in my dissertation. In Paper 1, I investigated the influence of different platform characteristics on platform size and their influence on platform value. Here, I combined research on platforms and platform ecosystems with research on switching costs and lock-in effects. I focused on payment platforms in three different financial markets. The payment platform providers are banks, fintechs, and technology companies. In Paper 2, we analyzed the impact of digital platforms on cooperation activities between direct competitors in the financial market. Our research is based on platform and coopetition theory as well as on social network theory. We examined the network created by the cooperation activities between competitors in the financial sector. In Paper 3, we expanded our focus to digital platforms in different markets and combined insights from platform theory and business model research. We examined which factors of a platform business model characterize a successful digital marketplace.

1.2.2 Structure and Content of the Three Papers

To provide an overview of the structure and content of the three papers, the general characteristics of each paper are summarized in Table 6.

	Paper 1	Paper 2	Paper 3
Chapter	Chapter 2	Chapter 3	Chapter 4
Title	The payment market as a new digital battlefield: The impact of platform size on payment platform value	Keep your friends close, but your enemies closer: Coopetition in the Platform Economy—A social network analysis	Success formula: Can Business Model Success on Digital Marketplaces be Evaluated? A Mixed Method Approach
Authors	▪ Laura Stiller	▪ Laura Stiller ▪ Dr. Dr. Stefanie Steinhauser	▪ Laura Stiller ▪ Dr. Dr. Stefanie Steinhauser ▪ Erich Renz ▪ Alexander Zanon
Research Question	What platform characteristics favor platform size and have an impact on platform value on payment platforms?	How do platforms influence coopetition in financial markets and which factors influence network development in financial markets?	Which factors of the business model, as well as network structure and network behavior influence the success of digital marketplaces?
Theory	Platform Theory Platform Ecosystems Switching Costs Lock-In Effects	Platform Theory Coopetition Theory Social Network Theory	Platform Theory Business Models
Methodology	*Qualitative:* Multiple case studies	*Quantitative:* Social network analysis (ERGM)	*Quantitative:* Multiple linear regression model
Data & Research Context	Secondary data from payments in financial markets in Germany, the US, and China, 2018 to 2019	Secondary data of firms operating in the financial market in Germany, 2020	Secondary data of 100 international firms listed in the database angel.co, 2019
Status	<u>Under Review:</u> Information Systems Journal (VHB[2]: B)	<u>Accepted:</u> Academy of Management 2021 <u>Reject & Resubmit:</u> Journal of Information Technology (VHB[2]: A)	<u>Published:</u> Academy of Management Proceedings 2020, (1), 18728 <u>Under Review:</u> European Management Journal (VHB[2]: B)

Table 6: Overview of my Dissertation

[2] "Verband der Hochschullehrer für Betriebswirtschaft e.V." (VHB) evaluates scientific journals relevant to business research. The classification mentioned refers to VHB-Jourqual 3 from 2015. Source: http://vhbonline.org/en/service/jourqual/vhb-jourqual-3, accessed on March 26, 2021.

In **Paper 1**, I examined platform characteristics of payment platforms that influence the value of the payment platform and strengthen its competitive position. In doing so, I contribute not only to a better understanding of payment platforms, but also to the characteristics and modes of operation of digital platforms in highly regulated markets: the financial markets. My research builds on previous theoretical considerations and investigations, interlocks different research areas, and applies these theoretical concepts to payment platforms. I developed a theoretical framework to analyze how individual platform characteristics affect platform size and thus the value of payment platforms. My framework builds mainly on the research streams on platforms, data, switching costs, and lock-in effects. I then derived propositions from the theoretical framework and examined them in an empirical study. To analyze the propositions, I created a unique dataset consisting of data from 56 banks, 179 fintechs, and 11 technology companies that are financial service providers from Germany, US, and China. As a research method, I applied a multiple case studies analysis according to Yin (2014). The German, US, and Chinese financial markets each represent one case in my study. I analyzed the data based on the propositions and investigate similarities and differences between the three different financial markets. The results of the case studies suggest that the regulation of each country may have an impact on platform characteristics such as the degree of openness of payment platforms. Moreover, the results show that not all market participants have a level playing field when introducing a payment platform to the market.

In the co-authored **Paper 2,** we investigated the influence of platforms and other important factors on cooperation activities between competitors in the German financial market in order to draw a more refined and comprehensive picture of coopetition networks. We investigated various drivers of coopetition—external drivers (i.e., platforms, AI, blockchain technology, and banking license), relation-specific drivers (i.e., type of company and position in the network), form of coopetition, and endogenous network effects. Previous studies show that the influence of individual platforms often results from a platform ecosystem that is joined by different companies, sometimes even direct competitors. However, there is a limited understanding of how networks are created around platforms and why direct competitors join forces and start cooperating with each other. We derived hypotheses from the literature analysis and built a unique database with various secondary data sources to test the developed hypotheses. We employed a social network analysis approach, namely, an exponential random graph model (ERGM), to analyze 371 companies in the German financial sector. The findings from the social network analysis suggest that platforms have a significant positive impact on coopetition. Further, the findings imply the influence of regulatory requirements as well as relationship and partner characteristics on coopetition and network development.

In the co-authored **Paper 3**, we analyzed different platforms in different industries and investigated possible success factors of multi-sided platforms. In doing so, we contribute to a better understanding of the interactions between business models and digital platforms as well as of the influence of individual business model dimensions on digital platforms. Based on the literature on network effects, platforms, and business models, we developed a codebook that supports quantitative document analysis. Our approach is based on the taxonomy of business models developed by Täuscher & Laudien (2018), which we expanded with new findings from the platform and business model literature in order to derive success factors for multi-sided platforms. To test the hypotheses, we built a database based on angle.co. Our dataset comprises a sample size of 100 international companies. We studied the data collected using multiple linear regression in order to determine their influence on the success of the platforms, which we defined as received funding and turnover. Our analysis suggests that several value propositions, central members, or key partners, and the addressing of B2C and B2B customers can have a positive effect on success. The findings further demonstrate a positive effect if users can take on several platform roles, if several revenue sources exist, and if platforms offer their value proposition via websites as well as mobile application.

After providing a summary of the content of each paper in this section, I will give an overview of the methodology used in the three papers in the following section.

1.2.3 Methodology of the Three Papers

I addressed the two central research questions of my dissertation by using different research methods in the three papers, employing thereby a qualitative as well as a quantitative research approach. The research design and research method in Paper 1 is based on an exploratory research approach in the form of a case study methodology (Yin, 2014). I addressed the research question of how platform characteristics favor platform size and have an impact on platform value on payment platforms. In Paper 2 and Paper 3, on the other hand, I followed a quantitative research approach. In Paper 2, I focused on the research question of how platforms influence coopetition in financial markets and which factors influence network development in financial markets. To examine the impact of platforms and the various influencing factors as well as the resulting network, I applied a social network analysis. In Paper 3, I examined which factors of a business model, as well as to what extent network structure and network behavior influence the success of digital marketplaces. Therefore, I applied a multiple linear regression model.

In the following, an overview of the three different research methods is provided. A more detailed description of the research methods is included in Chapter 2.3 for Paper 1, Chapter 3.3 for Paper 2, and Chapter 4.3 for Paper 3.

In the qualitative **Paper 1,** a multiple case study was applied. According to Yin (2014), case study research is an empirical explanatory approach to explore contemporary phenomena within their real-world context. Case study research is often applied to answer research questions that address the context ("how?") or the reason ("why?") of a phenomenon, but also to examine already existing theories (Eisenhardt, 1989; Yin, 2014). According to Yin (2014), the typical approach for conducting a case study is undertaken in several steps (see Figure 2).

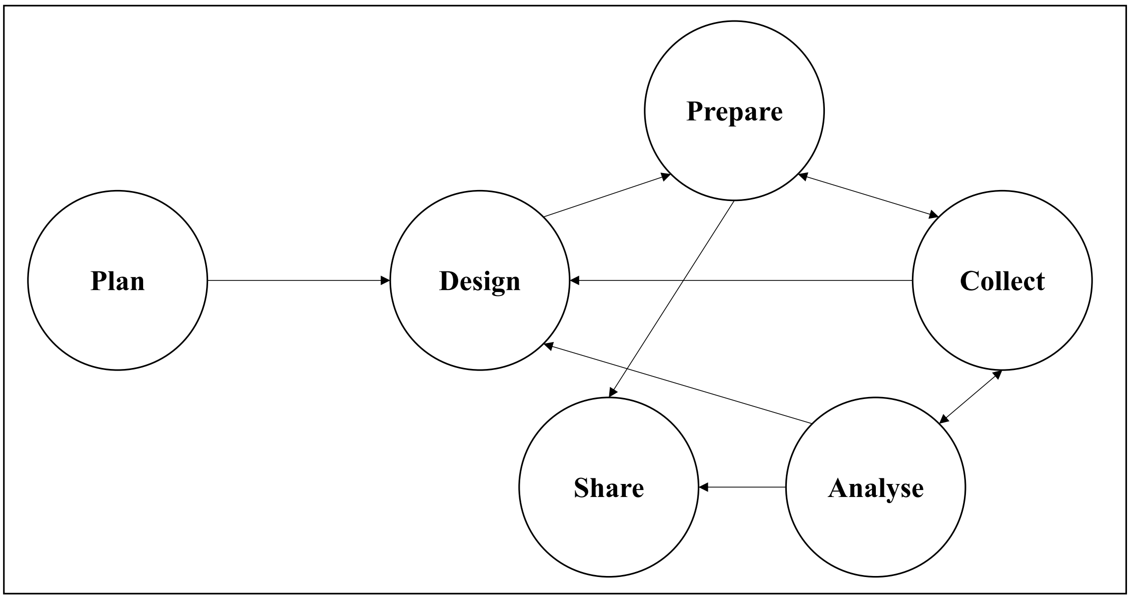


Figure 2: Approach for Conducting a Case Study[3]

At the start, the study has to be planned and the appropriate case study design has to be chosen. For the study in Paper 1, I used an embedded multiple case design as my study includes different markets and different units of analysis. This is followed by the study preparation, which serves to structure the analysis and ensure that all critical topics are covered. The next step is data collection. In the case study research approach, data from different sources can be used. The data used in my research included data policy guidelines, press releases, industry articles, and consumer protection regulations. To ensure a high level of construct validity, internal and external validity as well as reliability in the data analysis of my research, I followed the analytic techniques suggested by Yin (2014) (see Table 7).

[3] Own representation based on Yin (2014).

Analytic technique	Description
Pattern Matching	This logic compares an empirically based pattern with the assumptions made in advance from theory.
Explanation Building	The goal is to analyze the case study data by developing an explanatory approach that can explain the phenomenon shown in each case.
Time-Series Analysis	Investigation of changes in the units of analysis of the different cases over time.
Logic Models	The logic model intentionally analyzes cause-effect chains of events over time.
Cross-Case Synthesis	Cross-case synthesis is used to analyze similarities and differences in the various cases.

Table 7: Analytic Techniques to Analyze Data in Case Studies[4]

In the quantitative **Paper 2**, we used a social network analysis at the macro level and employed an exponential random graph model (ERGM) to analyze various secondary data from a unique dataset that was created with data from digital platforms, annual reports, and press releases related to the companies studied. Moreover, we expanded the database to include the regulatory requirements of BaFin for the German financial market. In order to test our hypotheses, we applied an exponential random graph model (ERGM) (see Lusher et al., 2013) by using the PNet software (P. Wang, Robins, & Pattison, 2009). The outcome variable of ERGMs is the overall structure of a network. The network we are analyzing is represented as an adjacency matrix containing the observed y_{ij} for each pair of firms i and j. The random variable Y_{ij} takes the value 1 if there is a given connection between i and j, and 0 if there is not. The effective number of observations is N x (N-1), where N is the number of nodes in the network (Lomi et al., 2014). In our studied network, the number of nodes is 371, which is equal to the number of analyzed companies. Thus, the number of observations is 137,270.

[4] Own representation based on Yin (2014).

In the quantitative **Paper 3**, we employed a multiple linear regression model to study the data collected in order to determine their influence on the success of platforms. We established a morphological box with different categories and business model dimensions that allows us to organize and describe a platform business model by combining its characteristics. Our data collection was conducted through the database angel.co. Here we filtered potential research objects by marketplace until we had a sample size of 100 companies. The hypotheses were tested with the statistical program STATA by applying a multiple linear regression model to test their influence on the success of the platforms.

This chapter introduced digital platforms, coopetition, and business models and provided an overview of my dissertation. The three papers that are the central part of my dissertation are presented in Chapter 2, 3 and 4. The papers were submitted to different journals. Since the requirements of the journals on the structure of the papers are different, the structure of the three papers in my dissertation differs slightly.

2. Paper 1

The Payment Market as a New Digital Battlefield: The Impact of Platform Size on Payment Platform Value

2.1 Introduction

How we pay for goods and services has changed a lot in recent years. Today, we pay for our purchases using smartwatches, for taxi rides with our mobile phones, and restaurant visits with friends are settled via PayPal. The COVID-19 pandemic has also contributed significantly to a change in payment behavior and the increasing use of contactless payment platforms. In addition, less everyday payment transactions such as foreign bank transfers, which for a long time had to be handled at great cost by banks like WesternUnion, can now be completed easily and for low fees through TransferWise. What these new payment services have in common is that they are processed via digital platforms. As is the case in many other industries, digital platforms also act as a game changer in the field of payment transactions and are bringing many new competitors into the market. Banks themselves introduced online banking in the mid-1990s; however, it was only after the financial crisis in 2008, with the market entry of the so-called fintechs and, a short time later, the big technology companies, that a new era in the market for payment transactions began. The term fintech combines “financial services” and “technology” and refers to companies that combine financial services with cutting-edge technologies. Today, the former leading banks find themselves having to compete with innovative fintechs and technology giants like Apple, Google, and Co. Digital payment platforms have changed the conditions in the payment market considerably. It has developed into a digital battlefield in which banks, fintechs, and technology companies compete for the dominance of their payment platform.

In numerous studies in recent years, researchers have investigated the phenomenon of platforms. Platforms are a subcategory of two-sided markets, which have been the focus of research since the 1980s (Rochet & Tirole, 2003; Evans, 2003; Rochet & Tirole, 2006;

Eisenmann et al., 2006; Boudreau & Hagiu, 2009). These two-sided or multi-sided markets are based on so-called network effects, which implies that the value of a platform increases as its installed base of users increases (Katz & Shapiro, 1985; Shapiro et al., 1998; Parker & Van Alstyne, 2005). Moreover, various studies have analyzed the characteristics of platforms and their influence on existing business models of firms as well as on entire industries (Gawer & Cusumano, 2002; Evans & Schmalensee, 2016; Parker et al., 2016; Van Alstyne, Parker, & Choudary, 2016). However, platforms are not isolated, but are surrounded by an ecosystem similar to those we know from nature (Moore et al., 1997; Iansiti & Levien, 2004b; Tiwana et al., 2010; Tiwana, 2013; Gawer & Cusumano, 2014; Shipilov & Gawer, 2019).

Platforms can have different degrees of openness. Recent studies show that the degrees of openness of platforms and their platform ecosystems have a decisive influence on organizational and technical levels (Ghazawneh & Henfridsson, 2013; Benlian et al., 2015; Ondrus et al., 2015). The same is applicable for platforms in the payment market, where Ondrus et al. (2015) examined the impact of openness on the market potential of payment platforms. As further studies have shown, the payment market is an interesting research area with regard to new technological developments and the influence of platforms, (Ondrus et al., 2015; Kazan & Damsgaard, 2016; Kazan et al., 2018; Gomber et al., 2018). In my paper, I build on existing findings and investigate the question of how platform characteristics favor platform size and impact platform value on payment platforms? My research question contributes to a better understanding of the influence of payment platform characteristics supporting platform size and their impact on payment platform value. Similar to other research on platforms, I assume in my research that network size and strength increase the chances of reaching a critical mass on the payment platform and thus contribute to a competitive advantage. To answer my research question, I empirically investigate payment platform characteristics supporting platform size. My theoretical framework is based on the platform-based competitive analysis framework by Cennamo (2019). Here, I focus on the strategic dimension platform size, which follows a winner-takes-all logic. I adapt the platform-based competitive analysis framework to my findings from my literature review on payment platforms. Based on the results of my theoretical analysis, I derive propositions to investigate the influence of different payment platform characteristics on platform size. In a next step, I investigate the formulated propositions using a case study analysis in which I examine different payment platforms of different platform financial service providers in the payment market. These include banks, fintechs, and technology companies. My case study analysis focuses on the German, the US, and the Chinese financial markets. I chose these case studies in order to investigate different financial service providers and their payment platforms in three different countries and thus achieve a high degree of generalizability. Finally, I discuss the results of my research and summarize the key findings, point out limitations, and present theoretical and practical implications of my work.

2.2 Theoretical Background and Propositions

A key characteristic of a platform is that it creates an interactive ecosystem where two or more platform users can exchange goods, services, or social currency (Hagiu & Wright, 2015a; Parker et al., 2016). Platforms that bring together different groups of users, such as buyers and sellers, are typically defined as multi-sided platforms (Boudreau & Hagiu, 2009). However, the market mechanisms of platforms are not new; two-sided markets have been the focus of research since the 1980s (Rochet & Tirole, 2003). Two-sided markets provide infrastructure and rules that enable interaction between two different but interdependent user groups (Eisenmann et al., 2006). The value of the two-sided market increases for the users in Group A if the number of users in Group B rises (Evans, 2003). Examples of the effects of two-sided markets include newspapers, which connect subscribers and advertisers; credit cards, which link consumers and merchants; or Uber, which matches drivers and passengers. Multisided markets create ecosystems in which different user groups can interact with each other. (Eisenmann et al., 2006; Evans & Schmalensee, 2013).

2.2.1 Network Effects and Critical Mass

While two-sided markets are active in most industries, they differ from traditional product and service offerings in one essential aspect. In the manufacturing industry, production efficiency is mainly increased through economies of scale and thus competitive advantages can be achieved. In the case of two-sided markets, however, so-called network effects are regarded as the driving force behind economic value creation and competitive advantages (Shapiro & Varian, 1998; Parker et al., 2016). These network effects stem from the bringing together of multiple user groups on the platform. Network effects are central to network size and strength as they enable the growth of a network. At their core, network effects describe the interrelation between the number of users and the value of the platform for the individual user. Therefore, the platform value increases for the individual user as its installed base of users increases (Katz & Shapiro, 1985). In addition, a distinction is made between direct and indirect network effects. In the case of direct network effects, the platform value increases proportionally to the number of users in the same user group. Examples of direct network effects include social media or peer-to-peer (P2P) payment platforms, as they become more valuable if more users join the platform (Shapiro & Varian, 1998). Indirect network effects occur when the value of the platform depends on the number of users in another user group (de Reuver et al., 2018). For instance, trading platforms become more valuable for consumers if there are many merchants offering products and services. However, the challenge for multi-sided platforms is getting both user groups on the platform to succeed; this is referred to as the "chicken and egg" dilemma. To attract consumers, the platform should have many merchants; however, they will only register if they know that there are many consumers on the platform (Caillaud & Jullien, 2003; Rochet & Tirole, 2003). In order to scale a network, the two user groups must grow proportionally to each other.

A network thus becomes more and more attractive for its users with increasing size and complements, which in turn prompts additional users to join the network and thus generates further direct and indirect network effects. These causal relationships reflect the concept of positive feedback (Zerdick, Schrape, Artope, Goldhammer, Heger, Lange et al., 2013), which strengthens positive as well as negative network effects, resulting in strong ones being strengthened and weak ones being weakened (Shapiro & Varian, 1998). The decisive factor for the success and the competitiveness of a platform, however, is whether it reaches a critical mass of users. The concept of critical mass describes the need for a minimum number of users on both sides of the platform to enable the sustainable growth of the platform. It is also important to reach a critical mass as quickly as possible as early adopters on the respective sides leave the platform if they have to wait too long for other users to join (Marwell & Oliver, 1993; Evans & Schmalensee, 2010). Accordingly, it is important for platform providers to build up a network and quickly achieve a critical mass on all sides of the platform after market entry in order to create a competitive advantage (Kay, 1995; Ondrus et al., 2015).

A suitable launch strategy for platforms can be an important prerequisite for achieving a critical mass as soon as possible. Parker and Van Alstyne (2014) identify four different types of platform launch strategies for platforms: subsidy, seeding, micro-market launch, and piggybacking. Companies that have many resources can subsidize platforms and attract new users to the platform (Parker & Van Alstyne, 2014). For example, some banks offer new customers a financial incentive when they open a new account. On two-sided platforms, a seeding strategy helps to increase the participation of one user group and makes participation more attractive for the other user group (Boudreau, 2012; Hagiu & Spulber, 2013). The micro-market launch strategy, on the other hand, describes an entry strategy that initially focuses on a niche group. Even a giant like Facebook, which was founded in 2004, started with a micro-market launch strategy where the platform was only accessible to Harvard undergraduates (Ellison, Steinfield, & Lampe, 2007; Parker & Van Alstyne, 2014). When using the piggybacking strategy, platforms look for a big brother. Small companies that have hardly any users attach themselves to a strong partner. PayPal is a well-known example of this as it initially partnered with eBay to enter the payment market (Parker & Van Alstyne, 2014). Thus, the right market entry strategy can be an important cornerstone for building a user base more quickly.

2.2.2 Platform Ecosystem and Openness

Most two-sided markets are winner-takes-all markets, which means these markets are usually dominated by only a few large platforms and are highly competitive (Noe & Parker, 2005). This is why it can be advantageous to merge with other companies and build up partnerships to compete for the success of the platform (Eisenmann et al., 2006). The design of the platform ecosystem plays an essential role in the cooperation with other partner companies and influences the scope of the cooperation. Baldwin and Woodard (2009) describe the construction of a platform as a system consisting of a stable core component and a peripheral component. The peripheral component can also be viewed as an ecosystem around the platform. The association with the ecosystem that we know from nature is often transferred to corporate networks since corporate networks are also characterized by a large number of loosely connected participants who are dependent on each other for their effectiveness and survival (Iansiti & Levien, 2004b). Parallel effects can be observed for platforms (Gawer & Cusumano, 2014; Jacobides et al., 2018; Shipilov & Gawer, 2019; Cusumano et al., 2020).

From a technical perspective, the platform ecosystem includes a collection of complements, such as apps, to the core technical platform. These are additional products designed to increase the attractiveness of the platform. These components are mostly supplied by third-party providers (Ondrus et al., 2015). The plugging-in of third-party providers into existing platform ecosystems is based on technologies such as Application Programming Interfaces (APIs). These enable developers to use data and functions for applications without being hampered by the underlying system complexity of the platform (Feuer, 2019).

From an organizational point of view, the platform ecosystem describes the cooperation of companies that contribute to the platform with their products or services through a common interest in the prosperity of the platform (Selander, Henfridsson, & Svahn, 2013; de Reuver et al., 2018). In most cases, a platform ecosystem can be described as “open”. This is the case if participation in its development, marketing, or use is not restricted (Eisenmann, Parker, & Van Alstyne, 2009; Yoffie & Cusumano, 2015). Choosing an optimal degree of openness for a platform is decisive for a company's business model (Gawer & Cusumano, 2014). Ondrus et al. (2015) examine the influence of openness on the market potential of platforms. They define three investigation levels: the user level, the provider level as well as the technology level. This approach serves to separate actors and technologies from each other and to examine the openness of the individual groups separately. Cennamo (2019) follows this classification of different groups on platforms in his developed platform-based competitive analysis framework.

Openness at the user level is demonstrated by platform providers using strategies to attract new user groups to the platform. Financial service providers are increasingly using a multibanking strategy to open up their payment platform to additional user groups.

Multibanking means that the user can manage accounts from different financial service providers via one payment platform. Fast and secure transmission is used for communication with other banks. The banks provide a technical connection standardized by, for example, the German banking industry. This is the prerequisite for secure communication between the financial institutions. The access data of the payment platform is used for merging. In this way, turnover and account balances are exchanged, and accounts and securities accounts remain up to date (Deutsche Bank, 2018; Korsch, 2019). Moreover, peer-to-peer (P2P) payments are another way for financial service providers to open up their payment platform to additional users and attract new users to the payment platform. In the past, both demand- and supply-side factors have driven an increase in new developments for P2P payments. On the demand side, the key factors have been the emergence of new marketplaces through e-commerce and the demand from consumers to monitor and control online payments. On the supply side, the main factors were technological advances such as smartphones, faster Internet speeds and higher computing power (Bradford & Keeton, 2012). The majority of online P2P payments via payment platforms are made as follows: The sender of the money must either have an existing account or sign up for the P2P payment service on a payment platform. Depending on the P2P service, the money can be withdrawn from a bank account, a credit card, or a previous balance. The money is then transferred to the recipient's payment platform account, and an email is sent to the recipient. The recipient of the money must already have an existing account or sign up for the service on the payment platform (Kuttner & McAndrews, 2001; McHugh, 2002). At the user level, users particularly benefit from the openness of the platform as it reduces switching costs (West, 2003; Eisenmann et al., 2006; Boudreau, 2010).

The openness of platforms at the provider level means that the platform provider can expand the product and service portfolio on the platform through the complements of the complementor network. The design of openness of digital platforms comprises the organizational regulation of the rights of complementors as well as the design of openness of technologies such as APIs and software development kits (Ghazawneh & Henfridsson, 2013; de Reuver et al., 2018). Depending on whether the firms can be assigned to the same industry or not, partnerships in the form of collaborations or coopetition can emerge.

By collaborating with other providers, additional resources can be made available to the platform provider and costs for the platform can be shared. The benefits that arise from collaboration can contribute to increasing market potential (Ondrus et al., 2015). Accordingly, I propose:

Proposition 1: Multibanking and P2P payments strengthen the degree of openness of payment platforms and reinforce network size and strength of the end-user network of payment platforms.

Proposition 2: Opening a payment platform to additional external providers increases the amount of complements and reinforces network size and strength of the complementor network.

2.2.3 Data, Switching Costs, and Lock-in Effects

Data is considered the "new oil" or the "new gold," and its importance and potential impact on business models is constantly increasing as valuable information can be gained through data (Mohr & Hürtgen, 2018). Data are formed from characters of a character set according to defined syntax rules, that describe objects and object relations of the real world by their characteristics and thus represent them (Bodendorf, 2006; Mertens, Bodendorf, König, Schumann, Hess, & Buxmann, 2017). In an increasingly digitized corporate world, data represents an intangible asset that contributes to the value creation of companies (Zechmann & Möller, 2016; Möller, Otto, & Zechmann, 2017). While data has often been a by-product of business processes in the past, the role of data in companies is now evolving. Data is already an enabler for products, particularly as a result of growing digitization in companies and the development of data-based (add-on) services (Spiekermann, Wenzel, & Otto, 2018; Krotova, Rusche, & Spiekermann, 2019). Platform providers are able to collect information about users via platforms. Through platforms and associated technologies, platform providers can collect more user data than ever before (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Grover, Chiang, Liang, & Zhang, 2018). The combination of IT assets, such as data, and organizational resources can create innovative products and services that result in a competitive advantage for the platform provider (Nevo & Wade, 2010). Moreover, the resulting information asymmetry enables platform providers to collect further user data to retain users within their ecosystem (Sharpe, 1990; Ongena & Smith, 2001; Von Thadden, 2004). The more data about users a platform gains, the more "sticky" the platform becomes for the platform users. This leads to information asymmetries between market participants as not all market participants have access to the same information about users (Akerlof, 1978).

Switching costs play a central role in keeping users on the platform or in the platform ecosystem. The term "switching costs" refers to economic and psychological costs incurred by a buyer when switching from one supplier to another (von Weizsäcker, 1984; Klemperer, 1987b; Farrell & Shapiro, 1988). Therefore, switching costs can be seen as barriers that bind customers or users to products or services (Porter, Michael, & Gibbs, 2001; Jones, Mothersbaugh, & Beatty, 2002). According to Klemperer (1987), there are three types of switching costs: transaction costs, learning costs, and artificial costs or contract costs. Jones et al. (2002) also group switching costs into three types; however, they further distinguish between continuity costs, learning costs, and sunk costs. The concept of switching costs has long been used to retain customers. Even in the digital age, switching costs are still used on websites and Internet platforms. For example, customers register on platforms and invest time in familiarizing themselves with the website (Chen & Hitt, 2002). Customers who trust an online provider, are more likely to reveal personal information. Companies that collect personal data from their customers can build a close relationship with their customers and offer products and services that are customized to their preferences, which in turn strengthens trust and loyalty (Reichheld & Schefter, 2000). On platforms, the combination of network effects and switching costs results in a lock-in effect (Farrell & Klemperer, 2007). Once a firm's products are incompatible with other firms' products, switching costs and network effects can permanently lock users into an ecosystem. These lock-in effects prevent users from changing platforms, which in turn gives the platform a lucrative ex-post market power over users (Farrell & Shapiro, 1988; Farrell & Klemperer, 2007). Users who have invested in a product or service are tied to the associated range of services offered by the platform ecosystem (Shapiro & Varian, 1998). Although complementary products or services are offered by other platforms, users again choose their current platform (Shy, 2002). Thus, lock-in effects have a high strategic significance for platforms as they contribute to maintaining the installed base of the platform. The lock-in effect can be seen as a necessary prerequisite for achieving a critical mass (Zerdick et al., 2013). Hence, I propose:

Proposition 3: The more data the payment platform provider collects about payment platform users, the better payment platform providers and the complementor network can tailor financial products and services to their end-user network.

Proposition 4: The higher the switching costs and lock-in effects for payment platforms, the larger the network size and payment platform value for the installed base.

2.3 Method and Results

2.3.1 Cases from the German, US, and Chinese Payment Markets

To address my research question, I conducted a comparative and interpretative multiple case study within the field of payments. Based on three case studies, I examined the extent to which the assumptions of the four propositions apply to digital platforms in the payment market. In addition, I observed regional differences between the various payment platforms in the financial markets in Germany, the USA, and China. Using a multiple case study approach allows me to answer these "how" and "why" questions. My research results are the product of observations and investigations of platforms in the field of payments using a real-world case study approach, where I as the researcher have no control over the study object (Yin, 2014). In this analysis, I follow the embedded multiple case design since the initially formulated theoretical framework is applied through three case studies with different framework conditions, which increases the robustness of my research results (Eisenhardt, 1989; Yin, 2014).

2.3.2 Setting, Case Selection, and Data Collection

The global payment market has changed dramatically in recent years (Gomber et al., 2018; Gozman, Hedman, & Sylvest, 2018). Since the financial crisis in 2008, new competitors have entered the market. First, the so-called fintechs entered the payment market. In addition, technology companies, which we already know from other industries, have also entered the market in recent years. Technology companies such as Apple, Google, and Alibaba are continuously expanding their business models in various industries and are increasingly penetrating the payment market.

Through their market entry, these new competitors have also introduced innovative business models into the payment market. Fintechs and technology companies use digital platforms to sell their products and services. The concept of platforms, in particular multi-sided platforms, is not new to the payment market, which is often cited as an example of multi-sided platforms as payment systems have to attract both sides, consumers and merchants, to one platform in order to succeed (Evans, 2003; Rochet & Tirole, 2003; Chakravorti & Roson, 2006; Rysman, 2009; Ondrus et al., 2015; Kazan & Damsgaard, 2016; Kazan et al., 2018).

While it was the banks themselves that introduced online banking to their customers in the mid-1990s (Pikkarainen, Pikkarainen, Karjaluoto, & Pahnila, 2004), it was the fintechs that relied on technology-based business models and used digital platforms to improve, supplement, or replace existing offerings and thus make banking processes more user-friendly and transparent (Dhar & Stein, 2017; Ankenbrand, Dietrich, & Bieri, 2018). The large technology companies, in turn, have been at the forefront of building and growing platforms and platform ecosystems. In the meantime, banks also using digital platforms and are anxious to maintain their market position.

In the case study, I analyze the structure of payment platforms and payment platform characteristics. I selected three financial markets: the German, the US, and the Chinese. Within these three financial markets, my units of analysis are banks, fintechs, and technology companies. In a few cases, however, it is difficult to make a clear distinction between fintechs and technology companies as some companies, such as PayPal, can be classified into both categories. Moreover, while companies such as Alipay or WeChat Pay are referred to as fintechs in the Chinese market, in this study, they are assigned to the technology company category.

My objective is to increase the variance between the three different cases and the different players within the payment market. In total, I examine 56 banks, 179 fintechs, and 11 technology companies in the German, US, and Chinese financial markets. The first step was the allocation to different financial segments. As soon as the analyzed companies were active in the payments segment, the analysis was carried out to determine whether it was a digital platform. Therefore, the following criteria had to be fulfilled: two or more participants on the platform; the provision of an interactive ecosystem on the platform; and the exchange of goods, services, or social currency via the platform (Eisenmann et al., 2011; Hagiu & Wright, 2015a; Parker et al., 2016; Dhar & Stein, 2016). In total, I examined 92 digital platforms in payments, of which 34 were in Germany, 33 in the US, and 25 in China (see Table 8). The data collection was conducted in the time period from May 2018 through to the end of October 2019.

Financial market	Unit of analysis	Total	Payments	Digital platform
Germany	Bank	20	14	14
	Fintech	81	37	16
	Technology company	8	16	4
USA	Bank	20	16	16
	Fintech	75	35	12
	Technology company	10	5	5
China	Bank	16	16	16
	Fintech	23	14	2
	Technology company	7	7	7

Table 8: Cases and Units of Analysis Selected to Support Propositions

As the payment market is highly dynamic and evolving rapidly, it is challenging to attain reliable data and ensure its long-term validity. Several reports in journals and even newspapers shed light on the current changes and new competitors in the payment market. Previous studies have examined payment platforms; however, the influence of the structure of the platform and the platform characteristics on payment platform value as well as the differences between payment platforms among banks, fintechs, and technology companies in different countries are yet to be investigated.

Shortly after data collection began, it became clear that the respective platform providers were not interested in disclosing information about strategic features of the platform. This was due to reasons of confidentiality. Thus, I collected publicly available data from various online sources such as the companies' platforms, data policy guidelines, press releases, industry articles, and privacy policy guidelines. The advantage of secondary data is that a superordinate and value-free representation of the market conditions is ensured. According to Yin (2014), documents are highly relevant in case study research as they are consistently and permanently available, provide broad coverage of different events, and were not created in relation to the case study (Yin, 2014).

The propositions are derived from theory and provide a frame of reference for the case study. Moreover, the propositions narrow down the investigation and provide the data required for the case study investigation. I build up a database for analyzing and coding the collected data for all three cases. The structure of the database resulted from the findings of the literature analysis, where I examined previous studies to identify essential platform characteristics. In order to answer my research question and to analyze the three selected cases, I specifically collected the data required to support my propositions. Thus, I analyzed various online sources and examined the platforms, focusing particularly on evidence of their degree of openness, data collected about users as well as switching costs and lock-in effects. The data from the privacy policy guidelines were divided into four categories: personal data, transaction data, data on user behavior, and lifestyle data. In order to ensure the objectivity of the classification of the data into the four categories, an inter-rater reliability test was carried out. The execution of the case study follows the logical sequence described by Yin (2014).

2.3.3 Model

I analyze my data following the platform-based competitive analysis framework developed by Cennamo (2019), which analyzes the platform competition dynamics in digital markets. In this framework, Cennamo (2019) describes when competition in platform markets erupts into winner-takes-all battles, and when platform providers can prevent direct competition by differentiating themselves from other platforms based on platform distinctiveness. The two strategic dimensions in the model are *platform size* and *platform identity*. These two dimensions define whether the competitive dynamics in digital markets follow a *winner-takes-all* or a *platform distinctiveness logic*. In addition, there is a competitor analysis dimension that is aligned with key insights from platform competition and acts as a moderator of the relationship between platform value and platform competition. Depending on whether the digital market follows a *winner-takes-all* or *platform distinctiveness* logic, the relative impact of platform size or platform distinctiveness on platform value is influenced. This relationship and the intensity of platform competition are influenced by existing platforms operating in the same competitive field.

In markets where winner-takes-all competitive dynamics occur, platform providers gain market share primarily through network effects. This is especially the case in two-sided or multi-sided markets. The direct and indirect network effects are important here for reaching critical mass, which in turn is crucial for positive feedback between the end-user network and the complementor network as well as the number of complements. Thus, the positive feedback gets continuously reinforced and increases the value of the platform. In terms of the end-user network, Cennamo (2019) identifies the installed base, network size & strength, and lock-in & switching costs as platform characteristics that affect platform value. In addition to these, I identified further platform characteristics from my literature analysis that have an impact on payment platform value, one of which is the degree of openness of the platform for users while the other is the collected data about users and user behavior on payment platforms. For the complementor network, Cennamo (2019) identifies the amount of complements, network size & strength, and lock-in & switching costs as relevant platform characteristics that have an impact on the value of the platform. Again, based on the findings of my literature analysis, I added two characteristics: the degree of platform openness for providers as well as the collected data about users and user behavior on payment platforms. In digital markets that follow a winner-takes-all logic, the winner is the one who has built the largest network on and around its platform. Differentiation or better products or services play only a subordinate role here. This is different in digital markets that follow a distinctiveness logic. Some platforms deliberately follow the strategy of excluding some users on their platform whom they do not want to serve. Two central building blocks of a platform for differentiation are the platform architecture and the platform scope. Cennamo (2019) refers to recent studies that have investigated how platforms can differentiate themselves from others in digital markets. These studies show that platform differentiation can occur through market positioning (Cennamo & Santalo, 2013; Bresnahan, Orsini, & Yin, 2014), distinct content and complements (Cennamo & Santalo, 2013; Seamans & Zhu, 2014), or distinct and superior platform technological capabilities (Schilling, 2003; Zhu & Iansiti, 2012).

My research shows that payment platforms in the German, US, and Chinese financial markets predominantly follow a winner-takes-all logic, which is why I will focus on the competitive dynamics of the winner-takes-all logic in this paper whereas platform architecture and platform identity will only be discussed marginally (Figure 3).

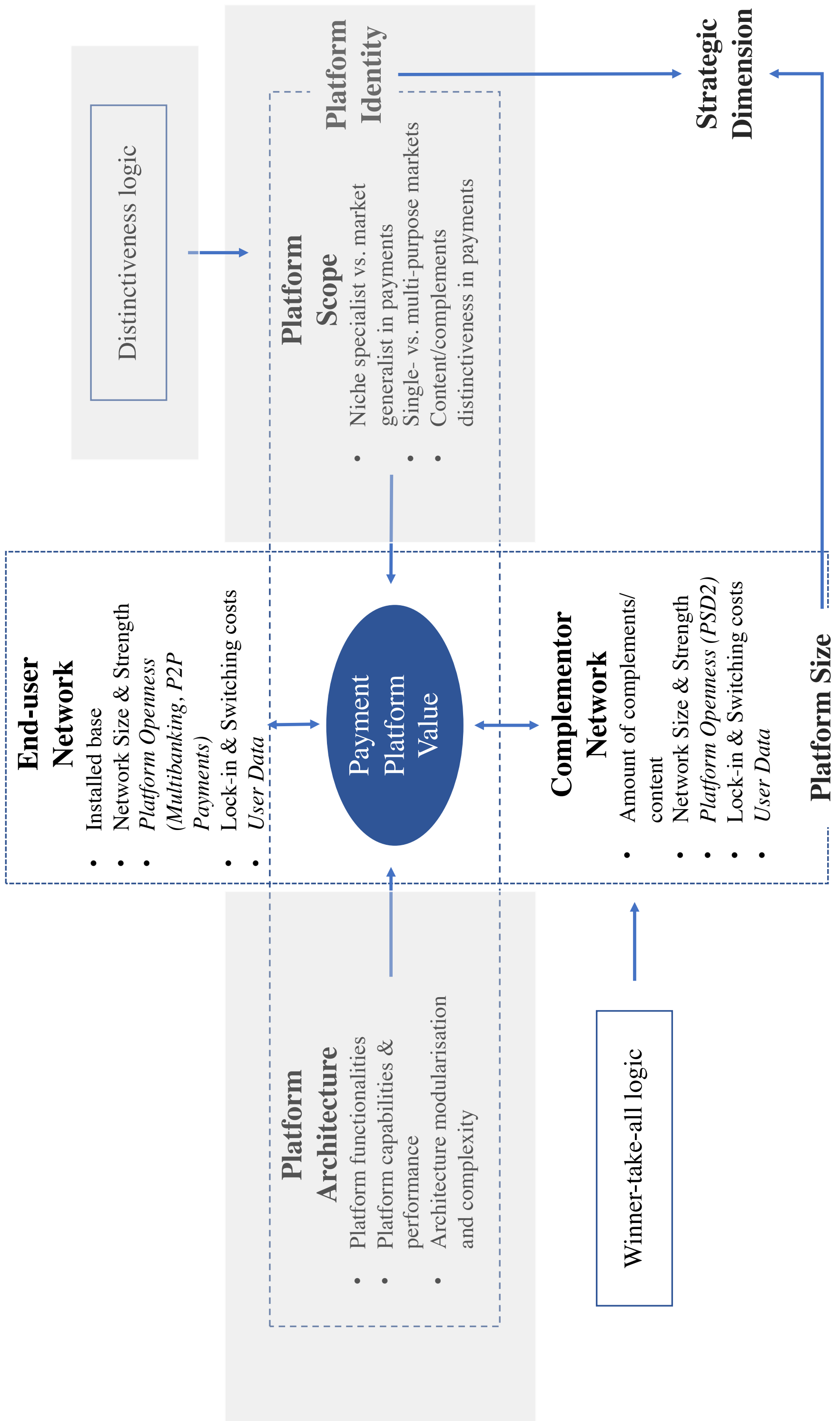


Figure 3: Platform-based Competitive Analysis Framework in Payment Market[5]

[5] Own representation based on Cennamo (2019).

2.3.4 Results

The results of my research on payment platform characteristics in the German, US, and Chinese financial markets are summarized at the end of this section. In the following, I discuss the individual propositions of my research.

P1: Multibanking and P2P payments strengthen the degree of openness of payment platforms and reinforce network size and strength of the end-user network of payment platforms.

To examine the effects of openness of mobile payment platforms at the user level on reinforcing the platform's network size and strength, I analyzed 92 payment platforms of banks, fintechs, and technology companies. The degree of openness of payment platforms varies between the different platform providers and the three financial markets examined. The degree of openness of the end-user network on payment platforms determines whether users have quick and easy access to the payment platform and thus influences the activity of the user side. An increasing number of users in the end-user network result in stronger direct network effects on the payment platform, which in turn reinforces the network size and strength of the payments platform. Financial service providers can promote the end-user side on the payment platform, especially through multibanking or P2P activities on the payment platform. With multibanking, the platform provider enables the end-user network to integrate additional financial products from other financial service providers, such as accounts from other banks.

Especially in the German financial market, banks offer multibanking on their payment platforms for their end-user network. Of the banks surveyed, seven banks offer multibanking in the German market however, the extent of integration varies between them. For example, Deutsche Bank's digital platform displays third-party checking accounts, custody accounts, foreign currency accounts, and PayPal. On the ING-DiBa digital platform, on the other hand, only current accounts and credit cards from other banks are provided (Watermann, 2018). The multibanking approach is also supported by the European Union and drives payment platform providers to open the degree of openness of the platform further for the user but also on the complementor side. The new

EU directive PSD2, which came into force in January 2018, is designed to improve innovation, competition, and efficiency (European Commission, 2017). This gives users the right to use a third-party service provider and obliges the account-holding payment service providers to provide third-party service providers with an interface through which credit transfers can be initiated, account information downloaded, or the coverage of card transactions queried (Bundesbank, 2019). This new directive allows users more choice in payment service providers, which results in reduced switching costs for users and contributes to the openness of the platform. Multibanking promotes direct network effects on payment banking platforms as users no longer need to leave the payment platform to access their other accounts. In addition, banks can attract new users by increasing the degree of openness of the platform and thus expand the end-user network. The increasing direct network effects strengthen the platform network. Comparable legal guidelines do not exist in the USA or China.

The majority of US banks and all banks in China instead offer P2P payments through third-party providers via their payment platforms, generating thereby direct network effects on their payment platforms. With P2P payments, users can transfer money directly to each other. So, if friends want to transfer money to each other, they all have to be on the platform. 13 US banks offer P2P payments via their payment platforms through Zelle, and in China, P2P payments are predominantly made via WeChat Pay or Alipay (Zelle, 2019). As a result, P2P payment options create direct network effects whereas the additional offers by third-party providers reinforce indirect network effects on these platforms. None of the German banks offer P2P payments via their payment platform.

Fintechs also offer P2P or multibanking solutions via their payment platforms and thus promote indirect network effects on their payment platforms. However, the access requirements for fintech platforms are simpler and faster than those for banks or technology companies. With most fintechs, the registration process is completely digital and completed in just a few steps. This makes it easy for new users to access the payment platform. The degree of openness of the payment platforms of fintechs stands out as open and thus promotes the acquisition of new users, which strengthens the end-user network of the payment platforms. In most cases, only a login to the platform is necessary. However, the majority of fintech payment platforms exhibit indirect network effects

rather than direct network effects. Those fintechs examined show hardly any differences in their structure between the three financial markets.
Payment platforms offered by technology companies are very contrasting in terms of their degree of openness to end users. Technology companies such as Apple, Google, Samsung, or Huawei do not open up their payment platform to end users who are not part of their platform ecosystem. For example, users who wish to use Apple Pay services can only do so if they have an iOS device available. The same applies to Samsung Pay or Huawei Pay, where users need to have certain smartphone models in order to use the payment services offered (Samsung, 2019; Huawei, 2019). These payment platforms are embedded in the already existing platform ecosystem and are designed to make it easy for existing users to use their new services. As a result, a migration of existing users to the payment platform takes place. For example, an iPhone user uses Apple Pay because he or she is already part of the platform ecosystem around the payment platform. On the other hand, payment platforms of other technology companies such as Alipay from Alibaba, WeChat Pay from Tencent, or PayPal, are very easily accessible for all user groups. Thus, the use of payment platforms from these technology companies is not dependent on a specific device or operating system. In addition, these platforms increasingly offer P2P payments and thus generate indirect network effects that strengthen the end-user network. The degree of openness of these payment platforms is significantly higher, and new users can join the end-user network. However, in order to use Alipay and WeChat Pay, you must have a bank account in China.
In terms of increasing network size and strength on a payment platform, the payment platforms of banks and technology companies have a competitive advantage over fintech's payment platforms. Both banks and technology companies already have an established network with an installed user base. This makes it easier for them to generate network effects and increase their chances of reaching a critical mass. In the case of fintechs, on the other hand, an installed user base is usually not yet established. Accordingly, it is more difficult for fintechs to generate network effects to achieve a critical mass and to establish an end-user network and complementor network on their payment platforms.

P2: Opening a payment platform to additional external providers increases the amount of complements and reinforces network size and strength of the complementor network.
In addition to the end-user network, the complementary network is also crucial for the size and strength of a payment platform. For a platform to reach critical mass, the user groups on both sides of the platform must grow simultaneously. The growth of providers on the platform can strengthen indirect network effects, which in turn have a positive impact on direct network effects. The more financial service providers are active on the platform, the more attractive a payment platform becomes for the end customer network. This is because the range of financial products and services for the end user network is continuously increased. Just a few years ago, it was hardly imaginable that financial service providers would start cooperating with each other. Today, however, more and more cooperation between competitors can be observed in financial markets. The degree of openness of a platform for providers, however, influences the growth of a payment platform. My results show that the degree of openness for external providers of the payment platforms studied differs across the three financial markets.

Most Chinese banks do not open their payment platform to other financial service providers. This is evident from the fact that most banks do not offer API interfaces or a development area for external providers to their payment platform. Exceptions include the banks ICBC, CCB, and Bank of China, and the credit card provider UnionPay, which open their payment platform to external providers. However, Chinese banks have various cooperation partners on their payment platforms. Most banks cooperate with UnionPay, WeChat Pay, and Alipay. A total of 24 cooperation partners were identified, including, for example, Huawei Pay, Apple Pay, or 99Bill.

In the US financial market, the majority of banks open their payment platforms to external providers. My results show that most banks offer an API interface and support external providers by offering developer areas for third-parties. In contrast to German banks, US banks also have many cooperation partners. All platforms investigated cooperate with Apple Pay, thus the majority cooperate with Google Pay and Zelle. In addition, some banks cooperate with lesser known payment providers such as Gamin Pay or Fitbit Pay.

In the German financial market, the PSD2 regulation results in a special handling of third-party providers on payment platforms, which affects all financial markets in Europe. The

German banks are affected by the EU Directive PSD2 and have to grant third-party providers access to their customers' accounts via APIs (European Commission, 2017; MoneyToday, 2019). Here, a directive specifies a certain degree of openness on the payment platform in order to give external providers access to payment platforms. This regulation is intended to strengthen competition between different financial service providers in the EU and to reduce information asymmetries between financial service providers. Despite this new regulation, only a few collaborations could be identified on the payment platforms of German banks, and they are predominantly with Apple Pay and Google Pay.

The fintechs in the three financial markets studied also show no significant differences in terms of managing the degree of openness of their payment platforms for the complementor network. There is no uniform management of the degree of openness for the complementor network among fintech payment platforms. My results show that some of the fintech platforms open their payment platform to external providers by providing API interfaces and developer areas for third-party providers. Further, it is notable that fintechs use other platforms to enter the payment market by using a piggybacking strategy to launch their platform. With this strategy, fintechs join already established financial service providers or payment platforms and profit from an already existing network when entering the market. In addition, there are fintechs in all three markets that enter into cooperation agreements with financial service providers or share their services with competitors, thus extending the reach of their platform as well as their payment platform network.

All of the technology companies studied open their payment platforms to external providers in order to expand their complementor network. The cooperation partners of the technology companies in the area of payment transactions in all three markets are primarily banks. However, my research shows that the complementor network varies greatly between the different technology companies. Apple Pay has about 3183 partner banks in the USA, whereas Google Pay cooperates with 19 US partner banks. Further, technology companies use their collaborations and partner network not only to strengthen and expand their complementor network, but also to enter a market in the first place. Technology companies often do not meet the necessary regulations to enter a financial market. Thus, they enter into cooperation with already established financial service providers in order to become active in the financial market.

In summary, my research results show that the majority of the financial service providers studied are opening their platform to external providers in order to expand their financial products and services on the payment platform and to strengthen and expand their complementor network (see Table 9). In addition, 92.8% of the payment platform providers that open their platform to third-party providers establish collaborations with other financial service providers.

P3: The more data the payment platform provider collects about payment platform users, the better payment platform providers and the complementor network can tailor financial products and services to their end-user network.

As in other industries, the importance of data in financial markets is increasing. It is therefore hardly surprising that all the financial service providers investigated in the German and US markets collect data from users via their payment platform. For Chinese payment platforms, no information about the collection or use of user data was available. Banks, fintechs as well as technology companies use cookies on their payment platforms to collect data from their end-user network. Cookies are text information that can be stored in the browser on the user's computer for each website visited. They enable the payment platform provider to collect data about the user during each platform visit. For example, Deutsche Bank uses cookies for performance analysis and collects session data, location data, and system data, and uses social plug-ins via Facebook or Twitter (Deutsche Bank, 2019). The analysis of my research shows that the financial service providers collect personal data, lifestyle data, data about user behavior, and data about the transactions via their payment platforms. However, my findings reveal that banks, fintechs, and technology companies take different approaches to collecting and using data via their payment platform.

My data analysis shows that the majority of data collected by banks via payment platforms is transaction data, through which the payment platform providers receive information such as the amount of the user's income and where, when, and to what extent the user makes purchases. In addition, the analysis shows that banks, in comparison to technology companies and fintechs, collect and possess a lot of personal data about the platform users. For example, banks have information about where their users live, how many children they have, legitimacy data about the users, or what profession they have. Furthermore, they collect even more sensitive information such as the living conditions of the platform users and their religion.

In contrast, the analysis of the data regulations of technology companies shows that they predominantly collect lifestyle data and data on user behavior across their entire platform ecosystem. For example, technology companies have information about users' upcoming events, their music tastes, the videos they have seen, and where they are at the moment. In addition to this data, they also possess personal data and transaction data about platform users. Fintechs, on the other hand, have not distinguished themselves by collecting data from a specific category.

Furthermore, my results show that financial service providers sell the data collected from their end-user network via their payment platform to their complementor network or to third parties. At the same time, payment platform providers purchase data about their end-user network from third parties. For example, the US bank JP Morgan Chase shares user data with third-party service providers and affiliated websites and businesses to improve services across the product families as well as with other companies to offer users co-branded services, products, or programs (JP Morgan Chase, 2016).

The same can be observed at technology companies; they also sell data from their end-user network to third parties. For example, Google may provide certain personal information about the user to the company or vendor from which the user has made a purchase. When users add a third-party payment method to their Google payments account, personal information may be shared with the third-party provider if it is necessary for providing the payment service. This includes name, profile picture, email address, IP address and billing address, phone number, information about the device being used, location, and activity on Google Account (Google, 2019).

However, no references to profiling could be identified on payment platforms of technology companies. In contrast, I found that the majority of German banks as well as some US banks use the collected user data for profiling purposes. Fintechs share user data with third parties too, but only 14 of the examined fintechs purchase data from third parties or through tele media. Moreover, profiling is also not very common on fintechs payment platforms.

Data about users and their behavior serves as an important resource for all financial service providers. Those investigated use their payment platform to generate user data. The data collected provides the financial service providers and their complementor network with information about the payment platform users' living situation, income levels, preferences, spending behavior, and much more. Financial service providers and their complementor network use this information to better tailor their financial products and services to customer needs. Through this information and the resulting knowledge about the end-user network, users can be bound to the platform in the long term and information asymmetries can be built up between the different financial service providers. The information asymmetries between financial service providers resulting from the different levels of information about users could affect competition opportunities in the payment market. This could lead to financial service providers who collect the most information about their users gaining a competitive advantage in the payment market, as they can better assess their users and offer them suitable financial products and services.

P4: The higher the switching costs and lock-in effects for payment platforms, the larger the network size and payment platform value for the installed base.

On payment platforms, lock-in effects result from the interaction of direct and indirect network effects and switching costs. In particular, due to the dynamics created by network effects on the payment platform, the network size of a platform's end-user network and the complementor network are related and mutually reinforce each other's influence on the payment platform value. However, the data collected about users can also strengthen lock-in effects on payment platforms since the data collected can be used to offer users customized financial products and services that competitors cannot offer due to their lack of knowledge about the user. No differences in the emergence of switching costs and lock-in effects on the payment platforms of the different financial service providers could be found between the German and the US financial market. The lock-in effects on Chinese payment platforms could not be further investigated as no information was available on the collection or use of user data.

My research results show that for banks, the lock-in effects result from direct and indirect network effects, user data, and switching costs. The switching costs that arise on the payment platforms of the banks studied for the end-user network and the complementor network are medium to high. This means that users and complementors of these payment platforms incur high costs if they want to switch payment platforms. Thus, the end-user network as well as the complementor network remain on the payment platform. With increasing network size, the benefits for the platform participants on the payment platform increase further, which leads to an increase in the payment platform value for the end-user network as well as for the complementor network. The increased platform value further reinforces the lock-in effects of the payment platform. These advantages scale up with the network size of the end-user network as well as the complementor network, further increasing the value of the installed base of the payment platform.

Fintechs also generate lock-in effects on the payment platform due to network effects, user data, and switching costs. However, 21 of the payment platforms of the fintechs studied only have low switching costs, which means that the dynamics of the lock-in effect on these payment platforms are low. Thus, the end-user network and the complementor network of the payment platforms of fintechs can switch payment platforms more easily. By making it easier for platform participants to leave the payment platform, it is more challenging to maintain the network effects and increase the value of the payment platform for the installed user base.

Technology companies also use lock-in effects on their payment platforms, which are composed of network effects, user data, and switching costs. My research results show that payment platforms of the technology companies have predominantly high switching costs, especially for the end-user network. Payment platforms like Apple Pay, Samsung Pay, and Huawei Pay have high switching costs because their service can only be used with their devices. If you use an iPhone, you are automatically bound to Apple Pay and locked into Apple's payment platform. In order for the iPhone user to use Google Pay, for example, the iPhone user would have to buy an Android smartphone, which represents very high switching costs for the user. Thus, technology companies that already have a large platform ecosystem and a large end-user network automatically have a large end-user network on their payment platform. This in turn is very attractive for external providers and strengthens the complementor network, which further increases the value of the payment platform’s installed user base.

The results of my research show that switching costs and lock-in effects are particularly prevalent on payment platforms of banks and technology companies. Banks as well as technology companies use lock-in effects to further strengthen the direct and indirect network effects on their payment platform, which in turn strengthens the network size and strength of the end-user network and the complementor network. Through the strengthened platform network, the value of the payment platform increases for all platform participants, which strengthens lock-in effects and switching costs, making it difficult for users and complementors to switch to a competing payment platform and further increasing the value of the payment platform's installed base.

	Germany			USA			China			Proposition matching
Unit of analysis	Bank	Fintech	Technology company	Bank	Fintech	Technology company	Bank	Fintech	Technology company	
Direct NE	0	2	1	13	8	1	0	0	2	P1
Indirect NE	13	10	4	16	8	4	16	2	5	P2
Personal data	14	27	5	16	11	5	–	–	–	P3
Transaction data	14	14	3	16	9	5	–	–	–	P3
Lifestyle data	0	0	3	0	0	4	–	–	–	P3
User behavior data	13	27	5	15	11	5	–	–	–	P3
Data transfer to third parties	14	21	4	12	10	5	–	–	–	P3
Data transfer from third parties	9	9	3	7	6	4	–	–	–	P3
High SC	5	4	2	1	0	4	2	0	4	P4
Medium SC	9	3	2	15	2	1	14	0	3	P4
Low SC	0	9	0	0	10	0	0	2	0	P4
Lock-in effect	14	10	4	16	12	5	16	–	7	P4
Open platform ecosystem	10	8	4	10	6	5	4	2	7	P1 & P2
Closed platform ecosystem	4	8	0	6	6	0	12	0	0	P1 & P2
Platform launch strategies	6	11	4	16	7	5	3	2	7	P1 & P2

Note: NE: network effects, SC: switching costs.

Table 9: Platform Characteristics to Support Propositions

2.4 Discussion and Conclusion

The four propositions were supported by using real-life payment platforms from 92 different providers in three different countries. The analysis of the propositions indicates the positive influence of the analyzed platform characteristics on payment platform value. Up until now, very little research has been undertaken on the interaction of network size & strength, platform openness, user data, switching costs, and the resulting lock-in effects on payment platforms. In this study, I illustrate the influence of the individual characteristics on payment platforms. The opening of a platform and the associated platform ecosystem at the end-user network can be used to increase the number of users of the end-user network. For payment platforms, this can be done by letting the platform provider, e.g., a bank, also allow users who have an account with another bank onto their payment platform. The openness of a payment platform at the complementor network can result in a growth in the number of additional complements in the form of financial products or services on the payment platform. This in turn can lead to an expansion of the payment platform product portfolio and thus to an increase in the attractiveness of the platform for users. As a result, the number of users increases, which in turn attracts more providers to the payment platform. The increased number of users on the payment platform consequently reinforces network effects.

The grown number of users in the end-user network means that the payment platform provider can collect more user data and thus further expand its databases and improve the data analytics on its payment platform. Through improved data analysis, the financial products of the payment platform provider as well as the financial products and services of the complementor network can be better tailored to the needs of payment platform users. Through data analytics and knowledge about the user and user behavior, not only can financial products be improved, but financial service providers can reduce costs and risks through knowledge about the users. In this way, the payment platform provider and the complementor network can create better risk profiles of users. Improved risk analysis enables financial service providers to further reduce their default risk. In addition to risk analysis, financial service providers can also address their users in a more targeted manner, provide them with better advice, and offer them the right financial products straight away. Further, it can be observed that financial service providers are offering more and more services based on self-learning systems. For example, many financial service providers offer chatbots, recommender systems, or robo-advisors via their payment platform. In the age of learning systems, data is becoming increasingly important because it is the basis for learning systems. In the future, the most innovative financial service providers will be those that manage to collect and evaluate the most relevant data from users, as this will enable them to continuously improve their financial products and services. By offering the most innovative financial products, these financial service providers will again attract new users, which will strengthen both the end-user network and the complementor network.

Payment platforms use switching costs to keep their end-user network as well as their complementor network on the payment platform and to make it difficult for them to switch to a competing payment platform. The combination of switching costs, direct and indirect network effects as well as the knowledge attained about the user through the collected data create lock-in effects on payment platforms. These lock-in effects are created on payment platforms to prevent users on both sides of the platform, the end-user network as well as the complementor network, from leaving the payment platform. Thus, lock-in effects support network dynamics on payment platforms by strengthening the network, and they secure the already installed base of the platform, which is important for the further growth of the platform size and thus for increasing in the value of the payment platform.

The studied characteristics show that payment platforms are in a market environment that follows the competitive logics of winner-takes-all markets, where competitive advantages are created by building scale fast, establishing the end-user network and the complementor network, and thus limiting market space for competitors that would operate under diseconomies of scale. In the payments platform market, similar to other platform markets in two-sided markets, this competitive dynamic results primarily from network effects, which increase the chances of achieving a critical mass on payment platforms. As soon as a payment platform has reached a critical mass, positive feedback for the end-user network and the complementor network on the payment platform occurs. The increasing attractiveness and size of the network is reinforced over time, further increasing the value of the payment platform and building a sustainable competitive advantage. The competitive dynamics in a winner-takes-all market such as the payment market mean that the payment platform with a large network is likely to gain market share and dominate the payments market.

Some limitations result from the selection of the three different cases to support my propositions. First, no generally valid statements can be made for financial markets worldwide based on the findings on the three financial markets in Germany, the USA, and China. The financial markets are regulated markets in which regulation exerts a decisive influence on market conditions. In the financial markets analyzed, the regulatory framework is different, which makes it difficult to compare the payment platforms of the different market participants. Particularly in the German market, which is subject to EU regulation, the PSD2 and GDPR regulations have a decisive influence on payment platform providers. This applies in particular to the validation of Proposition 1, Proposition 2, and Proposition 3. Further, the data I collected for the analysis of the propositions comes from secondary sources, so I cannot fully verify the reliability of the data. Finally, with Chinese payment platforms, data was often only accessible to a limited extent. Even though a native speaker helped to examine the Chinese payment platforms, there were some linguistic limitations.

My study offers both theoretical and practical implications. With the intention of providing a better understanding of payment platforms, this paper contributes to explaining the interdependencies between platform openness, network size & strength, user data, switching costs and lock-in effects on payment platform value. Moreover, I examined payment platforms of technology companies, which have only been analyzed to a lesser extent in previous studies. My findings provide valuable insights for creating competitive advantage for practitioners involved in building a payment platform.

In summary, I have applied various theoretical concepts from existing literature to payment platforms. Here, I focused particularly on the platform size dimension from the platform-based competitive analysis framework by Cennamo (2019). To enrich prior research, I applied the platform-based competitive analysis framework on 92 payment platforms and analyzed 82 data protection regulations with the aim of determining platform size on payment platform value. I added the variables platform openness and user data to the model. Further I analyzed the concepts on openness of platforms, network size & strength, switching costs, the value of data for payment platforms, and the emergence of lock-in effects on payment platforms. To answer my research question, I performed a multiple and comparative case study within the German, US, and Chinese financial markets. I examined payment platforms of banks, fintechs, and technology companies in all three markets. In order to achieve theoretical generalizability, the findings from the literature analysis were applied to the cases as an analytical tool for identifying similarities and coherences on payment platforms. The key findings of my study show that regulation of the respective countries can have an influence on the degree of openness of payment platforms. This can be seen in the German financial market through the PSD2 regulation. In addition, the results show that not all market participants have the same prerequisites when they launch a payment platform in the market since banks and technology companies already have an existing user groups in their platform ecosystem that can migrate easily to the payment platform. I also found that banks, in contrast to technology companies, mostly collect personal data and transaction data while technology companies mainly possess lifestyle data and data on user behavior. User data is considered a valuable strategic resource that, in combination with network effects and switching costs, results in a lock-in effect for the end-user network and complementor network on payment platforms.

The ongoing new developments in the payment market lead to many new unanswered questions regarding payment platforms and changing user behavior. It would be particularly interesting if future studies investigate how the strategic dimension platform identity, platform architecture, and platform score, from the platform-based competitive analysis framework by Cennamo (2019), affect the payment market and influence the competitive dynamics. Furthermore, future studies could address the limitations of my work as payments in all three markets are very dynamic and constantly changing. In addition, researchers could empirically validate and expand my propositions by analyzing other payment platforms in different financial markets.

3. Paper 2

Keep Your Friends Close, But Your Enemies Closer: Coopetition in the Platform Economy— A Social Network Analysis

3.1 Introduction

In today's industries and markets, platforms are ubiquitous, and a majority of all high-technology products and services are integrated into platform ecosystems (Gawer & Henderson, 2007; Gawer, 2011; Parker et al., 2016; Cusumano et al., 2020). Platforms are no longer only found in the consumer, retail, or entertainment sectors, but are now increasingly penetrating regulated markets and playing a key role in expanding and fostering innovation (Gawer, 2011). This phenomenon can also be observed in financial markets. Since the financial crisis of 2008, an increasing number of young start-up companies, so-called fintechs, that combine financial services with cutting-edge technologies have entered the financial market (Gomber et al., 2018). The term fintech combines "financial services" and "technology" (Alt & Puschmann, 2016). Many of the fintechs use a platform-based business model and offer financial products and services to their customers via their platform. The best known and pioneer of all fintechs is PayPal. As if that's not enough, in recent years, the dreaded tech giants like Apple, Google and Samsung have also been pushing their way into the financial market. Aren't the tech giants, now considered the most valuable companies in the world, the platform gods par excellence?

Today, the established banks and insurance companies that have dominated the financial market for the past centuries are facing and competing with young fintechs and the big technology companies. Here, another phenomenon emerges: the rivals on financial markets not only work against each other, but also join forces and cooperate with each other in some areas. This phenomenon is called "coopetition" and is made up of the terms "cooperation" and "competition" (Bengtsson & Kock, 2000; Dagnino & Padula, 2002; Bengtsson & Kock, 2014; Bouncken et al., 2015; Gnyawali & Ryan Charleton, 2018).

The constantly increasing dynamics as well as the growing uncertainty and volatility in markets is changing the way companies act in terms of business cooperation (Powell et al., 1996; Bengtsson et al., 2010). Cooperations between companies can not only serve as an important source of sustainable competitive advantages through their use of emerging synergy effects, but they can also ensure the survival of companies under strongly changing conditions. Current developments show that traditional industries are evolving towards complex ecosystems and that classical cooperation is no longer sufficient. Instead, business relationships are being further developed. Competing companies are increasingly recognizing the need to share their resources and skills (Bengtsson & Raza-Ullah, 2016) in order to generate value from cooperation with competitors and to create a "win-win-situation" (Brandenburger & Nalebuff, 1996; Das & Teng, 2000; Dagnino & Padula, 2002; Walley, 2007; Bouncken et al., 2015; Gnyawali & Ryan Charleton, 2018; Czakon, Gnyawali, Le Roy, & Srivastava, 2020; Bengtsson, Raza-Ullah, & Srivastava, 2020). The financial market is changing rapidly due to new trends. The most significant of these trends are innovations in information and communication technologies, which are changing the regulated sector significantly (Alt & Puschmann, 2016; Smolinski, Gerdes, Siejka, & Bodek, 2017; Schuster & Hastenteufel, 2019). The development of digital innovation requires new complementary knowledge of the players on the financial market (Klus, Lohwasser, Holotiuk, & Moormann, 2019; Hornuf, Klus, Lohwasser, & Schwienbacher, 2020). As a result, traditional industry players recognize the need to cooperate with existing and new players in order to jointly use their skills and resources (Drasch, Schweizer, & Urbach, 2018; Klus et al., 2019). As mentioned above, financial markets present regulated contexts. In regulated sectors such as finance or healthcare, regulations strongly affect how organizations act and compete. The relevance of regulatory requirements was found to persist in the digital age. Hence, regulations have to be considered in research accordingly (e.g., Steinhauser, Doblinger, & Hüsig, forthcoming; Peng & Heath, 1996; Scott, 2014; Hinings, Gegenhuber, & Greenwood, 2018; Steinhauser, 2020). In the financial sector, a banking license presents a crucial regulatory requirement that may influence coopetition activities.

Hoffmann et al. (2018) point out that network analysis is the most promising method for studying coopetition networks because in order to advance research in this context, researchers have to look beyond immediate dyadic relations. The ubiquity of networks among individuals, companies, and industries has attracted a rising number of studies that draw on network concepts and methods (Borgatti, Mehra, Brass, & Labianca, 2009; Kim, Howard, Cox Pahnke, & Boeker, 2016). Research on social networks showed that actions and outcomes of organizations are determined by the sets of interactions and relationships (Granovetter, 1985) the organizations are embedded in (Ahuja, Polidoro Jr., & Mitchell, 2009; Stern, Dukerich, & Zajac, 2014). Extant research has investigated properties of networks, the kinds of ties that actors are likely to form, and which actors may become more central (Kim et al., 2016). However, in order to determine how different network structures, offer distinctive constrains or benefits to organizations embedded in them, a better understanding of why and how organizational networks emerge is of crucial importance (Salancik, 1995; Stuart & Sorenson, 2007; Ahuja, Soda, & Zaheer, 2012). Networks may emerge in response to opportunities made available by partners or when organizations seek partners with specific characteristics (e.g., homophily). These factors can also cause changes to the structure of networks. In addition, relationships among organizations can also be influenced by the presence or absence of other ties in the network (e.g., Park & Luo, 2001; Contractor, Wasserman, & Faust, 2006; Kim et al., 2016). Traditional network analysis focused on regression methodologies that are based on the assumption that the formation of ties between two actors is independent of the other actors and ties in the network. Thus, research has rarely investigated how complex combinations of processes shape the structural characteristics of a network simultaneously (Kim et al., 2016). This shortcoming may be problematic when new tie formation presents an interdependent process that is influenced by the characteristics of the actors as well as by their existing ties (e.g., Contractor et al., 2006; Ahuja et al., 2012). In order to address this gap in research, we employ a relativity new analytical approach in our study that allows the examination of multiple interdependent processes in network formation: exponential random graph models (ERGMs), a class of social network methodologies that examines the formation of ties at the network level (Robins, Pattison, Kalish, & Lusher, 2007; Lusher, Koskinen, & Robins, 2013). ERGM analysis accounts for emergent network structures, potential cross-dependencies, and other effects that cannot be addressed by conventional approaches on the dyadic level (Kim et al., 2016).

To date, only a relatively small number of studies have employed ERGMs (e.g., Lomi, Lusher, Pattison, & Robins, 2014; Kim et al., 2016; Brennecke & Rank, 2017), but not to study coopetition networks.

Our research questions are: *How do platforms influence coopetition in financial markets and which factors influence network development in financial markets?* By addressing these questions, we can contribute to a better understanding of the role of coopetition in the platform economy as well as identify influencing factors for network development.

In order to answer our research questions, we built on data collected in the German financial market. Our network, which we analyze by employing an ERGM, comprises of 371 companies that are active in the German financial market. We investigate three different groups of influencing factors for coopetition: external drivers (i.e., platforms, AI, Blockchain technology, and banking license), relation-specific drivers (i.e., type of company and position in the network), the form of the coopetition, and endogenous network effects. Although previous research has recognized the importance of various drivers of coopetition, most studies have not considered networks that drive coopetition and networks that are created through coopetition.

The structure of our paper proceeds as follows. In the next section, we discuss the theoretical foundations of platforms, networks, and coopetition. Furthermore, we discuss different drivers of coopetition in interorganizational networks and present our hypotheses. Next, we describe our methodological approach. In the penultimate chapter, we present our descriptive results, the results of our ERGM, and the Goodness of fit of our analysis. Finally, we discuss the results of our social network analysis, point out limitations of our work, and propose future research suggestions.

3.2 Theoretical Background and Hypotheses

3.2.1 Platforms and Networks

Digital platforms are omnipresent in all industries today. Platforms connecting different groups of users, such as buyers and sellers, are referred to as multisided platforms (Boudreau & Hagiu, 2009). Multisided platforms create an interactive ecosystem for multiple user groups by providing an infrastructure and setting regulations for the interaction on the platform (Hagiu & Wright, 2015a; Parker et al., 2016). An important feature for all platform types is the presence of direct and indirect network effects or network externalities. Network externalities imply that the value of the platform or technology increases as its installed base of users increases (Katz & Shapiro, 1985; Shapiro & Varian, 1998).

In recent years, much research has been conducted on multi-sided platforms in the field of information systems to better understand the dynamics around multi-sided platforms. Already in the 1980s, Katz and Shapiro (1985) researched network externalities that would later be a key success driver for digital platforms. Since the 2000s, there has been much research activity in the area of two-sided markets that reflect the basic idea of platforms (Evans, 2003; Rochet & Tirole, 2003; Eisenmann et al., 2006). Ever since, there has been a significant increase in research on multi-sided platforms (de Reuver et al., 2018) covering platform competition (Rochet & Tirole, 2003; Parker & Van Alstyne, 2005; Eisenmann et al., 2006; Armstrong, 2006; Van Alstyne et al., 2016), platform leadership and innovation (Gawer & Cusumano, 2002, 2008; Cusumano et al., 2020), platform governance (Darking et al., 2008; Tilson et al., 2010; Parker et al., 2020), platform openness (Ghazawneh & Henfridsson, 2013; Benlian et al., 2015; Ondrus et al., 2015), platform envelopment (Eisenmann et al., 2011), and platform ecosystems (Iansiti & Levien, 2004b, 2004a; Tiwana, 2013; Gawer & Cusumano, 2014; Jacobides et al., 2018; Shipilov & Gawer, 2019).

Recently there has been an increase in research on platform ecosystems and their impact on the competitive environment. However, little attention has been paid to the exact delimitation between ecosystems and networks. What ecosystems and networks have in common is that they regard organizations as open systems whose actors are strongly influenced by their environment (Scott, 1992; Pfeffer & Salancik, 2003; Shipilov & Gawer, 2019). Moreover, both ecosystems and networks help build up connections between multiple organizations. Thus, these organizations can extend and improve their own products and services by interacting with other organizations with complementary resources, technologies, or knowledge and make their products or services more valuable to the user. Further, ecosystems and networks have in common that they differ from

markets, as the latter only use price mechanisms to coordinate activities between organizations (Shipilov & Gawer, 2019).
However, according to Powell, Staw, and Cummings (1990), ecosystems differ from networks in that networks are meshes of standardized formal or informal alliances between the network participants. In ecosystems, the mechanisms for coordination are more flexible and open, and there are no coordination mechanisms for hierarchically organized control (Hagiu & Wright, 2015b; Shipilov & Gawer, 2019). Furthermore, ecosystem research considers relationships between participants from various industries and fields of activity while network research focuses on relationships in a specific industry. Moreover, in ecosystems multilateral interdependencies, modularity, and governance rules are important for a functioning interaction of cooperation or competition between different ecosystem members. These factors shape the emergence, development, and performance of ecosystems. In contrast, networks are built on bilateral dependencies, identified trust, social norms, and information transfer and are use them to manage the bilateral interdependencies between network participants (Shipilov & Gawer, 2019).

3.2.2 Coopetition

When investigating networks, we focus on a special form of cooperation, namely coopetition, cooperation activities between competitors. All definitions in the literature have in common that in coopetition, two conflicting logics of interaction between the parties exist simultaneously, namely cooperation and competition. This means that the focus is on the simultaneous pursuit of the two strategies (Nalebuff & Brandenburger, 1997; Bengtsson & Kock, 2000; Tsai, 2002; Luo, 2007; Chin, Chan, & Lam, 2008; Bengtsson & Kock, 2014; Bengtsson & Raza-Ullah, 2016; Gnyawali & Ryan Charleton, 2018; Lascaux, 2020). On the one hand, there are self-interests through competition while on the other hand, the relationship is characterized by common interests that are pursued through cooperation (Bouncken et al., 2015). According to Brandenburger and Nalebuff (1996), organizations try to achieve the common goal of the biggest cake through coopetition, after which the struggle for the biggest piece of the cake begins. This not only creates tension between value generation and value recording, but also an emotional ambivalence (Raza-Ullah, Bengtsson, & Kock, 2014). Therefore, the necessity arises to distinguish cooperation from coopetition, e.g., on the basis of actors or activities (Dowling et al., 1996; Bengtsson & Kock, 2000).

With the help of game theory, Brandenburger and Nalebuff (1996) developed a theoretical approach to coopetition that considers business life as a game in order to present possible strategies and decisions. It can be explained in terms of how companies generate value through coopetition and create a win-win situation by not only competing but also cooperating with each other (Brandenburger & Nalebuff, 1996; Nalebuff & Brandenburger, 1997; Bengtsson & Kock, 2014; Dorn et al., 2016). Shortly thereafter, Dowling et al. (1996) developed another theoretical approach to explaining coopetition, based on Pfeffer and Salancik (1978) resource dependency approach and on Williamson (1975) transaction cost theory. In addition to these theories, network theory also provides a basic concept in which the participating companies obtain information about other actors and their partners through coopetition, as well as access to resources and knowledge (Gnyawali & Park, 2009; Bengtsson & Kock, 2014; Bengtsson, Kock, Lundgren-Henriksson, & Näsholm, 2016). Our work is primarily based on the theoretical approaches of network theory.

Different factors that drive coopetition in various industries can be identified. Dowling et al. (1996) differentiate between internal environmental factors such as the importance of resources and external environmental factors such as industrial concentration or networking. Padula and Dagnino (2007) also see the change in environmental factors and the knowledge structure of companies as important influencing factors for coopetition. These include, for example, internally available resources and capabilities to generate competitive advantages (Bengtsson & Kock, 2000), the length of product life cycles, R&D costs, regulatory bodies or laws, technological capabilities, or resource complementarity (Dorn et al., 2016). In addition to internal and external influencing factors for coopetition, Bengtsson and Raza-Ullah (2016) further identify relation-specific factors that can also be identified as important drivers of coopetition.

3.2.3 Drivers of Coopetition in Interorganizational Networks

Bengtsson and Raza-Ullah (2016) conducted a systematic review of research on coopetition and discovered in their analysis that there are different drivers that push firms to cooperate and compete at the same time. These individual drivers were summarized and classified into three categories, namely, external, relation-specific, and internal drivers. Since we are looking at organizations from an outside-in perspective and concentrate on interorganizational networks in our analysis, we focus on external and relation-specific drivers. In addition, we investigate the form of coopetition chosen by the different organizations and categorize the form of cooperation into strategic alliances, shareholdings, or supplier relationships.

External drivers

External environmental factors such as industrial concentration, market regulation, or new technological requirements are external drivers of coopetition (Dowling et al., 1996; Bengtsson & Raza-Ullah, 2016). In addition, changes in growth level or uncertainty and instability in an industry drive organization to pursue coopetition (Luo, 2004; Padula & Dagnino, 2007; Ritala, 2012). Companies especially enter into coopetition when industries are undergoing major changes and original competitive advantages of companies are lost, barriers to market entry are reduced, or technological complexity increases (Dai, 2010; Bengtsson & Raza-Ullah, 2016).

It is precisely these phenomena that can currently be observed on the financial market. Old-established banks and financial service providers are coming under increasing pressure from new competitors and new technological requirements in the financial market. The increase in new technological demands on financial products and financial services is further fueled by new competitors entering the financial market, such as fintechs and technology companies (Gozman, Liebenau, & Mangan, 2018; Gomber et al., 2018). These new competitors penetrate the financial market and combine banking products and services with different new technologies. The technologies currently affecting and changing the financial market the most are digital platforms, artificial intelligence (AI), or blockchain applications (Global Investor, 2019).

Bengtsson and Raza-Ullah (2016) identify technological convergence as an external driver for cooperation among competitors. Technological convergence results from increasing specialization and development of complex systems and a combination of technologies from different industries (Sahaym, Steensma, & Schilling, 2007; Bengtsson & Johansson, 2014). This can be observed in digital platforms, which are created when organizations cooperate with each other and integrate their different technological and strategic capabilities (Broring, 2010). Moreover, intensive technological change and technical complexity can be further identified as external drivers of coopetition (Afuah, 2000, 2004; Dai, 2010). When organizations are faced with technological requirements that are too complex, they look for a firm to support them in meeting the technological challenges (Bengtsson & Raza-Ullah, 2016). In financial markets, it can be observed that many banks are approaching new technological challenges by cooperating with fintechs. After all, it was fintechs in particular that used new technologies such as AI or blockchain in their financial products and services. Frequently, product-related cooperations can be found where established financial service providers use fintech technologies to expand their service portfolio or to gain access to new distribution channels (Hornuf et al., 2020). In addition to technological challenges, Gnyawali and Park (2009) identify increasingly shorter product life cycles and high R&D costs as external drivers of coopetition for technological innovation. Product life cycles are becoming shorter due to rapidly changing customer needs and the magnitude and speed of technological changes (Chen & Li, 1999). In addition, high R&D costs are a strong incentive to cooperate with competitors with a large resource base (Gnyawali & Park, 2009).

Regulatory requirements can also be external drivers of coopetition (Bengtsson & Raza-Ullah, 2016). Particularly in regulated markets, cooperation between competitors can be promoted by regulatory requirements or government subsidy policies (Wang, Ji, & Ming, 2010; Mascia, Di Vincenzo, & Cicchetti, 2012). This is the case in financial markets. As they need to meet the regulatory requirements of the financial market, obtaining a banking license is argued to be one of the main motives behind fintechs and technology companies entering into cooperation with established financial service providers. The acquisition of a banking license is usually too complicated and too expensive for a fintech start-up when entering the market. Without a banking license, many fintechs and technology companies could not offer their products and services on the financial market (Klus et al., 2019; Hornuf et al., 2020). Hence, we propose:

Hypothesis 1a: Companies are more likely to form coopetition ties if they employ a platform technology.
Hypothesis 1b: Companies are more likely to form coopetition ties if they employ new technologies such as AI or Blockchain.
Hypothesis 1c: Companies are more likely to form coopetition ties if they possess a banking license.

Relation-specific drivers

Besides external influencing factors, Bengtsson and Raza-Ullah (2016) identified relation-specific drivers. Relation-specific drivers focus on the categorization and examination of partner- and relational characteristics (Bengtsson & Raza-Ullah, 2016). In the case of partner characteristics, resources and capabilities are important influencing factors for a cooperation among competitors. Thus, companies are more likely to enter into a cooperation with a competitor if the latter can demonstrate strategically important resources or know-how (Luo, 2007; Gnyawali & Ryan Charleton, 2018). In addition, a large gap between the capabilities of the respective companies, such as industry-specific knowledge, technological knowledge, or organizational systems, can lead to cooperative relationships (Padula & Dagnino, 2007). Established players in the financial market can be important cooperation partners for fintechs and technology companies. In addition to capital, which is particularly relevant for fintechs, established financial service providers can provide fintechs and technology companies with important strategic resources such as access to a broader customer base or superior financial regulatory expertise. These can help fintechs and technology companies to operate or to improve their own digital services (Hornuf et al., 2020).

Relationship characteristics are equally important , because companies are embedded in networks of relationships that are formed by numerous structural interrelationships between and among partners on the intra-organizational level as well as on the inter-organizational level (Peng & Bourne, 2009; Bengtsson & Raza-Ullah, 2016). In order to analyze networks from a business perspective, the network structure is crucial. The network structure literature focuses on the relative positions of companies within the networks as well as the networks structure itself, including measures such as density, cohesion, clustering, and loose-coupling (Conway & Steward, 1998; Ritala & Huizingh, 2014; Tsujimoto, Matsumoto, & Sakakibara, 2014; Bengtsson & Raza-Ullah, 2016). Gnyawali and Madhavan (2001) argue that the competitive dynamics in a network are mainly influenced and determined by the network centrality, structural autonomy, structural equivalence, and network density. Furthermore, the centrality of a company and its structural autonomy have been shown to be positively related to its volume of competitive activity (Gnyawali, He, & Madhavan, 2006). Companies that occupy different positions in a network may possess different characteristics, capabilities, partners, and resources. Hence, coopetition ties between companies with different positions may grant them access to complementary resources. Accordingly, we propose:

Hypothesis 2a: Companies are more likely to form coopetition ties with competitors that belong to a different type of company.
Hypothesis 2b: Companies are more likely to form coopetition ties with companies that occupy a different position in the network.

Form of coopetition

The form of coopetition can be distinguished with regard to a vertical (different value-added stages, e.g., buyer & seller) and horizontal (between companies of the same value-added stage) direction of cooperation in the value chain. Within a vertical relationship, companies can be in direct or indirect competition with each other. In a horizontal relationship, on the other hand, competing companies are in a relationship with each other, for example, through a strategic alliance, a joint venture, or a supplier relationship (Dowling et al., 1996; Bengtsson & Kock, 2000, 2014; Dorn et al., 2016; Hoffmann et al., 2018). The form of coopetition is often distinguished according to the characteristics of the two fields of competition and cooperation (Walley, 2007).

The final form of cooperation can take different forms of coopetitive interactions (Bengtsson et al., 2010). A strategic alliance is a common form of cooperation to support innovative activities (Teece, 1992). The strategic alliance is a formal agreement between companies aiming to optimize the achievement of individual and common goals through the exchange of resources while maintaining competition (Mowery, Oxley, & Silverman, 1996; Das & Teng, 2000). Resources can be for example, knowledge, human resources, capital, licenses, or organizational capacities (Doz, Hamel, & Prahalad, 1989; Gnyawali & Park, 2009). Another form of collaboration is a cooperation with capital commitment, such as the joint venture or a shareholding. This form of cooperation is geared to a long-term time horizon and enables participating companies to spread risk (Anderson, 1990; Hill & Hellriegel, 1994; Park & Russo, 1996). However, companies very rarely cooperate in a holistic way, but rather limit themselves to individual sub-areas of their business and enter into supply cooperation (Biervert, 2013).

Drasch et al. (2018) identified the described forms of coopetition in coopetition activities between financial service providers. First, financial service providers can act as service providers, enabling competitor's products and services by providing resources such as a banking license, IT infrastructure, security reputation, or access to customers. Second, it can be observed that financial service providers act as investors and acquire shares of fintechs. Third, financial service providers can act as service consumers who use a competitors' innovation to improve their own products or processes. Here financial service providers enter into a supplier relationship with another financial service provider and purchase a specific product or service. These products and services can be, for example, finance-specific IT products or services such as white label platforms or the management of API interfaces. Drasch et al. (2018) further identify that most of the cooperations between financial service providers are strategic alliances (78%). Acquisitions (5%) and joint ventures (1%) only play a minor role. They argue that when it comes to novel technological solutions, most financial service providers act as service consumers and enter into a supplier relationship. Accordingly, we propose:

Hypothesis 3a: Companies are more likely to form coopetition ties if the coopetition takes the form of a strategic alliance.
Hypothesis 3b: Companies are more likely to form coopetition ties if at least one of the companies that form the tie holds a share in the other company.
Hypothesis 3c: Companies are more likely to form coopetition ties if the coopetition takes the form of a supplier relationship.

3.3 Methods

3.3.1 Data

We build a unique database for our study from various secondary data sources. Our data sources include digital platforms, annual reports, and press releases related to the companies studied. It comprises platform characteristics, partnership and cooperation characteristics as well as information about the companies' products and services. In addition, we have expanded the database to include the regulatory requirements of BaFin for the German financial market. Our data collection took place from January 2020 to March 2020.

3.3.2 Measures

For our empirical analysis, we estimate a model for the probability of coopetition ties among companies as a function of (1) dyadic attributes, (2) company-specific attributes, and (3) endogenous network effects.

Dependent variable

In our analysis, the presence of coopetition ties among companies is the dependent variable. Hence, we employ an undirected network. The resulting coopetition network can be represented as a 371 x 371 binary adjacency matrix that records the presence (1) or absence (0) of coopetition ties for each possible pair of companies in the sample.

Dyadic attributes

In this study, we employ three dyadic attributes in order to control for the form of cooperation that the coopetition ties entail. *Strategic alliance* is operationalized as a binary matrix valued as 1 for a tie in form of a strategic alliance and 0 otherwise. Analogue, *Share* is presented in a matrix that takes the value 1 if at least one of the companies that form a tie holds a share in the other company. Finally, *Supplier* is operationalized as a binary matrix with the value 1 if one of the companies that have a tie supplies any form of service or product to the other (e.g., management of API interfaces or white label banking) and 0 otherwise.

Company-specific attributes

Company-specific attributes are included in order to capture the effect of these attributes on companies' propensity to form coopetition ties.

Type of company. We argue that companies may be more likely to form ties with a different type of company that can provide them with resources that they lack. Thus, we include a variable that measures whether a company forms ties with a different type of company (types: bank, fintech, technology company, insurance): *Type of company (mismatch)*.

Technology attributes. We include actor-level variables for the presence of the following digital technologies in a company to control for their effect on the formation of coopetition ties: *Platform*, artificial intelligence (*AI*), and *Blockchain* technology. For each technology, we include a binary variable distinguishing between companies that employ the technology (1) and companies that do not employ the technology (0).

Regulatory attribute. Furthermore, we include a variable that controls for the existence of a *Banking license* in a company. The binary variable takes the value 1 if a company has a banking license and the value 0 if the company does not have one.

Network-based attributes. Furthermore, we control for network-based attributes of the individual company. We argue that differences in the position of a company in a network may affect the formation of coopetition ties. Thus, we control for differences between the companies in terms of (i) *Degree centrality (difference)* and (ii) *Betweenness centrality (difference)*.[6]

Company-specific control variables. Finally, we include actor-level control variables to control for their influence on the formation of coopetition ties. Differences in size and age of a company may influence their formation of coopetition ties. Size is measured by the *Number of employees (difference)* while the *Company age (difference)* is measured in years. Finally, we control for differences in the geographic location of a company by

[6] We calculated the degree and betweenness centrality by applying the UCINET software (Borgatti et al., 2002).

including a variable that measures whether the headquarters of a company are located in Germany or not: *Nationality (mismatch)*.

Endogenous network effects

In addition, we included endogenous network effects in our model in order to account for the tendency of social networks to self-organize into a variety of meaningful structural patterns (Pattison & Robins, 2002; Robins, Pattison, & Woolcock, 2005). By doing so, we take into account the effects that embody theoretical claims on the processes that drive the emergence of network patterns (Lomi et al., 2014; Brennecke & Rank, 2017). These effects should not be omitted since otherwise invalid findings on the effects that are of theoretical interest may result because the findings may actually be attributed to structural mechanisms driving the emergence of ties (Robins et al., 2007; Snijders, 2011). By including these variables, we are able to capture network dependencies in our data and to make inferences about the effects of actor-level variables (Lomi et al., 2014). In this study, we consider the following endogenous network effects.

The simplest form of dependence that exists at the dyadic level is the overall tendency of companies to create ties (*Edge*). However, dyadic dependencies alone are unlikely to sufficiently capture the endogenous effects of a social network (Snijders, 2011; Lomi et al., 2014). Thus, we also take into account starlike configurations, where a single company is at the center of several ties (*Spread*). These configurations reflect the finding that ties in social networks are rarely distributed evenly (Robins, Pattison, & Wang, 2009). Since the number of starlike configurations is a function of degrees, this effect controls for the degree distribution of the coopetition network (Snijders, Pattison, Robins, & Handcock, 2006). We call this effect *Spread* because its consequence is to increase the variance in the degree distribution. Thus, network centralization is characterized by high positive values of this parameter (Robins et al., 2009; Lomi et al., 2014). Furthermore, we incorporate the tendency of network ties to occur more frequently between companies that share common contacts, i.e., *Closure* (Davis, 1970; Rank, Robins, & Pattison, 2010). This effect leads to network clustering (Robins et al., 2009). Finally, we also include a parameter for non-closure. Here, two companies are connected by longer open paths (*Multiconnectivity*) (Pallotti, Lomi, & Mascia, 2013). This effect may indicate the presence of structural holes in the network (Burt, 1992; Lomi et al., 2014). Table 10 summarizes the parameters of endogenous network effects represented in the empirical model specification that we discuss in the next section.

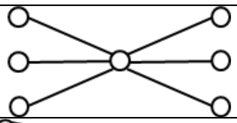
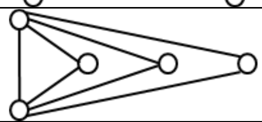
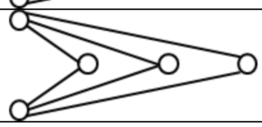
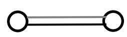
Parameter	Visualization	Interpretation
Endogenous network effects		
Edge		Baseline propensity to form coopetition ties
Spread (starlike configuration)		Tendency for variation in the degree to which companies form ties with others
Closure (alternating triangles)		Tendency for cyclic closure
Multiconnectivity (alternating 2-paths)		Tendency for multiple connectivity
Actor-specific effects		
Activity		Tendency for companies with a certain attribute to form network ties
Homophily		Tendency for network ties among companies that are similar with respect to an attribute
Dyadic covariates		
Form of the coopetition		Tendency for a dyad of companies that employ a specific form of cooperation (strategic alliance, share, supplier) to form a coopetition tie

Table 10: Network Patterns Included in the ERGM

3.3.3 Models

We analyze our data by applying an exponential random graph model (ERGM) (see Lusher et al., 2013). For this purpose, we employ the PNet software (Wang, Robins, & Pattison, 2009). The outcome variable of ERGMs is the overall structure of a network. Thus, they do not operate at the dyadic level like other statistical approaches in network analysis. Each potential network tie between actors is therefore considered as a random variable (e.g., Lomi et al., 2014; Brennecke & Rank, 2017). The observed network is represented as an adjacency matrix that contains the observed y_{ij} for each pair of companies i and j. The random variable Y_{ij} takes the value 1 if a given tie exists between i and j and the value 0 otherwise. The effective number of observations is N x (N-1), with N being the number of nodes in the network (Snijders et al., 2006; Robins et al., 2009; Lomi et al., 2014). In our network, the number of nodes is 371, and the number of dyads is therefore 137,270. In contrast to the more conventional logit model, ERGMs do not assume independence between the dyads. Rather, they even allow the specification and estimation of specific sources of dependence (as explained in the previous section). ERGMs capture both randomness and structure in networks. As for the structure part, each positive (negative) parameter estimate for a given configuration indicates that there is a larger (smaller) number of that configuration in the network than expected by chance (conditional on the other effects in the model) (Lomi et al., 2014). Formally, ERGMs are probability models for the structure of network ties with actor attributes and dyadic covariates as exogenous predictors. Following Lomi et al. (2014) they can be statistically described as:

$\Pr(Y = y \mid X = x) = \left(\frac{1}{\kappa}\right) \exp\left(\sum_k \theta_k Z_k(y, x)\right)$, (1) where (i) Y is the n x n array of network tie variables, with realizations y; (ii) X is an n x p array of individual attribute variables with realizations x; (iii) $Z_k(y,x)$ is a network statistic that can be calculated for a particular network realization y that may also depend on the vector x of attributes; (iv) θ_k is the parameter corresponding to the statistic $Z_k(y,x)$; and (v) κ is a normalizing quantity included to assure that (1) is a valid probability distribution. The summation is taken over all network effects included in a given model (Lomi et al., 2014).

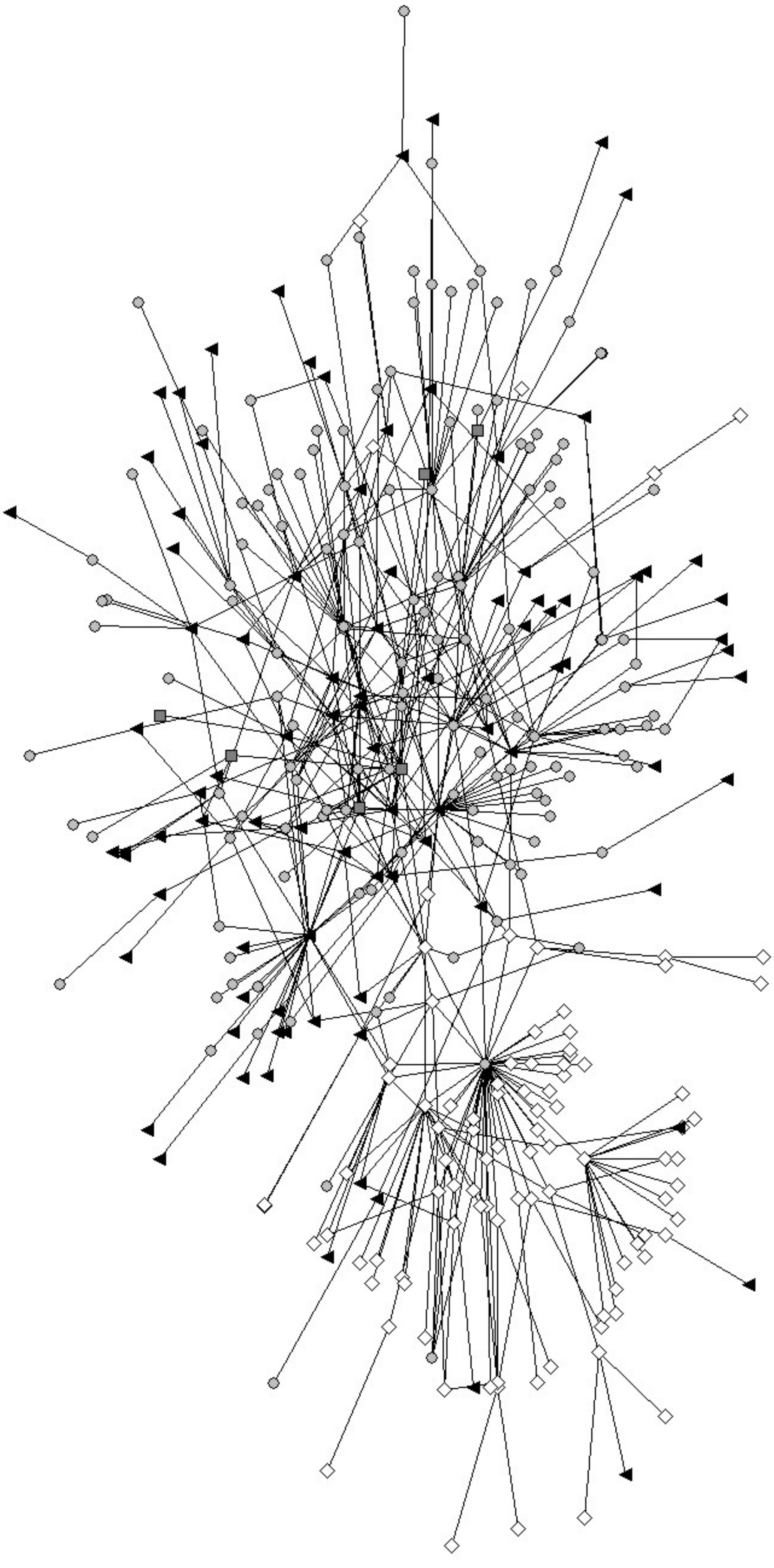
The equation (1) explains a probability distribution of networks with *n* nodes. The statistical probability of observing any particular network *y* in this distribution (including the network that is actually observed) is dependent on both the statistics $Z_k(y,x)$ for the network *y* and attribute vector *x* and on the corresponding parameters θ_k for all effects in the model. For a reliable parameter estimation, Markov chain Monte Carlo maximum likelihood (MCMCML) estimation is applied (e.g., Snijders et al., 2006; van Duijn, Gile, & Handcock, 2009). The configurations of the network can be interpreted as outcomes of potentially attribute-dependent endogeous network processes in which ties become patterned in various ways (Lomi et al., 2014).

The model above (1) can also be used to study the specific effects of company attributes on network ties to control for endogenous network processes. These attributes can enter the model specification in two ways (Lomi et al., 2014). First, there is the *activity effect*. Companies with a higher level of a specific attribute (*x*) may tend to express more network ties. Second, an actor-specific variable can enter the model in the form of a *homophily or difference effect*. In that case, network ties are assumed to be more or less likely between companies that are different with respect to the presence or the level of a specific attribute. A positive (negative) parameter for the homophily statistic implies a tendency towards homophily (heterophily) in the formation of coopetition ties whereas a positive (negative) effect for the difference statistic is associated with a tendency towards heterophily (homophily). For categorial variables, a *mismatch* statistic is used that counts the number of ties for which two companies have mismatching values of the attribute. A positive (negative) parameter implies that network ties are more (less) likely between companies that do not share membership in the same category (Lomi et al., 2014).

3.4 Results

3.4.1 Descriptive Results

The coopetition network has a density of 0.141. Thus, 14.1% of all 137,270 possible ties between the 371 companies actually exist in the observed network. Figure 4 presents the network diagram of the coopetition network in the German financial sector. The descriptive statistics at a company level are summarized in Table 11.



Note: circle: fintech, square: tech company, triangle: bank, diamond: insurance.

Figure 4: Coopetition Network in the German Financial Sector [7]

[7] The coopetition network was obtained by using the Netdraw software package (Borgatti et al., 2002).

	Variable	Mean	SD	Min.	Max.
1	Active cooperation	0.93	0.25	0.00	1.00
2	Form of the coopetition: Strategic alliance	0.63	0.48	0.00	1.00
3	Form of the coopetition: Share	0.14	0.35	0.00	1.00
4	Form of the coopetition: Supplier	0.06	0.24	0.00	1.00
5	Type of company: Fintech	0.41	0.49	0.00	1.00
6	Type of company: Bank	0.28	0.45	0.00	1.00
7	Type of company: Technology company	0.02	0.13	0.00	1.00
8	Type of company: Insurance	0.29	0.45	0.00	1.00
9	Technology: Platform	0.45	0.50	0.00	1.00
10	Technology: Artificial intelligence	0.06	0.24	0.00	1.00
11	Technology: Blockchain	0.02	0.14	0.00	1.00
12	Banking license	0.30	0.46	0.00	1.00
13	Degree centrality	2.76	4.14	1.00	46.00
14	Betweenness centrality	1,061.55	3,407.24	0.000	44,125.97
15	Number of employees	7,816.98	33,958.46	1.00	356,113.00
16	Company age	54.25	63.20	1.00	346.00
17	Nationality: Germany	0.77	0.42	0.00	1.00

Table 11: Descriptive Statistics at Company Level (N=371)

3.4.2 Results of ERGM

The results of our model estimation are summarized in Table 12. The size of the parameter estimates can be interpreted in terms of log odds, similar to a logistic regression. Thus, the factor by which the conditional odds of observing a coopetition tie increases for every increase of a variable by one unit can be calculated with the exponential function of the parameter value (Hunter, Goodreau, & Handcock, 2008; Robins & Daraganova, 2013). A positive (negative) parameter indicates that a pattern is observed more (less) often in the network than would be expected randomly, conditional on all other patterns in the model (Brennecke & Rank, 2017).

Variable	Model
External drivers	
Platform (activity)	0.5028 (0.1094)*
Platform (homophily)	0.8625 (0.2056)*
AI (activity)	0.0053 (0.1295)
Blockchain (activity)	-0.4014 (0.3014)
Banking license (activity)	1.2064 (0.1262)*
Banking license (homophily)	-3.4176 (0.3283)*
Relation-specific drivers	
Type of company (mismatch)	0.6679 (0.1469)*
Degree centrality (difference)	0.0938 (0.0166)*
Betweenness centrality (difference)	-0.0000 (0.0000)
Form of the coopetition	
Strategic alliance	0.2196 (0.1037)*
Share	0.8372 (0.1859)*
Supplier	1.6199 (0.4142)*
Company-specific control variables	
Number of employees (difference)	0.0000 (0.0000)*
Company age (difference)	0.0004 (0.0008)
Nationality (mismatch)	-0.1963 (0.0959)*
Endogenous network effects	
Edge	-6.5679 (0.2507)*
Spread	0.3750 (0.0829)*
Closure	-0.0909 (0.0882)
Multiconnectivity	0.0090 (0.0100)

* p<0.05; standard errors in parentheses

Table 12: Maximum Likelihood Estimates of the ERGM for Coopetition Ties

External drivers of coopetition. The effect of *Platform (activity)* is significantly positive (exp(0.5028) = 1.6533). Thus, companies that employ a platform technology are more likely to form coopetition ties. In addition, the *Platform (homophily)* effect is significantly positive (exp(0.8625) = 2.3691), indicating that a company is more likely to cooperate with a competitor if both employ a platform technology. The effects of *AI (activity)* and *Blockchain (activity)* on tie formation are not significantly different than would be expected randomly.[8]

If two companies both dispose over a banking license, they are less likely to form a coopetition tie, as indicated by the significant negative effect (exp(-3.4176) = 0.0328) of *Banking license (homophily)*. The effect of *Banking license (activity)*, in contrast, is significantly positive (exp(1.2064) = 3.3414). These findings support our argument that access to a banking license may present an important coopetition driver in this sector.

Relation-specific drivers of coopetition. The significant positive effect of *Type of company (mismatch)* shows that companies are more likely to cooperate with competitors that belong to a different type of company (e.g., traditional bank and fintech).

The significant positive effect of *Degree centrality (difference)* (exp(0.0938) = 1.0983) indicates that companies are more likely to form ties with companies that occupy a different position in the network. However, the effect of *Betweenness centrality (difference)* is not significant. The findings on *Degree centrality (difference)* are supported by the significant positive effect of the endogenous network effect *Spread* (exp(0.3750) = 1.4550). This variable characterizes the variance in a network's degree distribution. The positive value of this parameter indicates a tendency towards network centralization. The parameters *Closure* and *Multiconnectivity* show no significant effects.

Form of the coopetition. The effects of all three dyadic covariates that relate to the form the coopetition takes on are significant and positive: Coopetition ties are more likely if the cooperation relationship with a competitor takes the form of a *Strategic alliance*

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[8] Network ties wherein both companies employ AI or Blockchain technology could not be observed in our sample. As a result, we had to exclude the variables *AI (homophily)* and *Blockchain (homophily)* in order to prevent model degeneracy.

(exp(0.2196) = 1.2456), *Share* (exp(0.8372) = 2.3099), or *Supplier* (exp(1.6199) = 5.0526).

Control variables. The remaining patterns were included as control variables that account for endogenous network effects and exogenous influences on the formation of coopetition ties. The significant negative effect of the endogenous network variable *Edge* (exp(-6.5679) = 0.0014) indicates that coopetition ties occur infrequently outside of the more complex patterns included in the model.

Concerning the exogenous company attributes, the *Number of employees (difference)* exhibits a significant effect, yet without magnitude (exp(0.0000) = 1.0000). The effect of *Company age (difference)* is not significant. In contrast, companies are less likely to form coopetition ties if they differ in *Nationality (mismatch)* (exp(-0.1963) = 0.8218), i.e., if one companies is based in Germany and the other is not.

In sum, Hypotheses 1a is supported, Hypothesis 1c is partially supported, and Hypothesis 1b is not supported. In addition, Hypothesis 2a is supported and Hypothesis 2b is at least partially supported. Finally, Hypotheses 3a, 3b, and 3c are also supported.

3.4.3 Goodness of Fit

We evaluated the goodness of fit (GOF) based on the procedure suggest by Hunter et al. (2008) after we had estimated the model. The procedure is executed by simulating a high number of graphs from the fitted model and comparing the characteristics of the observed model to the characteristics of the simulated graphs. We simulated 300 million networks and built a sample of 1,000 graphs out of them. The results show a good model fit based on the criteria suggested by Robins et al. (2009). The GOF statistics of the effects that were included in the model were below the threshold value 0.1. In addition, the graph statistics that were included in the GOF analysis but not explicitly modeled had values below the recommended threshold of 2. Based on the model, the observed network can thus be reproduced adequately.

3.5 Discussion and Conclusion

New technologies and new competitors with platform-based business models are fundamentally changing the market structures of many industries. In our study, we examined the influence of various factors on the coopetition activities among competitors in financial markets. We conceptualize the German financial market as a network and investigate our research questions on how platforms influence coopetition in financial markets and which factors influence the emergence of networks in financial markets. Taking a network approach, our results show that new technologies, regulatory requirements, partner and relationship characteristics as well as the form of coopetition determine cooperation activities among competitors within an industry network.

We find that companies that apply a platform technology in their business model are more likely to engage in collaborative activities with their competitors. In addition, our results show that one company is more likely to enter into cooperation activities with another company if both companies use a digital platform. Thus, we can show that coopetition is strengthened by the influence of digital platforms. The value of a platform increases with an increasing number of users and providers as new users reinforce the network effects on the platform (Rochet & Tirole, 2003). When companies integrate additional products and services from other financial services providers on their platform, the value of the platform increases and thus the attractiveness of the company's platform for the user increases. Cooperation also offers advantages for financial service providers that are active on a platform of another company. By participating on a third-party platform, the financial service provider gains access to a new customer group. In addition, they can also attract new users to their platform. Increasing coopetition creates an industry-specific network around a platform, which greatly increases the value of a platform. Platforms are external drivers of coopetition and represent central nodes for the creation of a network on the German financial market. Our findings contribute to the literature on a better differentiation between platform networks and platform ecosystems. While the literature has so far focused on the formation of platform ecosystems, our findings contribute to a better understanding of the formation of platform networks.

We further find that AI and blockchain technologies currently have no influence on the cooperation activities of competitors. In our sample, only few companies have explicitly applied AI or blockchain in their business model, which may have contributed to the non-significant effects. AI and blockchain are novel and complex technologies. Both technologies could become more important for products and services in financial markets and become external drivers of coopetition. At the time of our study, we could not identify AI and Blockchain as external drivers of coopetition.

Furthermore, we can identify that a banking license is an important driver for coopetition in financial markets. Since financial markets are regulated markets (e.g., Scott, 2014), financial service providers must have a banking license to offer products and services on the financial market. Our results show that the effect of a banking license has both a positive and a negative effect on coopetition. On the one hand, our results show that companies that both possess a banking license are less likely to engage in coopetition activities. On the other hand, we find that access to a banking license is an important driver for cooperation between competitors in the financial market. Financial service providers that already have a banking license are less likely to cooperate with other financial service providers that own a banking license. Therefore, banks rarely cooperate with other banks. For fintechs, technology companies, and insurance companies, however, cooperation with banks is very important because it gives them access to a banking license. For fintechs and technology companies in particular, access to a banking license through cooperation with a bank is important in order to be able to offer products and services on the financial market. Thus, we can identify the banking license as an important external driver for coopetition in the financial market. Our results show that despite the strong technological influence and the resulting market changes on financial markets, regulation still plays a central role. The banking license thus represents a high barrier to market entry for new competitors on the financial market and protects the established financial service providers from new competitors. At the same time, the banking license is a strong external driver for new competitors to enter into cooperation with banks. Thus, our findings provide further evidence for the continuing importance of regulation for regulated sectors in the context of digital transformation (e.g., Steinhauser 2021, forthcoming; Steinhauser, 2020).

In sum, our findings concerning external drivers show that the question of how platforms influence coopetition in the German financial market can be answered by the fact that platforms have a positive influence on coopetition activities in the German financial market. The influence of platforms creates new cooperations between competitors on the German financial market. Furthermore, we identify the banking license as an influencing factor for coopetition that has a positive effect on the network development in the German financial market.

Our study further highlights the multilevel nature of the financial markets' network and extends research on relation-specific drivers of coopetition in financial markets. We find that companies are more likely to cooperate with competitors of a different type of company. Our results show that neither banks, insurance companies nor technology companies cooperate with their same type of company. The exception are fintechs. In some cases, fintechs cooperate with each other, but what it is striking is that in the case of fintech-fintech cooperations, one fintech owns a banking license. Our results confirm the assumption derived from the literature that companies are more likely to cooperate with a partner that offers different strategic resources and capabilities (Gnyawali & Ryan Charleton, 2018). Therefore, we can identify the effect of type of company as a relation-specific driver of coopetition.

We further find that companies are more likely to engage in cooperative activities with companies that have a different position in the network. Companies with differences in *degree centrality* are more likely to form coopetition ties. Thus, central companies with a large number of links are more likely to form ties with decentral companies with few links and *vice versa*. Our findings show that central players such as traditional banks may form coopetition ties with decentral companies largely due to the specific technological resources these decentral companies possess. On the other hand, decentral companies such as fintechs may engage in coopetition ties with central companies in order to gain access to their network and customers. Hence, the complementarity of their resources (Bengtsson & Raza-Ullah, 2016) drives their coopetition activities. In addition, the significant positive effect of the endogenous network effect *Spread* leads us to conclude that ties in the network of the German financial market are not distributed evenly and that there is a significant variance in the network's degree distribution. As a result, our findings indicate that the German financial market is characterized by a tendency towards network centralization.

In summary, the results of our study show that the mismatch of type of company and the difference in degree centrality are relation-specific drivers of coopetition in financial markets. Moreover, the relations-specific drivers identified are factors that contribute to the network development in the German financial market.

Finally, drawing on the literature on forms of coopetition (e.g. Dowling et al., 1996), we analyze in our study the influence of the different forms on the probability of companies entering into coopetition ties. We highlight that companies that have a cooperative relationship with a competitor in the form of a strategic alliance, shares, or a supplier relationship are more likely to enter into coopetition ties. If companies have already entered into a partnership with a competitor, the more likely they are to cooperate with this partner in other areas as well. Thus, the already existing connections in the network are increasingly strengthening. It is therefore important for companies to establish partnerships with other companies in order to assume a central position in a network. Our approach departs from those of other authors who consider the degree of balance between cooperation and competition (Bengtsson & Kock, 2000), the intensity of coopetition (Luo, 2007), or a differentiation of types based on the structures of the relationship (Bengtsson, Hinttu, & Kock, 2003). Instead, we focus on the form of coopetition, namely contractually regulated relationships such as a strategic alliance, shares, or a supplier relationship. By doing so, we contribute to research on how these forms of coopetition affect network formation.

Considered together, our results offer new insights on coopetition in the platform economy and show which factors influence network development. Our study highlights that new technologies can have a strong influence on cooperation activities with competitors. However, our results show that the influence of technologies is not always the same. Surprisingly, our investigations on the new and highly complex technologies AI and blockchain did not show any influence on the cooperation activities among competitors. However, according to the existing literature, these highly complex technologies are assumed to be external drivers of coopetition (Lin & Zhang, 2005; Oshri & Weeber, 2006; Dai, 2010). On the other hand, our results show a strong influence on coopetition activities for digital platform technology. Digital platforms become valuable when many users are active on the platform and drive networking among platform users. In the literature on platforms to date, platform ecosystems have been the primary focus, and the connections surrounding a platform are defined as ecosystems (Tiwana, 2013; Gawer & Cusumano, 2014; Jacobides et al., 2018). In our view, ecosystems and networks should be considered in a more differentiated way from each other. Ecosystems and networks have commonalities; however, they differ in one essential point: networks are formally regulated and fixed connections, whereas the platform ecosystem represents a loose network. We believe future studies should further elaborate the differences between platform networks and platform ecosystems and pay more attention to the specifics of networks around platforms. Future studies interested in examining networks in the platform economy could take our results as a reliable point of departure.

Some limitations advise caution in the interpretation of our results but also state clear directions that future research might pursue. The first limitation concerns the static nature of our research design. We have selected all banks, fintechs, technology companies, and insurance companies that were active on the German financial market at the time of our data collection. Thus, we are only able to capture the activities and represent the network at one point in time and cannot account for its evolution. However, financial markets are highly dynamic and market structures change quickly due to the temporal structure of our data we are not able to study and visualize these changes. To fully investigate the evolution of networks, future research could conduct long-term studies to investigate and represent the evolution of networks. The second limitation is related to our research method. Our research method is quantitative in nature; therefore, our results cannot give any information about qualitative characteristics of network relationships. Future studies could take a qualitative research approach to gain fine-grained insights on the quality of coopetition. The third limitation of our work that opens up opportunities for future research relates to our consideration of only one specific industry and country. Since our study was conducted in the context of a single, highly regulated industry, the generalizability of our findings is limited. As a result, explorations in other empirical contexts are necessary to validate our results.

In closing, our paper contributes to the growing interest in the Platform Economy. We provide new insights into the existing literature on platforms by showing how platforms influence coopetition. We further extend the theoretical knowledge on platform networks by applying the approach of Shipilov and Gawer (2019) to differentiate between platform ecosystems and platform networks and generate new insights on what factors influence platform networks.

4. Paper 3

Success Formula: Can Business Model Success on Digital Marketplaces be Evaluated? A Mixed Method Approach

4.1 Introduction

Multi-sided platforms are ubiquitous and have become an integral part of everyday life. Today, platforms represent an ever larger and rapidly growing part of the global economy (Evans & Schmalensee, 2016; Parker et al., 2016). Business models that do not rely on their own assets are experiencing rapid growth due to the high and fast scalability via the internet (Hagiu, 2009). The networks of such platforms are becoming increasingly complex, which is why strategies need to consider more than just network effects and therefore require a deeper understanding of platform-based business models (Eisenmann, Parker, & van Alstyne, 2006). McIntyre and Srinivasan (2017) divide the predominant streams of research in the platform literature into three perspectives that differ primarily in their definition of multi-sided platforms. First, the perspective of industrial organizational economics deals with the investigation of the origin of network effects and the resulting emergence of dominant platforms (Parker & van Alstyne, 2005). Second, the representatives of the technology management point of view mainly deal with the question of how platform providers can enthuse complementary parties (e.g., developers) for the platform in order to offer an added value. From a technology management perspective, a platform is a technological architecture used by different actors to conduct research and drive innovation (Gawer, 2014). Third, the perspective of strategic management deals with the competitive advantage and strategies of platforms (Eisenmann, Parker, & van Alstyne, 2011).

In this paper, we use the concept of multi-sided platform to subsume business models that serve both as intermediaries for the flow of products, services, and social currency as well as direct interactions between several sides (Ruutu, Casey, & Kotovirta, 2017; de Reuver et al., 2018). These platform-based business models face the same challenges: (1) to provide sufficient added value to the users of the platform and (2) to reach a critical mass of users (Caillaud & Jullien, 2003; Rochet & Tirole, 2003; Parker & Van Alstyne, 2005; Evans, Hagiu, & Schmalensee, 2006). With our research, we aim to contribute to a better understanding of business models of multi-sided platforms. Our article is based on the taxonomy of business models by Täuscher and Laudien (2018), which we expand with new findings from the platform and business model literature in order to derive success factors for multi-sided platforms, especially digital marketplaces (Täuscher & Laudien, 2018). The heterogeneity of the platform concept and the associated diversity of differentiation characteristics leave open the question of which factors ultimately distinguish different types of platforms (McIntyre & Srinivasan, 2017; de Reuver et al., 2018; McIntyre et al., 2020). This circumstance makes it necessary to have a uniform definition in order to identify potential success factors. Since digital marketplaces are the subject of our empirical analysis, we developed the central question for this paper: *Which factors characterize successful digital marketplaces?* Based on this question, we structure the paper as follows: In Section 2, we present current research related to multi-sided platforms and business models. In Section 3, we introduce our research methodology. The empirical analysis is described in Section 4. Section 5 contains a discussion of the results. In Section 6, we show implications for future research. We conclude our paper with a discussion on limitations in Section 7.

4.2 Theoretical Background and Research Questions

According to Barney (1991), it is the strategic resources, i.e., the differentiation features, that determine a competitive advantage and thus the success of a company. Companies that can generate and utilize above-average added value have a competitive advantage (Afuah, 2009). A parallel to the business model literature can be seen here. Osterwalder and Pigneur (2010) define the business model as the “rationale of how an organization creates, delivers, and captures value.” Therefore, the logic according to which a company generates and makes accessible value for itself and its customers is decisive. When launching a multi-sided platform, the added value that comes from the technical sophistication of the platform itself (e.g., through superior user experience) may still be sufficient to attract new users. Especially the innovators and early adopters classified according to diffusion theory accept such innovations at an early stage (Rogers, 1983). However, in order to reach the mass market and to cross the threshold for a critical mass of active users, a sufficiently large and growing number of users is required (Evans & Schmalensee, 2010). In their simplest form, platforms have only two sides, which can be extended at will within the framework of technical feasibility and strategic orientation (Muzellec, Ronteau, & Lambkin, 2015; Hagiu & Wright, 2015a). The network effects result from the development of the installed base, the progressive adaptation, or diffusion of the platform and thereby advance to a strategic resource (Katz & Shapiro, 1985; Farrell & Saloner, 1986; Boudreau, 2012). The added value or benefit generated by the use of digital marketplaces is of crucial importance for their adoption or diffusion (Evans, 2009). This raises the question of what determinants are needed to generate enough added value to ultimately be able to speak of a successful platform. The solution to the *added value* challenge is the basis for overcoming the *critical mass* challenge (Evans & Schmalensee, 2010). From this perspective, business model theory offers a good starting point for drawing conclusions about the success of a digital marketplace. With regard to relevance and the number of business model dimensions, there is relative heterogeneity in the literature (DaSilva & Trkman, 2014; Denicolai, Ramirez, & Tidd, 2014; Hartmann et al., 2016). In order to gain clarity in this respect, we derive the first research question: *Which factors of the business model influence the success of digital marketplaces?*

As already mentioned, the installed base becomes part of the value proposition of a digital marketplace. Against the background of the *added value* challenge, the question arises of how the value of such a network is determined. From a neoclassical point of view, the value of a network is measured by the number of users (Farrell & Saloner, 1986; Katz & Shapiro, 1986; Gandal, 1995). Recent publications, however, deem this singular focus too simplistic (Swann, 2002; Dellarocas, 2003; Shankar & Bayus, 2003; Choi, Kim, & Lee, 2008; Soh, 2010). Afuah (2013) therefore expands the spectrum of influencing factors on the platform success to include the network structure and behavior in the network with their respective subcategories (Afuah, 2013). To the best of our knowledge, there are no empirical studies to date that have investigated the influence of these factors on the success of a digital marketplace. This leads to the second research question: *Which* *factors of network structure and network behavior influence the success of digital marketplaces?*

Looking at the present work and the complex of topics dealt with against this background, a heterogeneous picture emerges. Networks and network effects are the basic drivers for platforms and are extensively researched concepts. The number of publications on platforms also tends to indicate a tapped field of research and thus induces an explanatory approach (McIntyre & Srinivasan, 2017). However, some authors criticize the common approach of determining the value of a network simply by its size as too simplistic (Dellarocas, 2003; Choi et al., 2008; Soh, 2010; Afuah, 2013). Afuah (2013) therefore adds numerous new factors to the existing understanding. In addition, Eisenmann, Parker, and van Alstyne (2006) and Afuah (2013) criticize that the underlying drivers of platforms have so far received little attention in research. The comprehensive analysis of the platform literature by McIntyre and Srinivasan (2017) shows that, as with the business model literature, this is still a fragmented field of research. However, in-depth research on platforms against the background of business model theory is rarely found. One of the few exceptions is research by Muzellec, Ronteau, and Lambkin (2015). It can therefore be said that the combination of the two sub-areas in particular represents an incomplete state of research. As a consequence, this work is aimed at advancing the current state of research and thus contributing to the development of theory, so that an explorative approach seems appropriate.

From Multi-Sided Platforms to Digital Marketplaces

Multi-sided platforms are mostly used in the context of high-tech – however, the underlying concept has been around for much longer. Even in ancient times, marketplaces acted as intermediaries to enable interaction and transactions between several parties (McIntyre & Srinivasan, 2017). Thus, platforms are referred to by economists as two-sided markets (Wright, 2004). Wright (2004) differentiates, similar to (Evans et al., 2006), between: (1) platforms as intermediaries, (2) platforms to facilitate transactions, (3) promotional or supported platforms, and (4) software platforms. Gawer and Cusumano (2014) further distinguish between internal or company-specific platforms as well as external or industry platforms. Company specific and industry platforms mainly differ in the degree of openness of the platform towards complementary third-party providers along different dimensions. We therefore understand a multi-sided platform as a digital infrastructure that enables different actors to interact with each other.

In the literature digital marketplaces are often considered as multi-sided platforms (Hagiu, 2014; Evans & Schmalensee, 2016; Evans, 2016). According to Bakos (1998), a marketplace fulfils three tasks: (1) Linking buyers and sellers, (2) supporting transactions, and (3) ensuring institutional infrastructure. The characteristics of digital marketplaces are similar: (1) Linking independent buyers and sellers through a platform, (2) providing direct contact between buyer and seller to complete the transaction without being highly automated, (3) providing an institutional and regulatory framework for transactions, and (4) not offering and producing their own products or services. Condition (3) excludes platforms that aggregate various other marketplaces through an algorithm while condition (4) excludes platforms that primarily produce products and services themselves and additionally allow other suppliers to use the platforms. Digital marketplaces are therefore more than just a sales channel and can be evaluated as an independent business model (Täuscher, 2016; Täuscher & Chafac, 2016).

The measurement of the success of digital marketplaces has not yet been uniformly defined and is controversially discussed. According to Brunn, Jensen, and Skovgaard (2002), a digital marketplace is successful if it is profitable. Moreover, Sculley and Woods (1999) argue that the success of Internet firms should be assessed on the basis of gross turnover rather than net profit. Zhu and Iansiti (2012) use platform market share as an indicator of success. Similarly, Laseter and Bodily (2004) argue that the success of a digital marketplace should be assessed on the basis of turnover.

From Network (Effects) to Network Value

Multi-sided platforms operate in different markets where networks and network effects are the fundamental drivers for growth, competition, and strategy (Eisenmann et al., 2006; Shapiro & Varian, 1998). A network is a collection of interconnected nodes. The nodes represent interfaces of the edges and therefore exist and function as such only within the network (Castells, 2004). We focus on virtual networks where, unlike real networks, the connections between the nodes are not primarily physical but immaterial. A power grid, for example, is a real network, while Facebook is a virtual network (Amit & Zott, 2001). This generates added value not only at the macro level of the network, but also at the level of the individual nodes. For example, in the case of an app for sending and receiving messages, the value of the app for the individual user (node) lies not only in the software itself, but much more in the number of other active users, the installed base (Swann, 2002; Afuah, 2013). Thus, the value of the network for an individual increases with the number of other users in the network. These externalities arising from the network are called network effects (Katz & Shapiro, 1986). A distinction can be made between direct and indirect network effects (de Reuver et al., 2018). Whereas direct network effects result from an increase in benefits due to an increase in users of the same site, indirect network effects describe an increase in benefit through an increase in the number of users in a complementary user group (Katz & Shapiro, 1986; Boudreau & Jeppesen, 2015). It is desirable to enter the market as early as possible in order to address users and build up an installed base. The goal is to quickly generate positive network effects (Lee & O'Connor, 2003; Choi et al., 2008). Network effects are of central importance for achieving critical mass on the platform (Evans & Schmalensee, 2010). A critical mass describes the minimum number of users that is sufficient for self-sustaining growth of the user base and that increases the market shares of platforms (Shapiro & Varian, 1998).

The value of a network is different from the perspective of the network user and the network provider. From the provider's point of view, a network is valuable if it contributes to the value generation of the company or its competitive advantage. From a network member's point of view, a network is valuable if it contributes to the fulfillment of their needs (Parker et al., 2016). Extant literature shows that the value of a network is measured by more than just its size, and that a network perspective is crucial in business model research (Amit & Zott, 2001; Zott & Amit, 2009, 2010; Afuah, 2013; Steinhauser, 2019). However, Afuah (2013) states that the neoclassical picture of network effects and the resulting size hypothesis as a basis for measuring the value of a network.

From Business Model Theory to Platform Business Models

The relevance and awareness of business models in research and practice has steadily increased in recent years. Although the term business model is one of the central terms of the internet economy, there is still no uniform definition (George & Bock, 2011; Klang, Wallnöfer, & Hacklin, 2014). Chesbrough and Rosenbloom (2002) define a business model as a coherent framework that takes technological characteristics and potentials as inputs and converts them through customers and markets into economic outputs. In most definitions, however, the following six dimensions can be found: (1) customer segment, (2) value proposition, (3) revenue streams, (4) key resources, (5) key activities, and (6) cost structure (Hartmann et al., 2016). The (1) customer segments refer to the various target groups of the company. The (2) value proposition describes the totality of products and services that generate value for a specific customer segment. The revenues that a company generates from the different segments are taken into account by the dimension (3) revenue flows. The (4) key resources are the necessary prerequisites for a company to generate value and include the most important intangible and tangible resources. (5) Key activities describe the most important activities of a company to operate the business model. Similarly, the dimension (6) cost structure considers all costs incurred in the operation of the business model (Osterwalder & Pigneur, 2010).

Platforms bring new operational and strategic challenges compared to a traditional business model. While in a linear business model the intermediary stands between the end customer and the manufacturer, the platform merely provides the infrastructure for the platform users. This allows the parties to interact directly on the platform (Hagiu & Wright, 2015a). This is accompanied by a high degree of connectivity between the actors and low geographical restrictions (Javalgi, Martin, & Javalgi, 2007). Digital business models, in addition, are models characterized by low search and transaction costs and a high degree of transparency or less information asymmetry (Evans & Schmalensee, 2016).

Hypotheses Development

Our first research question examines the influence of business models on the success of digital marketplaces. According to (Afuah & Tucci, 2003), the business model is the first determinant of a company's success. Osterwalder and Pigneur (2010) divide the business model into three superordinate categories: *value creation*, *value delivery*, and *value capture (Hypotheses 1–3)* (Osterwalder & Pigneur, 2010; Täuscher & Laudien, 2018).

The elements *network structure* and *network behavior,* which are examined within the framework of our second research question, can also be classified in the above-mentioned category system because they create added value for the user. However, the factors postulated by Afuah (2013) are specifically related to added value in networks. It is also important to consider whether these factors can be assumed to influence the success of platforms, as such an investigation has not yet been carried out. The granular structure of the system allows the potential success factors to be classified *(Hypotheses 4–5;* see Table 13 for an overview of the research question and hypotheses).

Key Question: Which factors characterize successful digital marketplaces?
Question 1: Which factors of the business model influence the success of digital marketplaces?
Hypothesis 1: Factors in the value creation category have a significant positive impact on the success of digital marketplaces. **Hypothesis 2:** Factors from the value delivery category have a significant positive influence on the success of digital marketplaces. **Hypothesis 3:** Factors from the value capture category have a significant positive influence on the success of digital marketplaces.
Question 2: Which factors of network structure and network behavior influence the success of digital marketplaces?
Hypothesis 4: Factors of the network structure have a significant positive influence on the success of digital marketplaces. **Hypothesis 5:** Factors that can be assigned to behavior in the network have a significant positive influence on the success of digital marketplaces.

Table 13: Research Questions and Hypotheses

4.3 Methodology

4.3.1 Codebook Development

Analogous to the approach of Hartmann, Zaki, Feldmann, and Neely (2016), Täuscher (2016), and Täuscher and Laudien (2018), we set up a morphological box with categories and business model dimensions derived from literature. The development of a morphological box allows us to organize and describe a platform business model by the combination of its characteristics. Through the comprehensive picture on the platform, we also captured factors critical to success. Table 14 shows the final version of the codebook to be used as a basis for data collection. We added new attributes to Täuscher & Laudien's taxonomy for marketplace business models to determine the value of a network and its characteristics and captured factors critical to success (Afuah, 2013; Lee, Park, & Park, 2013). Basically, the individual success factors can be assigned to three superordinate categories *Value Creation*, *Value Delivery*, *and Value Capture,* which we will discuss in the following subsections (Osterwalder & Pigneur, 2010; Teece, 2010).

Value creation

Business model attributes in the *Value Creation* category reflect the mechanisms of the company that contribute to creating the value proposition (Johnson, Christensen, & Kagermann, 2008). Starting with the key value promise of the platform, this dimension gives rise to four possible forms of added value for the customer: a low price, low cost, or efficiency *(Key Value Proposition 1)*; the emotional value, which is created through superior user experience or the image associated with the use *(Key Value Proposition 2)*; the social value through interaction with other users *(Key Value Proposition 3)*; and a combination of the aforementioned value propositions *(Key Value Proposition 4)*. The transaction content and transaction type can be differentiated even further. The transaction content is divided into product *(Transaction Content 1),* service *(Transaction Content 2),* and product and service *(Transaction Content 3)*. The transaction type can be divided into digital *(Transaction Type 1),* and offline *(Transaction Type 2)*. In combination, a differentiation into digital marketplaces is possible, digital marketplaces offer physical products (e.g., household goods), digital products (e.g., digital music), online services (e.g., webinars), or offline services (e.g., transports) (Wirtz, 2010). According to (Choudary, 2015), the key activities of a digital marketplace can be divided into data services *(Key Activities 1),* community building *(Key Activities 2),* and content generation and curation *(Key Activities 3)*. Here, data services refer to the analysis and visual preparation of sales data for interested sellers. Content generation and curation are supporting activities, such as helping to create profiles, that have an impact on sellers. It does not seem to make much sense to include a form for the combined appearance of these activities, since digital marketplaces ultimately always contribute to community building. A combined expression ‘several’ would therefore impede the selectivity of the analysis. In contrast to Täuscher and Laudien (2018), we do not examine the pricing on platforms in detail. Due to the already large number of variables, only those that are suspected of having a large explanatory value should be included in the model. From our point of view, how the prices are achieved on the platform does not appear to be decisive for the success of the digital marketplace. More important, however, is the usage fee for the platform, which is discussed in the *Value Capture* category.

The evaluation system serves to reduce opportunistic behavior and to strengthen confidence in the digital marketplace (Afuah, 2013; Dellarocas, 2003). This ultimately also includes the factors required by Afuah (2013) on behavior in the network. This can be implemented by user ratings, where users evaluate each other for past transactions *(Review System 1)* or using standardized metrics via the digital marketplace *(Review System 2)*. Although a rating system is typical for digital marketplaces, it is not a mandatory characteristic (Pavlou & Dimoka, 2006). In this way, we cannot enter a valuation system and a combination of different valuation systems *(Review System 4)* for the characteristic values *(Review System 3)*. Furthermore, opportunistic behavior can also be avoided by trusting platforms and their users. This can be achieved with certification, which is issued by the digital marketplaces. Certification can take place via an independent organization *(Certification 1),* the digital marketplace itself *(Certification 2),* a combination of an independent organization and the digital marketplace *(Certification 3),* or cannot take place at all *(Certification 4)* (Lewis & Weigert, 1985; Chiles & McMackin, 1996; Uzzi, 1997). Further dimensions are fed by the network structure factors that, according to Afuah (2013), influence the value of the network. These factors comprise the possibility of transactions, number of roles that a user can assume, and the centrality of members. Thus, the following characteristics for the dimensions result from the argumentation preceding: Possibility of transaction on request *(Possibility of transactions 1),* only through one side *(Possibility of Transactions 2)*, or from multiple parties *(Possibility of Transactions 3)*. A user can either assume several roles *(Number of Roles 1)* or only one role *(Number of Roles 2)*. The situation is similar with the centrality of members. Either the digital marketplace is used by central members *(Centrality of Members 1),* or not *(Centrality of Members 2)*. Since no explicit information on the centrality of members is available, this dimension is assessed as an approximation of the presence or absence of key partners on the platforms.

Value delivery

This category contains a total of four business model dimensions. These describe the factors that convey value to specific customer groups. In addition to the geographical scope with the characteristics global *(Geographic Scope 1),* regional *(Geographic Scope 2),* and local *(Geographic Scope 3),* the dimensions customer segments, industry focus, and platform type are analyzed. Possible customer segments are C2C *(Customer Segments 1)*, B2C *(Customer Segments 2)*, B2B *(Customer Segments 3)*, and B2C and B2B *(Customer Segments 4)*. With the industry focus, it is either possible to address one niche *(Industry scope 1)* or several industries *(Industry Scope 2)* (Dai & Kauffman, 2001; Schief, Pussep, & Buxmann, 2013). With the distinction between web-based platform *(Platform Type 1),* mobile application *(Platform Type 2)*, and a combination of both *(Platform Type 3)*, the dimension platform type represents the access to the user or customer, which is why it equals the dimension of the channels (Osterwalder & Pigneur, 2010).

Value capture

The *Value Capture* category also includes four business model attributes and describes how the value generated by the customer is translated into revenue and profit (Teece, 2010; Abdelkafi & Täuscher, 2016). The key revenue streams for marketplaces result either from commissions *(Key Revenue Streams 1)*, subscriptions *(Key Revenue Streams 2)*, advertising *(Key Revenue Streams 3)*, service revenues *(Key Revenue Streams 4)*, or a combination thereof (*Key Revenue Streams 5)* (Schlie, Rheinboldt, & Waesche, 2014). Another important factor is the revenue source. This can be generated by sellers *(Revenue Source 1),* buyers *(Revenue Source 2),* third parties *(Revenue Source 3)*, by a combination of these factors *(Revenue Source 4)*, or even not yet exist *(Revenue Source 5)* (Muzellec et al., 2015; Täuscher & Chafac, 2016). To further refine, the pricing can either be fixed

(Pricing Mechanism 1), market driven *(Pricing Mechanism 2),* or differentiated for the different user groups *(Pricing Mechanism 3).* If price differentiation is involved, a distinction can be made between attribute-based *(Price Discrimination 1),* location-based *(Price Discrimination 2),* or quantity-based price differentiation *(Price Discrimination 3),*as well as between several differentiation types *(Price Discrimination 4),* or no price differentiation at all *(Price Discrimination 5)* (Osterwalder, 2004).

Performance measurement and other information.

In order to find out how these factors affect the success of digital marketplaces, we also collected separate criteria for measuring success. The maximum of the cumulative funding received by the respective platform is used to assess the success. In addition, we analyzed turnover as a control variable.[9] The dimension *Other information* is mainly used for descriptive statistical analysis. Here we surveyed year of foundation, country, federal state/province of the headquarters, number of employees, industry, and whether the founder is still active as CEO in the company.

4.3.2 Data Collection

As the main goal of our paper is to examine the relationships between the basic drivers of digital marketplaces and their success, we first developed a morphological box with the factors derived from the literature. Via angel.co, we filtered potential research objects by marketplace and then examined them in more detail. In order to be considered in the investigation, two basic criteria must first be met: (1) It must be a digital marketplace and (2) the necessary data can be collected completely. If an enterprise does not meet one of

[9] Market modelling is always associated with a more or less high degree of uncertainty, depending on the input variables and the assumptions made. For these reasons, we follow Sculley and Woods (1999), Laseter and Bodily (2004) in assessing the success of digital marketplaces, using turnover as a measure. In addition to the turnover, we also collect the funding received. The amount of funding received indirectly reflects the potential of the business model and is the result of a decision-making process conducted by experts. In this respect, funding data provide an indirect factor for determining the success of the target population. The level of funding can therefore be interpreted as a longer-term assessment of the company's success. Furthermore, it could be demonstrated that the expectation of the future development of a platform has an impact on the adoption decision. For this reason, the cumulative funding received should be used as a dependent variable and the turnover as a control variable to assess the success of the enterprise.

the two criteria in the list, it cannot be used for data collection. In this case, we analyzed the next company in the list. We repeated this process until the sample size of 100 companies was reached. The size of the sample was set at 100 because of the relatively high burden of data collection. In addition, it is based on previous comparable research projects with the same sample size and more resources (Hartmann et al., 2016; Täuscher & Laudien, 2018).

	Classification	Dimensions	Characteristics			
Value Creation	Business Model in the narrower sense[a]	**Key Value Proposition**	**Price/Cost/Efficiency**	**Emotional Value**	**Social Value**	**Several Value Propositions**
			Key Value Proposition 1	Key Value Proposition 2	Key Value Proposition 3	Key Value Proposition 4
		Key Activities	**Data Services**	**Community Building**	**Content Generation**	
			Key Activities 1	Key Activities 2	Key Activities 3	
		Centrality of Members	**Existing**	**Not Existing**		
			Centrality of Members 1	Centrality of Members 2		
	Concretization of Value Proposition (BM in the broader sense)[b]	**Trans-action Type**	**Digital**	**Offline**		
			Transaction Type 1	Transaction Type 2		
		Trans-action Content	**Product**	**Service**	**Product & Service**	
			Transaction Content 1	Transaction Content 2	Transaction Content 3	
	Network Structure	**Number of Roles**	**Several**	**One**		
			Number of Roles 1	Number of Roles 2		
		Possibility of Trans-actions	**Upon Request**	**One-Sided**	**Multi-Sided**	
			Possibility of Transactions 1	Possibility of Transactions 2	Possibility of Transactions 3	
	Network Behavior	**Review System**	**User Ratings**	**Ratings via Marketplace**	**Several**	**None**
			Review System 1	Review System 2	Review System 3	Review System 4
		Certifi-cation	**Independent**	**Via Marketplace**	**Several**	**None**
			Certification 1	Certification 2	Certification 3	Certification 4
Value Delivery	Business Model	**Geographic Scope**	**Global**	**Regional**	**Local**	
			Geographic Scope 1	Geographic Scope 2	Geographic Scope 3	
		Customer Segments	**C2C**	**B2C**	**B2B**	**B2C & B2B**
			Customer Segments 1	Customer Segments 2	Customer Segments 3	Customer Segments 4
		Industry Scope	**Niche/One Industry (vertical)**		**Broad (horizontal)**	
			Industry Scope 1		Industry Scope 2	
		Platform Type	**Web-Based**	**Mobile App**	**Web & App**	
			Platform Type 1	Platform Type 2	Platform Type 3	

Value Capture	**Business Model**	**Revenue Source**	**Seller**	**Buyer**	**Third Party**	**Several**	**None**
			Revenue Source 1	Revenue Source 2	Revenue Source 3	Revenue Source 4	Revenue Source 4
		Key Revenue Streams	**Commission**	**Subscription**	**Ads**	**Service**	**Several**
			Key Revenue Streams 1	Key Revenue Streams 2	Key Revenue Streams 3	Key Revenue Streams 4	Key Revenue Streams 5
	Concretization UQ (Business Model in the broader sense)	**Pricing Mechanism**	**Fixed**	**Market-Driven**	**Differentiated**		
			Pricing Mechanism 1	Pricing Mechanism 2	Pricing Mechanism 3		
		Price Discrimi-nation	**Attribute**	**Location**	**Quantity**	**Several**	**None**
			Price Discrimination 1	Price Discrimination 2	Price Discrimination 3	Price Discrimination 4	Price Discrimination 5
Criteria for Measuring Success		**Funding**	**Turnover**				
Other Information		**Year of Foundation**	**Country**	**State/ Province**	**Number of Employees**	**Founder/ CEO**	**Industry**

[a] Business models in a narrower sense refers to the dimensions that can be directly referenced with the dimensions in the business model canvas.

[b] Business models in a broader sense contains further factors for the specification of the value proposition and the revenue source.

Table 14: Codebook for the Collection of Empirical Data

If a company met the requirements, we analyzed it by using the dimensions of the morphological box shown in Table 14. The websites of the respective digital marketplace itself, angel.co, crunchbase.com, owler.com as well as other renowned websites, are used for the analysis of the companies. The analysis of secondary, historical data by means of document analysis is widely used in the field of innovation and technology management (Christensen, 1992; Hüsig, 2012). Yin (2014) points out that the documents have a certain subjectivity due to the author and therefore urges us to reflect critically on the statements against this background.[10] At this point, it should again be emphasized that the possibility of collecting this data by means of interviews is to be classified as less promising due to its high strategic relevance (Zollenkop, 2006). In order to document the survey, a database was set up to record the totality of the surveyed companies as well as the rejected companies with a reason for rejection. In addition, a second database was created in which the collected dimensions of the morphological box per company were documented.

Sales, funding, number of employees, and year are recorded metrically. The name of the company, the location, and the industry are nominally scaled and are mainly used for descriptive statistical analysis. The remaining variables are coded dichotomously (available = 1, not available = 0).

The cumulative funding received is collected via the websites angel.co, and crunchbase.com. During the survey, we took care to ensure that no values were added twice. We then determined the maximum of the two values for the regression. The maximum is used because a higher information density can be assumed here with regard to the financing rounds and the amount of funding received. The information about the amount of the turnover comes from owler.com. Owler.com is a website where users can provide estimates and, if known, actual values concerning a company.[11] Data on the number of employees was usually available from all three websites. The web pages

[10] Yin (2014) refers in his remarks to a qualitative content analysis within the framework of a case study. Nevertheless, the reference to reflection also seems justified in the present case of quantitative content analysis and is more beneficial than detrimental to the quality of research.

[11] The information available on Owler includes turnover, number of employees, and the CEO. As the companies analyzed are start-ups and young companies, information on turnover is rarely directly accessible. Owler therefore offers at least a good approximation to collect these values anyway.

angel.co and crunchbase.com specify these in intervals, while owler.com uses absolute values. Owler.com data is based on little verified values; we therefore used the values of angel.com and crunchbase.com. Since the intervals of the two websites are not all identical, we determined centers of the intervals. We compared these centers with the values of owler.com. If the intervals were the same, these were adopted; if the intervals were unequal, the one selected was the one with the middle that showed the smallest deviation from the value called up by owler.com. This resulted in the adjusted number of employees.
In order to be able to collect as unbiased a sample of companies as possible, we updated the list of marketplaces generated with the help of angel.co manually several times. This results in a constantly new and random sequence of marketplaces. A continuous comparison with the first database prevents a company from being analyzed several times.

4.3.3 Models

In order to test our hypotheses, we used multiple linear regression models. The inclusion of several independent variables in the regression model results in the following regression equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_j X_j + \ldots + \beta_J X_J + u$$

It contributes to the quality of the model to include as few independent variables as possible in the model. A reduction of independent variables can be achieved by theoretical considerations or by a data-driven selection of independent variables. We divided the individual variables into blocks in our codebook. These variables are included separately in the regression analysis. Following this approach, we can also answer our research questions. For example, RQ1 focuses on business models, while RQ2 is interested in network structure and network behavior. Three methods are available for the data-driven selection: (1) forward selection, (2) backward elimination, and (3) stepwise regression. For all methods, a level must be determined a priori, that determines the significance level for the inclusion of the variables in the model. For (1) forward selection, the independent variable that correlates most closely with the criterion variable is included first. Then the variable whose F-value is the highest and at the same time significant is added. This is repeated until there are no more variables left that provide a significant additional explanation. The (2) backward elimination is contrary to the (1) forward selection. In the first step, all independent variables are included in the model, and the variables that provide the least explanatory contribution in the case of a non-significant F-value are gradually removed. The procedure is completed when there are no more variables whose F-value is not significant. A combination of (1) and (2) represents the procedure of (3) stepwise regression. Here, the individual independent variables are first included in the model with a forward selection. By adding variables, it is possible that a variable that has already been included may no longer make a significant contribution. If a previously defined significance level is exceeded, this variable is removed from the model. Due to the high number of independent variables (58), both methods are used. Initially, Q1 and Q2 are to be investigated in blocks. Within the blocks, (3) stepwise regression is used. We made a distinction between different model specifications. In these, we examined different independent variables for their influence on the obtained funding and turnover.

4.4 Results

4.4.1 Descriptive Analysis

The data set generated comprises 100 randomly selected platforms that meet the criteria on platforms and digital marketplaces and whose data were fully available. From a total of 340 companies that were tested against these criteria, 240 platforms could not be included in the analysis due to definitional reasons (43%), missing data (24%), or language barriers (2%). Although 31% of the platforms initially examined were still listed on the AngelList, they had to cease business operations due to insolvency. In addition to the name and an identification number per marketplace, 66 data points were collected and documented in the morphological box in order to analyze the companies comprehensively. The *value creation* category has nine dimensions with 28 different characteristics, the *value delivery* category four dimensions with a total of 12 possible characteristics, and the *value capture* category has four dimensions with 18 characteristics. The remainder can be assigned to the categories *criteria for measuring* *success* and *other information.* This comprises eight characteristics, which were used for descriptive analysis. This results in a total data set with 6800 data points.

The majority (89%) of the companies analyzed are based in the USA. A clear focus can thus be identified in this respect. Within the USA, the majority of the companies surveyed came from California (58%) and New York (13%). One explanation for this could be that angel.co is a US-American website and therefore increasingly addresses domestic platforms. Particularly with regard to the large proportion of platforms from California, a connection to Silicon Valley and the strongly developed start-up culture there also seems obvious. Only one digital marketplace each was investigated from Canada, Germany, France, the Philippines and Thailand, two from Australia, and four from the United Kingdom. For the digital marketplaces, 75% were founded after 2010. In the sample, the oldest digital marketplace was founded in 2005 and the youngest in 2016; the average age of the companies is 6.5 years.

The various sectors of the marketplaces surveyed could be determined via crunchbase.com. In total, the companies analyzed can be assigned to twenty different industries. The three strongest sectors are professional services (31%), education (13%), and hospitality (9%). The number of employees was determined from up to three different sources. The websites angel.co and crunchbase.com indicate the number of employees at intervals, while owler.com indicates a single value. Due to the higher transparency regarding the origin of the data on angel.co and crunchbase.com, these values were preferred and referenced with owler.com values in case of inequality. For this purpose, the centers of the intervals were formed, and the interval selected whose center has the smallest deviation from the number of employees found on owler.com. In general, the personnel situation of start-ups and young companies can be described as very volatile. It became obvious that with 58% most companies have less than 50 employees and only a small share of 12% have more than 200 employees.

Value Creation

82% of platforms promise low prices, low costs, or higher efficiency. 11% have multiple key value propositions. The content of transactions is usually a service (77%) or a product (22%), rarely a combination of both (3%). The exchanged product or service is a digital variant in only 23% of cases. Otherwise, real products or services are traded locally. For most platforms, the key activity is to match different platform participants (community building: 76%). In 69% of platforms, there is a rating system where users can rate other users, whereas 28% do not offer any rating system. 79% of platforms carry out their own user certification, 17% have no certification at all, and only 2% of multi-sided platforms offer certification via an independent seal of quality. Transactions can be initiated either on request (51%), or only from one side (48%). Only one company offered the opportunity for both sides to establish contact. This corresponds in some way to the number of roles a user can take on the platform. 90% of platforms provide a role for users, meaning that a seller cannot be a buyer at the same time without creating another account. Which is why it is not particularly surprising that 99% of transactions are initiated by one party, the buyer. Finally, only 33% of platforms have members with high centrality.

The number of rating systems on platforms is continuously increasing. It is evident that between 2010 and 2012, there will be a large increase in user rating systems as well as ratings from the platform itself. The value of platforms without a rating system is stagnating. A similar picture emerges in the certification options on platforms. Between 2010 and 2013, there is a rapid increase in proprietary user certifications. It is interesting to note that, in contrast to the assessment system, the number of platforms without any type of certification also increased until 2013 and remained largely constant thereafter platforms with certification by an independent seal or several types of certification are rare.

Value Delivery

The majority of platforms focus on one industry (61%), while 39% operate across industries. A relatively balanced picture emerges for the addressed customer segments. Thus 19% exclusively address B2B customers, 16% lead a peer-to-peer platform, 22% trade with several customer segments and 43% operate in the B2C environment. 45% of these markets are regional, 44% global, and 11% local. Looking at this in relation to the customer segments that address globally, regionally, or locally operating companies, it is evident that B2B platforms primarily serve a global customer base, whereas B2C platforms are, in comparison, mainly represented globally and locally. In the B2C and

C2C area, the platforms initially focus on a specific industry, in contrast to the platforms that operate in the B2B or several customer segments where no clear trend can be seen.

Value Capture

62% of platform revenue comes from a commission, 16% from multiple revenue streams, 14% from subscriptions, and 8% from service revenue. 11% of the platform usage fees are based on the market price. 36% set a fixed price, whereas 53% call up differentiated prices for use. In 26% of cases, price differentiation is dependent on the characteristics of the product or service, 21% of platforms set prices based on quantity, and 8% use several criteria to set prices differently. 43% of sales come from buyers, 41% from sellers, 14% from multiple sources, and 2% exclusively from third parties. Revenues are largely generated through commissions across all customer segments. The remaining revenue streams are more or less balanced. Revenues are most frequently generated with buyers and sellers. The low share of revenues via advertisers (third parties) can probably be explained by the target population of the sample. Since the platforms that we analyzed are predominantly start-ups and young companies, they have a supposedly low installed base of users. This is why they are hardly attractive for advertisers due to their small reach. Regardless of the customer segments, buyers are mainly involved in value creation via commissions, while sellers are asked to pay roughly the same amount for all revenue streams. A striking feature here is that a commission prices either buyers or sellers and not several sources of revenue streams. The companies mainly use differentiated pricing for the use of platforms, followed by fixed prices.

4.4.2 Inferential Analysis

Our model shows that Specifications 1, 2, 3, 9, 10 provide highly significant results while Specifications 4–8 very significant results. Here it becomes clear that the explanatory content for Specification 1 is highest with a corrected R^2 of 0.23 (see Table 15). Due to the large size of the results and the partial overlap of the significant factors, the focus at this point should be primarily on specification 1 and the overall uncovered significant factors.

Specification	Included variables	Corrected R^2	F	F-sig
1	All independent variables collected	0.23	6.74	0.000
2	All variables (Business model in the narrower sense)	0.16	7.16	0.000
3	All variables (Business model in the broader sense)	0.16	7.16	0.000
4	Variables of the dimension *Value Creation* (Business model in the narrower sense)	0.09	6.02	0.003
5	Variables of the dimension *Value Creation* (Business model in the broader sense)	0.09	6.02	0.003
6	Variables of the dimension *Value Delivery* (Business model in the narrower sense)	0.07	4.67	0.012
7	Variables of the dimension *Value Capture* (Business model in the narrower sense)	0.10	6.81	0.002
8	Variables of the dimension *Value Capture* (Business model in the broader sense)	0.10	6.81	0.002
9	All variables of the *Network* structure and *Network Behavior*	0.14	6.23	0.001
10	Variables of the *Network* structure	0.11	7.23	0.001
11	*Network Behavior* Variables	-	-	-

Table 15: Coefficients of Determination for Specifications

Table 16 shows that results are significant at the 1% level for *Revenue Source 4* and *Number of Roles 1*, and at the 5% level for *Key Revenue Streams 5, Customer Segments 4,* and *Price Differentiation 3.* All factors except *Key Revenue Streams 5* have a positive influence on the success of the digital marketplace. In addition to the factors uncovered in Specification 1, further effects could be uncovered in the respective specifications. An overview with the highest level of significance in each case can be found in Table 16.

Variable	**Sig**	**β**	**F-Value**	**F-Sig**	**Cor. R^2**	**Tolerance**	**VIF**	**Durbin/ Watson**
Revenue Source 4	.001	.34	6.74	.00	.23	.85	1.17	1.91
Number of Roles 1	.003	.27				.99	1.01	
Key Revenue Streams 5	.020	- .23				.83	1.20	
Customer Segments 4	.044	.18				.99	1.01	
Price Discrimination 3	.044	.18				.96	1.04	

Table 16: Regression with all Factors Dependent on Funding

It is evident that considerably more factors had a significant influence than the regression of all factors on the respective dependent variable shows. This can probably be attributed to the large number of independent variables and the comparatively small number of observations. When a regression of different subgroups of the independent variables is conducted, which contains a smaller number of factors, effects with a smaller strength can also be uncovered (Cohen, 1992). It can also be observed that the dependent variable *Funding* had significantly more factors identified than the regression to *Turnover*. In addition, the regression to *Funding* revealed the only negative influences *(Certification 4, Key Revenue Streams 5).*

Influence	**Funding**	**Influence**	**Turnover**
+*	Centrality of Members 1		
-†	Certification 4		
+*	Customer Segments 4	+*	Customer Segments 4
-*	Key Revenue Streams 5		
+*	Key Value Proposition 4	+**	Key Value Proposition 4
+**	Number of Roles 1	+†	Number of Roles 1
+*	Price Discrimination 3		
+*	Platform Type 3		
+**	Revenue Source 4	+*	Revenue Source 4

† p < .10
* p < .05
** p < .01

Table 17: Identified Significant Variables for Regression to Funding & Turnover

4.5 Discussion

Our first research question focuses on business model factors that influence the success of digital marketplaces. Looking at Specification 1, *Key Value Proposition 4* and *Revenue Source 4* are significant positive influencing factors. This applies to both *Funding* and *Turnover* regression. In the *Funding* regression, *Key Revenue Streams 5* was also identified as a significant factor, but with a negative sign. A closer look at the individual categories reveals a more differentiated picture.

Key Value Proposition 4 and *Centrality of Members 1* proved to be significant with positive coefficients in the regression of *Value Creation* factors to *Funding.* When regressing to *Turnover, Key Value Proposition 4* is also significant with a positive sign. **H1** can thus be supported (see Table 18). In the *Value Delivery* category, a significant positive factor of *Customer Segments 4* and *Platform Type 3* was found in the *Funding* regression. The analysis on *Turnover* showed a significant positive influence of *Customer Segments 4.* Thus, **H2** can be supported. A significant positive effect of *Revenue Source*

4 can be observed here with the regression to *Funding* as well as *Turnover.* In addition, a significant negative effect can be observed with *Key Revenue Streams 5*. Due to the negative effect of *Key Revenue Streams 5,* **H3** cannot be supported.

It can be noted that in regression across all factors, several value propositions as well as several revenue sources have a positive effect on the success of digital marketplaces. These effects are confirmed by the success control variable *Turnover*. In the case of *Funding*, we also identified a negative impact of several revenue streams. The negative direction of the influence is the opposite of the expectation that a positive correlation occurs when several revenue streams exist. Several revenue streams generally lead to more revenue and thus, as defined in our paper, to more success. The individual factors of regression with all variables can be found in the respective partial analyzes. In the *Value Creation* category, the significant positive influence exerted by central members is particularly noteworthy. A positive significant influence of the platform type was also demonstrated in the *Value Delivery* category. It is beneficial if digital marketplaces search for access to the customer both via a website and an app.

Our second research question focuses on factors of network structure and network behavior that have an influence on the success of digital marketplaces. By including all factors, a significant positive correlation between *Number of Roles 1* and *Centrality of Members 1* can be observed. The effect of *Number of Roles 1* is confirmed by the control variable *Turnover*, whereas the influence of *Centrality of Members 1* was only visible in *Funding* regression. In addition, a significant negative effect can be observed with *Certification 4.* This only occurred during regression to *Funding.* The separate analysis of the network structure yielded the same result as the regression with all variables of network structure and behavior in the network. **H4** can therefore be supported. Contrary to what can be assumed from regression with all factors of our second research question**,** no significant relationship could be established with the factors of behavior in the network. Accordingly, **H5** cannot be supported.

The analysis of the network structure and the behavior in the network revealed interesting effects. It is surprising that the factors postulated by Afuah (2013) on network behavior in the sample have no significant positive influence on the success of digital marketplaces. Only a negative effect in the absence of certification of platform users became apparent.

This is therefore a hygiene factor. With regard to the network structure, central members and key partners as well as the possibility for users to take on several roles have a positive influence on the success of digital marketplaces.

Overall, some significant correlations could be observed. The factors presented in Table 18 can be cited as probable determinants of success. The assumed positive influence of the determinants from the *Value Creation* category (**H1**) and the *Value Delivery* category (**H2**) was supported. **H3**, i.e., the influence of the *Value Capture* factors, could only be partially supported. Although several revenue sources had a positive impact, several revenue streams had a negative impact on success. In contrast, the positive influence of the *Network Structure* (**H4**) was supported. In contrast, no significant positive effects could be detected in the factors of *Network Behavior* (**H5**). Only a negative influence can be observed in the absence of provider certification.

	Influence	Factor	Impact on the Success of Digital Marketplaces	Influence	Factor	Impact on the Success of Digital Marketplaces
	Funding			*Turnover*		
Q1						
H1	+	Centrality of Members 1	Central members have a positive effect			
H1	+	Key Value Proposition 4	Offering multiple value propositions has a positive impact	+	Key Value Proposition 4	Offering multiple value propositions has a positive impact
H2	+	Customer Segments 4	Addressing B2C & B2B customers has a positive effect	+	Customer Segments 4	Addressing B2C & B2B customers has a positive effect
H2	+	Platform Type 3	If PF makes its value proposition accessible via Web & App, this has a positive effect			
H3	-	Key Revenue Streams 5	Several key revenue streams have a negative impact			
H3	+	Price Discrimination 5	Volume-based price differentiation has a positive effect			
H3	+	Revenue Source 4	Several revenue sources have a positive impact	+	Revenue Source 4	Several revenue sources have a positive impact
Q2						
H4	+	Number of Roles 1	If users can take on several roles, this has a positive effect	+	Number of Roles 1	If users can take on several roles, this has a positive effect
H5	-	Certification 4	A lack of certification has a negative effect			

Table 18: Significant Influencing Factors of the Research Questions

4.6 Implications for Research

By revealing several determinants of success, this paper contributes to a better understanding of platforms and digital marketplaces (McIntyre & Subramaniam, 2009). Previous work has mainly dealt with strategies and less with the development of platforms by selecting strategically important factors. Furthermore, these studies were mostly of qualitative nature or based on simulations. To the best of our knowledge, this paper is the first to examine these factors. The morphological box for this area of application, which was tested in accordance with Täuscher and Laudien (2018), could be examined. Future work could examine the results using a different or larger sample. In particular, a more targeted analysis of the categories using a larger sample could also reveal weaker effects and improve the quality of the model. Future studies could also analyze the difference between different industries, customer segments, or platform types in order to gain a deeper insight into the functioning and dynamics of platforms. An integration of the neglected factors or the establishment of a dynamic model also offer possible starting points.

4.7 Limitations

Although the sample size surveyed is suitable for detecting strong effect sizes, unlikely to detect small to medium effects depending on the number of regressed independent variables. This can lead to important factors not being included in the model. To counteract this, variable groups were formed in the various hypotheses and these were analyzed independently of each other. As far as the model is concerned, the question remains of whether funding and sales are actually suitable for measuring the success of digital marketplaces. Against the background of the availability of the data, hardly any alternatives worth mentioning were possible. A qualitative analysis based on expert interviews could provide insights into other relevant key figures. Furthermore, the model is static and thus does not meet the demand for a dynamic model. In addition, the model largely ignores the group of third-party complementors. According to McIntyre and Srinivasan (2017), however, these have a significant influence on indirect network effects. Third-party complementarity thus provides a fruitful area for future research.

5. Conclusion

In my dissertation, I investigated which characteristics of platforms and factors of a business model platform providers can use in the strategic orientation of their platform to improve its market position (Research Question 1), and the influence of platforms on coopetition as well as their impact on network formation (Research Question 2) in regulated markets, such as the financial market. I meshed together insights from the research areas on digital platforms (Gawer & Cusumano, 2002; Evans, 2003; Constantinides et al., 2018), coopetition (Dowling et al., 1996; Nalebuff & Brandenburger, 1997; Bengtsson & Kock, 2000; Bouncken et al., 2015), and business model (Amit & Zott, 2001; Osterwalder & Pigneur, 2010; Teece, 2010) research to address my overall research questions. By meshing the different research areas together, I aimed to contribute to a better understanding of market and competitive structures in platform markets.

In the three papers of my dissertation, I addressed more specific research questions to provide detailed insights into platform markets. In this chapter, I present the findings of my research as well as their overall contribution. In Section 5.1, I summarize the main findings of my three papers and their contribution to answering my overarching research questions. Section 5.2 highlights the contributions of my findings to literature on platform and on coopetition research. I then address my dissertation's practical implications for policy makers and managers in Section 5.3. In Section 5.4, I provide an overview of the limitations of my thesis. Finally, I conclude my dissertation in Section 5.5.

5.1 Summary of Main Findings

My research contributes to the understanding of digital platforms and their impact on market structures, especially in financial markets. In my first research question, I considered how platform providers in financial markets can improve the strategic alignment of their platform in order to strengthen their market position. I addressed this research question mainly in my first and third paper. In my second paper, I addressed my second research question, which focuses on investigating whether platforms impact coopetition in highly regulated markets, such as the financial market, and how platforms impact network formation in these industries.

In **Paper 1**, I built on platform theory and connected this new research area with established research areas such as switching costs and lock-in effects and explored how platform characteristics favor platform size and have an impact on platform value on payment platforms. Based on an analysis of the existing literature, I developed a platform-based competitive analysis framework to examine the impact of platform size on the value of payment platforms. My study draws on secondary data from 2018/2019 among 56 banks, 179 fintechs, and 11 technology companies in the German, US, and Chinese financial markets.
The results of my case study analysis provide an explorative analysis of the different platform characteristics on platform size and platform value of payment platforms in the three different financial markets. The characteristics studied in my research show that payment platforms are active in multisided markets that follow the competitive logics of winner-takes-all markets, where competitive advantages are created by building scale fast (Cennamo, 2019). The opening of a payment platform and the associated ecosystem at the end-user network can be used to increase the number of users of the end-user network. This can be achieved by the platform provider allowing new users to access its payment platform through multibanking and also expanding the openness of the payment platform in the complementary network so that the number of additional complements in the form of financial products or services on the payment platform grows. Further, direct network effects can be strengthened with P2P interactions. This process results in reinforcing network effects on the payment platform (Rochet & Tirole, 2003). Payment platform providers use switching costs to keep their users as well as their complementors on the payment platform. Lock-in effects on payment platforms are created by combining switching costs, direct and indirect network effects as well as the knowledge attained about the user through data analytics. Especially banks and technology companies use lock-in effects on their payment platform to support network dynamics and to secure the already installed base of the payment platform, which is important for the further growth of platform size. The competitive dynamics in payment platform markets, as with other

platform markets in two-sided markets, result primarily from network effects. If a payment platform generates direct as well as indirect network effects, the chances of reaching critical mass on payment platforms increases. When a payment platform reaches critical mass, there is a positive feedback loop for users and complementors on the payment platform. The competitive dynamics in the payment market imply that the payment platform with the largest network has the highest chance of gaining market share and will dominate the payment market. My research results show that the payment platforms of banks as well as the payment platforms of technology companies have the most potential to do so. Banks and technology companies have a clear competitive advantage over fintechs because they have more user data at their disposal and can collect and make greater use of user data in a more targeted manner. Furthermore, they also have a great advantage in the build-up process because they already have existing customers or users who migrate to the platform right from the start and thus reach a critical mass more easily. The characteristics of fintech payment platforms make it difficult to build large ecosystems around the platform and thus to achieve a central market position. Finally, payment platforms change the market and competitive structures in financial markets by focusing the corporate strategy significantly on the growth of the payment platform and the expansion of the platform ecosystem.

In **Paper 2**, we investigated the influence of digital platforms and other important factors on cooperation activities between competitors in the German financial market. We examined external drivers, relation-specific drivers, form of coopetition, and endogenous network effects as drivers of coopetition. To test the developed hypotheses, we drew on secondary data from 2020 among 371 companies in the German financial sector. Our results from a social network analysis indicate that companies that apply a platform technology in their business model are more likely to engage in collaborative activities with their competitors. Moreover, a company is more likely to enter into cooperation activities with another company if both companies use a digital platform. Thus, our results show that coopetition is strengthened by the influence of digital platforms. Increasing coopetition creates an industry-specific network around a platform in financial markets, which greatly increases the value of a platform. Our results indicate that platforms represent central nodes for the creation of a network on the German financial market and are external drivers of coopetition. Another important external driver for coopetition emerging from our research is the banking license. Financial markets are regulated markets, therefore companies offering their products and services on the financial market must hold a banking license. We found that access to a banking license is an important driver for cooperation between competitors in the financial market; however, our results show that companies that both possess a banking license are less likely to engage in coopetition activities. Thus, the effect of a banking license has both a positive and a negative effect on coopetition. The banking license can be seen as a high barrier to market entry for new competitors on the financial market and protection from new competitors for the established financial service providers from new competitors. Our results on external drivers provide evidence that regulation in regulated markets continues to play a decisive role even under the influence of platforms (Steinhauser, 2019). Moreover, our study shows the multilevel nature of the financial markets' network. We extend research on relation-specific drivers of coopetition in financial markets as we found that companies are more likely to cooperate with competitors from a different type of company and that the difference in degree centrality is a relation-specific driver of coopetition in financial markets. We also provide new insights into forms of coopetition in the German financial market as we show that companies that have a cooperative relationship with a competitor in the form of a strategic alliance, shares, or a supplier relationship are more likely to enter into coopetition ties. To summarize, our findings contribute to the literature on a better differentiation between platform networks and platform ecosystems and offer new insights on coopetition in the platform economy.

In **Paper 3**, we identified possible success factors of multi-sided platforms. We developed a codebook based on the literature of network effects, platforms, and business models to support our quantitative document analysis. To test the developed hypotheses, we drew on data from the database angle.co with a sample size of 100 randomly selected platforms that meet the criteria on platforms and digital marketplaces and whose data were fully available. The results from our multiple linear regression models indicate that the presence of key partners on the platform has a positive impact on the success of a digital platform. If a company manages to motivate its key business partners to participate on the platform, the platform ecosystem can be expanded. In addition, our results show that companies that manage to offer multiple value propositions for their users on the digital platform can increase the chances of success for their platform. If the platform provider enables access to the value proposition of the digital platform via a website as well as via an app, this shows a positive influence on the success of the platform. Moreover, companies can increase the chances of success of their platform by expanding their target groups through an offer on the platform that is aimed at both B2B and B2C customers. In addition, our research results show that it is beneficial for platform providers to generate multiple revenue streams on their platform. With respect to the network structure of the platform, our results suggest that network effects and thus the network structure can be increased by allowing platform users to take on several roles on the platform. Our research found that the business model dimensions *value creation* and *value delivery* as well as the *network structure* factors are crucial for the success of a platform and should be considered by platform providers when aligning the platform strategy. By revealing several determinants of success, our research provides further insights on how the structure as well as the alignment of a business model can positively influence the success of digital platforms and thus strengthen the competitive position in platform markets.

In the Table 19 below, I summarize the key findings of my three papers.

Main Findings		
Paper 1	**Paper 2**	**Paper 3**
Research Question 1	***Research Question 2***	***Research Question 1***
Payment platforms open up their platform ecosystem by enabling **multibanking** and **P2P** transactions. This in turn strengthens network externalities and increases payment platform scale.	Companies that operate a platform are more likely to engage in **collaborative activities** with their **competitors**.	Presence of **key business partners** and **multiple value propositions** are identified as success factors for platform-based business models.
Banks and technology companies have a **competitive advantage** over fintechs. They collect large **amounts of data** and already have an existing **user base** from previous activities, which makes it easier to reach critical mass.	Digital platforms and banking licenses are **external drivers** for coopetition in the financial markets.	Access to the value proposition of the digital platform via **web** as well as via **app** are identified as success factors for platform-based business models.
In addition to switching costs and network effects, **user data** is a central component of lock-in effects for payment platforms.	**Relation-specific drivers** of coopetition in financial markets are **different types of company** and **difference in degree centrality.**	Addressing **B2B** and **B2C** customers and **several revenue sources** are identified as success factors for platform-based business models.
Payment platforms follow the **competitive logics** of **winner-takes-all** markets.	Platforms influence **network development** and **create networks of collaboration** in financial markets.	The **network structure** factors of a business model are crucial to the success of the digital platform.

Table 19: Summary of Main Findings of the Three Papers

5.2 Implications for Research

The findings of my cumulative dissertation contribute to research on digital platforms and their influence on market and competitive structures. To this end, I meshed the research area of digital platforms with business model research and the research areas of coopetition.

5.2.1 Contributions to Research on Digital Platforms

Digital platforms are the central object of investigation in my dissertation. In my three papers, in which I examined platforms from different perspectives, I make important contributions to the research on digital platforms.

In my first paper, I examined core concepts of digital platforms. With the results of my research, I show that the degree of openness of platforms makes a central contribution to the development of the end-user network as well as the complementor network. My work extends the research of Ondrus et al. (2015) on the impact of openness on the market potential of digital platfroms. I show that the option of multibanking on payment platforms as well as the use of P2P payments has a positive influence on the degree of openness of payment platforms as they increase direct and indirect network effects and thus strengthen the end-user network on the platform. In addition, my findings imply that having multiple access points to the platform's value proposition has a positive impact on the platform's success. I further provide evidence that regulation in the form of laws such as the PSD2 regulation also has an impact on the degree of openness of platforms on the provider side. Here, my findings suggest initial successes in Europe's efforts to regulate competitive conditions on platform markets, such as the financial market. My research reveals that the issue of data on platforms and for platform providers is increasingly taking on a central role. Feedback effects on payment platforms are becoming increasingly important for the development of financial products and services. User feedback data is important data for the future product development of financial products and services. I further reveal that the issue of data that can be collected on platforms is increasingly taking on a central role for platform providers. Thus, feedback effects will become increasingly important on payment platforms for the development of automated and self-learning financial products and services in the future (Mayer-Schönberger & Ramge, 2018). The earlier payment platform providers collect user data in a targeted manner and use it as an essential key to product development—and improvement, the better self-learning systems can be trained and sustainable competitive advantages created (Ramge, 2020). My research results further provide new insights into the already established research area of switching costs (von Weizsäcker, 1984; Klemperer, 1987a, 1995; Jones et al., 2002). In my study, I investigated switching costs on digital payment platforms and found that platform providers can use switching costs to keep platform users on the platform as well as in their platform ecosystem. Switching costs can be built up in platform markets, especially through user data and the resulting knowledge about users. The large platform companies in particular manage to build up high switching costs for their users by linking hardware products with software products. Hence, switching costs are important platform characteristics for stopping users from leaving the platform and for strengthening network effects on the platform, which in turn are central to the success of a platform. Switching costs thus continue to be important strategic tools for companies in digital markets. I further implied that switching costs in platform markets are closely related to lock-in effects. Here, I make a significant contribution to the existing literature on lock-in effects (Arthur, 1989; Farrell & Klemperer, 2007) by showing that in contrast to previous literature, lock-in effects on platforms were composed of switching costs, network effects, and user data. Previous research had only identified switching costs and network effects as components of a lock-in effect in digital markets (Witt, 1997; Porter et al., 2001; Farrell & Klemperer, 2007). However, my research results indicate that data and the knowledge resulting from data are another important component for the emergence of lock-in effects on platforms. User data enables platforms to identify customer needs and preferences and to tailor their products to these needs. In the era of self-learning systems that are integrated into digital platforms, data becomes even more important. User data creates feedback effects on digital platforms, and they in turn enable self-learning systems to continuously improve and adapt the products in the entire platform ecosystem as well as the platform itself. In summary, I contribute to the research on digital platforms by providing insights on which characteristics platforms in financial markets exhibit and how these affect platforms.

In addition to platform characteristics, I provide new insights on the research streams of platform ecosystems and platform networks in my second paper. While the literature to date has focused on the formation of platform ecosystems, my findings contribute to a better understanding of the formation of platform networks. Moreover, previous literature on digital platforms does not distinguish consistently between platform ecosystems and platform networks, or only explain differences between them (Shipilov & Gawer, 2019). In my research, I suggested that it is not only necessary to distinguish between the two terms and to explain the differences, but also to show how platform networks emerge around platforms. I described how platform ecosystems are connections between organizations that are not strictly hierarchically organized, whereas platform networks are. Further, I showed that the connections in platform networks emerge primarily through partnerships among organizations, such as a strategic alliance. I visualized the network of the German financial market and that platforms have a significant impact on the formation of network structures in platform markets. As companies enter into collaborations, new connections emerge within the network and the platform networks continuously evolve. It is increasingly important for firms in platform markets to become part of the network and to achieve a central position in the network. In particular, companies that do not use an open platform ecosystem should actively build their network structure; otherwise, no network can be established around the platform. Platform providers that use an open ecosystem, on the other hand, are less dependent on actively recruiting network participants. Open platforms allow different participants to participate and join the platform ecosystem through e.g., open standards. Nevertheless, building a platform network can also be useful for platforms with an open platform ecosystem as it allows platform providers to build network connections and partnerships specifically with strategically important partners. Summarizing, my research results on platform ecosystems and platform networks provide insights on how companies operating a platform manage to carve out a central position in their industry networks.

In my third paper, I linked the research areas on digital platforms and business models. With the findings from this paper, I provide new insights into the development of business models on digital platforms as well as in digital markets. In contrast to previous work, which has mainly focused on platform strategies and less on the development of platforms through the selection of strategically important factors, I contribute to a better understanding of success factors of digital platforms. I pointed out that business models built on platforms have higher chances of success if they offer multiple value propositions on the platform. In addition, my results imply that the chances of success are also increased by targeting the platform more broadly to B2B and B2C customers. Thus, my results show that business model factors from the value creation category as well as from the delivery category can be determinants of success on platforms. In addition, the integration of multiple revenue sources on the platform proves to be a success factor on platforms in my study. Accordingly, the delivery category proves to be another determinant of success on platforms. In conclusion, my research on success factors on digital platforms contributes to a better understanding of business models of platforms and shows how the different business model dimensions affect platforms.

5.2.2 Contributions to Research on Coopetition

Aside from contributing to research on digital platforms, I also make important contributions to the reseach field of coopetition. In Paper 2, I contribute to coopetition research by analyzing the influence of digital platforms on the formation of coopetition ties. I showed that companies that use a platform technology in their business model are more willing to collaborate with their competitors. Moreover, my research results indicate that coopetition is strengthened by platforms and that companies in platform markets are more likely to come under pressure to cooperate with direct competitors. I explained that coopetition can have a positive impact on increasing the attractiveness of platforms for their users, as the value of the platform is increased through cooperations with strategic partners. I applied a social network analysis illustrating coopetition connections in the German financial market to demonstrate that platforms are external drivers for coopetition. In doing so, I showed that technologies such as AI and blockchain, on the other hand, have no impact on the emergence of coopetition connections. Thus, the influence of technologies does not have a significant impact on coopetition per se, and digital platforms occupy a unique position. Moreover, I showed that regulation has a high impact on market structures in regulated markets. I suggested in my research that the banking license, which turns out to be an entry requirement for financial markets, is an external driver of coopetition. I argued that firms that already have a banking license and have thus overcome market entry barriers are unlikely to establish coopetition ties. Hereby, I reinforced the existing literature on the influence of strategic resources as a key motivator for coopetiton formation (Gnyawali & Ryan Charleton, 2018). Furthermore, I make a significant contribution to a better understanding of relation-specific drivers of coopetition. First, I showed that companies are more likely to cooperate with competitors from a different type of company. This is further evidence that companies practicing coopetition choose cooperation partners that bring complementary resources. Second, I described how position in the network is also a key relation-specific driver in platform markets. Thus, firms with differences in degree centrality are more likely to form coopetition relationships. I further argued that centralized firms with a large number of connections are more likely to form ties with decentralized firms with few connections and vice versa. Third, my study proves that the mismatch of type of company and the difference in degree centrality are relation-specific drivers of coopetition in platform markets. I further contributed to research on coopetition by examining the impact of formal partnerships on coopetition. Here, I found that firms that have a cooperative relationship with a competitor in the form of a strategic alliance, shares, or a supplier relationship are more likely to enter into coopetition relationships in platform markets. In addition, it became apparent that companies that have already entered into a partnership with a competitor are likely to cooperate with that partner in other areas as well. My findings indicate that the already existing ties in the network are becoming increasingly stronger. In summary, my research results contribute significant new insights into coopetition in the platform economy and show which factors influence network development in platform markets.

5.3 Implications for Practice

In addition to theoretical implications, the results of my dissertation also provide important implications for practice. The practical implications are addressed to policy makers who regulate platform markets as well as to managers who build or operate digital platforms.

5.3.1 Implications for Policy Makers

The insights of my three papers provide important implications for policy makers. While the results from Paper 1 and Paper 3 primarily answer the question of what characteristics of platforms and platform ecosystems as well as factors of a business model platform provider can be used in the strategic orientation of their platform to advance the market position of their platform and thus address managers at first glance, important insights for policy makers can also be derived from the research. These insights are important for policy makers as they show how different regulations on market and competition regulation affect platform providers in financial markets. In Paper 2, my results support the claim that regulation in regulated markets remains a key driver of market and competition structures even under the influence of digital platforms. Thus, legislation continues to have a major impact on market and competitive structures in these regulated markets. My results show that the bank license is a very important external driver of coopetition in highly regulated financial markets, thus the banking license has a crucial influence on network formation in financial markets.

The considerations regarding the regulation of platform markets are highly relevant and cross-sectoral. In the context of my work, I dealt in particular with the financial market as a regulated market. In recent years, two central guidelines for market and competition structures have come into force that serve to regulate competitive structures as well as to protect consumers in general. The Payment Services Directive 2 (PSD2)[12] is an EU directive for the regulation of payment services and payment service providers, especially on digital payment platforms, whose goals are to increase security in payment transactions, to strengthen consumer protection, to promote innovation, and to increase competition in the market (Bundesbank, 2019). The General Data Protection Regulation

[12] Directive (EU) 2015/2366 of the European parliament and of the council of 25 November 2015 on payment services in the internal market, amending Directives 2002/65/EC, 2009/110/EC and 2013/36/EU and Regulation (EU) No 1093/2010, and repealing Directive 2007/64/EC, Official Journal of the European Union L 337/35.

(GDPR)[13], in turn, is an EU regulation that unifies the rules for the processing of personal data by private and public data processors in the EU. The GDPR is intended to ensure the protection of personal data within the European Union and to guarantee the free movement of data within the European Single Market. Unlike the PSD2 directive, the GDPR is aimed at all markets, not just the financial market. The PSD2 regulation directly affects platform providers in financial markets. This regulation obliges platform providers to provide competitors with interfaces to their platform. The intention of this directive is to promote innovation as well as competitive opportunities. Thus, the providers of financial platforms open up to competitors. However, my research results show that this directive only contributes to a small extent to improving competitive opportunities. As part of my research, I studied the general data protection regulations of all investigated financial service providers in Europe. Here, it is evident that banks, fintechs, and technology companies collect personal data, transaction data, lifestyle data, and user behavior data. It also shows that there are significant differences between the financial service providers. Data is the basic prerequisite for the application of self-learning systems, as self-learning systems are trained and improved by data. As self-learning systems become more widespread in platform markets, and in my study specifically in financial markets, data is taking on an increasing importance for financial service providers. From my results, it is evident that technology companies as well as banks hold the most data about their users and use sophisticated systems to extract more user data. This poses the risk of unfair competition since the financial service providers that hold and collect the most data can offer the best financial products and services tailored to their users. Thus, information asymmetries can be built and competitive advantages achieved. This process is then reflected on the digital platforms. The platform providers that collect and analyze the most data can offer the best financial products to their users and also design the platform itself in such a way that is optimal for their users. This makes the

[13] Regulation (EU) 2016/679 of the European parliament and of the council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation), Official Journal of the European Union L 119/1.

platform more attractive for users, which in turn attracts more users to the platform and sets network externalities in motion. My research results suggest that the financial service providers who have the most data can also develop their platform and further expand their market position. Thus, barriers to market entry are getting higher, and the competitive opportunities for competitors who own and collect less data are weakening. Data is the driving force for platform providers to further expand their platform and to achieve a monopoly position. My results show that neither the PSD2 regulation nor the GDPR counteract these mechanisms. Policy makers are called upon to develop measures to counteract the increasingly unequal competitive opportunities between different financial service providers in platform markets. Especially with regard to data collection and the resulting unequal competitive opportunities for different market participants, policy makers should counteract these inequalities with new regulations. In contrast to the GDPR directive, policy makers should take a more differentiated approach in a new directive and distinguish between the types of companies. The GDPR directive addresses the dog breeding club as well as large technology companies such as Google, Amazon, or Apple. New regulations should differentiate more here and target the large and powerful technology companies more precisely.

In my study, I further provided insights into the prevailing competitive structures of the German financial market. Here I showed that coopetition takes place and is promoted by regulation. My results show that the banking license is an external driver of coopetition ties in financial markets. Coopetition mainly takes place between unequal direct competitors, i.e., technology companies with banks, banks with fintechs, or fintechs with technology companies. However, my findings indicate that banks do not enter into coopetition ties with each other. It can therefore be assumed that this is due to non-complementary resources, which also reinforces the central role of the banking license as an external driver of coopetition in financial markets. However, if technology companies succeed in penetrating the financial market in the future and further expanding their market position and market power, banks could also begin to cooperate with other banks in order to pool their resources. From a regulatory perspective, these trends should be monitored, as competitive conditions could be weakened and the competitive dynamics of winner-take-all markets could be strengthened. My results emphasize that regulation has far-reaching effects on competition in platform markets. Policy makers planning new regulations should strongly consider the impact of regulations on network formation in platform markets, as networks in platform markets have an important impact on market structures. In addition, policy makers should reconsider access to a banking license. On the one hand, easy access to a banking license, through cooperations, enables an opportunity-oriented and innovation-friendly environment for fintechs. On the other hand, however, this environment also allows dominant platform companies easy and fast access to the market and enables them to rapidly build market power. This is where policy makers could readjust and differentiate between different competitors to regulate market power and competitive opportunities.

In summary, the results of my research enrich the current discussions in academic and policy bodies about the danger of changing market and competitive structures in which a few platforms develop a monopoly-like position and a strong market power, and are thus highly topical for policy makers.

5.3.2 Implications for Managers

My thesis offers significant recommendations to managers of companies or organizations active in platform markets, especially in financial markets. My recommendations are focused on companies operating or building their own platform as well as on companies rethinking their strategic positioning in competitive and market structures in platform markets. Platform providers in financial markets should focus on the value generation of the platform when building their financial platform. Value generation arises in particular from positive network externalities. Thus, the financial platform should be open and designed for a large target group. Multibanking or P2P payments can strengthen growth on the customer side. The build-up of switching costs and lock-in effects helps platform providers to keep users on the platform for the long term. The complementor network should be built based on two strategic considerations. The platform ecosystem should also be as open as possible on the complementor side through APIs, so that complementors have easy access to platform users and expand the portfolio of financial products and services. However, an open platform ecosystem in the European financial market is not yet sufficient for generating competitive advantages. The European PSD2 guidelines preempt platform providers from granting access to the platform to additional providers on the financial market. My findings show that platform providers should plan and target the ecosystem and network arround the platform in addition to the actual platform. By building strategic partnerships, the platform's network can be further developed in a targeted manner and new resources can be integrated into the platform. Therefore, based on my findings, I recommend that platform providers should strategically plan their platform network by specifically searching for suitable strategic partners. Strategic partners should extend the network around the platform with complementary resources to increase the reach and attractiveness of the platform. The platform ecosystem, in turn, can be built in a less targeted manner. Here, platform providers should build open platform structures, make access easy for their target groups, and encourage participation in the platform ecosystem. Moreover, my results indicate that participation on platforms can be increased if platform users can flexibly change sides on the platform. Accordingly, platform providers should consider the change of different roles on the platform in strategic planning.

The idea of networking in platform-based business models is crucial. Managers are increasingly being asked to think across organizational boundaries. Digital platforms are increasingly giving rise to collaborations between companies in the financial sector in order to further expand platform ecosystems and platform networks. In this way, companies can continuously increase the product and service portfolio of their platform and thus make it more attractive for users. At the same time, financial service providers can also offer their products and services as third-party providers on additional platforms to further expand their reach. Furthermore, cooperation with direct competitors, coopetition, is becoming increasingly important. Whereas in the past financial service providers were mainly concerned with themselves, digital platforms are driving financial service providers to cooperate with each other. Platform managers should encourage their employees to look beyond the classic fields of activity for new cooperation partners in other areas in order to further expand their network. In addition, a rethinking process should be initiated at established companies that operate a platform as the previous business model often has to be adapted on platform markets and business processes have to be thought of differently.

Furthermore, I raised awareness of the threat of new competitors as it can be observed that the major platform companies are continuously entering new markets and business areas as well as further expanding their market position. Since 2018, Google, Apple, Amazon, and Samsung have been active in the German financial market. The financial market is a regulated market, which is why companies that want to offer financial products or services must meet strict requirements and have a banking license. However, the major technology companies have partially circumvented these requirements by entering into collaborations with financial service providers that hold a banking license. The technology companies are putting a lot of pressure on the established banks. My results indicate that incumbents in financial markets can only maintain their market position if they independently build large platforms as well as platform networks and pool resources with each other. Technology companies use the payments market to gain a foothold in financial markets. However, market entry into other financial segments such as financing, in particular consumer finance, can be assumed to be the next obvious step. Thus, technology companies will enter further market segments in financial markets and expand their market shares. Therefore, I recommend managers who operate a platform for banks and fintechs to further expand their partner network and join forces to be able to stand up to the big technology companies. Once the technology companies have established themselves in the various segments, it will become increasingly difficult for the established market participants to secure market shares.

My findings provide important insights and implications for academia, policy makers, and managers of organizations. However, my thesis is not without limitations. The limitations of my thesis will be described in the following section.

5.4 Limitations

The three studies embedded in my thesis and, consequently, the findings of my thesis are subject to several limitations. These limitations mainly result from the scope I defined for my the thesis, the different research approaches I followed, as well as from the different cases and data sources I selected.

In my dissertation, I primarily chose financial markets as my empirical setting in order to support my research questions. Financial markets are highly regulated markets worldwide, which makes these markets very complex and poses specific challenges. In Paper 1, I examined the German, the US, and the Chinese financial markets, while Paper 2 focuses exclusively on the German financial market. The results of my studies are thus limited to a regulated sector, which limits the generalizability of my findings to other markets. Therefore, in order to validate my findings, further research should be conducted in additional, less strictly regulated markets. I studied platforms in financial markets both at the microeconomic level and at the macroeconomic level. Nevertheless, the holistic picture of the impact of platforms on market and competitive structures remains limited. The motivation to analyze the impact of platforms on market and competitive structures on different markets in a holistic way therefore remains and offers further interesting areas for future research to increase the external validity by conducting additional studies to extend and further develop my findings in other markets such as the insurance or real estate markets.

In **Paper 1**, I applied a qualitative research approach by using multiple case studies. By applying case studies, I gained numerous detailed new insights into payment platforms. However, the case studies approach has limitations. In total, I analyzed 92 payment platforms in detail; however, the sample size of my study is too small to generalize my findings. Therefore, I recommend that future studies extend my qualitative study with a quantitative approach with larger samples to increase the generalizability of the results. Furthermore, by focusing on the strategic dimension of platform size in winner-takes-all markets, my study has limitations in the platform-based competitive analysis framework in payment markets. Future studies should include the influencing factors *platform architecture* and *platform scope* and the resulting strategic dimension *platform identity* in their analysis in order to be able to perform a holistic competitive analysis in payment platform markets.

In **Paper 2**, we applied a social network analysis. However, the social network analysis we applied only provides a visualization of the network at one specific point in time. For this reason, we could not observe how the network and the different network actors change over time and how new entrants or new regulations affect the network. Therefore, it would be both compelling and enlightening if future studies were to examine and visualize the changes over time to identify other factors influencing the formation of networks in platform markets. Another limitation results from our quantitative research method. As a result, we only considered quantitative characteristics of network relationships and lack qualitative insights. Future studies could build on our findings and shed light on our research questions using a qualitative research approach in order to gain qualitative insights into coopetition in platform markets. As explained earlier, our research was conducted in the German financial market, which is a highly regulated market where, as our results show, regulation has a strong influence on the formation of coopetition ties. Thus, our results on the formation of coopetition ties and the resulting network are not generalizable to all platform markets. Another limitation results from our research setting. We limited our study to one country, so we could not assess to what extent the results are representative for other countries. Future studies could replicate our study in other empirical contexts to gain further insights from other markets and to validate our findings.

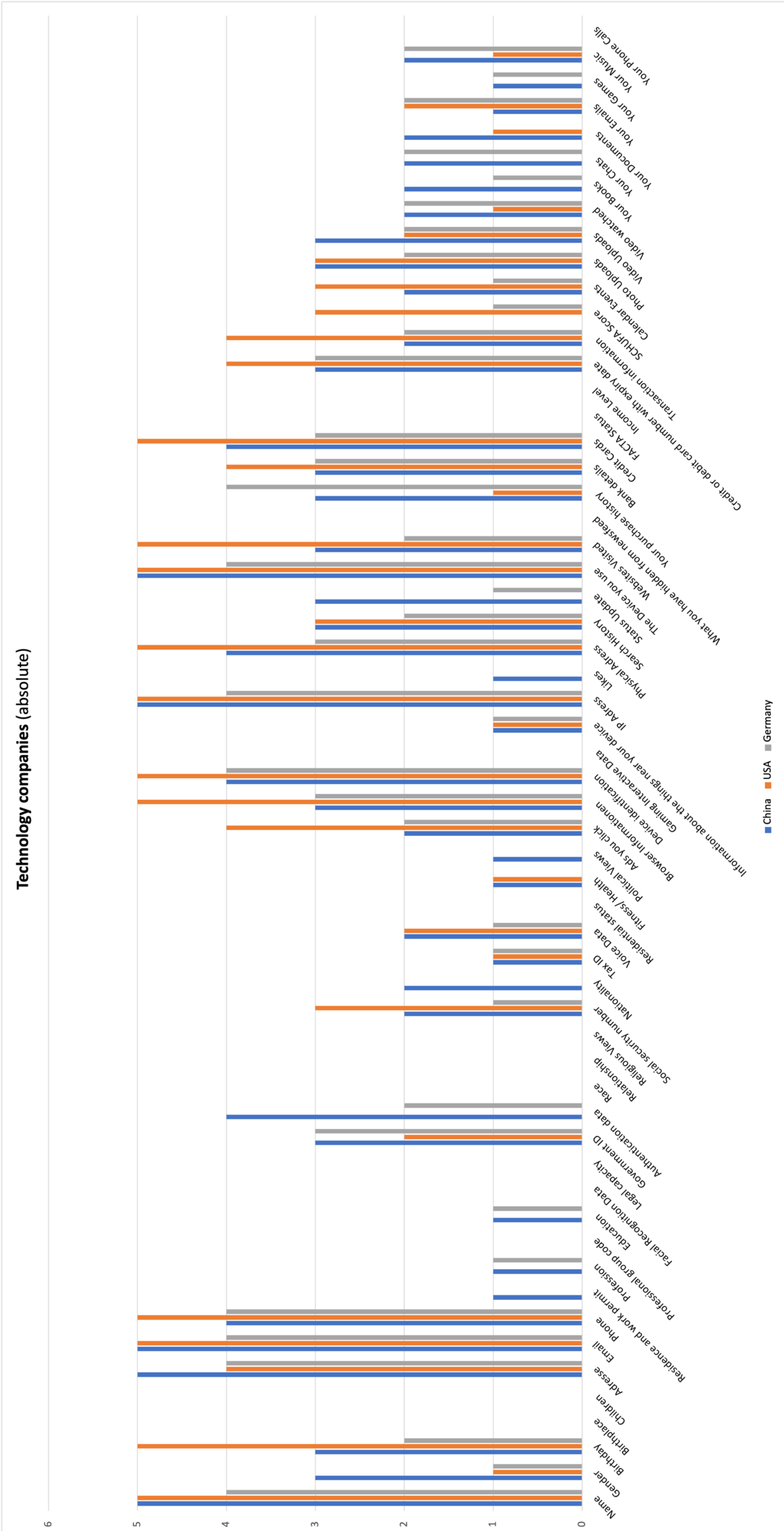
In **Paper 3**, we developed a morphological box and applied a multiple linear regression model. Limitations arise from our sample size. We only studied 100 platforms in B2C as well as B2B markets, which limits the generalizability of our results. Future research could increase the sample size and consider B2C and B2B markets separately to validate the results and identify potential differences between platform business models in B2B and B2C markets. Further qualitative studies based on expert interviews could be conducted in the future to provide further insights into other undiscovered relevant key figures. An additional limitation that could be addressed in future studies is the lack of analysis of the impact of third-party complementors on the platforms studied. According to McIntyre and Srinivasan (2017) third-party complementors have a significant impact on network externalities on platforms, thus providing an important area for future research.

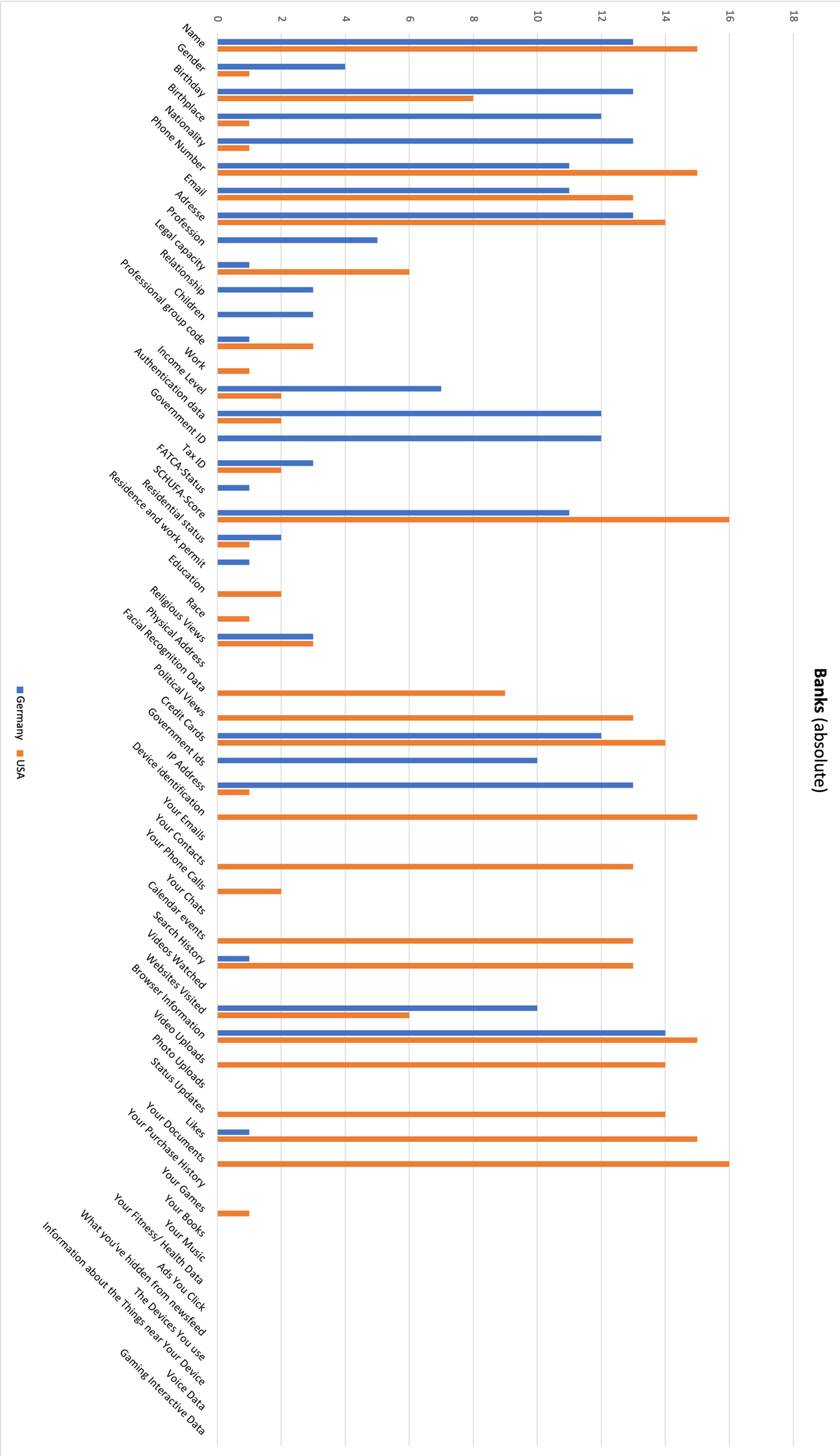
5.5 Concluding Remarks

Today, digital platforms are present in many industries, creating new markets and strongly transforming already existing markets. Digital platforms have also become a major research stream in recent years, especially in the management and IS literature. Nevertheless, platforms and their impact on the already existing market structures continue to raise many questions and remain a highly relevant and important field of research for our society today. With my dissertation, I contributed to a better understanding of digital platforms and networks and their impact on market structures. In particular, I provided important theoretical and practical insights for financial markets.

I meshed together the research areas of digital platforms, coopetition, and business model research and conducted three studies with different focus and research methods. Here, I contributed significantly to a profound understanding of how characteristics of platforms and platform networks as well as factors in the business model can be used by platform providers in the strategic orientation of their platform to improve the market position of their platform. I made another significant contribution to the research field on digital platforms by showing how platforms affect coopetition in highly regulated markets and how platforms affect network formation. My findings provided particularly valuable insights related to platforms in financial markets and contributed to new insights into the research fields on digital platforms and coopetition. My research demonstrated how digital platforms transform market and competitive structures and thus offer important implications for policy makers, managers, and platform providers.

Appendix: Data Collection of Financial Service Provider in Paper 1

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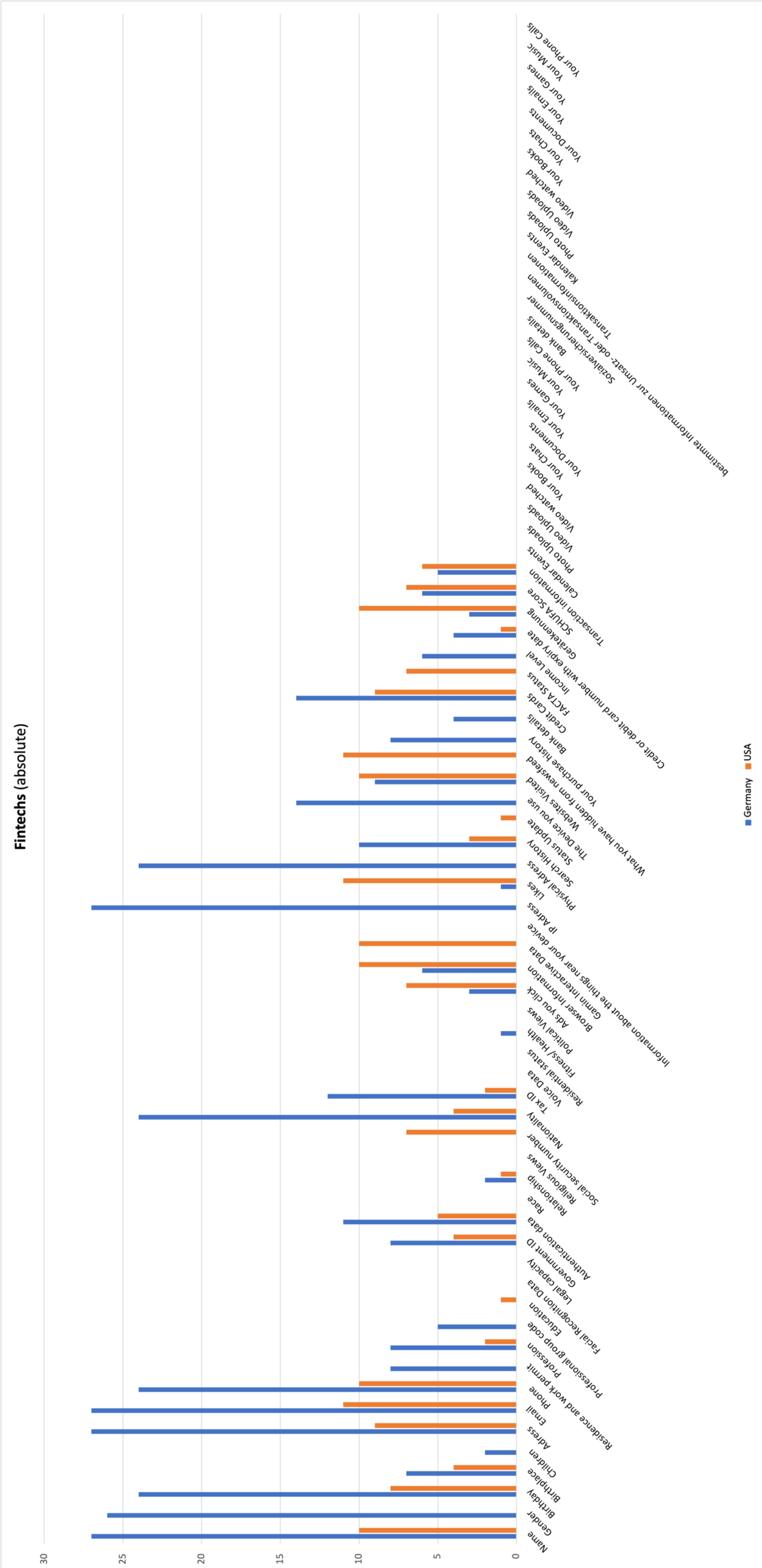
Legal capacity
Relationship
Children
Professional group code
Work
Income Level
Authentication data
Government ID
Tax ID
FATCA-Status
SCHUFA-Score
Residential status
Residence and work permit
Education
Race
Religious Views
Physical Address
Facial Recognition Data
Political Views
Credit Cards
Government Ids
IP Address
Device identification
Your Emails
Your Contacts
Your Phone Calls
Your Chats
Calendar events
Search History
Videos Watched
Websites Visited
Browser Information
Video Uploads
Photo Uploads
Status Updates
Likes
Your Documents
Your Purchase History
Your Games
Your Books
Your Music
Your Fitness/ Health Data
Ads You Click
What you've hidden from newsfeed
The Devices You use
Information about the Things near Your Device
Voice Data
Gaming Interactive Data



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Facial Recognition Data
Legal Capacity
Government ID
Authentication data
Race
Relationship
Religious Views
Social security number
Nationality
Tax ID
Voice Data
Residential Status
Fitness/ Health
Political Views
Ads you click
Gamin Interactive Data
Browser Information
Information about the things near your device
IP Adress
Physical Adress
Likes
Search History
Status Update
The Device you use
Websites Visited
What you have hidden from newsfeed
Your purchase history
Bank details
Credit Cards
Credit or debit card number with expiry date
FACTA Status
Income Level
Gerätekennung
SCHUFA Score
Transaction information
Calendar Events
Photo Uploads
Video Uploads
Video watched
Your Books
Your Chats
Your Documents
Your Emails
Your Games
Your Music
Your Phone Calls
Bank details
Sozialversicherungsnummer
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Kalendar Events
Photo Uploads
Video Uploads
Video watched
Your Books
Your Chats
Your Documents
Your Emails
Your Games
Your Music
Your Phone Calls

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