

Strategic Complement Certification in Platform-based Markets:

Evidence from the Mobile App Industry

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Abstract

In many platform-based markets, thousands of third-party complementors offer their products. To align their activities and augment the value of their ecosystems, platform owners have several strategic options. In this dissertation, I study an empirically prevalent strategy for governing platform-based markets: the selective endorsement of complements via certification. Previous research has found that complement certification increases platform value by reducing customers' search costs and supporting high-potential products, which may otherwise go unnoticed. However, there are critical knowledge gaps regarding the strategic role of certification in platform-based markets, particularly how platform owners select which complements to endorse, what factors influence these decisions, and how the complementor ecosystem responds to certification.

Using a dataset of app developer populations from Apple's App Store, I combine and extend prior work on platform governance and certification to address these gaps. First, I employ a novel theory-building approach based on machine learning methods to detect patterns in the platform owner's selection criteria. I find certification is awarded not only to encourage users to discover new apps but also to induce desired behaviors among developers. Second, I examine how the complementor ecosystem responds to certification. Using a neural-network-based text-embedding algorithm, I cluster similar apps in their respective app category. I find that certification has a generative effect on developers, which increases their innovation efforts after a competing app has been certified. My results also suggest that developers adjust their pricing strategies in response to certification. However, these effects vary across app categories, contingent on their level of competitive crowding.

Together, these studies build a framework for future research studying certification as a strategy to govern complementor activity on platform-based markets. I discuss the implications of my findings for the literature on platform governance, certification, and studies using machine learning methods in strategy research.

Keywords: *platform governance, certification, complementors, innovation, mobile app industry*

Zusammenfassung

Auf vielen plattformbasierten Märkten bieten Tausende von Drittanbietern (Komplementoren) ihre Produkte an. Um ihre Aktivitäten zu steuern und somit den Wert ihrer Ökosysteme zu erhöhen, stehen Plattformbetreibern mehrere strategische Optionen zur Verfügung. Diese Dissertation untersucht eine weit verbreitete Strategie zur Steuerung plattformbasierter Märkte: die selektive Unterstützung von Produkten durch Zertifizierung. Bestehende Studien haben gezeigt, dass solche Produktzertifizierungen den Wert von Plattformen steigern, indem sie Suchkosten für Kunden senken und Produkte mit hohem Potenzial hervorheben. Allerdings bestehen entscheidende Forschungslücken hinsichtlich der strategischen Rolle von Produktzertifizierungen in plattformbasierten Märkten. Insbesondere ist es unklar, wie Plattformbetreiber auswählen, welche Produkte sie unterstützen, welche Faktoren diese Entscheidungen beeinflussen und wie Komplementoren auf die Zertifizierung reagieren.

Um diese Forschungslücken zu schliessen, untersucht diese Dissertation einen Datensatz von App-Entwicklern, die ihre Apps auf Apples App Store anbieten. Erstens nutzt diese Arbeit einen neuartigen Ansatz zur Theoriebildung auf Basis von Machine-Learning-Methoden, um wiederkehrende Muster in den Auswahlkriterien für Produktzertifizierungen zu identifizieren. Die Untersuchung zeigt, dass Zertifizierungen nicht nur vergeben werden, um Nutzern bei der Suche neuer Apps zu unterstützen, sondern auch um gewünschte Verhaltensweisen bei den Entwicklern hervorzurufen. Zweitens analysiert diese Arbeit die Auswirkungen der Zertifizierung auf das Komplementor-Ökosystem. Dazu wird zunächst ein auf neuronalen Netzwerken basierender Algorithmus zur Texteinbettung genutzt, um ähnliche Apps in ihrer jeweiligen App-Kategorie zu gruppieren. Die Ergebnisse dieser Untersuchung zeigen, dass die Zertifizierung einen generativen Effekt hat, da App-Entwickler ihre Innovationsanstrengungen erhöhen, nachdem eine konkurrierende App zertifiziert wurde. Die Untersuchung zeigt ausserdem, dass Entwickler ihre Preisstrategien als

Reaktion auf die Zertifizierung anpassen. Diese Effekte variieren jedoch zwischen den einzelnen App-Kategorien, abhängig von der Intensität des Wettbewerbs.

Insgesamt legt diese Dissertation einen Rahmen für künftige Forschung zu Produktzertifizierungen als Strategie zur Steuerung der Aktivitäten von Komplementoren auf Plattformmärkten vor. Damit liefert diese Arbeit Implikationen für die wissenschaftliche Literatur zu Plattform-Governance, Zertifizierung und den Einsatz von Machine-Learning-Methoden in der Strategieforschung.

Stichworte: *Plattform-Governance, Zertifizierung, Komplementoren, Innovation, App-Industrie*

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List of Abbreviations

API	Application Programming Interface
ARIMA	Autoregressive Integrated Moving Average
AUC	Area Under Curve
B2B	Business To Business
CEO	Chief Executive Officer
CV	Cross-Validation
EDA	Exploratory Data Analysis
e.g.	exempli gratia (English: example given)
FE	Fixed Effects
i.e.	id est (English: that is to say)
iOS	iPhone Operating System
k	Thousand
LASSO	Least Absolute Shrinkage and Selection Operator
MB	Megabyte
ML	Machine Learning
NLP	Natural Language Processing
p.	page
pp.	pages
RFE	Recursive Feature Elimination
SDK	Software Development Kit
SMS	Strategic Management Society
SSRN	Social Science Research Network
U.S.	United States
VIF	Variance Inflation Factor
vs.	versus (English: against)

1 Introduction

1.1 Research Motivation

A platform is a system of interfaces—often embodied in products, services, or technologies—on which two or more parties can conduct transactions (Gawer, 2014; Kretschmer, Leiponen, Schilling, & Vasudeva, 2021; McIntyre, Srinivasan, Afuah, Gawer, & Kretschmer, 2020; Thomas, Autio, & Gann, 2014). In the past two decades, platforms have reorganized many markets (Lanzolla et al., 2020). For example, an increasing share of economic activity in the markets for mobile devices, video-gaming consoles, ride-hailing services, food delivery, textbook publishing, payments, and e-commerce has been mediated by platforms (see Table 1, for examples).

The strategy literature often describes such platforms as being “*multisided*” (McIntyre & Subramaniam, 2009; Parker & Van Alstyne, 2005; Rochet & Tirole, 2003) because they often need to bring a critical mass of two or more distinct participants together, such as buyers and sellers (for example, on e-commerce marketplaces) or complementors and users (for example, app developers and mobile device users) (Cennamo, 2019; Jacobides, Cennamo, & Gawer, 2018, 2020; McIntyre & Srinivasan, 2017; McIntyre et al., 2020; Oestreicher-Singer & Sundararajan, 2012). Many such platforms are organized in a hub-and-spoke form, with an array of peripheral third-party firms connected to the central platform to access its customers (e.g., Boudreau, 2010; Gawer & Cusumano, 2014; Hagiu, 2014; Jacobides et al., 2018; Rietveld & Schilling, 2021).

Table 1: Examples of Platform-based Markets

Market	Side One (Users)	Platforms	Side Two (Complementors)
Mobile operating systems	Mobile device users	Apple iOS, Google Android	Software application developers
Web browsers	Internet users	Google Chrome, Mozilla Firefox	Plug-In application developers
E-Commerce	Buyers	Amazon, eBay, Alibaba	Merchants
Photo sharing	Photo consumers	Instagram, Snapchat, TikTok	Photo makers
Audio streaming	Music consumers	Spotify, SoundCloud, Apple Music	Artists, record labels
Video streaming	Video clip watchers	YouTube.com, Netflix.com	Video clip makers, movie makers
Sponsored online search	Searchers	Google.com, Yahoo.com	Advertisers
Video games	Game players	Microsoft's Xbox, Nintendo's Switch	Game developers
Digital payments	Buyers	PayPal, Stripe.com,	Merchants
Ride-hailing	Passengers	Uber, Didi Chuxing	Drivers
Recruitment	Applicants	Monster.com, Indeed.com, JobScout	Recruiters
Food delivery	Orderer	Delivery Hero, Meituan Waimai, Ubereats	Restaurants

Sources: Company webpages.

Early platform literature emphasized the importance of indirect network effects for a platform's competitive advantage, especially during the initial ecosystem formation (e.g., Armstrong, 2006; Caillaud & Jullien, 2003; Parker & Van Alstyne, 2005; Rochet & Tirole, 2003, 2006). Mostly derived from formal models, this work suggests the use of pricing strategies that subsidize one side of the platform by using deep price discounts to attract the other side to join (e.g., Clements & Ohashi, 2005; Evans, Hagiu, & Schmalensee, 2006). Accordingly, “*platforms create more value for their users as they grow larger, and complementors have greater incentives to join and provide innovative complements*” (Cennamo & Panico, 2020, p. 2). For example, the more home buyers use an online marketplace to search and acquire residential properties, the more home sellers post their homes for sale on the platform. *Ceteris paribus*, this will lead to an increasing number of buyers and more sellers who are seeking to reach new potential buyers on the platform.

While indirect network effects provide an accurate explanation of the underlying platform mechanisms that derive their value from the mere number of transactions—like payment platforms, matching portals, or online marketplaces—more recent research has casted doubts on “the more, the better” premise in platform settings that are not only transaction facilitators but also offer the technological infrastructure through which other firms can build complementary innovations (Gawer & Cusumano, 2014; Yoo, Henfridsson, & Lyytinen, 2010; Zhou, Zhang, & Van Alstyne, 2020). For example, studies have shown that the novelty and quality of video games available for gaming consoles are just as important as the quantity (e.g., Binken & Stremersch, 2009; Cennamo, 2018; Markovich & Moenius, 2009; Panico & Cennamo, 2020; Seamans & Zhu, 2014, 2017). Thus, in platform-mediated settings, which are dependent on innovations generated from third-party complementors, platforms become “*semi-regulated marketplaces*” (Wareham, Fox, & Giner, 2014, p. 1211), enabling entrepreneurial action under the coordination of the platform owner (Cennamo & Santaló, 2019; Panico & Cennamo, 2020).

Moreover, other work has found that there is a flipside to a purely size-focused “*let-a-thousand-flowers-bloom*” approach, indicating that the overcrowding of

platforms with complements can lead to the emergence of many poor-quality complements, which in turn can negatively affect the consumer experience and ultimately a platform's competitive position vis-à-vis rival platforms (Boudreau, 2012, 2017; Hagiu, 2011).¹ In addition, an overwhelmingly large number of products available on a platform makes it increasingly difficult for complementors' products to stand out, which may lower their incentives to invest in increased quality and innovation (Casadesus-Masanell & Halaburda, 2014; Markovich & Moenius, 2009). Thus, the strategic imperative of organizing a platform is to best leverage the generative potential of complementors, and the key role of the platform owner is to manage the strategic tradeoff between the quality and availability of a large number of complements (Chu & Wu, 2021; Tajedin, Madhok, & Keyhani, 2019; Zhou et al., 2020).

A burgeoning stream of research has begun to examine how platform owners can mitigate this tradeoff by using “*platform governance*” (Rietveld & Schilling, 2021) to “*orchestrate innovation*” within their ecosystems (Nambisan & Sawhney, 2011). In this research, there is a growing consensus that platform owners must implement—in addition to pricing strategies to unlock network effects—non-pricing strategies to influence complementors' behavior and align their incentives to induce greater quality and innovativeness (Ceccagnoli, Forman, Huang, & Wu, 2011; Rietveld, Schilling, & Bellavitis, 2019; Wareham et al., 2014). Due to their central position in their ecosystems and their control over the platform's architecture, platform owners can exert considerable power over complementors (Adner, 2017; Jacobides et al., 2018; Tiwana, 2015). However, in contrast to conventional pipeline models of innovation, in which a firm can use hierarchies or markets to coordinate value-creating processes, a platform owner can only “*coax but it cannot coerce third*

¹ A recent example is Google's detection of several hundred malware-infected apps on its Android platform, where the data of the paid content subscribers were collected without consent (see <https://www.forbes.com/sites/zakdoffman/2021/06/26/apple-warning-for-google-android-play-store-users-as-dangerous-malware-exposed/>, accessed July 2021). Similarly, Amazon has been accused of listing banned, unsafe, or counterfeit products. Several high-profile sellers, including Birkenstock and Nike, announced that they had removed some of their products from the marketplace (see <https://www.wsj.com/articles/amazon-has-ceded-control-of-its-site-the-result-thousands-of-banned-unsafe-or-mislabeled-products-11566564990>, accessed March 2021).

parties into innovation behavior that enhances ecosystem welfare” (Parker & Van Alstyne, 2018, p. 3015). Despite growing scholarly interest in platform governance, the “*mechanisms that encourage complementary innovation still remain little understood*” (Foerderer, 2020, p. 4772).

There exist a number of strategic options to govern complementor ecosystems (see Rietveld & Schilling, 2021 for a review). This dissertation studies one empirically prevalent but less studied strategy: the platform owner’s endorsement of complements via *certification*. Certifications from the platform owner can be implemented in various ways, e.g., using badges to signal quality and trustworthiness (e.g., Hui, Saeedi, Shen, & Sundaresan, 2016), placing complements in the spotlight on the platform’s interface (e.g., Aguiar & Waldfogel, 2018), or providing users with curated lists of recommended products (e.g., Liang, Shi, & Raghu, 2019). Empirically, complement certification is a frequently used platform governance tool, with nearly all major platform-based ecosystems using some form of complement certification. For instance, Airbnb uses a “*Superhost*” badge to certify individual hosts, Spotify promotes “*Editorial Playlists*”, Amazon recommends products labeled with the “*Amazon’s Choice*” badge, eBay certifies “*Top-Rated Sellers*”, and Apple and Google endorse individual apps on their respective app platforms with an “*Editors’ Choice*” banner.²

While several studies have examined the performance effects of certification on the awarded complements (e.g., Aguiar & Waldfogel, 2018; Elfenbein, Fisman, & McManus, 2015; Hui et al., 2016; Liang et al., 2019),³ there are important knowledge gaps in terms of the strategic role of certification in platform-based markets, particularly how platform owners select which complements to endorse, what factors influence these decisions, and how the complementor ecosystem responds to

² Table 12 in the Appendix presents additional examples in greater detail.

³ Empirical observations provide strong support for the results of these studies. For example, products labeled as “Amazon’s Choice” can increase their sales conversion rate (realized purchases out of total product page views) by 25%, and Apps featured on Apple’s App Store can quadruple their downloads numbers during the endorsement (see <https://www.profitero.com/blog/2018/11/the-impact-of-amazon-badges-on-traffic-and-conversion> and <https://www.appannie.com/en/insights/market-data/impact-app-store-feature/>, accessed May 2021).

certification. As such, this increasingly important puzzle for firms in two-sided markets is still not completely understood. This dissertation extends the findings from previous literature on platform governance (e.g., Rietveld et al., 2019; Rietveld et al., 2021) and certification (e.g., Godes, Ofek, & Sarvary, 2009; Olson & Waguespack, 2020) in an attempt to address these gaps through two empirical studies.

1.2 Overview of Studies and Contributions

I conduct two separate but interrelated empirical studies that aim to create a more nuanced and precise understanding of certification as a strategy to govern platform-mediated markets. Using a unique dataset of app developer populations on Apple's App Store, an iconic platform ecosystem in the consumer electronics industry, I employ a combination of selected theoretical and methodological approaches to address my research questions.

Study 1: Detecting Patterns in Apple's Certification Strategy⁴

In the first study, I ask the following questions. (1) *“Which factors lead to complement certification from the platform owner?”* and (2) *“What is the relative influence of these factors on certification decisions?”* Consistent with these inductive research questions, I use a machine learning (ML) framework that enables me to detect patterns in Apple's app certification criteria. My analysis reveals that Apple exhibits two strategic behaviors: first, it selects new apps with unrealized value for users, and second, it rewards apps that showcase new platform technology, are highly productive, and help the platform monetize more effectively by offering upselling options. My interpretation of this pattern is that platform owners use certification not only to encourage users to discover new complements, but also to induce desired behaviors among complementors.

These findings enable a comprehensive consideration of the strategic role of certification and highlight the value of understanding the complex interactions

⁴ A proposal of this study has been recommended for inclusion in the conference program and has been nominated for the *Best Conference Paper Prize* and the *Conference PhD Paper Prize* of the 2021 Strategic Management Society (SMS) Annual Conference.

between platform owners and their complementor ecosystems more generally. Given the strong demand side benefits from certification for selected complements, platform owners can use certification to reward complements that are aligned with the platform's technology, strategy, and high standards for customer satisfaction. Additionally, these results suggest that complementors can anticipate certification and formulate strategic responses accordingly to increase their chances of being selected.

Study 2: Examining the Effects of Certification on Complementors' Value Creation and Capture Strategies

The second study follows a deductive research approach, asking, "*How does complement certification affect complementors' innovation efforts and pricing strategies?*" Drawing from the literature on certification and competition in multisided markets, I build a theoretical framework to investigate complementors' strategic behavior in response to Apple's certification. My central hypothesis is that certification has a generative effect, which increases the innovation efforts of both the complementors that received certification and their uncertified rivals. I also develop theory on how complementors adjust their pricing strategies after certification, predicting that recipient complementors will raise prices to realize short-term profits, and rivals will reduce prices to capture demand spillovers. However, I also theorize significant heterogeneity in those complementor responses when the competitive crowding at the market category level is considered. I compile a unique dataset to test my hypotheses. Using a neural-network-based text-embedding algorithm, I identify and cluster apps that compete with similar features and content in their respective app category. I then model Apple's certification patterns in a regression framework to examine developers' responses to the certification event of an app within their cluster.

Consistent with my hypotheses, I find that both recipients and rival developers increase their innovation efforts. However, I also show that high levels of competitive crowding attenuate this generative effect of certification. Moreover, the results also support my predictions on the heterogeneous effects of complementors' pricing strategies. Overall, this study highlights the significant implications of complement

certification for promoting complementor innovation and, more generally, underscores the critical strategic role of platform governance in orchestrating complementor behavior.

Contributions to Extant Research

My work contributes to several streams of literature. First, it adds to the emerging body of research on governance strategies in platform-based settings. Extant research has predominately focused on how platforms can use either pricing strategies (e.g., Caillaud & Jullien, 2003; Evans, 2003; Parker & Van Alstyne, 2005; Rochet & Tirole, 2003) or *hard* governance strategies, i.e., mechanisms that exert direct control over complementors (e.g., Boudreau, 2010, 2012; Casadesus-Masanell & Hałaburda, 2014; Parker & Van Alstyne, 2018), to manage complement quality and diversity. However, little is known about how platforms can implement non-pricing strategies effectively (Cennamo, 2019; Cennamo, 2021; Rietveld et al., 2019), and in particular, *soft* governance strategies that nudge complementors towards desired behavior without enforcing control or requiring substantial monetary investments (Foerderer, 2020; Foerderer, Lueker, & Heinzl, 2021). This dissertation adds to this work by studying the underlying mechanisms and implications of complement certification, an empirically prevalent and important *soft* governance strategy.

Extending prior work on certification in platform-mediated settings (e.g., Aguiar & Waldfogel, 2018; Hui et al., 2016; Liang et al., 2019), this dissertation shows how platform owners use this governance mechanism to orchestrate their supply side by aligning complementors with the ecosystem and inducing greater participation and innovativeness. In so doing, my work expands the previous explanations for how platform owners select complements for certification, which focus on demand side factors (Rietveld et al., 2019). My findings emphasize that platform owners use complement certification to pursue two strategic objectives: reducing search costs for the demand side and increasing quality incentives for the supply side. As such, this dissertation contributes to a growing set of studies in the platform governance literature that focuses on platform owner decision-making (e.g.,

Foerderer, 2020; Helfat & Raubitschek, 2018; Hukal et al., 2020; Parker & Van Alstyne, 2005; Zhu & Liu, 2018) by illuminating the underlying mechanisms that drive their governance decisions and their subsequent implications. In doing so, I respond to calls from platform researchers to study the “*mechanisms platform firms can employ to manage the tradeoff between the quality and the availability of a large number and variety of complements*” (McIntyre et al., 2020, p. 24).

Moreover, I add to the limited number of studies on platform governance that examine how complementors respond to governance strategies and how this affects their subsequent behavior on the platform (e.g., Rietveld et al., 2021; Wen & Zhu, 2019; Zhang, Li, & Tong, 2020). The overall lesson from my findings is that platform owners need to understand that complementors may respond equivocally to platform governance mechanisms, with firm perspectives (certification recipient or uncertified rival) and market level factors (category-level competition) being the main sources of heterogeneity in complementors’ responses. My findings also demonstrate that such heterogeneity can result in unintended side effects in complementor behavior. In doing so, this study enforces the notion of recent contributions that it is critical for platform owners to understand how their complementor ecosystems respond to governance mechanisms (e.g., Koo & Eesley, 2021; McIntyre, Srinivasan, & Chintakananda, 2020; Panico & Cennamo, 2020) and, in parallel, responds to calls from platform researchers to carefully examine the “*incentives and actions of third-party complementors*” (McIntyre & Srinivasan, 2017, p. 155).

Beyond the nascent stream of research on platform governance, there is an established body of literature on certification. While this body of literature offers rich insights into how certification affects customer and firm behavior, most of the studies were conducted in settings in which independent third-party certifiers, such as regulatory bodies, product critics, and media outlets, provided certifications (see Dranove & Jin, 2010 for a review). However, the underlying mechanisms are likely to change in a platform-based setting for at least two reasons. First, in most traditional settings, firms proactively *seek* certification and adjust their efforts to align with the predefined standards (e.g., King, Lenox, & Terlaak, 2005). However, in most two-

sided market settings, the platform owner *chooses* which products or firms should receive certification based on criteria that are not fully disclosed or are arbitrary (Hukal, Henfridsson, Shaikh, & Parker, 2020; Rietveld, Seamans, & Meggiorin, 2021; Rietveld et al., 2019). Thus, as opposed to traditional firms competing in non-platform settings, complementors cannot directly anticipate certification and must therefore carefully refine their strategies through complex trial-and-error processes to increase the likelihood of certification. Second, while some studies have examined the strategic behavior of the market intermediaries that provide certifications (e.g., Godes, Ofek, & Sarvary, 2009; Olson & Waguespack, 2020), these findings are limited to contexts in which intermediaries do not directly benefit from the products or firms they certify. In contrast, most platform owners are in a powerful position at the center of a two-sided market and own the interfaces needed for customer access (Cutolo, Hargadon, & Kenney, 2021). Thus, they are able to use certification strategically to manipulate complementor behavior and, in turn, extract value from the activities within their ecosystems.

This dissertation contributes to this literature in several ways. First, my findings extend the set of studies exploring the strategic behavior of market intermediaries that provide certifications (e.g., Olson & Waguespack, 2020; Seamans & Zhu, 2014) by examining the decision-making of a powerful platform owner that “certifies” the products provided by third-party complementors and, at the same time, owns the infrastructure to sell these products to its customers and, thus, takes a cut of their revenue. Hence, my work contributes to the certification research by illuminating how platform owners as market intermediaries use certification strategically to capture value from the firms and products they evaluate.

Second, the extant literature on certification has predominately examined how firms ex-ante adjust their efforts to receive certification (e.g., King et al., 2005), but how firms ex-post react to certification has remained an underresearched domain. As Rietveld et al. (2021) noted, two-sided markets are an ideal setting for studying the ex-post implications of certification, as platform owners often do not disclose the exact prerequisites to receive certification (as it is the case in this dissertation’s

empirical setting), and therefore, complementors cannot fully anticipate certification ex-ante. This allows for the separation of firm behavior before and after certification, mitigating potential endogeneity concerns. My study extends the small stream of literature on the ex-post implications of certification by illustrating how firms adjust their innovation efforts and pricing strategies and how underlying firm- and category-level factors shape the strength of this effect.

In parallel, these findings also address another important gap in the certification literature: the competitive implications of certification. Despite a growing scholarly understanding of the benefits accrued by firms that receive certification (e.g., Pollock & Gulati, 2007; Rao, 1994; Sine, David, & Mitsuhashi, 2007), little is known about the effects of certification on firms' rivals (Polidoro, 2013). I extend previous research by showing that there are real and significant competitive implications of certification, with uncertified rivals reconfiguring their value creation and capture strategies to maneuver their market positioning. Moreover, my findings extend the limited literature on the competitive implications of certification by identifying the competitive crowding of a niche as an important market-level moderator that may explain heterogeneity in terms of how rival firms respond to certification.

Finally, this dissertation also makes methodological contributions. I contribute to a nascent body of research that promotes and applies ML to construct theory in the strategy field (e.g., Choi, Menon, & Tabakovic, 2021; Choudhury, Starr, & Agarwal, 2020; He, Puranam, Shrestha, & Krogh, 2020; Leavitt, Schabram, Hariharan, & Barnes, 2020; Teodorescu, 2017; Tidhar & Eisenhardt, 2020). By using a combination of ML methods that include tree-based and regularized algorithms for prediction and variable selection (Study 1) and neural network algorithms for variable construction from textual data (Study 2), this dissertation demonstrates the applicability and usefulness of ML approaches in strategy research.

Managerial Implications

My empirical findings suggest several important implications for managers of firms in platform-based markets. From the perspective of complementors, this dissertation offers valuable insights into how platform owners choose complements for certification. My dissertation shows that complementors can predict platform owners' certification patterns and formulate strategic responses by adapting their product configurations, time-to-market processes, and monetization options accordingly. Thus, my findings help complementors anticipate the selection strategies of platform owners and, in turn, increase the likelihood of endorsement via certification.

For platform owners, this dissertation provides empirical guidance regarding the implications of certification for complementor behavior. My findings suggest that platform owners need to implement their certification strategies in ways that optimize and balance two strategic objectives: *encouraging user search* (i.e., reducing search costs for the demand side) and *promoting complementor innovation* (i.e., increasing quality incentives for the supply side). In particular, this dissertation shows that platform owners must carefully estimate how the competitive crowding of the platform's niches may attenuate the effectiveness of certification in stimulating complementors' innovativeness. Thus, platform owners may have to compromise when using certification in crowded niches to help users find high-quality complements, as it may discourage rival complementors' innovativeness in a side effect. Overall, my research helps platform owners understand how complementors may respond to soft platform governance, which may enable them to design and implement soft governance mechanisms like complement certification more effectively.

1.3 Organization

The remainder of this dissertation proceeds as follows. Chapter 2 presents a brief review of the related literature streams on platform governance and certification and discusses the research gaps. In Chapter 3, I introduce the empirical setting and

describe the data and research design. Chapters 4 and 5 are dedicated to the core empirical studies of this dissertation. Chapter 6 concludes by discussing the managerial implications and directions for future research.

2 Related Literature

This dissertation relates to two different but complementary streams of literature: research on platform governance and research on certification. The following chapter provides a comprehensive overview of prior work in these areas, synthesizes their key findings, and identifies the research gaps relevant for this dissertation.⁵

2.1 Research on Platform Governance

While there exist different types of platforms (see Cusumano, Gawer, & Yoffie, 2019 for a classification), in essence, they all mediate interactions between supply side “*complementors*” (Brandenburger & Nalebuff, 1996) and demand side users, with a platform owner that manages the activities in the ecosystem to ensure sustained value at the center of the platform (Boudreau, 2012; Gawer, 2014; Gawer & Cusumano, 2002; McIntyre et al., 2020).

Early literature on “*two-sided markets*” has highlighted the essential role of network effects for platforms in growing and creating value (e.g., Armstrong, 2006; Katz & Shapiro, 1985; Rochet & Tirole, 2006; Schilling, 2002). Mostly derived from formal models, these studies suggest pricing strategies that reduce the barriers to entry for one side of the platform and incentivize the other side to join (Caillaud & Jullien, 2003; Clements & Ohashi, 2005; Evans, 2003; Parker & Van Alstyne, 2005; Rochet & Tirole, 2003; Weyl, 2010).⁶ The implicit assumption in these studies is that

⁵ I reviewed both conceptual and empirical research published in leading management journals. As platforms and certification are also key themes in economics research, I also reviewed the leading journals in this field. Finally, I reviewed practitioner research. Employing the keyword search technique via Thomson Reuters’ Web of Science, I obtained a preliminary set of studies and then tracked the references on which these papers relied to identify additional references. Moreover, I reviewed research networks such as SSRN and ResearchGate to find working papers and other unpublished work related to my research questions. See Table 13 in the Appendix for a list of included journals and other literature sources.

⁶ Pricing strategies are mostly discussed as an effective way to solve the canonical “chicken-and-the-egg” approach of attracting both users and complementors to the ecosystem at its initial formation. Typically, most studies generate predictions on pricing strategies by (1) formulating a utility (or demand) function with indirect network effects, (2) modeling a simultaneous coordination game to

consumers place a higher value on platforms with a larger number of users (direct network effects) (Cennamo & Santalo, 2013), as they anticipate that such platforms offer a larger number and variety of complementary products and services (indirect network effects; for a critical review of the early platform literature and, especially, the pricing stream, see McIntyre & Srinivasan, 2017). As network effects are reinforcing, more participants on each side create more value, so platform owners need to stimulate network effects on both sides of their markets to grow and create value (Eisenmann, Parker, & Van Alstyne, 2011, 2006; Gawer, 2009).

The mechanisms described in early works on platforms provide deep insights into the dynamics of two-sided markets in which the primary source of value is the sheer number of transactions between its two sides, for example, payment platforms (e.g., PayPal, VISA, and MasterCard), matching portals (e.g., Tinder and Upwork.com), and e-commerce marketplaces (e.g., eBay.com and Alibaba.com). However, more recent research has cast doubt that this “the more, the better” premise adequately captures the innovation dynamics and coordination challenges for platforms that are not pure marketplaces but offer the technological infrastructure needed for other firms to build their complementary innovations (Cennamo, 2018; Cennamo & Santaló, 2019; Panico & Cennamo, 2020; Sampler, 2018; Thomas et al., 2014; Yoo, Henfridsson, et al., 2010). Studies focusing on platform ecosystems⁷ concerning mobile devices, video game consoles, or enterprise software show that the quality, novelty, and diversity of the complementary products offered on a platform are just as important as their quantity (e.g., Binken & Stremersch, 2009; Cennamo, 2018; Markovich & Moenius, 2009; Seamans & Zhu, 2014, 2017; Shi, Li, & Churnumpan, 2020).

derive the number of platform members as a function of the fees charged by the platform, and (3) computing optimal fees (see Rochet & Tirole, 2003, 2006, for examples).

⁷ In this dissertation, I follow previous studies and use the term “platform ecosystem” (e.g., Wen & Zhu, 2019; Cennamo & Panico, 2020; Kapoor & Agarwal, 2017). For an academic debate on the terminology of “platforms” and “ecosystems”, see Jacobides, Cennamo, & Gawer (2018) and Jacobides, Cennamo, & Gawer (2020).

Moreover, other research has found that a vast number of complements available on a platform can imply unintended negative consequences. On the complementor side, studies have shown that a large number of complementors could reduce their innovation incentives due to intense rivalry and direct competition (Boudreau, 2012; Boudreau & Jeppesen, 2015; Parker & Van Alstyne, 2005), resulting in the supply of low-quality complements (Casadesus-Masanell & Hałaburda, 2014; Chu & Wu, 2021; Markovich & Moenius, 2009; Venkatraman & Lee, 2004), or their abandonment of the ecosystem in favor of other, less crowded and more profitable settings (Cennamo & Santalo, 2013). On the user side, an overwhelmingly large number of products available may increase users' search costs due to complement redundancy (Boudreau & Jeppesen, 2015) or an increasing number of copycats (Miric, Boudreau, & Jeppesen, 2019; Miric & Jeppesen, 2020). Ultimately, unregulated platform growth (*“letting a thousand flowers bloom”*) may result in a negative customer experience, which may seriously harm the reputation and economic performance of the platform (Boudreau, 2012, 2017; Markovich & Moenius, 2009; Wareham et al., 2014). Based on these findings, there is a growing consensus that platform owners must not only drive network effects by adjusting pricing but also nurture the quality and innovativeness of their ecosystems and align complementors' incentives with the platform's strategic intent (Ceccagnoli et al., 2011; Hukal et al., 2020; Jacobides et al., 2018).

A burgeoning stream of platform research has thus begun to examine how platform owners can use non-pricing strategies to coordinate and regulate complementor behavior (e.g., Chen, Yi, Li, & Tong, 2021; Gawer & Henderson, 2007; Greve & Song, 2017; Rietveld et al., 2019; Tae, Luo, & Lin, 2020). Previous research on such *“platform governance”* (Rietveld & Schilling, 2021), also referred to as platform *“orchestration”* (Nambisan & Sawhney, 2011), can be broadly classified into two streams: *hard* governance and *soft* governance strategies (Foerderer et al., 2021).

Hard Platform Governance Strategies

Hard governance strategies employ mechanisms that exert direct control over complementors or require substantial financial investment. Many studies have highlighted the regulation of platform access in an effort to balance ecosystem size and complement quality control (e.g., Boudreau & Hagiu, 2009; Eisenmann, Parker, & Van Alstyne, 2009; Thomas et al., 2014). For example, platform owners can set restrictive rules for platform access (e.g., Boudreau, 2010), also referred to as “*gatekeeping*” (Zhang et al., 2020), or limit the number of complementors to avoid fierce competition (e.g., Boudreau, 2012; Casadesus-Masanell & Halaburda, 2014). In addition to managing the size of their ecosystems, platform owners can also influence its diversity using control-based governance. For example, in an effort to manage the diversity of its product offerings, Amazon’s self-publishing platform has shifted market power away from large publishers to stimulate supply from independent authors (Greve & Song, 2017). Other potential strategies to manage both complement quality and diversity can include the provision of platform resources (e.g., Ghazawneh & Henfridsson, 2013; Ozalp, Cennamo, & Gawer, 2018), for example, via formal exchange forums between platform owners and complementors (Foerderer, 2020), the enforcement of intellectual property rights (Huang, Ceccagnoli, Forman, & Wu, 2013), concordance with technical specifications (Kretschmer & Claussen, 2016), strict quality control (Parker & Van Alstyne, 2018), or rule setting (Claussen, Kretschmer, & Mayrhofer, 2013).

Other research has shown that some platform owners make direct investments into the ecosystem to manage complement quality (e.g., Claussen et al., 2013; Rietveld, Ploog, & Nieborg, 2020; Schilling, 2002). For instance, this can be implemented by monetarily incentivizing complementors to prevent them from supplying the same complementary product to rival platforms (Bakos & Halaburda, 2020; Landsman & Stremersch, 2011), also known as “*platform exclusivity*” (Cennamo & Santalo, 2013). In addition to exclusivity fees, monetary investments can also be implemented as rewards or subsidies. For example, Claussen et al. (2013) found that Facebook experienced a substantial increase in highly rated apps after it

started to reward highly rated developers by allowing them to send out more messages to users. Relatedly, other platform owners offer targeted incentives to a subset of sellers to improve complementors' quality provision, such as Uber giving bonuses to drivers who accept consecutive rides during busy hours or eBay providing fee discounts to sellers offering immediate handling and unlimited returns (Hui, Liu, & Chan, 2020).

Another prominent example of a hard governance strategy that requires considerable financial investment from platform owners is the vertical integration into specific complement categories by providing high-quality first-party content. This follows often the intent of stimulating complementors' value creation, particularly at an early stage of the platform's lifecycle (Cennamo, Gu, & Zhu, 2018; Cennamo, 2018; Foerderer, Kude, Mithas, & Heinzl, 2018; Hagiu & Spulber, 2013; Zhu, 2019), providing customers with complements of better quality than the ones offered by third-party complementors, or realize own opportunities for value capture (Wen & Zhu, 2019; Zhu & Liu, 2018).

Soft Platform Governance Strategies

In contrast to the rich literature on hard platform governance, only a small set of studies has begun to examine governance mechanisms that guide complementor behavior without substantial monetary investments or enforcing control. Such soft governance strategies can materialize in strategies that ex-ante (for example, via signals) or ex-post (for example, via awards) nudge complementors towards a desired behavior. For example, Hukal et al. (2020) found that owners of geodata platforms use opportunity and endorsement signals to communicate their intention in advancing distinct areas of their ecosystems. Similarly, Foerderer et al. (2021) showed how Google recognized developer innovation ex-post through annual awards and showcase other developers best-case examples of developer performance.

The focus of this dissertation is an empirically prevalent but less studied strategy for *softly* governing the quality and diversity of complementor ecosystems: the “*selective endorsement*” (Rietveld et al., 2019) of complements, also referred to

as “*platform recommendation*” (Liang et al., 2019) or “*complement certification*” (Elfenbein et al., 2015; Rietveld et al., 2021).⁸ Such certifications can be implemented in various ways, e.g., awarding badges to signal quality and trustworthiness (Hui et al., 2016), spotlighting complements on high-visibility customer interfaces (e.g., Aguiar & Waldfogel, 2018), or providing users with curated lists of recommended products (e.g., Liang et al., 2019).⁹ By using certification, platform owners attempt to resolve asymmetric information problems between complementors and users and reduce the search costs of the latter. Additionally, research has indicated that platform owners use certification strategically to create the perception of a greater breadth and depth of platforms’ portfolio of complements by drawing attention to previously undervalued complements, unlocking unrealized sales potential (Rietveld et al., 2019). Table 2 provides an overview of the previous studies on selective endorsement via certification in the context of platform-based ecosystems.

⁸ In the following, I will use the term “*complement certification*” following the most recent study on the phenomenon (Rietveld et al., 2021). However, I acknowledge that there are other terms describing the same phenomenon in both research and practice.

⁹ A related but separate platform governance strategy is the change in a platform’s matching or ranking algorithms to favor complementors in user’s search results (e.g., Dinerstein, Einav, Levin, & Sundaresan, 2018; Koo & Eesley, 2021). Usually, this does not involve certification and is customized to individual user search behavior.

Table 2: Selected Studies on Complement Certification

Author (Year)	Journal	Type of study (method)	Industry/Data	Findings/Contributions
Aguilar & Waldfogel (2018)	<i>National Bureau of Economic Research Working Papers</i>	Empirical, quantitative (fixed effects linear regression)	Music streaming, Spotify	Platform certification significantly raises complement performance and enhances complementors' visibility
Elfenbein et al. (2015)	<i>American Economic Journal: Microeconomics</i>	Empirical, quantitative (fixed effects linear regression)	E-commerce, Ebay.com	Platform certification provides greatest value when certification is rare, the market space is crowded, and for complementors without established reputations
Hui et al. (2016)	<i>Management Science</i>	Empirical, quantitative (fixed effects linear regression)	E-commerce, Ebay.com	Platform certification increases efficiency in the marketplace by increasing average complementor quality and reducing adverse selection through a higher exit rate for low-quality complementors
Hukal et al. (2021)	<i>MIS Quarterly</i>	Empirical, quantitative (fixed effects linear regression)	Geodata platforms, OpenStreetMap	Platform owners can increase complement volume and diversity by using certification
Liang et al. (2019)	<i>Information Systems Research</i>	Empirical, quantitative (fixed effects linear, probit, and logit regression)	Mobile apps, App Store	Platform certification raises short-term demand for certified complements and creates short-term spillover demand effects on related but uncertified complements
Rietveld et al. (2019)	<i>Organization Science</i>	Empirical, quantitative (fixed effects logit regression, difference-in-difference model)	Video game consoles	Platform sponsors do not simply certify best in class complements; they strategically certify complements to unlock unrealized sales potential
Rietveld et al. (2021)	<i>Strategy Science</i>	Empirical, quantitative (fixed effects logit regression, difference-in-difference model)	Microfinance, Kiva	Complementors adjust their product portfolios to align with certification, depending on underlying supply side and demand side factors
West (2003)	<i>Research Policy</i>	Empirical, qualitative (multiple case studies)	Computer platforms	Endorsement of complementors' technology from the platform owner leads to a supply of more innovative complements

2.2 Research on Certification

In his seminal contribution, Akerlof (1970) demonstrated that asymmetric information between the supply and demand sides of a market may lead to adverse selection, moral hazard, market inefficiency, or even market failure. In settings prone to asymmetric information problems, certification is an important cue that assists customers' decision making under uncertainty (Dranove & Jin, 2010). At its root, research on certification builds on signaling theory, which proposes that highly capable evaluators can transform unobservable credence attributes into observable search attributes, enabling stakeholders (e.g., customers) to draw better-informed inferences (Spence, 1974).

In line with this argument, previous research has shown that a variety of third-party intermediaries play an important market-clearing role by mitigating the uncertainty faced by customers assessing the prospects of a firm or product offering. For example, product critics provide third-party evaluations of a diverse range of products, including cuisine and wine (e.g., Benjamin & Podolny, 1999; Hsu, Roberts, & Swaminathan, 2012; Malter, 2014; Zhao & Zhou, 2011), movies (e.g., Eliashberg & Shugan, 1997; Hsu, 2006; Reinstein & Snyder, 2005), music (e.g., Salganik, Dodds, & Watts, 2006), books (e.g., Kovács & Sharkey, 2014; Sun, 2012), video games (e.g., Olson & Waguespack, 2020; Zhu & Zhang, 2010), and consumer goods offered on e-commerce marketplaces (Chen & Xie, 2005; Zhou & Duan, 2016). Similarly, certification bodies evaluate the compliance of products and firms with quality and safety standards (e.g., Hwang, Radhakrishnan, & Su, 2006), environmental standards (e.g., Rysman, Simcoe, & Wang, 2020), and hygiene standards (e.g., Jin & Leslie, 2003, 2009). Another source of consumer guidance is provided by media outlets, such as newspapers, online blogs, and television stations, delivering topical information and analyses of firms (e.g., Fang & Peress, 2009; Gurun & Butler, 2012; Kulchina, 2014; Pollock & Rindova, 2003; Tan, 2016).

The findings from the certification literature relevant to this dissertation can be organized into three main categories (see Dranove & Jin, 2010 for a review; Rietveld et al., 2021).

Effects of Certification on Firm Outcomes

The first category is concerned with the effects of certification on firm outcomes (e.g., Graffin & Ward, 2010; Polidoro, 2013; Rao, 1994). The main theoretical underpinning of the studies within this category is that certifications provide legitimacy or signal trustworthiness concerning a firm and its product offerings, and customers tend to rely on these signals when direct information is ambiguous or unavailable (Biglaiser & Li, 2018; Biglaiser, Li, Murry, & Zhou, 2020; Houde, 2018; Stahl & Strausz, 2017). As a consequence, certified products and firms enjoy substantial benefits compared to their noncertified counterparts. For example, Jin & Leslie (2003) studied the demand side effects of certification that prove restaurants' compliance with hygiene standards and found that guests buy more food from certified restaurants. Relatedly, King et al. (2005) found that certifications with the ISO 14001 management standard positively influence recipient firms' performance, and Pollock & Gulati (2007) found that certifications by venture capitalists help technology startup firms form strategic alliances.

The previous research also identified factors that influence the relationship between certification and demand, especially related to other available information sources (e.g., Gao, Gopal, & Agarwal, 2010). For example, Hui et al. (2013) found that the listing of certified products on eBay's marketplace in the U.S. has less of an impact on customer demand when a new buyer protection program is introduced. Elfenbein et al.'s (2015) study of eBay's marketplace extended these findings by showing that the demand side effects are stronger when certification is rare, the product space is crowded, and for sellers lacking established reputations. Zhou & Duan (2016) found that positive expert reviews can increase software downloads, but this effect is contingent on user-generated word of mouth.

Firm Efforts to Receive Certification

The second category of studies examines firms' ex-ante efforts to receive certification (e.g., Albano & Lizzeri, 2001; Iyer & Singh, 2018). The main assumption is that as there are substantial benefits from receiving certification (indicated by the findings in the first category) and, thus, firms have strong incentives to seek certification and adjust their behavior accordingly (e.g., Jiang & Bansal, 2003; King et al., 2005). While most studies have found that those firm efforts to receive certification enhances consumer welfare (e.g., Iyer & Singh, 2018; Marinovic, Skrzypacz, & Varas, 2018), in some cases, these incentives for firms to receive certification can lead to unintended or absurd effects on firm behavior. For example, Forbes, Lederman, & Tombe (2015) studied the incentives of airlines to manipulate arrival times to improve their on-time arrival record. Similarly, Dranove, Kessler, McClellan, & Satterthwaite (2003) found that hospitals may decline to treat seriously sick patients to avoid receiving poor grades in hospital certification reports.

Effects on Firm Behavior after Certification

The third category of studies on certification investigates changes in firms' behavior after receiving certification. In theory, given the findings from the first and second categories—certified firms benefit from greater demand and invest in receiving certification—firms have strong incentives to adjust their behavior to avoid losing their certification or to receive certification for other product offerings. However, there is only limited empirical evidence on the ex-post adjustment of firm behavior subsequent to certification (with few exceptions, e.g., Lu, 2012; Rietveld et al., 2021; Sufi, 2009). For example, Rietveld et al.'s (2021) study of the microfinance platform Kiva revealed that after the introduction of a badging program, badged microfinance institutions reoriented their loan portfolio offerings to align with the certification and further benefit from stronger demand side benefits.

2.3 Research Gaps

This dissertation expands the previous literature in several ways. First, several studies on platform governance have examined the impact of certification on complementor performance (e.g., Aguiar & Waldfogel, 2018; Elfenbein et al., 2015; Hui et al., 2016; Liang et al., 2019), but they have not explored the strategic role of complement certification, leaving essential questions in terms of its underlying mechanisms, as well as the implications for platform owners and their complementor ecosystems, unanswered. As a notable exception, Rietveld et al. (2019) examined in a study of the video game industry which games were selectively endorsed via the console makers certification regime. While this study indicated that platform owners tended to base their certification decisions on demand side factors, such as the unrealized sales potential of complements and categories to select individual complements for certification, it did not examine the role of supply side considerations in shaping these selection decisions. However, reconsidering the importance of indirect network effects in two-sided markets, the demand and supply side implications from an exogenous event are likely to be deeply intertwined, and thus, platform owners need also to consider supply side factors when using certification to strategically govern their complementor ecosystems.

As the certification literature indicates, certification aims not only at informing customers (i.e., the demand side) but also to inducing firms to supply better products (Zapechelnjuk, 2020), which echoes the notion of previous studies in platform research highlighting the strategic role of platform governance in promoting the greater participation and innovativeness of complementors (Adner, 2017; Jacobides et al., 2018; Panico & Cennamo, 2020). Given the strong performance effects of certification, it is reasonable to assume that platform owners may also consider factors that can stimulate their ecosystem's supply side when choosing individual complementors for certification. Moreover, in a two-sided market, the demand and supply sides are connected via indirect network effects (Parker & Van Alstyne, 2005). Thus, a profit-maximizing platform owner may design its certification strategy in ways that optimize and balance two objectives: encouraging user searching (i.e., the

demand side) and promoting complementor innovation (i.e., the supply side). However, empirical evidence on how platform owners make these selection decisions is scarce.

Second, these relationships are also subject to recent efforts in certification research. While the extant literature on certification has gained much knowledge on how certification affects demand from prospective end users and the associated benefits for certified firms (Dranove & Jin, 2010), only a small set of studies on certification have explored the strategic behavior of the market intermediaries that provide such certifications (Godes et al., 2009; Olson & Waguespack, 2020; Seamans & Zhu, 2017). However, most of these studies examine the strategic behavior of intermediaries that *indirectly* benefit from the entities they evaluate (e.g., DellaVigna & Hermle, 2017; Waguespack & Sorenson, 2011). For example, Olson & Waguespack (2020) found that professional media outlets reviewing video games and movies tended to delay publishing negative reviews for more commercially important products and adjusted their reviews to differentiate themselves from those of competing media outlets. These findings, while underscoring the importance of studying the strategic behavior of market intermediaries, are limited to settings in which the intermediary (i) does not sell the products it evaluates, and (ii) where firms proactively request certification. In the context of most platform markets, these roles overlap, as the platform owner is the intermediary but, at the same time, controls and monetizes customer access and thus *directly* benefits from the complement it certifies. Additionally, in most platform-based settings, the platform owner chooses which products or firms should be awarded certification, with the selection criteria often not fully disclosed. For these reasons, the underlying dynamics across these settings are likely to be different, and with the relationships between platform owners and complementors being complex and deeply intertwined, it is critical to study the strategic behavior of intermediaries that directly benefit from the entities they evaluate.

Third, prior studies in the certification literature have assessed how firms ex-ante adjust their efforts to receive certification, but little is known on how firms react

after being awarded certification. However, in the context of platform-mediated settings, it is critical for platform owners to understand how their complementor ecosystems respond to governance mechanisms (e.g., Panico & Cennamo, 2020). In a study of Kiva's microfinance platform, Rietveld et al. (2021) examined how complementors responded to the introduction of a certification program. While the authors showed that certification could help a platform owner achieve horizontal differentiation—with certified complementors adjusting their complement portfolios to align with the platform's certification—the study focused only on the effects on complementors that have received certification. However, a platform owner must also estimate the effects of certification of complementors that have *not* received certification. Given the strong performance benefits of certification and the fact that only a small fraction of complements is selected, it is particularly important to study the response of the remaining complementors to estimate their potential implications on the resulting competitive dynamics and changes to their supply side incentives.

The competitive implications of certification are also an understudied topic within the certification literature, with an exception being Polidoro's (2013) study on the pharmaceutical industry. The author investigated how the scientific and regulatory certification received by a firm receives affected its competitors' entry into a new field pioneered by the certified firm and found that certification offers effective protection for the firm against its rivals. However, in the hypercompetitive context of platform markets, with high technological agility, low barriers to entry, and low marginal costs for experimentation and product refinement (Yoo, Lyytinen, Boland, & Berente, 2010), it is likely that firms seek certification at all costs, especially given its performance-boosting effect, which may imply alternative theoretical relationships.

In sum, it remains unclear (i) how platform owners select complements for certification and the relative impact of demand and supply side factors on these selection decisions, (ii) how the underlying mechanisms unfold when actors with the authority to provide certifications directly benefit from the economic performance of the certified products, and (iii) how firms respond to the certification, and particularly, how these responses may differ between firms awarded certification and uncertified

competitors in the ecosystem. This dissertation addresses these knowledge gaps and extends the previous research through an empirical analysis of Apple's App Store, an iconic platform ecosystem.

3 Data and Methodology

3.1 Empirical Setting

The empirical setting of this dissertation is Apple’s mobile device ecosystem in the U.S., where third-party software developers can develop apps using the company’s software development kits (SDKs) and market them to Apple’s customers via the App Store. The App Store is a storefront application preinstalled on all iOS devices, such as iPhones and iPads, where users can browse, preview, and download apps. To date, more than two million apps have been released to the App Store, generating over \$230 billion in cumulative earnings for app developers.¹⁰

The App Store provides an important and relevant empirical context for investigating the underlying mechanisms and implications of selective endorsement via certification from platform owners. This setting is ideal to study my research questions for several reasons. First, with its 2017 redesign of the App Store, Apple shifted away from algorithm-based suggestions and introduced editorial app recommendations curated by a human team.¹¹ This team of editors regularly selects a small set of apps and temporarily promotes them on the App Store—also referred to as “*app featuring*” in the developer community. When iPhone and iPad users open the App Store on their devices, they arrive on the “Today” tab, on which Apple editors showcase several hand-selected apps to these users, usually via a brief written story, animated experience, or video clip. Additionally, these selected apps receive specific tags (i.e., visual certifications) such as the “Editors’ Choice” and “Games We Love” badges. In the presentation that accompanied its 2017 redesign of the App Store, Apple stated that its intentions for such editorial recommendations were to “*inform (Cool, I want to get that!)*”, “*help (I had no idea. Thanks!)*”, and “*inspire (Wow. That’s*

¹⁰ See <https://www.statista.com/statistics/276623/number-of-apps-available-in-leading-app-stores/> and <https://www.statista.com/chart/9671/developer-earnings-apple-app-store/>, accessed June 2021.

¹¹ Interestingly, Apple later expanded this form of human-based editorial recommendations to its other platforms such as Apple Music (with hand-curated playlists), Apple TV (with hand-curated movies and shows), and Apple News (with hand-curated local news articles). See also <https://www.apple.com/sg/newsroom/2021/01/apple-services-entertain-inform-and-connect-the-world-in-unprecedented-year/>, accessed March 2021.

super interesting)” (Apple, 2017) the visitors of the App Store. According to Apple, its editors base their decisions to feature a specific app on various generic factors, including high app quality, app design, and storytelling ability. However, Apple does *not* reveal the exact criteria for the selection process.¹²

For app developers, the benefits of being featured by Apple often include a surge in impressions, click-throughs, and downloads (see Liang et al., 2019, for an analysis of the demand side implications of Apple’s app featuring). I also reviewed several market reports and anecdotal case studies, and the consensus is that the impact of Apple’s featuring is significant, with the main benefits for developers being higher app visibility, increased download performance, and increased in-app revenue. This finding was also confirmed in the interviews I conducted with developers and in my quantitative research sample, with endorsed apps tripling their download numbers during endorsement.¹³

Second, the App Store provides accurate metrics for the critical constructs related to my research questions, including app performance, app design, app updates, app category, platform transitions, and competition. The growing number of studies using App Store data across diverse research foci attest to the accuracy and validity of these data (e.g., Agarwal & Kapoor, 2018; Askalidis, 2015; Boudreau, Jeppesen, & Miric, 2019; Bresnahan, Orsini, & Yin, 2014; Chen et al., 2021; Eaton, Elaluf-Calderwood, Sørensen, & Yoo, 2015; Ifrach & Johari, 2014; Kapoor & Agarwal, 2017; Miric & Jeppesen, 2020; Tidhar & Eisenhardt, 2020; Wen & Zhu, 2019; Zhang et al., 2020).

Finally, as argued above, the App Store (and other stores such as Google Play and Amazon Appstore) are economically important and a central part of the digital economy. In my research setting of the U.S. market, Apple has a market-leading

¹² Note that there is no paid placement for app featuring in the App Store. While developers can advertise their apps in the App Store’s search function (so-called App Store optimization), they cannot pay for app featuring. See <https://developer.apple.com/app-store/discoverability/>, accessed March 2021.

¹³ I estimate the average effects of app featuring on download performance in a subsample of my data. Results are presented in the Appendix.

position, with every second American owning some version of the iPhone.¹⁴ Thus, because smartphone devices and their connected app platforms have become a central part of everyday life, the app market is interesting and essential to examine in and of itself (Kapoor & Agarwal, 2017; Wen & Zhu, 2019; Yin, Davis, & Muzyrya, 2014).

3.2 Data Collection

I used several data sources: (i) archival material, (ii) interviews with app developers and industry experts, and (iii) quantitative datasets. I collected data in three stages. First, I collected in-depth archival material, including press articles; corporate press releases; technology blogs; publicly available interviews with Apple executives, industry experts and app developers; conference presentations; social media content; and industry analyst reports. In total, I read over 250 unique pieces material gathered from databases such as Factiva, LexisNexis, and the Internet Archive as well as web search engines.

Second, I conducted interviews with seven developers whose apps were featured by Apple.¹⁵ The interviews had three sections. The first section covered informants' background and role. The second was a detailed narrative on the app design, business model, time-to-market strategy, and other app-specific information of the featured app from the developer. My goal was to understand the major factors that were relevant to Apple's selective app certification on the App Store. The third section explored topics that arose during the interview or were present in the archival data. The interviews lasted between 30 and 45 minutes. Where necessary, I used follow-up interviews and emails to fill in any gaps. In addition, I interviewed two independent industry analysts from market research firms. These interviews were adjusted to fit the informants and allowed me to triangulate the insights of the developer informants and improve my understanding of the mobile app industry.

¹⁴ See <https://www.statista.com/statistics/236550/percentage-of-us-population-that-own-a-iphone-smartphone/>, accessed March 2021.

¹⁵ For the interview-based research, I mainly followed the guidance from Hannah & Eisenhardt (2018).

Third, I collected quantitative data to explore the relationships and variables identified from the two data sources at a larger scale. My main datasets, which I directly obtained from a mobile app analytics companies, included approximately 7,000 apps from game developers listed in the U.S. market between January 2019 and August 2020.¹⁶ I focus on the games category of the App Store because it is the largest category by the share of available apps,¹⁷ and also accounts for the largest proportion of mobile app revenue.¹⁸ Moreover, previous practitioner research and my interviews with developers confirmed that certification is critically for games (rather than other apps, e.g., utility apps such as PDF readers or fitness apps such as step counters) in terms of app performance and visibility.¹⁹

For each app, the dataset contained daily²⁰ observations that allowed me to capture information on a number of variables, including app characteristics, release dates, version history, price change events, user ratings, and download performance.²¹ My dataset also included detailed information on the main variable of interest in this dissertation: for each day of my observation period, I know whether an app was featured on Apple's "Today" tab on the U.S. version of the App Store, with the start and end dates of the featuring.²² I complemented my quantitative dataset with additional data from manual research and automated web scraping on Apple's official

¹⁶ Note that app analytics providers do not generate own data but accumulate data from the App Store over time. This may lead to some data points being estimated by algorithms rather than actual data (e.g., scraped from websites, retrieved by API).

¹⁷ See <https://www.statista.com/statistics/270291/popular-categories-in-the-app-store/>, accessed July 2021.

¹⁸ See <https://venturebeat.com/2021/06/28/sensor-tower-mobile-game-revenue-grew-18-in-the-first-half-of-2021/>, accessed July 2021.

¹⁹ See <https://www.appannie.com/en/insights/market-data/impact-app-store-feature/>, accessed May 2021.

²⁰ For some variables, observations are only available per month (e.g., average or median values estimated by the app analytics providers).

²¹ The apps included in the datasets are mostly drawn from a sample of apps with meaningful downloads as it is difficult to precisely track app performance at the tail of subcategories (Source: Interviews). Thus, the dataset mostly consists of apps that ranked at least once in the top 500 monthly ranking of the respective subcategories available in the dataset. This helps to increase data accuracy (i.e., more precise app performance measures).

²² Note that the present data only captures if a specific app received any featuring, but it does not contain details on the featuring format (e.g., text length, video, thumbnails, placement location, etc.). Formats may vary greatly ranging from a small placement at the bottom of the "today" tab with a short caption to an extended featuring in a high-visibility location.

web pages to retrieve detailed data on Apple’s hardware (e.g., the iPhone 11) and software update releases (e.g., iOS 13). These additional data were then later used in several variable computations.

Table 3: Overview of Data Sources

Source	Description	Collection
(1) Archival material	253 data pieces (61 articles, ²³ 38 press releases, and 154 web pages)	Retrieval from databases (Factiva, LexisNexis, Internet Archive) and web search engines
(2) Interviews	7 interviews with game app developers (average duration of 41 minutes)	Virtual interviews
	2 interviews with industry analysts (average duration of 44 minutes)	Virtual interviews
	Interview follow-ups	Emails and phone calls
(3) Quantitative data	Daily (and aggregated monthly) data on ~7k ²⁴ apps listed in the games category of the App Store Additional quantitative information required for variable computations (e.g., featuring dates, software release dates, software update content, pricing points, etc.)	Directly received from a mobile app analytics companies Manual search and automated collection (web-scraping)

3.3 Research Design

To study the research questions of this dissertation, I conduct two studies using different research approaches and methods. The first study follows an *inductive* research approach to detect patterns in Apple’s selection criteria for app endorsement. Consistent with this question-driven research, I use supervised ML methods to identify key predictors and relationships within the data to generate theory-building insights. ML is particularly well suited for my inductive research design in Study 1 for several reasons. First, in contrast to econometric models, which tend to overfit specific data, ML produces simple, accurate, and generalizable models, which is consistent with the theory-building aim of Study 1 (Choudhury, Allen, & Endres, 2021; Shrestha, He, Puranam, & von Krogh, 2020; Tidhar & Eisenhardt, 2020).

²³ Sample sources for articles include newspapers (e.g., *Financial Times*, *Wall Street Journal*), technology blogs (e.g., *TechCrunch*, *MacRumors*), magazines (e.g., *Forbes*, *Businessweek*), and industry reports (e.g., *App Annie State of Mobile in 2020*).

²⁴ Due to the relatively short lifespan of mobile apps (see Kapoor & Agarwal, 2017), not all apps included in the dataset were useful for analysis. Further, data availability and granularity differed among the apps included in the datasets.

Second, the research question of Study 1 is a binary classification problem (i.e., predicting whether or not an app is featured), which is a useful and state-of-the-art application for ML methods (Athey, 2018; Brink, Richards, & Fetherolf, 2016; Jung, Concannon, Shroff, Goel, & Goldstein, 2017; Varian, 2014). Third, several ML models incorporate features that are not apparent in traditional econometrics. For example, tree-based ensemble approaches such as random forest methods are particularly effective for highly nonlinear data and for identifying the most important predictor variables in terms of their contribution to prediction accuracy. This aligns well with my goal of discovering robust and accurate predictor variables for app endorsement within Study 1.

The second study follows a *deductive* research approach to estimate the implications of Apple's app endorsement on developers' subsequent innovation efforts. Consistent with this focus on inference, I test hypotheses derived from a priori theorizing with an econometric analysis for model estimation and the evaluation of coefficient (Mantere & Ketokivi, 2013). I also use ML-based methods in Study 2. However, in contrast to Study 1, I use such methods not for pattern discovery but for classifying the meaning embedded in unstructured textual data, which I use as variables in my econometric models (see Barlow, Verhaal, & Angus, 2019; Choi et al., 2021; Choudhury, Wang, Carlson, & Khanna, 2019; Furman & Teodoridis, 2020 for related ML applications).

While both studies were carried out in the same empirical context, separate samples were constructed for each study to account for the different research questions, variable computations, data availability, and methods. Creating two separate samples was also necessary because of the different research foci of the two studies: Study 1 focused on the time and actions *before* an app certification event to detect ex-ante patterns in Apple's selection mechanisms, and Study 2 focused on the time and actions *after* an app certification event to study the effects of certification on ex-post complementor behavior. I discuss detailed sample constructions, variable computations, and methods for each analysis in their respective chapters.

4 Platform Owners' Selection Criteria

4.1 Introduction

Over the last few years, an increasing share of economic activity has shifted to digital platforms. Thousands of small firms, often referred to as complementors, have entered platform markets to provide products and services to end users. For example, more than 350 million products are listed on Amazon's marketplaces,²⁵ and each day, more than 60,000 songs are added to Spotify's music streaming platform,²⁶ and approximately 5,000 new apps are released on Apple's App Store.²⁷ When the quantity of complements on a platform becomes overwhelmingly high, two critical challenges arise. First, consumers find it increasingly difficult to find the high-quality content they want, thereby reducing the platform's attractiveness for them (Parker, Van Alstyne, & Choudary, 2017). Second, complementors find it more difficult to achieve visibility among many competing product offerings, reducing their incentives to innovate and produce for the platform (Boudreau, 2012, 2017; Boudreau & Jeppesen, 2015). These developments not only reduce the revenue of platform owners but also lead to disadvantages for them against competing platforms.

One strategy frequently used by platform owners to mitigate such risks is the selective endorsement of complements. Such endorsement spotlights individual complements, enabling the platform owner to reduce customers' search costs and attract attention to underappreciated complements with high-value-creation potential. Examples of such endorsements include Apple's "Apps We Love" list, Airbnb's "Superhost" badge, Spotify's "Editorial Playlists", and PlayStation's "Platinum Games". Previous studies on selective promotion have examined the demand side implications of endorsement and found substantial benefits for endorsed complements

²⁵ See <https://www.bigcommerce.com/blog/amazon-statistics/#10-fascinating-amazon-statistics-sellers-need-to-know-in-2020>; accessed January 2021.

²⁶ See <https://www.musicbusinessworldwide.com/over-60000-tracks-are-now-uploaded-to-spotify-daily-thats-nearly-one-per-second/>; accessed March 2021.

²⁷; <https://www.statista.com/statistics/1020964/apple-app-store-app-releases-worldwide/>; accessed July 2021.

across various industry settings (e.g., Aguiar & Waldfogel, 2018; Elfenbein et al., 2015). However, while these findings pointed to the positive consequences of endorsement for the chosen complement's performance, less work has been conducted on the causes that underpin platform owners' decisions to selectively endorse individual complements out of thousands of competing, often similar, offerings from their complementor ecosystems.

When studying the demand side effects of selective endorsement in the context of platform-based markets, in most prior work, the exact selection criteria often remain relatively vague. A notable exception is Rietveld et al.'s (2019) study on the video game industry, which showed that user ratings and unexploited sales performance were important factors for the endorsement of complements. While the stimulation of complement demand is essential for driving indirect network effects and creating a competitive advantage over competing platforms (Armstrong, 2006; Parker & Van Alstyne, 2005; Rochet & Tirole, 2006), such demand-based criteria may reveal only part of the bigger picture in contexts where platforms not only are digital marketplaces but also offer complex technological infrastructures on which other firms can build their complementary innovations. Moreover, the success of such platforms requires ongoing investments in co-specialization (Jacobides et al., 2018; Kretschmer et al., 2021), and platform owners need to incentivize complementors to act according to the platform's central strategic objectives (Cennamo & Santaló, 2019). I argue that endorsement decisions are influenced not only by demand side factors but also by strategic considerations concerning how to align complementors to the ecosystem and reward greater participation and innovativeness. Put differently, I assume that endorsement decisions are influenced by a broader range of technological, strategic, and performance-related factors. Consequently, I consider the following question: *“Which factors lead to complement endorsement from the platform owner, and what is the relative influence of these factors on such decisions?”*

I empirically study my research question by examining how Apple chooses which third-party apps to promote in its App Store for iPhone users in the U.S. market. This setting is particularly appropriate, as Apple has introduced editorial

recommendations based on human-curated lists of featured apps and games since its 2017 redesign of the App Store. Additionally, this setting offers accurate measures across complement-, market-, and ecosystem-level constructs (e.g., Kapoor & Agarwal, 2017; Yin et al., 2014), allowing me to yield an understanding of the potential selection criteria for app endorsement. Consistent with my inductive research question, I use an ML framework (Shrestha et al., 2020) that enables me to detect robust patterns in the data and generate theory-building insights with variable selection techniques, guards against overfitting, and large-scale corroboration.

My study makes several contributions. First, I identify four constructs—complement newness, level of co-specialization, extent of upselling options, and innovation intensity—that allow me to predict which complements platform owners choose to promote. My findings extend prior studies on governance in platform ecosystems (e.g., Huang et al., 2013; Rietveld et al., 2020, 2019; Wareham et al., 2014), suggesting that platform owners use selective endorsement not only to manage the demand side of their platforms (i.e., guide users to undervalued complements; see Rietveld et al., 2019) but also to orchestrate their supply side (i.e., align complementors to the ecosystem and induce greater participation and innovativeness). As such, my findings contribute to recent advances in the platform governance literature that focus on platform owner decision-making (Foerderer, 2020; Helfat & Raubitschek, 2018; Parker & Van Alstyne, 2005) by illuminating the underlying selection criteria for complement certification and subsequent implications for platform innovation.

Second, my findings contribute to the literature on quality certification (for a review, see Dranove & Jin, 2010), especially to a small set of studies exploring the strategic behavior of the market intermediaries that provide such certifications (e.g., Olson & Waguespack, 2020; Seamans & Zhu, 2014). While most of this research is conducted in settings where independent third parties evaluate and certify products that they do not sell themselves, I examine the motivations and actions of a powerful platform owner that “certifies” the complements provided by third-party

complementors and, at the same time, provides them with the infrastructure to sell these offerings to its customers and takes a cut of their revenues.

Third, my findings suggest important strategic implications for platform complementors. If complementors want to increase their likelihood of endorsement from the platform owner, then they need to adapt their product configuration, time-to-market, and monetization strategies accordingly. Thus, my findings help complementors anticipate platform owners' selection behavior and increase the likelihood of endorsement, which may result in superior visibility and performance in crowded platform-based markets.

4.2 Background

The early economics literature emphasized that platforms need to stimulate network effects on both sides of their markets to grow and create value (e.g., Armstrong, 2006; Katz & Shapiro, 1985; Rochet & Tirole, 2006; Schilling, 2002). The main argument is based on the assumption that consumers place a higher value on platforms with a larger number of users (direct network effects), as they anticipate that platforms with more users offer a larger number and variety of complementary products and services (indirect network effects) (Cennamo & Santalo, 2013; McIntyre & Srinivasan, 2017). For example, the more consumers purchase iPhones, the more developers publish apps on Apple's App Store. Consequently, *ceteris paribus*, this will lead to additional iPhone purchases and the creation of more apps from new developers seeking to reach new iPhone users. Previous studies have mainly focused on platforms' pricing strategies to unlock such network effects and to bring both sides of the market to a consensus (Parker & Van Alstyne, 2005; Rochet & Tirole, 2003).

While this "the more, the better" premise holds in settings where the value of a platform is driven by the sheer number of transactions between its two sides—for example, on payment, matching, or advertising platforms—more recent research has raised doubts this premise does not capture the innovation dynamics and coordination challenges for platforms that are not pure marketplaces. For example, platform

ecosystems around mobile devices, video game consoles, or enterprise software provide the technological infrastructure needed for other firms to build their complementary innovations. In those settings, studies show that the quality, novelty, and diversity of the complementary products offered on a platform are just as important as their quantity (Binken & Stremersch, 2009; Cennamo, 2018; Kim, Prince, & Qiu, 2014; Panico & Cennamo, 2020).

Thus, a key challenge for platform owners is not only to drive growth via network effects but also to nurture the quality and innovativeness of their ecosystems and align complementary incentives to the platform's strategic intent (Ceccagnoli et al., 2011; Jacobides et al., 2018; Rietveld et al., 2019; Wareham et al., 2014). Previous research has examined a wide range of strategies that platform owners can pursue to manage their ecosystems and bind complementor behavior, such as royalty rates (e.g., Hagiu, 2006), restrictive rules for platform access (e.g., Zhang et al., 2020), threats of platform owner entry and vertical integration (e.g., Wen & Zhu, 2019), the sharing of proprietary knowledge (e.g., Foerderer, 2020) or the setting of common standards (Wareham et al., 2014).

The focus of this study is an alternative strategy to govern complementor quality and diversity: the platform owner's "*selective endorsement*" (Rietveld et al., 2019) of complements, also referred to as "*platform recommendation*" (Liang et al., 2019) or "*complement certification*" (Elfenbein et al., 2015). Such endorsements can be implemented in various ways, e.g., awarding badges to signal quality and trustworthiness (Hui et al., 2016), spotlighting complements on the platform's interfaces (Aguiar & Waldfogel, 2018), or providing users with curated lists of recommended products (Liang et al., 2019).

Although the selective endorsement of complements appears to be a relatively simple mechanism at first glance, a small set of early studies documented two important strategic functions in managing a complementor ecosystem and highlighted the complex strategic tradeoffs involved. First, selective endorsement informs platform users. With an overwhelmingly large number of products available on many

such platform ecosystems, it is increasingly difficult for users to discover the high-quality products they seek. Selective endorsement places a spotlight on specific complements, thereby reducing users' search costs. However, platform owners must carefully select which complements to promote, as excessive endorsement is counterproductive for the strategic intention of unlocking the value of individual complements (Elfenbein et al., 2015).

Second, selective endorsement enables platform owners to manage their complement portfolios' diversity. Effective product discovery via organic channels based on, e.g., sales ranks or consumer ratings, requires a sizable installed base of users, which most new-to-the-platform products lack (Liang et al., 2019). As a result, platform owners risk new products remaining undiscovered, failing to create value for the platform. In particular, Rietveld et al. (2019) found that platform owners strategically invest in upcoming complements to attract attention to underappreciated complements with high sales potential, actively influencing consumers' perceptions of the platform's overall depth and breadth. However, endorsing one complement will put other unendorsed complements at a competitive disadvantage, thereby altering the competitive dynamics in complementor markets (Liang et al., 2019). Thus, platform owners must anticipate potential unwanted side effects when using selective endorsement to manage the breadth and depth of their ecosystem.

While these two functions explored in the previous literature contribute to my understanding of selective endorsement to manage a platform's demand side, I argue that this perspective captures only part of the bigger picture, ignoring the role of selective endorsement in managing the supply side. The findings from the related literature on quality certification indicate that certification not only informs customers (i.e., demand side effects) but also stimulates firms to supply products of higher quality (i.e., supply side effects, see Hwang et al., 2006; Zapechelnyuk, 2020). I extend this notion to the context of platform markets, where excessive competitive crowding tends to reduce a complementor's future incentives to invest in increased quality and innovation (Boudreau, 2012; Casadesus-Masanell & Hałaburda, 2014; Markovich & Moenius, 2009). However, platform owners are dependent on active

support from complementors that continuously supply high-quality products to the ecosystem (Cennamo, 2018; Cennamo & Santaló, 2019; Ozalp, Cennamo, & Gawer, 2018). With substantial demand side effects for these endorsed complements, I assume that selective endorsement (i.e., “certification”) may serve as a powerful mechanism to impact complementors’ incentives and “reward” them for their investment, innovativeness, and customized configuration to the platform’s core.

In sum, while the extant literature has provided important insights into how demand side factors influence a platform owner’s decision to endorse complements selectively, it does not include the potential role of incentivizing and stimulating a platform’s supply side. I address this gap and extend the previous research by studying the relative impact of both demand and supply side factors on a platform owner’s decision regarding which complements to endorse.

4.3 Methods

I address my research question with a novel and question-driven approach to theory building known as “*algorithm-based induction*” (Shrestha et al., 2020). This approach leverages ML to detect patterns in data that can be used as inputs into abductive reasoning. Given the limited theory and empirical evidence on how platform owners select complements for certification (as described in Chapter 4.2), this method is appropriate for my study, as it allows for the inductive theorizing and testing of the constructed theory with large sample data (Shrestha et al., 2020). I follow an inductive analytical strategy that has three steps (see He et al., 2020 for the related application of inductive ML research approach).

In Step 1, the main goal is to identify the relevant constructs, underlying mechanisms, and theoretical relationships. In essence, this first step of my research is similar to case study research and involves an iterative process of refining insights, building underlying logical arguments, and relating them to existing theory (Eisenhardt, 1989; Eisenhardt & Graebner, 2007; Tidhar & Eisenhardt, 2020). I began by synthesizing the qualitative data gathered in the form of archival data and interviews (for details on data sources and collection, see Chapter 3.2) into a small

number of comprehensive cases (Yin, 2009), each tracking the developer's activities related to its certification event. I focused on relevant information that could be corroborated from multiple data sources and that had also been emphasized by informants. When details were missing, I obtained additional archival information or reached out to the informants for follow-up. For each case, I conducted a within-case analysis to address my research question.

After carefully examining my qualitative case data, I moved to a cross-case analysis by conducting exploratory data analysis (EDA) on different subsets of my quantitative dataset (Cox, 2017). For example, I selected different app categories, popular and less popular apps, and observation periods and explored the initial relationships from individual cases and compared them across multiple cases using visual (e.g., scatterplots, heatmaps, and boxplots) and numeric (e.g., pivot tables and correlation matrices) analyses. This procedure of manual analysis and nonparametric exploration of empirical observations allowed me to iteratively increase granularity by segmenting my data into potentially relevant dimensions. As my data-driven insights became more refined, I referred to previous literature (although limited with regard to my research question) to compare them with those of the existing research before turning back to my data. Once I identified substantial correspondence (i.e., theoretical saturation) among data, measures, and theory, I finalized the analysis (Glaser & Strauss, 1967). As a result, my analysis in Step 1 uncovered 11 variables that capture important features of Apple's app selection and featuring process. Table 4 presents the definitions of these variables.

Table 4: Variable Descriptions

Predictor	Description and Measurement
(1) New app (x_1)	A binary predictor that indicated if an app was released less than three months before the respective observation day. This measure is consistent with other studies of the App Store (e.g., Kapoor & Agarwal, 2017) and is intended to separate apps that are new to the platform from older apps. It should be noted that the App Store is an hypercompetitive context (D’Aveni, Dagnino, & Smith, 2010) with short average app lifetimes and meaningful sales occurring mainly in the first couple of months after the app’s release.
(2) Apps per developer (x_2)	Total count of the number of games that a developer has listed. This measure accounts for the size and breadth of a developers’ app portfolio.
(3) Popular developer (x_3)	A binary predictor that indicates if a developer has any app in its portfolio that reached the top 500 download ranking of the games category. The top 500 ranking lists all apps by their number of monthly downloads in descending order and is the key performance indicator for developers competing on the App Store (Kapoor & Agarwal, 2017). This measure helps separating popular from unpopular developers and accounts for potential diverging characteristics (see also Tidhar & Eisenhardt, 2020, for a similar construct).
(4) App quality (x_4)	This measure represents the consumer rating of an app. It is calculated as the number of one star, two stars, three stars, four stars, and five stars ratings divided by the total number of rates.
(5) Adaption speed (x_5)	Number of days between the release day of the latest iOS software generation in my observation period and the release day of the first app update after the iOS software release that integrates technical or content-based features of the new iOS software generation (iOS 13). For example, if an app released an update that contains a dark mode function, a key technical feature of iOS 13, three days after Apple made the respective SDK available, the value of the variable would be 3.
(6) App size (x_6)	App’s storage space in MB. Consistent with prior studies (e.g., Agarwal & Kapoor, 2018), I use this variable as a proxy for an app’s technical complexity (e.g., graphics, levels of gameplay, number of incorporated SDKs).
(7) iPad version (x_7)	A binary predictor that indicates if an app has an iPad version, i.e. this variable measures if the app is available to other devices in Apple’s ecosystem.
(8) In-app-purchases-avg value (x_8)	Weighted average value of the prices for in-app purchase options. In my dataset, 98% of apps included are freemium apps, meaning that they offer a basic version that is available for free. Users are allowed to purchase “add-ons” in series of micro-transactions (e.g., game items, levels of gameplay) or upgraded “premium” versions (e.g., subscriptions, ad-free versions).

(9) In-app-purchase options (x_9)	Number of in-app purchase options that include extra content and features such as digital goods, subscriptions, and other premium content. This variable is related to (x_8) and counts only the number of options available unbiased from each options price.
(10) Update frequency (x_{10})	Total number of updates of an app normalized by its age (observation day - app release day). This variable measures a developer's innovation efforts, i.e., the frequency of app updates released by the developer (e.g., adding new content or features, interface redesigns, and bug fixes). See Foerderer (2020), Wen & Zhu (2019), Yin et al., (2014) for similar constructs to measure developer's innovation efforts.
(11) Top rank (x_{11})	A binary predictor that indicates if an app was included in the top 500 of its respective category in the month prior to the observation day. This measure is consistent with other studies using download ranks to estimate app performance (e.g., Agarwal & Kapoor, 2018; Kang, 2018; Kapoor & Agarwal, 2017).

In Step 2, I use ML to select important predictor variables (feature selection) and remove redundant variables with little explanatory power from my initial set of variables (constructed in Step 1). ML uses two main techniques to predict robust, accurate, and generalizable associations (“patterns”) in the data (see Hastie, Tibshirani, & Friedman, 2009 for technical details). First, cross-validation (CV) helps prevent overfitting, i.e., avoid producing highly idiosyncratic results for the present sample (e.g., Athey, 2018; Brownlee, 2016; Varian, 2014). CV involves an algorithmic procedure of estimating models from training data and evaluating them through the use of testing data, limiting overfitting. Second, regularization helps improve model accuracy by “penalizing” excessive model complexity, which can be achieved by manual or algorithmic hyperparameter tuning, involving, e.g., limiting the number of regression coefficients, reducing the number of leaves in a decision tree, or allowing only second-order polynomials. In particular, studies have shown that simple models with fewer predictor variables appear to be surprisingly accurate compared to more complex models (Choudhury et al., 2021; Jung et al., 2017). Therefore, by preventing overfitting and excess model complexity, ML facilitates “*algorithm-supported induction*” (Shrestha et al., 2020), and yields results that enable replication by other researchers and in different datasets.

I implement my ML analysis with a framework that roughly follows the guidance of Shrestha et al. (2020) on the operationalization of algorithm-supported induction.²⁸ I begin by randomly splitting the entire dataset into two samples: a training set (sample I, 70% of the sampled data observations) for pattern detection and a holdout test set (sample II, 30% of the sampled data observations). Additionally, I store the variables identified in Step 1 in a vector, X , and create a vector, Y , that contains the binary target variable (whether or not the app was endorsed by Apple). Then, using sample I, I perform a feature selection analysis (Guyon & Elisseeff, 2003) to identify the predictors that have the highest explanatory power for Y . To ensure that

²⁸ ML analyses were performed using *Scikit-learn*, a popular module for the application of ML algorithms (Pedregosa et al., 2011). For some of the econometric analyses in this study, the *statsmodels* module was used (Seabold & Perktold, 2010).

this set of predictors $x_1, x_2, \dots, x_{11}$ is small (easy to interpret) and robust (unlikely to be the result of sampling errors), I follow a procedure that is typical for ML analyses (Choudhury et al., 2021): (1) I select several ML models, (2) I perform k-fold cross-validation to identify their optimal hyperparameters (“model tuning”), and (3) I evaluate their performance.

I choose three ML models in my feature selection analysis: a random forest algorithm, a gradient boosting algorithm, and a penalized logistic regression (least absolute shrinkage and selection operator (LASSO)). The random forest algorithm generates many decision trees (i.e., a random forest) using random subsamples of data and predictive variables and averages these decision trees to make predictions. Random forests have several advantages for my analysis. Because they generate a large number of uncorrelated decision trees, random forests provide accurate estimates of the most important variables in terms of their contribution to prediction accuracy. Additionally, they are particularly effective for highly nonlinear data, as is the case in this work. Like random forest, the gradient boosting algorithm also generates many decision trees. However, gradient boosting models build decision trees in a gradual, additive, and sequential manner, i.e., one at a time, to improve the weak learners in each sequence rather than averaging them at the end of the sequence (Wager & Athey, 2018). While this approach is more complex and its models are more difficult to tune, it often outperforms the simpler random forest approach, especially when working with unbalanced data, as is the case in this work (Brownlee, 2016).

I complement my tree-based feature selection with the LASSO algorithm (Tibshirani, 1996), which generates regression coefficients that minimize the sum of the squared residuals and includes a penalty term that is determined by the number of variables included in the model (Belloni, Chernozhukov, & Hansen, 2014). In essence, the LASSO penalizes less important features by making their respective coefficients zero, thereby eliminating them, which benefits my primary goal of feature selection. Additionally, the LASSO helps me with simple model creation by addressing concerns about overfitting the model with too many covariates by selecting

a set of predictors representing the best-approximating model for Y . Overall, this procedure of using three different algorithms for feature selection allows me to reduce the initial number of variables. The last step within Step 1 is to run a logistic regression with the identified set of predictive variables.

In Step 3, I evaluate the statistical and economic significance of my identified patterns by running the same logistic regression using the holdout sample (sample II). I also add control variables to my model and conduct further robustness checks. Overall, this research design allows me to generate a robust theory to predict if and when Apple chooses a particular app for endorsement on its App Store.

4.4 Sample

Drawing on the data sources described in Chapter 3.2, I constructed my sample as follows. First, I screened my sample for any apps that have missing data (e.g., app description or categorization is missing) and removed those apps from my research sample. Second, to control for unobservable variation over time and across apps as much as possible, I match apps by their month and year of launch and their primary subcategory within the games category (for example, action games, cards games or simulation games). Third, as my study's main focus is the time and activities of developers before their apps are featured by Apple, I aggregated daily app-level observations for my observation time period and cut-off observations on the first day that an app was featured. This allowed me to compare the characteristics and innovation activities of featured and nonfeatured apps more strictly. Additionally, since there were much more unfeatured than featured apps, it also prevented me from generating biased standard errors that lack precision because of the oversampling of nonfeatured apps. Finally, I removed all apps that were featured before my observation period, which helped me prevent biased results and address endogeneity concerns from apps that were featured before my observation period. My resulting sample contained 4,323 apps from 3,609 developers, with 936 featured apps and 3,387 matched control apps. My dataset size approximately matched those of other studies on the App Store (for example, Kapoor & Agarwal, 2017).

4.5 Results

Table 5 presents the descriptive statistics and correlations of the variables included in my dataset, with most of the correlations between my explanatory variables being moderate to low, indicating that multicollinearity was not an issue.

I began by splitting my entire dataset into two samples: a training set (sample I) that contains 70% (3,026) of sampled app-level observations for feature selection and pattern detection and a holdout test set (sample II) with 30% (1,297) of sampled app-level observations. Within sample I, I conducted a feature selection analysis. Using the gradient boosting (Model 1), random forest (Model 2), and LASSO (Model 3) algorithms, I was able to identify models that yielded accuracy scores between 0.82 (F1 score = 0.80) and 0.88 (F1 score = 0.88). I ran each model three times and conducted randomized k-fold cross-validation to ensure that the patterns were robust to sampling error. Table 6 reports the detailed model metrics and the configurations for hyperparameter tuning.

Table 5: Descriptive Statistics and Correlations of Initial Predictors

Statistic	N	Mean	SD	(Y)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(Y) Featured	4,323	0.21	0.41	1.00										
(1) New app (x ₁)	4,323	0.21	0.40	0.34	1.00									
(2) Apps per developer (x ₂)	4,323	1.95	9.74	-0.03	0.06	1.00								
(3) Popular developer (x ₃)	4,323	0.67	0.46	0.07	0.11	0.29	1.00							
(4) App quality (x ₄)	4,323	4.40	0.59	0.09	0.03	0.06	0.17	1.00						
(5) Adaption speed (x ₅)	4,323	191.55	77.63	-0.09	-0.07	-0.00	-0.02	0.00	1.00					
(6) App size (x ₆)	4,323	245.39	386.07	0.21	0.13	0.02	0.09	0.11	0.01	1.00				
(7) In-app purchases avg value (x ₇)	4,323	4.48	7.35	0.11	-0.01	-0.04	-0.01	0.10	-0.01	0.11	1.00			
(8) iPad version (x ₈)	4,323	0.78	0.40	0.11	0.07	0.14	0.23	0.25	0.00	0.24	0.18	1.00		
(9) In-app purchase options (x ₉)	4,323	5.01	4.11	0.23	0.00	-0.07	0.13	0.22	-0.02	0.29	0.38	0.37	1.00	
(10) Update frequency (x ₁₀)	4,323	3.78	4.10	0.17	0.17	-0.02	0.00	0.02	0.00	0.07	0.06	0.03	0.07	1.00
(11) Top rank (x ₁₁)	4,323	0.28	0.45	-0.05	-0.05	0.09	0.00	0.09	0.02	0.05	0.02	0.05	-0.01	-0.03

Notes: N=Number of apps, Y=Dependent variable, SD=Standard deviation

Table 6: Results of Machine Learning Analysis for Feature Selection

	Model 1: Gradient Boosting			Model 2: Random Forest			Model 3: Lasso Regression		
	Run 1	Run 2	Run 3	Run 1	Run 2	Run 3	Run 1	Run 2	Run 3
	<i>Gain-based</i>			<i>Impurity-based</i>			<i>Coefficients</i>		
<i>Predictor weights</i>									
New app (x ₁)	0.11	0.09	0.10	0.11	0.11	0.11	1.58	1.57	1.58
Apps per developer (x ₂)	0.03	0.03	0.03	0.03	0.03	0.03	0.00	0.00	0.00
Popular developer (x ₃)	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
App quality (x ₄)	0.05	0.06	0.05	0.06	0.06	0.06	0.00	0.00	0.00
Adaption speed (x ₅)	0.19	0.19	0.19	0.19	0.19	0.19	-2.13	-2.13	-2.13
App size (x ₆)	0.07	0.07	0.07	0.07	0.07	0.08	0.00	0.00	0.00
iPad version (x ₇)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
In-app purchases avg value (x ₈)	0.05	0.05	0.05	0.06	0.06	0.06	0.00	0.00	0.00
In-app purchase options (x ₉)	0.11	0.13	0.13	0.10	0.10	0.11	1.08	1.09	1.08
Update frequency (x ₁₀)	0.33	0.32	0.32	0.33	0.33	0.33	1.21	1.21	1.21
Top rank (x ₁₁)	0.05	0.05	0.05	0.05	0.05	0.05	-0.09	-0.09	-0.09
<i>Overall model metrics</i>									
Logistic loss	-0.32	-0.32	-0.32	-0.33	-0.33	-0.33	-0.39	-0.39	-0.39
Accuracy (in sample I)	0.89	0.89	0.89	0.88	0.88	0.88	0.82	0.82	0.82
Precision	0.89	0.89	0.89	0.90	0.90	0.90	0.80	0.80	0.80
Recall	0.89	0.89	0.89	0.90	0.90	0.99	0.82	0.81	0.82
F1-score	0.88	0.88	0.88	0.89	0.89	0.89	0.80	0.80	0.80
True positives	2301	2301	2301	2331	2330	2331	2262	2263	2262
True negatives	398	398	398	388	388	388	221	220	221
False positives	267	267	267	277	278	277	444	444	444
False negatives	60	60	60	30	30	30	99	99	99

Notes: Precision, Recall, and F1 scores are calculated using the weighted average method. All models were tuned using 10-fold cross-validation. *Gradient Boosting:* Optimal hyperparameters: `n_estimators` (number of sequential trees to be modeled) = 500, `learning_rate` (impact of each tree on the final outcome) = 0.01. *Random Forest:* Optimal hyperparameters: `criterion` (function to measure the quality of a split) = entropy, `min_samples_leaf` (minimum number of samples required to be at a leaf node) = 41, `max_depth` (maximum depth of the tree) = 6, `min_impurity_decrease` (initiate a node split if this split induces a decrease of the impurity greater than or equal to this value) = 0.0005. *Lasso Regression:* Optimal hyperparameters: `C` (inverse of regularization strength) = 0.1.

Consistently across all three algorithms, four variables—new app (x_1), adaption speed (x_5), in-app purchase options (x_9), and update frequency (x_{10})—emerged as robust predictors of app features. Consequently, the remaining variables in my initial set of predictors – apps per developer (x_2), popular developer (x_3), app quality (x_4), app size (x_6), iPad version (x_7), in-app purchase average value (x_8), and top rank (x_{11}) – turned out to not be important in predicting whether an app was featured.

Overall, my feature selection yielded significant improvements in prediction within sample I. To demonstrate these improvements, I ran a logistic regression with all variables $\{x_1, \dots, x_{11}\}$ in sample I and another logistic regression with only the selected features $\{x_1, x_5, x_9, x_{10}\}$. The model without feature selection had an accuracy of 0.79, a logistic loss of -0.43 (standard error of 0.04), and an area under the curve (AUC)²⁹ of 0.76. The prediction of the model with feature selection outperformed that of the standard model in terms of all metrics, with an improved accuracy of 0.83, a reduced logistic loss of -0.33, and an increased AUC of 0.78 (see Figure 1 and Figure 2 for a visual representation). The last step in my feature selection analysis was to run a standard logistic regression (Model 4) with the four extracted variables $\{x_1, x_5, x_9, x_{10}\}$, the significance levels of which are reported in Table 7.

²⁹ The Area Under Curve (AUC) measures the ability of a classifier to distinguish between two classes (in the present analysis: app was featured or not). The higher the AUC, the better the performance of the model.

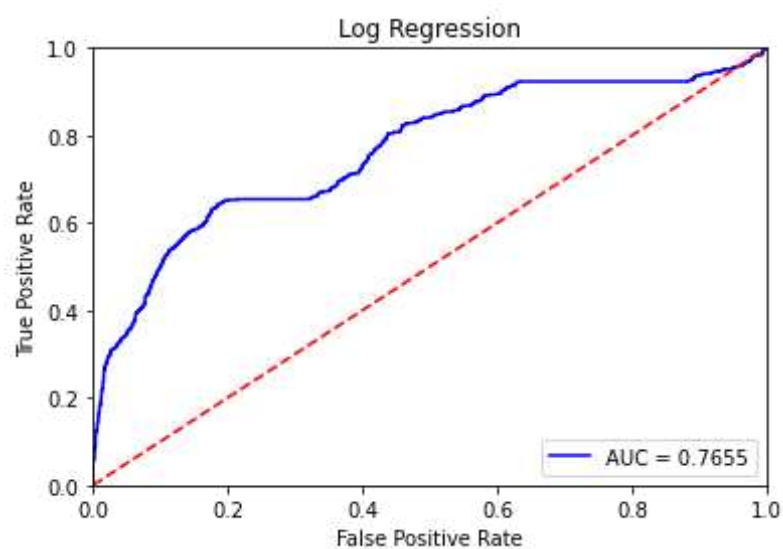
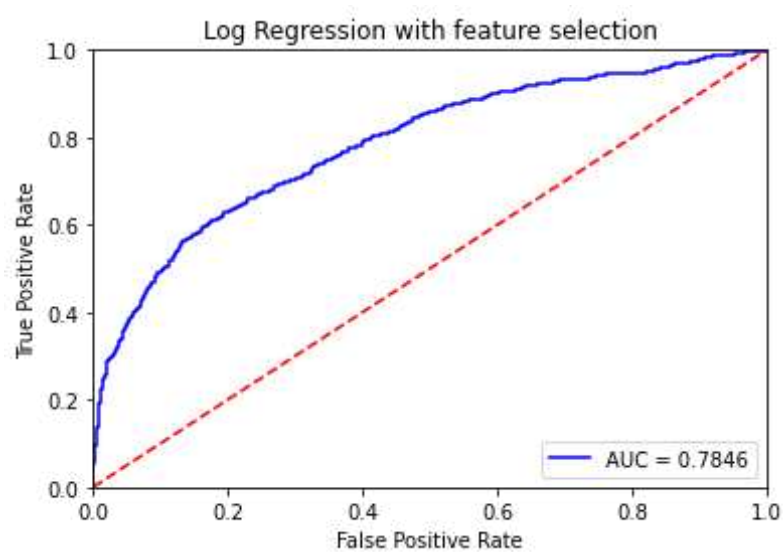
Figure 1: Logistic Regression without Feature Selection in Sample I**Figure 2: Logistic Regression with Feature Selection in Sample I**

Table 7: Logistic Regression in Sample I

<i>DV: Featured</i>	Model 4
Update frequency	4.4095*** (1.1257)
In-app-purchase options	1.2557*** (0.1129)
Adaption speed	-2.3336*** (0.3122)
New app	1.6185*** (0.1149)
Constant	-0.5259** (0.2743)
Observations	3,026
Log-likelihood	-1295.3
McFadden's Pseudo R ²	0.19

Notes: Robust standard errors reported in parentheses. ***p < 0.01; **p < 0.05; *p < 0.10.

The third and final step in my analysis was to replicate this logistic regression model in the holdout sample (sample II). Since this was the first study to examine platform owners' selection criteria for complement endorsement in my context, I was not able to draw upon prior work to generate control variables. However, I added two control variables that were critical in prior studies of the App Store (e.g., Agarwal & Kapoor, 2018; Kapoor & Agarwal, 2017) and that may also influence my predicted endorsement patterns. First, I controlled for app quality to rule out potential concerns that my results were biased by a small set of high-quality apps. Second, I controlled for an app's previous inclusion in the monthly top 500 apps per download to ensure that my results were not driven by an app's download performance prior to being featured by Apple. Additionally, I included three types of fixed effects (FE): population FE to control for unobserved heterogeneity between apps launched in different months, FE apps listed in different categories, and time FE to account for potential time-based events that may influence app features such as U.S. public holidays and work vs. weekend days.

Table 8 presents the regression models that estimate the log likelihood of app featuring given my identified predictors, controls, and fixed effects. Model 5 is a baseline model with control variables, Model 6 includes the main effects from the four variables identified in the ML analysis, and Model 7 estimates the main effects on the entire dataset (samples I + II).

Table 8: Logistic Regression in Sample II and Sample I + Sample II

<i>DV: Featured</i>	Model 5	Model 6	Model 7
Update frequency		6.9174*** (6.0364)	6.2502*** (1.5420)
In-app-purchase options		1.3982*** (0.1974)	1.2581*** (0.0988)
Adaption speed		-1.9264*** (0.4837)	-2.1811*** (0.2602)
New app		0.8117*** (0.2364)	1.5169*** (0.1029)
App quality	2.9566*** (0.9811)	1.2133 (1.1366)	1.7534 (0.5687)
Top rank (previous month)	-0.2896** (0.1546)	0.0297 (0.1770)	-0.1560 (0.0953)
Constant	-3.9620*** (0.9161)	-2.4496** (1.1220)	-2.3246*** (0.5635)
Population fixed effects	Yes	Yes	Yes
Category fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	1,297	1,297	4,323
Log-likelihood	-657.01	-505.32	-1810.82
McFadden's Pseudo R ²	0.11	0.24	0.20

Notes: Robust standard errors reported in parentheses. ***p < 0.01; **p < 0.05; *p < 0.10.

My controls in Models 5-7 loaded mostly as expected from my ML analysis, suggesting that an app's quality (x_4) and its inclusion in the top ranks in the previous month (x_{11}) have a positive and negative but nonsignificant influence on the overall predictive model, respectively. Overall, the results showed significant support for my predictions built out of sample I. First, I found support for a strong positive association ($p < 0.01$) between an app's newness (x_1) and the likelihood of the app being featured, indicating that Apple tends to favor new apps over old apps in its featuring practices. Second, I found a significant ($p < 0.01$) negative relationship between the time it takes for an app to incorporate new features (x_5) from Apple's software releases and the likelihood of the app being featured, which indicates that apps that incorporate key features of new iPhone versions and make customizations quickly according to Apple's software updates may benefit from being featured. Third, my results revealed a significant positive relationship between the higher number of in-app purchase options (x_9) and the likelihood of Apple's endorsement, which indicates that apps offering extra content and features such as digital goods, subscriptions, and other premium content directly within their app's interfaces may also benefit from a higher likelihood of the app being featured. Finally, I found a significant relationship between the frequency of the updates released to an app and the likelihood of being featured on the App Store. This finding supports the idea that frequently innovating an app may correspond with increased visibility from being featured.

4.6 Robustness Tests

I conducted three sets of robustness tests.³⁰ First, I replicated my analysis with a different combination of algorithms. In the feature selection analysis, I replaced the gradient boosting and random forest algorithms with other tree-based algorithms, such as the Extra Trees classifier (Geurts, Ernst, & Wehenkel, 2006) and the XGBoost classifier (Chen & Guestrin, 2016), and the LASSO regression with a logistic regression with recursive feature elimination (Brownlee, 2016). In total, I ran my procedure with three new algorithmic combinations, with each of these combinations

³⁰ Tabulated results are presented in the Appendix.

performing similarly in terms of predictive accuracy on sample I and resulting in similar variable selection. See Table 14 and Table 15 for results.

Second, I followed Shrestha et al. (2020) and explored potential quadratic relationships and two-way interactions within my set of identified predictors $\{x_1, x_5, x_9, x_{10}\}$. I constructed a matrix with all possible two-way interactions and squares (in total, four linear, four square, and eight two-way interactions) and fed it into a LASSO model to reduce the number of polynomials. However, including interaction effects did not significantly increase the accuracy of predicting an app being featured in my dataset. Specifically, the more “complex” model including interaction effects displayed lower accuracy scores than my models with main effects. Table 16 presents results.

Finally, I used alternative measures for some of my variables. I used different time windows for the new app variables (three months and six months) and a continuous measure for an app's age. I used different levels for the top rank variable (top 250 and 500 apps per download in games category). I also differentiated between app updates targeting an app's performance (such as bug fixes and minor improvements) and its content (such as adding new modes of gameplay or new features) to account for potentially varying impacts on my target variable. To do so, I followed prior studies (e.g., Foerderer, 2020; Foerderer et al., 2021; Liang et al., 2019) and classified the updates by their version code (e.g., version code 10.1 indicates a major update and 10.1.1 indicates a minor update). As a validity check, I also used the textual descriptions of the release notes to classify the updates into either a “performance update” or a “content update” using distinct keywords such as “bug fix”, “improvement”, “update”, and their synonyms. Overall, I found that my results are mostly robust across these variations in the variables (see Table 17 for results).

4.7 Conclusions

Due to their central position and market power, platform owners can use selective endorsements to reduce customers' search costs, manipulate individual complements' performance, and govern their complementor ecosystems. Using a

large dataset of app developer populations on Apple's App Store, I employed an ML framework to detect patterns in Apple's app endorsement strategy. My analysis revealed three important predictors of how platform owners choose complements to endorse: a complement's newness, the speed at which complementors adjust their complement offerings to a new platform technology, a complement's number of upselling options, and the intensity of additional product revisions and innovations. I interpret these findings to suggest that platform owners' selection criteria are influenced by complex strategic considerations to not only manage the demand side of their ecosystems (i.e., attract attention to complements with unrealized sales potential) but also induce intended complementor behavior (i.e., reward complementors that configure their product offerings to provide an advantage to the platform).

Contributions

My study contributes to platform strategy research in several ways. First, the previous literature on selective endorsement has predominantly examined the consequences of selective endorsement on a platform's demand side and the associated positive implications for complement performance. In contrast, I focus on the underlying causes that influence whether or not a complement is selected for endorsement and illuminate the factors that may influence platform owners' selection criteria.

Second, I extend previous studies that have highlighted the role of demand-based factors on the likelihood of complements being chosen for endorsement (Rietveld et al., 2019). While my inductive analysis also reveals that Apple tends to choose new apps for endorsements, I extend these findings by considering additional theory on selection criteria, stipulating that platform owners leverage selective endorsement to reward specific complementor behavior. Third, my findings echo the notion of mutual dependence and co-specialization in the previous literature on platform ecosystems (Brunswick, Almirall, & Majchrzak, 2019; Jacobides et al., 2018). Entering a platform involves a continuous investment from complementors,

for example, costs resulting from adjustments to product configurations (e.g., Kapoor & Agarwal, 2017) or numerous and frequent product refinements (Yoo, Boland, Lyytinen, & Majchrzak, 2012). These adjustment costs often increase repeatedly, e.g., when a platform transitions to a new technology generation and improves its existing functionalities or adds new features (e.g., Cennamo, 2018; Ozalp et al., 2018). My findings indicate that platform owners may use selective endorsements to incentivize complementors to invest in co-specialization (Jacobides et al., 2018; Tavalaei & Cennamo, 2020) and align their products neatly with their platforms.

Finally, my study extends the previous literature examining how platforms extract value from their complementor ecosystems (Dhanaraj & Parkhe, 2006; Greve & Song, 2017; Iansiti & Levien, 2004; Van Alstyne, Parker, & Choudary, 2016) and how platform owners influence complementor pricing strategies (Dinerstein, Einav, Levin, & Sundaresan, 2018; Wen & Zhu, 2019; Yoffie & Kwak, 2006). While the monetization of a complement's offering is a discretionary decision of complementors in my setting (Tidhar & Eisenhardt, 2020), my findings suggest that platform owners may use selective endorsement to influence complementors' pricing strategies to target them and influence them toward upselling options that benefit the ecosystem's value creation.

My findings also contribute to the established literature on certification. While this literature has acquired much knowledge on how certification affects either demand from prospective end users or supply from certified firms (Dranove & Jin, 2010), a small set of studies has begun to explore the strategic behavior of the market intermediaries that provide such certifications (Olson & Waguespack, 2020; Seamans & Zhu, 2017). However, most of this research has been conducted in settings where third parties, such as media outlets, certification bodies, or product critics, evaluate and certify products that they do not sell themselves or benefit directly from economically. In my setting, the platform owner "certifies" the complements provided by third-party complementors and, at the same time, provides the infrastructure needed to market them to its customers, taking a cut of their revenue. Illuminating the strategic behavior of platform owners is particularly important for many of today's

industry settings, where platforms have gained enormous market power. This study shows that they use this power to govern their ecosystems, and as my findings demonstrate, incentivize complementors via certification to act according to the platform's strategic objectives.

Limitations and Future Research

The limitations of this study suggest at least four avenues for future research. First, my study is limited to a single empirical setting, and the validity of my findings needs to be established across other industry contexts. While I am optimistic that similar patterns of complement endorsements in related mobile device platforms such as Google Play will be identified, an interesting research question to explore would be if my findings hold in other platform-mediated settings in industries such as enterprise software, e-commerce, and video gaming industries. Additionally, I focus on one particular form of selective endorsement: the placement of a complement in the spotlight of a digital marketplace. In other contexts, endorsement may take different forms, such as badges, certificates, or curated lists of complements provided by the platform owner. Future research could seek to identify how the patterns identified in this study may differ from other forms of selective endorsement.

Second, while I recognize the heterogeneity of apps and developers by collecting data on their characteristics, innovation behavior, and pricing strategies, I cannot observe other app- and complementor-level factors that may affect Apple's endorsement patterns. For example, one might imagine that an app launched by a popular personality (e.g., soccer star Cristiano Ronaldo's app "*Kick'n'Run*") might receive Apple's endorsement, even though it does not share any of the patterns identified in the data. Future work should therefore examine other characteristics of complementors in this context.

Third, my study focuses on the interplay of selective endorsement and complementors' innovation dynamics within one platform ecosystem. Although I identify robust predictors of Apple's app endorsements in my data after controlling for several ecosystem-level covariates and fixed effects, my data do not allow me to

select the broadest possible set of variables that could affect platform owners' selection criteria. For example, I acknowledge that platform owners' selection criteria may also be shaped by factors outside of the ecosystem, such as competitor moves, media coverage, and macroeconomic factors. Future research could examine whether and how such dynamics outside the ecosystem expand and moderate the relationships found in this work.

Finally, my dataset is limited to a short timeframe. While I can identify patterns of endorsements over this relatively short period, data availability constrains me to draw inferences over longer time frames.³¹ Thus, an interesting stream of future research could investigate if and how selective endorsement criteria change over time and explore the potential drivers of these changes, such as complementors' responses, architectural changes to the platform, and other strategic considerations.

³¹ The results are limited to the assumption that the selection criteria remain constant over the observation period. However, it also cannot be ruled out completely that there are unobserved changes to the selection strategy during the observation period.

5 Effects of Certification on Complementor Behavior

5.1 Introduction

Platforms provide infrastructures that facilitate transactions between supply side complementors and demand side users (Jacobides et al., 2018, 2020; McIntyre & Srinivasan, 2017; McIntyre & Subramaniam, 2009). Instead of a hierarchy or market, platforms use complex rules, constraints, and incentives to align the interests of different players and govern their activities (Boudreau & Hagiu, 2009; Gawer, 2014; Kretschmer et al., 2021; McIntyre et al., 2020). Previous research has shown that platform governance takes many forms, such as strategies for managing complement quality (e.g., Boudreau, 2012, 2017; Boudreau & Jeppesen, 2015; Casadesus-Masanell & Halaburda, 2014; Cennamo, 2018), the manipulation of how much value is captured by complementors (e.g., Greve & Song, 2017; Wen & Zhu, 2019; Zhu & Liu, 2018), and the degree to which complementors share knowledge to increase innovation (e.g., Foerderer, 2020; Huang et al., 2013).

While there are different strategies for governing a platform, they all share a similar challenge: as complementors are independent firms, platform owners cannot enforce desired complementor behavior but must provide incentives and stimuli that reward complementors for inducing the desired behavior (Parker & Van Alstyne, 2018; Rietveld et al., 2019; Sampler, 2018). Thus, a critical part of a platform governance strategy is anticipating how the complementor ecosystem interprets and responds to different governance mechanisms (Rietveld et al., 2021). However, these effects and underlying mechanisms are poorly understood (Barach, Kaul, Leung, & Lu, 2019; Panico & Cennamo, 2020). I put this aspect at the center of this study.

I examine complementors' response to a governance strategy frequently used by platform owners: the endorsement of selected complements through certification (Aguiar & Waldfogel, 2018; Elfenbein et al., 2015; Rietveld et al., 2019). Certification places a spotlight on individual complements and helps users identify high-quality complements in crowded platform markets (Hui et al., 2016). Examples of such

endorsements include Amazon’s “Amazon’s Choice” badge for superior products, Airbnb’s “Superhost” badge for recommended places to stay, and Fiverr’s “Fiverr’s Choice” for reliable freelancers.

My theoretical framework is motivated by the certification literature (Hui et al., 2016; Polidoro, 2013) and studies on competition within two-sided markets (e.g., Boudreau, 2012). My central hypothesis is that certification has a generative effect on the ecosystem, with both the complementors that received certification and uncertified rivals increasing their innovation efforts. I also develop theory on how complementors adjust their pricing strategies after certification, predicting that recipient complementors will raise prices to realize short-term profits, and rivals will reduce their prices to capture demand spillovers. I further theorize that these effects are contingent on the competitive intensity of the respective complement category.

The empirical context for testing my hypotheses is Apple’s App Store platform ecosystem in the U.S. market, in which third parties develop apps and market them to users of iPhone and iPad devices. This setting is particularly appropriate, as Apple introduced human-curated app certifications (“Apps We Love”, “Games We Love”, and “Editor’s Pick”) during its 2017 redesign of the App Store. Certified apps enjoy high visibility on the App Store and often benefit from a substantial increase in user demand (see the Appendix for an analysis of the demand side implications of certification in this dataset; for a related analysis, see Liang et al., 2019). My data enables me to study how complementors that received certification and, given that Apple selects only a few apps for certification, their direct rival complementors strategically respond to certification.

My empirical analysis consists of two parts. First, I use a neural network-based text-embedding algorithm to identify apps that use similar features and content. This approach allows me to build clusters of apps that are in direct competition and are likely to compete for the same users. Second, I model Apple’s certification patterns in a regression framework to examine developers’ responses to the certification event of an app within their cluster. I find evidence for a generative effect of certification

that increases the likelihood of increasing innovation efforts for both recipient and rival developers. However, consistent with my hypotheses, I find that high levels of competitive crowding attenuate this generative effect of certification. Moreover, I find support for my predictions on the heterogeneous effects of complementors' pricing strategies. Overall, these results indicate the significant implications of complement certification for promoting complementor innovation and, more generally, underscore the critical strategic role of platform governance in orchestrating complementor behavior.

5.2 Related Literature

This study contributes to several streams of literature. First, I add to the literature on platform governance and, more generally, to that on multisided markets. Most of this research has focused on how platform users can use pricing strategies to unlock indirect network effects to grow the ecosystem (e.g., Caillaud & Jullien, 2003; Evans, 2003; Parker & Van Alstyne, 2005; Rochet & Tirole, 2003). However, there is growing consensus that platforms must also implement non-pricing strategies to manage complement quality and diversity (Cennamo & Santaló, 2019; Panico & Cennamo, 2020; Rietveld et al., 2019). This study focuses on a prominent non-pricing governance strategy, provides insights into complementors' responses, and carefully examines the factors that drive heterogeneity in these responses.

Moreover, studies examining complement certification have primarily focused on the demand side effects (i.e., the response of the user side) (e.g., Aguiar & Waldfogel, 2018; Elfenbein et al., 2015; Rietveld et al., 2019) but only a few studies have examined the corresponding supply side implications (i.e., the response of the complementor side) (e.g., Hukal et al., 2020; Jullien & Pavan, 2018; Rietveld et al., 2021). For example, Hukal et al. (2020) found that the certification of third-party content contributors increased the volume and diversity of supplied data to OpenStreetMap's web-based geodata platform. While such findings contribute to understanding the *average* effects of complement certification on the complementor ecosystem, treating the ecosystem as a monolith of homogenous firms may risk

overlooking significant differences in complementors' responses. My work adds to this research by exploring heterogeneity in complementor responses in two ways: first, by examining differences in complementors that have received certification and rivals that have not and, second, by accounting for different levels of competition across different niches of a platform market. Increasing the level of granularity from previous research thus allows me to show how platform owners can use certification more effectively to govern the supply side of their ecosystems.

In addition, this study adds to the limited set of studies on complementor strategies (e.g., Claussen, Essling, & Kretschmer, 2015; Eisenmann et al., 2011; Kretschmer & Claussen, 2016; Li & Agarwal, 2016; Miric & Jeppesen, 2020; Tavalaei & Cennamo, 2020). Previous research in this literature stream has mostly focused on complementors' value creation activities (e.g., Foerderer et al., 2021; Hukal et al., 2020) and less on complementors' strategies for value capture (with the exception of Wen & Zhu, 2019). By taking an integrative perspective on complementors' considerations regarding innovation and pricing, my theoretical arguments and empirical findings contribute to a more precise and nuanced understanding of the complex strategic trade-offs that complementors must face when responding to exogenous governance mechanisms implemented by platform owners.

Second, my empirical results on complementors' response to endorsements from the platform owner inform the literature on certification in two ways. As discussed in Chapter 2, the extant literature on certification has predominately examined how firms ex-ante adjust their efforts to receive certification (e.g., King et al., 2005), but how firms react after certification has remained an underresearched domain. As Rietveld et al. (2021) note, two-sided markets are an ideal setting in which to study the ex-post implications of certification, as platform owners often do not disclose the exact prerequisites required to receive certification and therefore, complementors cannot fully anticipate certification ex-ante. This setting allows for the separation of firm behavior before and after certification, mitigating potential endogeneity concerns. My results suggest that complementors increase their innovation efforts after a competing complement has been awarded certification,

showing a generative effect of certification for the platform ecosystems. However, I also find that this effect is contingent on the competitive crowding of the market's niche. This expands previous research in emphasizing that (i) firms' response to certification is real and significant and (ii) driven by heterogeneity resulting from different levels of competition across market categories.

In addition, my findings also address another important gap in the certification literature: the competitive implications of certification. Despite a growing scholarly understanding of the benefits accrued by firms that receive certification, little is known about the effects of such certification on firms' rivals. Previous research has found that certification protects against competitive threats by uncertified rivals (Polidoro, 2013). My results extend this finding by showing that, on average, certification increases innovation efforts from competitors, but a high degree of category-level competition may decrease firms' incentives to launch further innovations in response to a rival's certification. This implies that the value of certification may increase with higher levels of competition, as it discourages uncertified rivals from expanding their competitive position. My findings thus extend the nascent literature on the competitive implications of certification by identifying competition as an important market level moderator.

5.3 Hypotheses Development

Consistent with prior literature, I define complementors' innovation efforts as the rate at which a complementor develops its products (Tiwana, 2015; Wen & Zhu, 2019). Previous literature suggests that the high technological agility of digital products and equivocal customer needs requires numerous experimentations and product refinements (e.g., Boudreau, 2012; Yoo et al., 2012). In the context of this study, such innovation efforts geared at complementors' existing product portfolios materialize in the form of app updates. Such updates can take different forms and may target app improvements (e.g., bug fixes) or expansions (e.g., adding a new feature or additional content) (see also Comino, Manenti & Mariuzzo, 2019).

In addition, because firms create value via innovation and capture it through pricing, it is reasonable to assume that complementors will formulate their value creation and capture strategies via a joint decision. Hence, this study examines how complementors adjust not only their innovation efforts but also their pricing strategies in response to certification from the platform owner. On most digital platforms, complementors can set the prices of innovations at their discretion. However, most complementors offer their products free of charge and generate revenue from in-app purchases for premium offerings (Arora, Ter Hofstede, & Mahajan, 2017; Rietveld et al., 2020). Thus, I define a complementors' pricing strategy as the value of the associated in-app-purchase offerings.

In the following, I develop hypotheses on (i) the response strategies of recipient complementors (i.e., the firms that received certification), (ii) the response strategies of rival complementors (i.e., the firms that are direct competitors of recipient complementors), and (iii) heterogeneity in complementor response strategies due to different levels of competition across complement categories.

Response Strategies of Recipient Complementors

I begin developing my theory by discussing the innovation strategies of recipient complementors in response to certification (i.e., their propensity to release product updates after their certification). I expect that recipient complementors will increase their innovation efforts for several reasons. First, as argued in Chapter 2.1, prior research highlights that certification leads to substantial increases in visibility and reputation for the recipient firms (e.g., Pollock & Gulati, 2007; Rao, 1994). In the context of digital app markets, certification from the platform owner is also likely to attract the interest of other entities outside the platform, such as online bloggers, social media contributors, and journalists of specialized websites, increasing users' curiosity and motivating them to start using the app. Thus, certification raises the complementor's profile with potential customers, so it is more likely to be called upon when customers wish to make a purchase (Aguiar & Waldfogel, 2018).

Moreover, research on new product development indicates that firms capitalize on initial market success by releasing product refinements and improvements. For example, Rothaermel & Deeds (2004) found that firms release incremental product updates after initial market success. Similarly, Voss, Sirdeshmukh, & Voss (2008) found that firms focus on product refinements once they have garnered a market reputation. In the context of this study, developers may try to capitalize on the exogenous boost in demand after certification from the platform owner by increasing their innovation efforts and releasing complement updates. Thus, by continuously offering new product content, complementors may increase the rate at which a product is indexed in the platform's product or seller search criteria. This may prolong the exogenous benefits of certification and organically make the complements more accessible to prospective customers.

Second, recipient complementors may also increase their innovation efforts to serve their existing customer base better. By continuously providing customers with evolving content, complementors can significantly expand the lifespan of their product offerings (Foerderer et al., 2021; Ho-Dac, Kumar, & Slotegraaf, 2020; Hwang et al., 2006). This is important for retaining customers over time, especially the engaged ones that move quickly through the product offering's content (in my context, levels of gameplay, for example). Moreover, new content may provide additional stimuli for non-paying consumers who use the basic product offering to upgrade to the premium version to use these features.

Taken together, I argue that endorsed complementors may increase their innovation efforts to both stimulate and retain consumer attention, and the frequent release of new product versions with expanded content or feature enhancements is a strategy they may effectively use for this purpose (Liu, Au, & Choi, 2014). Therefore, I expect that:

Hypothesis 1a (H1a). *Following certification from the platform owner, recipients will increase their innovation efforts.*

I also examine how complementors may adjust their pricing strategies following certification from the platform owner. As the literature on certification indicates, certification increases the legitimacy of the receiving firms and products from the customers' perspective (Rao, 1994; Stuart, Hoang, & Hybels, 1999). As a result, several studies indicate that firms can charge higher prices because customers may pay a premium for products that have received certification due to reduced uncertainty (Hui et al., 2016; Hui, Saeedi, Spagnolo, & Tadelis, 2018; Wimmer & Chezum, 2003). Thus, profit-maximizing complementors may increase their pricing to exploit customers who value the complementors' product offerings most and, therefore, may be somewhat insensitive to the higher prices (Frank & Salkever, 1997).

In addition, complementors may raise prices to increase their opportunities for short-term value capture. In our context, gaming app lifecycles are relatively short, and meaningful demand often diminishes after a few months (similar to video games, see, e.g., Binken & Stremersch, 2009; Cennamo, 2018; Zhu & Zhang, 2010). As the popularity of their games can become obsolete within a short period of time, complementors have a strong incentive to increase their pricing to capitalize on the short-term demand gains of certification by increasing their prices in the short-term. For these reasons, I argue that

Hypothesis 1b (H1b). *Following certification from the platform owner, recipients will increase complement pricing.*

Response Strategies of Rival Complementors

After certification of one complement in a market niche, I expect rival complementors to increase their innovation for their product offerings for two reasons. First, previous literature indicates that certification of a complement may be a strong signal of a platform owner's interest in this particular market niche (Hukal et al., 2020; Rietveld et al., 2019). Given the dynamic nature of platform markets and the rapid evolution of customer preferences, complementors continuously evaluate the market opportunities for their product offerings to allocate their limited resources most effectively (Tiwana, 2015). However, the demand for market niches is often

uncertain, making product success somewhat stochastic (e.g., Clements & Ohashi, 2005; Foerderer et al., 2021; Rietveld & Eggers, 2018). Certification of one complement in a market niche may resolve part of this uncertainty, showcase the complement features that are likely to lead to product success, and therefore signal promising opportunities for value capture. Thus, rival complementors will be incentivized to invest their constrained resources to increase the innovation efforts for their own product offerings and aim to replicate their certified competitors' success.

Second, a key characteristic of platform-based markets is the presence of network effects, which can lead to substantial demand spillovers from successful complements to other similar complements (Haviv, Huang, & Li, 2020). As argued above, complementors that have received certification enjoy prominent positioning, which may create potential such demand spillovers. Several studies have found evidence for demand spillovers after certification (e.g., Foerderer et al., 2018, 2021; Liang et al., 2019; Raj, 2021). For example, in a study also located in Apple's App Store, Liang et al. (2019) observed that rivals of a complement that received certification benefitted from demand spillovers for their own product offerings. Similarly, Foerderer et al. (2018) found that Google's release of the Google Photos app led to a surge of third-party apps in the photography app category, as complementors expected to free-ride on demand and attention spillovers. Thus, rival complementors may also increase their innovation offers in order to benefit after the certification of a competing complement. Based on these reasons, I argue that:

Hypothesis 2a (H2a). *Following a rival's certification from the platform owner, complementors will increase their innovation efforts for their own complements.*

In addition, I expect that complementors will also adjust their pricing strategies after the certification of a rival complement. I argued above that recipient complementors will increase their prices to capture a premium from their certification. Conversely, I expect rival complementors to reduce their prices to differentiate their product offering from the certified ones and present their apps as cheaper alternatives.

Moreover, as argued above, rival complementors may speculate about benefiting from demand spillovers (Liang et al., 2019). Reducing prices would increase rival complementors' popularity among potential customers and thus increase the likelihood of capturing value from such spillovers.

Hypothesis 2b (H2b). *Following a rival's certification from the platform owner, complementors will reduce complement pricing for their own complements.*

Moderating Effect of Category-level Competition

In the preceding hypotheses, I theorized *average effects* of certification on complementors' innovation and pricing strategies. However, there might be heterogeneity in complementor responses due to different levels of competition between different categories. In many platform markets, complementors compete within distinct niches, such as different types of products on e-commerce marketplaces (Hui et al., 2016; Zhu & Liu, 2018), various music genres on streaming platforms (Aguilar & Waldfogel, 2018) or different app categories on smartphone platforms (Kapoor & Agarwal, 2017; Tidhar & Eisenhardt, 2020). Previous research has shown that competitive intensity often varies drastically between platform market niches (Barlow et al., 2019; Tavalaei & Cennamo, 2020; Tiwana, 2015; Yoo, Henfridsson, et al., 2010).

Analyzing the competitive implications of certification is particularly important in my setting, with prior studies showing that in digital platform markets, complementors track each other's activities closely and formulate their strategies in response to competitor moves (Kang, 2018; Wang & Miller, 2020; Xue, Song, Rai, Zhang, & Zhao, 2019). Specifically, Hui et al. (2018) provide empirical evidence that certification increases the competitive intensity among sellers on eBay's marketplace. Building on these findings, it is essential to examine how firms may adjust their strategies in response to the altered competitive dynamics resulting from certification.

To understand competition as a potential source of heterogeneity in complementors' strategies, I follow previous platform research that examines how

competition shapes complementor behavior (e.g., Boudreau, 2012; Boudreau & Hagiu, 2009; Boudreau & Jeppesen, 2015; Boudreau et al., 2019; Kapoor & Agarwal, 2017; Venkatraman & Lee, 2004; Yin et al., 2014). There is a growing consensus in this literature that high levels of competition within a platform market may hurt complementors' incentives to supply new complements or improved versions of existing complements. Several scholars studied the competitive dynamics of platforms for mobile devices and online multiplayer gaming and found empirical support for such a competitive crowding effect (Boudreau, 2012; Boudreau & Jeppesen, 2015; Casadesus-Masanell & Hałaburda, 2014; Markovich & Moenius, 2009). Motivated by this stream of literature, I seek to understand how my predictions on complementors' response strategies are affected by the level of competition.

I argued above that certification may motivate recipient complementors to increase their innovation efforts in an attempt to capitalize on the increased visibility and grow the long-term demand of their complements. However, previous research has demonstrated that when competition is high on a platform market niche, complementors that receive certification may enjoy fewer demand side benefits (Elfenbein et al., 2015). As a result, they will also have lower incentives to release complement updates. In addition, with many competing product offerings, complementors may see limited prospects for long-term value creation in this particular product market space (Eckhardt, 2016) and, thus, may reconsider deploying more resources into a certified complement. Instead, with higher competition, they may focus more aggressively on short-term value capture by increasing their pricing (Thomas, 1999).

As a result, I expect that, under increasing competitive intensity, recipient complementors are less likely to release complement updates but are more likely to increase their pricing. Accordingly, I predict:

Hypothesis 3a (H3a). *The positive effect of certification on recipients' innovation efforts will be weaker with high levels of category-level competition.*

Hypothesis 3b (H3b). *The positive effect of certification on recipients' on complement pricing will be stronger for complementors with high levels of category-level competition.*

For rival complementors, I expect a similar response regarding their innovation efforts but a diverging response regarding their pricing strategy. Under high levels of competition, rival developers may have fewer incentives to release additional complement updates. I argued above that, on average, rival complementors may increase their innovation efforts after a direct competitor receives certification in an attempt to replicate the competitor's success and capture demand spillovers. However, with many additional developers entering the market niche, the chances of freeriding on the certification of a rival may diminish, and the associated benefits to complementors of continuing to work in this category are likely to be significantly reduced. Also, rival complementors may have less opportunity for short-term value capture. In contrast to recipient complementors, which may benefit from an above-average demand and increased reputation from their certification even in a competitive market environment, rival complementors will have little pricing power, and increasing pricing will likely reduce their revenues, as consumers tend to be relatively price-sensitive in platform market niches that are overcrowded (Arora et al., 2017; Rietveld, 2018). Instead, I expect them to reduce their prices to adjust to the increased competition in their market niche. As a result, I argue:

Hypothesis 4a (H4a). *The positive effect of certification on rival complementors' innovation efforts will be weaker with high levels of category-level competition.*

Hypothesis 4b (H4b). *The negative effect of certification on rival complementors' complement pricing will be stronger with high levels of category-level competition.*

5.4 Sample and Variables

Sample

Drawing on the data sources described in Chapter 3, I constructed the sample as follows. First, I identified all game apps in the dataset that have been featured during my observation period, January 2019 to August 2020. For all of these apps, I checked if they have been featured prior to my observation period to avoid biased results from apps that are featured beforehand. I removed all apps that had at least one featuring event prior to the observation period. Second, using the unique developer ID that every developer on the App Store receives when it first launches an app, I tracked all other apps that the respective developer of the featured app has released to the game category during the observation period. To ensure that I have collected all apps released for each developer in my dataset, I used a combination of manual and automated search on Apple iTunes pages. Third, I used a combination of ML methods and third-party databases to identify apps that compete for similar users by providing apps with similar content and functionality. To identify those similar apps, I followed previous studies (e.g., Barlow et al., 2019; Wang, Li, & Singh, 2018) that also leveraged app titles and descriptions to detect similar apps. When launching an app on the App Store, developers must give the app a title (e.g., “Clash of Clans”) and write a brief description, which offers them the opportunity to highlight an app’s key characteristics and content to prospective users. I identified similar apps using the following procedure. I began by preprocessing all app descriptions using natural language processing techniques to identify the primary language for each app’s description (to exclude all apps that have non-English descriptions), remove stop words (e.g., “the”, “with”, “and”), and stem nouns, verbs, and adjectives to their word roots (e.g., “game” is the stem for “gaming”) before producing the measures calculating the similarity between apps. As a result, the processed app descriptions are reduced to a list of all the word stems used in a particular app’s processed text description. In the processed sample, the app title length ranged from 3 to 27 characters with a median length of 13.4 characters, and the description length ranged from 104 to 1,374 characters with a median length of 493.37 characters. As a final

preprocessing step, I merged all app titles with the corresponding processed app descriptions in a single text file for each app identified in Step 1 of my sample construction.

I then fed the descriptions in a neural network-based text-embedding model called Doc2Vec (Lau & Baldwin, 2016; Le & Mikolov, 2014), which is part of the open-source *Gensim* module (Řehůřek, Sojka, & Others, 2011), which contains unsupervised ML algorithms that transforms a set of unlabeled documents (corpus) into a low dimensional vector representation for each document (in the present case, app titles and descriptions) (Maslova & Potapov, 2017). Those vector representations preserve the semantic-spatial similarities between the app titles and descriptions so that semantically similar app titles and descriptions are embedded near each other. Because the underlying neural network-based algorithm incorporates many parameters, it is beneficial to use a large external corpus to pre-train the parameters and improve prediction accuracy (Le & Mikolov, 2014). I used a pre-trained Doc2Vec model based on extensive data from search queries, encyclopedia web pages and news articles; an approach that is also applied in other research implementing ML methods to detect similarities between song lyrics (Yu, Tang, Raposo, & Chen, 2019), debate statements (Lawrence et al., 2017), and social media postings (Burtch, He, Hong, & Lee, 2021). Leveraging this pre-trained model to create an initial embedding space, I then further fine-tuned the model using my dataset. Based on the detected similarities by the trained model, I calculated cosine similarities for the focal featured app's vector and the vector for each of the remaining non-featured apps in my sample. The resulting similarity score indicates how similar an app is to the focal featured app. For example, a similarity score of 1.0 would indicate an identical app title and description, while a score of 0.0 would indicate that the apps in comparison do not share a single same word in either title or description. In my sample, the mean similarity score is 0.21.

As a robustness check, I validated this list of similar apps with additional third-party information and manual review. I draw a random sample of 10 apps out of my total sample for this study and compared the list of similar apps with data from App

Magic. App Magic provides its customers with a feature called “similarity score”³² that identifies similar apps based on multiple app characteristics and by tracking the “You may also like” recommendations list in the App Store.³³ I compared my list of similar apps against App Magic’s list and found large congruency up to the top four most similar apps for each featured app in my data. After this threshold, I noticed an increase in the number of false positives, i.e., apps that the model assigned a high similarity score with a focal featured app, but the apps were offered in different app categories. To avoid potential bias in my dataset, I conservatively removed apps that are not included in the top four similar apps for each featured app.

In a final step, I merged all apps identified in the previous steps of the sample construction process and assembled a panel data set for my observation period. To avoid oversampling unfeatured apps that may generate biased estimates, I limited the observation period (six months; three months before the first certification event and three months after, see also Liang et al., 2019, for a related sample construction). This format enables me to (1) assess the implications for app endorsement on subsequent developer behavior, (2) distinguish between featured and unfeatured apps, and (3) implement the app and time FE in my regression specifications. The final sample includes 4,206 (807 apps that received certification and 3399 rival apps).

Variables

Dependent variables. I examine the impact of platform certification on two variables at the app-level: developer’s innovation efforts and pricing. I measure *innovation efforts* by the number of new app versions released in a month. This measure of innovation efforts is consistent with extant studies that use app updates to capture digital innovation in similar settings (e.g., Boudreau, 2012; Tiwana, 2015; Wen & Zhu, 2019). While this measure allows me to capture all relevant product releases such as new app features, bug fixes, or technical improvements, I acknowledge that minor and major updates may require different levels of innovation

³² This procedure is congruent with other studies using comparable measures from other app analytics providers to track similar apps (for example, Kesler, Kummer, & Schulte, 2017; Wen & Zhu, 2019).

³³ See <https://appmagic.rocks/essentials/similarity-graph>, accessed November 2020.

efforts. Thus, I later implement a robustness test using major updates as the dependent variable and yield similar results. Also, to account for the time it takes for a developer to prepare and launch an update after Apple’s endorsement event, I used a time lag of one month for the dependent variable. In the section on robustness tests, I also implemented lags with two months and three months windows. I compute the measure *app price* by taking the rolling monthly weighted average value of the in-app-purchase options that an app offers. I use in-app-purchase options as the majority of apps in my dataset are freemium apps. In my context, freemium means that users can download and the game app for free and then can buy upgrades (e.g., additional levels of gameplay, items, subscriptions, extra content, ad-free versions, etc.) via in-app-purchases.^{34 35}

Independent variables. I include three independent variables in my analysis. First, I used a dummy variable that indicates if an app was featured at least one day in a given observation month (*featured*). Second, I used another dummy variable that indicates if a rival app was featured at least one day in a given observation month (*featured rival*). Third, I include a variable that indicates the level of competition within a category in a given observation month. Consistent with prior studies on the competitive dynamics of platform, I measure *category competition* by the number of additional app releases from new developers each month (e.g., Rietveld & Eggers, 2018).

Control variables. I control for a number of covariates that may influence my dependent variables. First, I control for *app age*, as older apps may be updated more frequently, e.g., to implement new software and adjust to new hardware standards of the iPhone. Second, I control for the number of days since the last major update to an

³⁴ App developers can choose the prices for in-app-purchases at their own discretion. However, Apple may reject in-app-purchase options with prices that it deemed “irrationally high” in an effort for player protection (Source: Developer interviews).

³⁵ Data availability constrains this study from differentiating which price point relates to which item available for purchase. Thus, average prices may be inflated for games that offer many different items at different available prices (see below on control variables and section 5.7 for a robustness check). Further, the data set does not offer granular pricing data for every app. In these cases, end-of-month values or mean imputations (sklearn.impute) were used as proxies.

app (*version age*) (see Liang et al., 2019 for a similar control measure). Third, I control for *platform age* by measuring the days since the latest release of the iOS software. As may findings from Chapter 4 indicate, platform transitions play a key role in Apple's certification patterns, and as such, their impact on developers' innovation efforts should be addressed in the controls for this study as well. Concerning my second dependent variable, *app price*, I control for the *app size* in MB as a proxy for the apps complexity in terms of content and technology (see also Agarwal & Kapoor, 2018). For example, apps with greater size may have, e.g., more levels of gameplay, more complex graphics, and more features, and thus may also charge higher prices. To avoid any bias from these differences in pricing on my second dependent variable, I include this additional control in my regression analyses.

5.5 Analysis

The primary objective in my empirical analysis is to estimate the effects from certifications in isolation from other unobserved app-specific and time-specific confounding factors *at the same time*. I implement this idea by estimating regressions that control for unit and time fixed effects, a method also referred to as two-way fixed regressions (de Chaisemartin & D'Haultfœuille, 2020; Imai & Kim, 2021). Two-way fixed effects regressions have become increasingly popular in strategy research and especially in platform research (e.g., Boudreau & Jeppesen, 2015; Cennamo & Santalo, 2013; Taeuscher & Rothe, 2021) as they are useful when estimating causal effects from panel data, but it is implausible that a treatment effect is constant over time (de Chaisemartin & D'Haultfœuille, 2020). In my data, using two-way fixed effects regressions enables me to control for cross-sectional variation in my panel data, isolate my time-variant variables from static differences at the app level, and substantially reduce the risk of omitted variables.

I estimate the effects of certification on complementor innovation behavior with the following regression specifications:

$$\log(Updates)_{i,t} = \alpha_i + \lambda_t + \beta X_{i,t} + \beta_0 + \varepsilon \quad (1)$$

$$\log(App\ price)_{i,t} = \alpha_i + \lambda_t + \beta X_{i,t} + \beta_0 + \varepsilon \quad (2)$$

Where the log of an app i 's (indicated by t) *updates* (Equation 1) and *app price* (Equation 2) is regressed on $\beta X_{i,t}$, a vector of covariates including the independent variables, their interactions, and control variables discussed earlier. α_i is an app-level fixed effect that absorbs all observed and unobserved time-invariant app characteristics (such as differences in their technology, product design, and quality) and λ_t is a set of time dummies that absorbs time-varying factors common to all apps (e.g., bias from potential seasonality or clustering of certifications at specific points in time). The models further include a constant β_0 and an error term ε . For the analyses, the *statsmodels* (Seabold & Perktold, 2010) and *linearmodels* (linearmodels, 2017) modules were used.

5.6 Results

Table 9 presents summary statistics.³⁶ On average, apps in my dataset are updated every three months. The average price of an app's in-app-purchase options is approximately \$5, but some apps charge average prices of almost \$70. Category-level competition varies greatly, with an average of about 130 new apps entering a category every month during the observation period. To account for skewness, I use log transformations for the dependent variables *updates* and *app price* variables in the regression analysis. I also computed variance inflation factors (VIFs) to detect whether there is multicollinearity among my independent variables. The average VIF equalled 3.21, and none of the VIF scores exceeded 10, the commonly accepted threshold indicating a potential bias (Hadi & Chatterjee, 2015), suggesting that multicollinearity is not a concern in my models.

³⁶ Summarized statistics are based raw feature data. In the analysis, raw feature vectors were preprocessed (standardization, encoding) to construct the regression estimators. For a methodological reference, see

<https://scikit-learn.org/stable/modules/preprocessing.html#encoding-categorical-features>.

Table 9: Summary Statistics

Variable	Obs.	Mean	SD	Min	Max	Median
Updates	25,236	0.412	1.239	0	14	0
App price	25,236	4.798	8.141	0	69	4
Featured	25,236	0.067	0.008	0	1	0
Featured rival	25,236	0.103	0.044	0	1	0
Category competition	25,236	129.034	90.846	43	381	165
App age	25,236	4.569	1.897	0	31	4
Version age	25,236	0.477	1.445	0	12	3
Platform age	25,236	4.689	2.348	0	12	6
App size	25,236	162.435	376.845	90	2100	234

Notes: Obs. = Observations³⁷, SD = Standard deviation, Min=Minimum, Max=Maximum.

Table 10 and Table 11 present results. Models 1-4 test Hypotheses H1a-H2b, Models 5-8 test Hypotheses H3a-H4b. Overall, the results show significant support for my hypotheses on the main effects (H1a-H2b). First, in line with Hypothesis H1a, I find a positive relationship between developer's innovation efforts after receiving certification for an app ($p < 0.01$). This finding suggests that recipient developers increase their innovation efforts after certification. Supporting Hypothesis H1b, I also find evidence for a positive and significant relationship between certification and price ($p < 0.01$). In line with hypotheses H2a and H2b, I find that rival developers increase their innovation efforts ($p < 0.1$) and discount their prices ($p < 0.05$), respectively.

Turning to my hypotheses on the moderating effects of category-level competition, the results show significant, but lower support for most of the hypotheses. In line with hypothesis H3a, I find evidence ($p < 0.1$) for a negative moderating effect on developers' innovation efforts under higher levels of competition. Supporting H3b, I find that a positive moderating effect on recipient developers' pricing ($p < 0.05$). While I also find evidence for H4a, indicating that category-level competition negatively impacts rival developers' innovation efforts

³⁷ Computed for daily values.

($p < 0.05$), the results do not support H4b. Hence, the interaction term between *featured rival* and *category competition* is statistically insignificant.

Table 10: Regression Estimates for Hypotheses 1a-2b

	Model 1	Model 2	Model 3	Model 4
<i>Dependent variable</i>	<i>Log(Updates)</i>	<i>Log(App price)</i>	<i>Log(Updates)</i>	<i>Log(App price)</i>
Featured	0.268*** (0.031)	0.091*** (0.025)		
Featured rival			0.117* (0.004)	-0.192** (0.024)
App age	-0.056** (0.003)		-0.066*** (0.002)	
Version age	0.012* (0.002)		-0.077*** (0.002)	
Platform age	-0.006 (0.000)		-0.001* (0.000)	
App size		0.029*** (0.004)		0.017*** (0.002)
Constant	1.908*** (0.066)	1.968*** (0.055)	1.899*** (0.067)	1.917*** (0.078)
App FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Number of apps	807	807	3,399	3,399
Observations	4,842	4,842	20,394	20,394
Adjusted R ²	0.24	0.19	0.23	0.16

Notes: Robust standard errors in parentheses and clustered at the app level. Log(Updates) is lagged by one month. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 11: Regression Estimates for Hypotheses 3a-4b

	Model 5	Model 6	Model 7	Model 8
<i>Dependent variable</i>	<i>Log(Updates)</i>	<i>Log(App price)</i>	<i>Log(Updates)</i>	<i>Log(App price)</i>
Featured	0.234*** (0.046)	0.056*** (0.014)		
Featured rival			0.092** (0.006)	0.011** (0.002)
Category competition	-0.022** (0.004)	0.034*** (0.002)	-0.062*** (0.009)	0.043*** (0.002)
Featured * Category competition	-0.011* (0.002)	0.041** (0.037)	-0.016** (0.007)	0.003 (0.001)
App age	-0.044** (0.013)		-0.059*** (0.013)	
Version age	0.004* (0.001)		0.008** (0.003)	
Platform age	-0.002 (0.000)		-0.004 (0.001)	
App size		0.056** (0.001)		0.149*** (0.078)
Constant	1.784*** (0.043)	1.994*** (0.078)	1.678*** (0.095)	2.167*** (0.101)
App FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Number of apps	807	807	3,399	3,399
Observations	4,842	4,842	20,394	20,394
Adjusted R ²	0.25	0.22	0.23	0.19

Notes: Robust standard errors in parentheses and clustered at the app level. Log(Updates) is lagged by one month. ***p < 0.01; **p < 0.05; *p < 0.10.

5.7 Robustness Tests

In my econometric approach to estimate the effects of app endorsement on complementors' subsequent innovation efforts, I incorporated features that help mitigate out alternative explanations and endogeneity concerns. The inclusion of FE at the app level allows me to control for time-invariant idiosyncratic differences among the apps in my dataset. Also, by using time-period FE, I am able to control for other macroeconomic or platform-level trends that may impact complementors' innovation efforts. In addition, I conducted several additional robustness checks that corroborate my findings.³⁸

The main robustness tests concern the dependent variables. First, I used a larger time window for my first dependent variable. In my main analysis, I used a time window of thirty days to capture a developer's innovation efforts. However, some developers may take longer to develop, code, and release updates. To account for this, I ran my analyses on hypotheses H1a, H2a, H3a, and H4a with a sixty-day time window. My analysis remains consistent with this variation in my dependent variable (see Table 18 for results).

Second, I also conducted my analyses with an alternative measure for my second dependent variable *app price*. In particular, I replaced the weighted average of the in-app-purchase options with the median value. This may help to rule out potential concerns that average values might be skewed due to different prices charged for, e.g., low prices for additional game items and high prices for additional levels of gameplay or subscriptions. Taking the median value helps to mitigate these concerns, and I yield comparable results for H1b, H2b, H3b, and H4b (see Table 19).

I also conducted a number of robustness tests with further variations of my dependent, independent, and control variables. I replaced the dummy variables *featured* and *featured rival* with continuous variables (*featured days* and *featured rival days*) that measure the number of days an app (or a rival's app, respectively) was

³⁸ I refer to the Appendix for the tabulated results of the robustness tests.

endorsed in a month, i.e., the duration of an app featuring. These alternative variables help me mitigate out potential concerns that complementor response may be driven not only by the pure instance of the app featuring but also by the variance in its duration. Moreover, similar to study 1, I also differentiated between app updates targeting an app's performance (such as bug fixes and minor improvements) and its content (such as new adding new modes of gameplay or new features) to account for potentially varying impacts on my target variable. To do so, I followed prior studies (e.g., Foerderer, 2020; Foerderer et al., 2021; Liang et al., 2019) and classified the updates by their version code (e.g., version code 10.1 indicates a major update and 10.1.1 indicates a minor update). As a validity check, I also used the textual descriptions of the release notes to classify the updates into either a "performance update" or a "content update" using distinct keywords such as "bug fix", "improvement", "update", and some of their synonyms. In addition, I aim to address concerns of reverse causality by implementing a one-month lag to the moderator variable *category competition*. Overall, these alternative variable computations produce similar findings.

Finally, for approximately 80% of the cases in my dataset, a developer had a single app listed in the games category in the same month. However, one may worry that the results may differ for developers that compete with a single app or a portfolio of multiple apps. In my main analysis—since my level of analysis is at the firm and not the app—if a developer had more than one app listed in the games category in the in the same month, I treated those cases as a single firm-level observation (which is consistent with other studies, e.g., Kapoor & Agarwal, 2017). In the robustness tests, I ran my models on the subset of developers that had more than one app to estimate any differences for these portfolio developers. I used FE at the developer level to control for unobserved heterogeneity between the developers that may include differences in, e.g., firm age, firm experience, or marketing resources. While I found

differences in the coefficients and their significance levels, the findings mostly hold with alternative variable computations and robustness tests.³⁹

5.8 Conclusions

Platform governance research emphasizes the importance of governance strategies to guide complementors' behaviors and align their interests to the platform's key strategic intent. However, less is known about complementors' responses to governance mechanisms and what factors cause heterogeneity in their behavior. In this study, I examined how complementors respond to one particular governance mechanism: the selective endorsement of complements through certification. I find that certification affects both recipient and rival complementors and may motivate them to adjust their innovation and pricing strategies. I also find significant heterogeneity in complementor responses due to different levels of competition across complement categories.

Contributions

These findings contribute to platform governance and certification research in several ways. First, my work extends prior work that primarily focused on the demand side implications of complement certification. However, in a two-sided market, demand and supply side effects cannot be separated and are likely to influence each other. In this study, I show how complementors respond to the certification of a rival product offering, which benefits from an increase in user demand, by adjusting their innovation efforts and pricing strategies and, thus, shaping the supply side dynamics of the platform. Hence, my findings thus explain how the demand and supply implications of certification are interlinked and contribute to a more comprehensive understanding of the underlying dynamics.

Second, my findings extend prior research on platform governance by assessing how complementors respond to governance strategies and how this affects

³⁹ Tabulated results from the additional alternative variable computations and further robustness tests are not reported here to save space.

their subsequent behavior on the platform (e.g., Rietveld et al., 2021; Wen & Zhu, 2019; Zhang et al., 2020). Examining the response from the complementor ecosystem is essential for platform owners to estimate the effectiveness of platform governance and identify potentially unwanted side effects. In particular, while I show that certification motivates both recipient and rival complementors to increase their innovation efforts, rival complementors reduce their prices to consolidate their market positions. In turn, as the platform's monetization is directly connected to complementors' revenues, platform owners may risk lower revenues as well.

Moreover, I extend prior work by showing potential sources of heterogeneity in complementors' response strategies to platform governance mechanisms implemented by platform owners. I detect two sources of heterogeneity. First, I find that recipient and rival complementors formulate different response strategies based on distinct considerations of opportunities for value creation and value capture. Second, I find that differences in the level of competition across the categories in Apple's App Store lead to diverging outcomes in complementor behavior.

Finally, my work extends the certification literature by examining how firms adjust their value creation and capture strategies *after* certification, a previously underresearched area (Rietveld et al., 2021). In the context of this study, this is particularly important, as platform owners need to estimate how complementors respond to certification to design their certification strategies in ways that ultimately benefit the platforms. Moreover, this study contributes to the limited knowledge on the competitive implications of certification by illustrating how certification affects rival firms in adapting their innovation efforts and pricing strategies and how these effects vary with the level of competitive intensity.

Limitations and Future Research

Like any study, this work has limitations, which provide several avenues for future research. First, data availability constrained me from examining several app developer characteristics. While I have detailed data on the apps supplied by these developers, I do not have detailed data on the developer firms (e.g., number of

employees, programming and marketing resources, experience, firm-level profitability, etc.). Following prior studies, I try to mitigate this issue using developer-level fixed effects in the robustness section. However, more detailed firm-level data would allow the detection of potential sources of heterogeneity in complementor responses. Future research could thus use survey-based research to collect such data (e.g., like in the work of Miric et al., 2019) and explore developer characteristics in greater detail.

Second, as some of the variables are available at an aggregated level, my analysis is constrained to identify some underlying daily or weekly dynamics. While I share this limitation with other studies that have been conducted in the context of Apple's App Store (e.g., Kapoor & Agarwal, 2017), more granular data would allow generating deeper insights on the timing and intensity of complementor reactions to certification.

Third, one assumption in my study is that the demand side of Apple's App Store is held constant. Data availability also constrains me from estimating the effects of different iPhone versions available on the market (for example, some older iPhone versions are still produced and sold even when a new version is launched). iPhone sales data is not available in such granularity that would be needed to estimate how fluctuations in unit sales, price variations, product bundling options, and other demand related factors may drive developers' innovation and pricing strategies. However, while these effects are hard to quantify without detailed information, the developers and industry experts interviewed during this study estimated them to have a minor and insignificant impact on the research questions of this dissertation.

Finally, the data set is limited to a relatively short timeframe of about 20 months. While this allows me to capture several relationships between the variables, I am unable to draw inferences over longer time frames. Thus, an interesting stream of future research could investigate if and how complementors change their response strategies over time and explore potential drivers of those changes.

6 Discussion and Conclusions

Platform-based markets are prevalent in today's economy. Understanding how platform owners manage and govern ecosystems that often comprise thousands of third-party firms is of critical importance for platform scholars, complementors, and customers alike. In this dissertation, I take a step forward in examining one popular platform governance strategy—the selective certification of complements from the platform owner. Using a large dataset of app developer populations on Apple's App Store, I study the underlying mechanisms (i.e., how platform owners select individual complements) and implications (i.e., how complementors respond to certification) of complement certification, addressing two important but previously underresearched questions in research on platform governance and the broader literature on quality certification (see Figure 3 for an overview of this dissertation). My findings extend previous strategy research and offer managerial guidance on the underlying mechanisms and implications of governance in platform-mediated settings.

Figure 3: Overview of Dissertation Studies and Findings

Overarching Research Topic Strategic Complement Certification in Platform-based Markets		
	Study 1 (Chapter 4)	Study 2 (Chapter 5)
Thematic Focus	Selection strategy of platform owners for complement certification	Response strategy of complementors to certification
Research Questions	Which factors lead to complement certification from the platform owner, and what is the relative influence of these factors on such decisions?	How does complement certification affect complementors' innovation and pricing strategies?
Type of Study	Inductive theory-building	Deductive theory-testing
Positioning	Platform governance literature Certification literature Literature on market intermediaries	Platform governance literature Certification literature Complementor strategy literature
Methods	ML methods for variable selection and prediction (Random Forest, Gradient Boosting, LASSO regression, logistic regression)	ML methods for variable computation (NLP, topic modelling) Two-way fixed effects regression
Empirical Setting	Games category of Apple's App Store	
Main Findings	Apple awards certification not only to encourage users to discover new apps but also to induce desired behaviors among developers Main selection criteria are high levels of co-specialization, a greater number of upselling options, and greater innovation intensity	Complementors adjust their innovation and pricing strategies in response to certification The direction of complementor responses varies between recipients of certification and uncertified rivals Category-level competition is an important moderating factor
Managerial Implications	Complementors can predict platform owners' certification patterns and formulate strategic responses by adapting their product configurations, time-to-market processes, and monetization options	Platform owners can use certification to stimulate the innovation efforts in a market category, but must pay attention to firm-level heterogeneity (recipient vs. rival) and different intensities of category-level competition
Linking Elements	This dissertation builds a framework to study the dynamics <i>before</i> certification (to detect ex-ante patterns in platform owner's selection mechanisms) and after certification (to estimate the effects of certification on ex-post complementor behavior)	

Before discussing this dissertation's conclusions, I address two caveats that need to be considered when discussing the implications and generalizability of my findings. As in any empirical study, one may worry whether the documented patterns and mechanisms merely reflect coincidence. For example, Apple could have used an independent process rather than data on app markets to identify which apps to select for certification. Although this is difficult to rule out given the absence of a direct observation of Apple's internal operations, several indications suggest that how apps are selected for certification is beyond coincidence. If the curation processes of the App Store were entirely independent of data related to third-party apps (such as the data collected in this work) or a result of mere coincidence, then the relationships identified in the first study would not be highly significant in all models of the logistic regressions across different random data subsets. Moreover, as several interviews with Apple executives and testimonies from Apple CEO Tim Cook in the recent Fortnite trial⁴⁰ indicate, Apple uses a highly deliberate strategy to curate the App Store platform and manage developers' activities in its ecosystem. Regardless of any alternative, unobservable explanations for how Apple selects apps for certification, my research shows that developers can predict Apple's selection decisions and formulate strategic responses accordingly.

Relatedly, one may worry that developers' responses to certification are a result of coincidence or driven by factors that are not directly observable. Two arguments have helped me rule out randomness and alternative explanations. First, several mobile analytics providers offer tools for developers to track if and when related apps receive certification from Apple,⁴¹ which indicates that Apple's app featuring is both relevant and important for developers and that developers may closely watch

⁴⁰ In early 2021, an antitrust case was opened between Apple and the popular app developer Epic Games, which accused the iPhone maker of operating an illegal monopoly by ruling over developers with excessive governance and high commissions on app revenues. In this trial, Apple CEO Tim Cook and other executives were asked to give testimony on Apple's platform governance strategy during the trial. See <https://www.ft.com/content/fc8fd505-2e75-4646-b2a7-34d32796f32a> and <https://www.wsj.com/articles/behind-the-epic-apple-trial-is-a-booming-app-market-worth-fighting-over-11621157405>, accessed June 2021.

⁴¹ For example, see SensorTower's "Featured App History" (<https://sensortower.com/solutions/app-intelligence>) or App Magic's "Featuring Score" (<https://appmagic.rocks/>), accessed May 2021.

competitors' certifications to formulate their competitive strategies. Second, my data allow me to control for and rule out a number of alternative explanations that may bias my results, including unobserved heterogeneity at the app and developer levels, the effect of platform transitions, and other macroeconomic or platform-level trends.

In the remainder of this chapter, I summarize the contributions of this dissertation (Chapter 6.1), derive managerial implications (Chapter 6.2), and discuss opportunities for future research (Chapter 6.3).

6.1 Summary of Contributions

This dissertation contributes to several streams of literature: research on platforms, on certification and market intermediaries, and on the use of ML for theory building in strategy research.

Platform Literature

This dissertation adds to platform research. First, it contributes to the growing number of studies on governance strategies in platform-based markets. A large part of platform research has predominately focused on how platform owners can use pricing strategies to unlock indirect network effects to grow the ecosystem (e.g., Caillaud & Jullien, 2003; Eisenmann et al., 2006; Evans, 2003; Rochet & Tirole, 2003). However, especially in settings in which a platform's value is not entirely driven by the number of transactions, there is a growing consensus that platforms must also implement non-pricing strategies to incentivize complementors to supply products of greater quality and diversity (Cennamo, 2019; Cennamo & Santaló, 2019; Zhou et al., 2020). This dissertation contributes to the growing body of research on non-pricing governance strategies by studying the mechanisms and implications of complement certification, an empirically prevalent tool that is intensively used by platform owners across a wide range of different industry settings (Aguilar & Waldfogel, 2018; Elfenbein et al., 2015; Hui et al., 2016; Hukal et al., 2020; Liang et al., 2019; Rietveld et al., 2021; Rietveld et al., 2019).

In doing so, my dissertation illuminates the research on platform governance in two ways. The findings of the first study expand the previous explanations of how platform owners select complements for certification, which highlights the importance of demand side criteria such as complements' unrealized sales potential (e.g., Rietveld et al. 2019). In my analysis of the patterns in Apple's certification strategy, I find that Apple promotes new apps—which is in line with the demand stimulation argument of previous studies—but I also find that Apple favors apps that showcase the iPhone's technological features, provides continuously new content that keeps users engaged, and offers in-app-purchase options that help monetize the platform. These findings underscore the strategic role of certification and demonstrate that platform owners use certification to orchestrate their supply side and strategically align complementors with their ecosystems, promoting greater participation and innovativeness. For complementors, this means that they can predict certification patterns and formulate strategic responses accordingly.

The findings of the second study extend the prior research on platform governance by studying how complementors respond to governance strategies and how this affects their subsequent behavior on the platform (Rietveld et al., 2019; Wen & Zhu, 2019; Zhang et al., 2020). Examining the response from the complementor ecosystem is essential for platform owners to estimate the effectiveness of platform governance and identify potentially unwanted side effects. My theoretical arguments and empirical results illuminate prior research on the effects of certification on complementor's innovation efforts and pricing strategies and identify the competitive crowding in niches of a platform-based market as an important factor that may drive the direction and strength of these effects. In so doing, this dissertation contributes to a more precise and nuanced understanding of how complementor ecosystems respond to governance mechanisms.

Taken together, my dissertation offers a framework that illustrates the firm and market level dynamics that occur both *before* and *after* certification. In so doing, it sheds light on how platform owners can use a *soft* governance strategy to nudge complementors towards desired behavior (Foerderer, 2020; Foerderer et al., 2021).

This complements the emphasis on prior work on *hard* platform governance strategies that mostly enforce strict control over the ecosystem (e.g., Parker & Van Alstyne, 2018) or requires substantial monetary investments (e.g., Foerderer et al., 2018; Zhu & Liu, 2018). In contrast, certification is a governance strategy that is relatively easy to implement and does not require significant investments in technology, operations, or business development. However, as may findings indicate, it may still be an effective governance mechanism to “*orchestrate innovation*” (Nambisan & Sawhney, 2011) in complementor ecosystems.

Certification Literature

My findings add to research on certification in several ways. First, my dissertation contributes to a small set of studies on the strategic behavior of the market intermediaries that provide certifications (e.g., Olson & Waguespack, 2020; Seamans & Zhu, 2014). Most of this research has been conducted in settings where independent third-parties evaluate and certify products that they do not sell themselves and where firms proactively request certification. My study extends this research by illuminating the decision-making of a market intermediary (i.e., the platform owner) that is able to choose which product offerings provided by third-party firms should be awarded certification and, at the same time, provides the infrastructure needed to sell them to its customers and takes a cut of their revenue. My findings reveal two strategic behaviors of Apple as a market intermediary that uses certification: first, it selects apps to unlock their unrealized value for users, and second, it rewards apps to strategically align complementors with its platform’s key strategic objectives: stimulating value creation on the platform (i.e., innovations from third-party complementors) and increasing value capture (i.e., platform monetization). As such, these findings add to prior literature by illuminating the underlying decision-making that drives the strategic behavior of market intermediaries in platform-mediated settings.

Second, previous certification research has predominately examined how firms ex-ante adjust their efforts to receive certification (e.g., King et al., 2005), but how

firms react after certification has remained an underresearched but important topic (Rietveld et al., 2021). In the second study, this dissertation offers an analysis of how firms reconfigure their value creation and value capture strategies in response to certification. Extending the limited prior work in this area, my findings emphasize that (i) firms' response to certification is real and significant and (ii) driven by heterogeneity at the firm and market levels.

Finally, previous certification research has paid significant attention to benefits accruing for firms that receive certification, but little is known about the effects of this certification on their competitors. My dissertation extends the notion in the previous research that certification protects against competitive threats by uncertified rivals (Polidoro, 2013) in several ways. As the main effect, I find that certification has the opposite effect and that rival developers increase their innovation efforts to freeride on the enhanced visibility of the endorsed app. However, this effect is attenuated by higher degrees of competitive crowding, which firms may correlate with bleaker prospects for value capture. My findings thus extend the nascent literature on the competitive implications of certification by identifying competitive intensity in a niche as an important market level moderator that enables certified firms to predict the responses of their rivals.

Strategy Research Methods

This dissertation also makes methodological contributions. A small but emerging body of research in the strategy field has begun to apply ML to build theory (e.g., Choi et al., 2021; Choudhury et al., 2020; He et al., 2020; Leavitt et al., 2020; Teodorescu, 2017). This study contributes to this nascent stream in several ways. First, my dissertation adds to other work (e.g., Bell, Koren, & Volinsky, 2008; Hannah, Tidhar, & Eisenhardt, 2021; Jung et al., 2017; Tidhar & Eisenhardt, 2020) by showing that simpler models with a few very important variables (such as those in my study) outperform more complicated models in terms of both predictive accuracy and interpretability. As a result, such simpler models allow researchers to generate

theory that is more accurate, simple, and generalizable, enabling replication (Athey, 2018; Hey, 2010; Mullainathan & Spiess, 2017; Varian, 2014).

Second, my study presents a straightforward and useful suite of complementary ML methods. The combination of numerous algorithms provides several advantages (Shrestha et al., 2020). Tree-based algorithms, such as random forests and gradient boosting, are effective in detecting nonlinear relationships and selecting the most important predictors (Dash & Liu, 1997). Penalized logistic regressions (LASSO) are useful for estimating coefficient sizes and directions as well as removing noninformative variables from prediction models (James, Witten, Hastie, & Tibshirani, 2013; Tibshirani, 1996). While there exists a plethora of other approaches in which ML can be applied (see Choudhury et al., 2021 for an overview), this study presents a straightforward, complementary, and replicable approach.

Finally, the application of NLP methods in the second study illustrates how strategy researchers may use ML to integrate various data sources that can extend pure quantitative datasets (Safadi, Boudreau, & Faraj, 2021; von Krogh, Ben-Menahem, & Shrestha, 2021). My study joins a growing number of studies that utilize NLP techniques for text analysis) (e.g., Barlow et al., 2019; Choi et al., 2021; Choudhury et al., 2019; Furman & Teodoridis, 2020), demonstrating how NLP techniques can overcome the limitations of conventional text analysis methods (e.g., keyword counts, manual topical coding) and, at the same time, generate insights from textual data more efficiently, even on a large scale (such as those in my study).

6.2 Managerial Implications

This dissertation provides several important managerial implications.

Managerial Implications for Complementors

While previous studies on selective endorsement have underscored the enormous positive implications for complement performance in platform-mediated settings, they have provided limited insights for complementors to receive such

endorsements. From the perspective of complementors, this dissertation offers valuable insights into how platform owners choose complements for certification.

My study proposes three ways in which complementors may invest their constrained resources to increase their likelihood of receiving certification effectively. First, developers may design their time-to-market strategies in anticipation of a platform generation's lifecycle so that they can incorporate new platform technology into their product offerings quickly and, in this way, may gain significant advantages from certification early after the transition. Second, developers may adapt their innovation strategy to release incremental product updates more frequently and more substantial product updates less frequently. This experimental approach with frequent product refinements may help platforms not only address equivocal user needs (see also Boudreau, 2012; Tiwana, 2015; Yoo et al., 2012) but also substantially increase the attention from the platform owner by signaling a high rate of continuous content expansion and technical improvements. Finally, developers may carefully design their monetization strategy and enable upselling options. For example, by offering different in-app-purchase options that may include subscriptions, paid extra content, or ad-free app versions, such apps have a higher likelihood of endorsement than do those using single-payment pricing.

In sum, my findings help complementors anticipate platform owners' selection behavior by adjusting their product configuration, time-to-market, and monetization strategies accordingly. This may increase their likelihood to receive certification, and in turn, generate high visibility and superior performance in crowded platform markets.

An interesting question is to what extent these managerial implications can be generalized to different platform-based markets in other industries. For industries characterized by high technological agility, weak barriers to exit/entry for complementors, and intense competition between rival platform owners, I am optimistic that the core argument may hold: platform owners use complement certification strategically to manage their supply side, and thus, complementors can

increase their chances of being certified by aligning themselves with the platform's strategic intent. For example, similar to the mobile app industry, platforms for video gaming consoles (e.g., Nintendo's Switch), hardware operating systems (e.g., Microsoft's Windows), and cloud infrastructure (e.g., Oracle's Cloud) are dependent on a continuous supply of high-quality products offered by third-party complementors and compete with many rival platforms in terms of core technology.⁴² Thus, I expect to observe similar patterns of certification to incentivize complementors to supply complements that use the latest versions of the underlying platform technology, release frequent expansions and refinements of their product offerings, and offer attractive options for platform monetization.

However, recent research (e.g., Gómez-Losada & Duch-Brown, 2019) and anecdotal evidence from practitioners such as consultants in the e-commerce industry indicate that at least some of the implications for complementor strategy also inform managers in less technology-focused industries.⁴³ For example, it is assumed that merchants using Amazon's fulfillment services (i.e., Amazon receives the margin on fulfillment) rather than using their own proprietary fulfillment solutions (i.e., the merchant receives the margin on fulfillment), may increase their likelihood of receiving the "Amazon's Choice" badge and ultimately have a higher chance of selling their products to prospective customers. In line with this, an indicative analysis of a sample on products listed on Amazon's German marketplace conducted at an earlier stage of this doctoral work (Dexheimer, 2020) shows that that among other factors, Amazon may use its certification to certify complementors that closely align with the platform and contribute to its monetization.

⁴² Most of these examples use some form of complement certification. Nintendo promotes "Featured Free-to-Play Games", Microsoft endorses apps with the "New and Rising" label, and Oracle Cloud pins "Featured Apps" at high visibility places within its cloud applications store.

⁴³ For example, see

<https://amzscout.net/blog/amazon-choice/#UseAmazonFBAfororderfulfillment>;

<https://pattern.com/blog/how-to-get-amazon-choice-badge/>; <https://www.edesk.com/blog/amazon-choice-badge/>; accessed May 2021.

Managerial Implications for Platform Owners

For platform owners, my findings provide empirical guidance on how the complementor ecosystem may respond to certification. First, my research shows that the impact of certification is real and significant, with complementors adjusting their innovation efforts and pricing strategies in response. Thus, platform owners may consider certification as an effective *soft* mechanism to govern their ecosystems.

Second, my dissertation demonstrates that platform owners need to understand that complementors may respond equivocally to platform governance mechanisms contingent on if they received certification or not. In particular, my research suggests a generative effect of certification on both recipient and rival complementors, which may ultimately increase the value for the whole ecosystem, as complementors are incentivized to improve and expand their product offerings. Moreover, endorsing one complement likely leads to a window of opportunity for less popular complementors to freeride on the increased visibility of the certified products (see also Liang et al., 2019), thereby potentially increasing the variety among different complements that may ultimately lead to a better user experience.

However, I also find that complementors tend to discount their prices after a direct rival received certification. As such, when selecting a complement for certification, my research demonstrates that platform owners may expect potentially unwanted effects on rival complements that have not been certified. While data availability constrains me from estimating the potential impact of these price reductions on the linked revenues of the platform owner, my findings make a strong case to carefully anticipate how uncertified complementors respond to certification, and how this may in turn, have implications for the platform's monetization.

Finally, platform owners may consider the competitive situation of the complement categories or markets in which they intend to endorse a complement with certification. As I found that competition negatively impacts the generative effect from the complementor ecosystem, platform owners may use certification, especially in less crowded settings, as it more effectively stimulates value creation among

complementors. However, as I argued above, platform owners need to design their certification strategies in ways that optimize and balance two objectives: encouraging user search (i.e., the demand side) and promoting complementor innovation (i.e., the supply side). Thus, in some cases, they may have to compromise and use certification in crowded niches to help users find high-quality complements, but potentially discourage complementors' innovativeness.

This core argument can also be generalized to managerial guidance on other forms of platform governance in addition to certification. This dissertation makes a strong case for carefully estimating the reciprocal effects between the supply and demand sides of a platform market. Thus, when platform owners implement any governance mechanism, they cannot pursue an isolated effect that targets one side of the platform but must consider the consequences for the other side of the platform as well.

6.3 Limitations and Future Research

There are several ways that this research can be extended.⁴⁴ First, my findings and inferences are limited to a single empirical setting, and the validity of my findings needs to be established across other industry contexts. Also, with my focus on gaming apps, which are “*experience goods*” (Reinstein & Snyder, 2005), primarily designed for hedonistic purposes, my results may be tied to the characteristics of the mobile gaming industry. For example, publishers that develop games may use different update cycles and in-app purchase monetization strategies than publishers of nongaming apps such as fitness, notetaking, or lifestyle apps. This may be partially explained by the fact that most game developers are small, resource-constrained startups. Moreover, Apple may use app endorsements more often for gaming apps than for nongaming apps, as the gaming category is the most crowded app category, and users may find it more difficult to identify high-quality apps. While I am optimistic that similar patterns of complement endorsements in related mobile device

⁴⁴ The following suggestions for future work address broader avenues that may extend this dissertation. For the specific limitations for the two studies, I refer to the conclusions sections of Chapters 4 and 5.

platforms such as Google Play will emerge, looking into platform-mediated settings in industries such as enterprise software, e-commerce, and services that focus (i) on non-hedonistic goods and (ii) where the complementor population is not highly skewed towards small startups, could enrich the findings of this study.

Second, I have focused on one particular soft governance strategy (Foerderer et al., 2021)—complement certification. However, there are many other forms of soft governance strategies such as pricing incentives, awards, promotions, and rankings, which also aim to shape complementors' behavior (e.g., Dinerstein et al., 2018; Koo & Eesley, 2021; Tiwana, 2015; Weyl, 2010). While these governance strategies may differ in their strategic intent and operationalization, the implementation of any soft governance strategy can be interpreted as an exogenous effect on the two sides (supply and demand) of the platform market. Thus, an interesting question for future research to explore is how the findings of this dissertation can be generalized to other forms of soft platform governance. Moreover, while my dataset allowed me to study the underlying mechanisms and implications of certification, I was limited in studying these effects in isolation. However, in practice, certification is likely to be implemented in combination with other governance strategies. The variety of different approaches observed in different empirical settings offers interesting opportunities for future research to study platform governance from a more holistic perspective. For example, one promising research question may be how platform owners decide among different governance strategies to reach a certain objective, and more importantly, how different governance strategies may complement or distract each other.

Third, my findings are limited to the extent that I could not observe interactions between the complementor and the user side beyond the platform. For example, developers may approach users via other channels, such as social media, to promote their apps beyond Apple's App Store. By creating "online buzz", developers may attract attention to their product offerings, which may ultimately influence the decision of the platform owner to award such an app certification. However, like other studies in the mobile app industry (e.g., Agarwal & Kapoor, 2018; Kapoor & Agarwal, 2017; Yin et al., 2014), data availability prevents me from observing the activities of

developers outside of the platform. Future work may build on recent studies in adjacent settings (Gu & Zhu, 2020; Hagiu & Wright, 2015) and examine how dynamics that occur outside of the ecosystem shape the dynamics on the platform level.

Fourth, in this dissertation, I focus on a setting in which the platform owner has a market-leading position. While this setting is typical for the platform economy, in which platforms such as Amazon, Facebook, Google, and Microsoft have also gained enormous market power, I expect similar results in terms of governance patterns and complementor behavior. However, platform governance and platform owners' position of power are inextricably linked (Cusumano, Gawer, & Yoffie, 2021; Cusumano, Yoffie, & Gawer, 2020), and when a platform owner does not have strong market power, different dynamics may unfold. For example, in my setting, individual complementors have little ability to resist platform governance, and their performance is dependent on their alignment with the platform's strategic intent. However, if the platform owner lacks market dominance, then complementors may have incentives to use their power to influence its certification decisions in their favor. Future research may thus explore settings in which platform owners and complementors have a more balanced power relationship.

Finally, the dataset and analysis are limited to a rather short timeframe. While I can observe significant dynamics related to app certification within Apple's App Store, I am unable to draw inferences over longer time frames. Thus, future research could extend my research by exploring how governance strategies evolve over time (e.g., Hannah & Eisenhardt, 2018), how they affect complementors and users differently, and how different choices of governance strategies impact a platform's competitive advantage (e.g., Simcoe & Watson, 2019).

A Appendix

A.1 Appendix for Chapter 2

Table 12: Selected Empirical Examples of Complement Certification

Platform	Industry	Certification regime	Year	Description
Amazon Marketplace	E-Commerce	Amazon's choice	2015	Algorithm-based recommendation of products and brands, exact selection criteria undisclosed
Apple App Store	Mobile Apps	Editors' Choice	2017	Human curated recommendations of apps and games, exact selection criteria undisclosed
Google Play Store	Mobile Apps	Editors' Choice	2017	Human curated recommendations of apps and games, exact selection criteria undisclosed
Ebay	E-Commerce	Top Rated Seller	2013	Automated certification once prespecified criteria are met
AirBnB	Housing	Superhost	2009	Automated certification once prespecified criteria are met
Fiverr	Freelancer	Fiverr Pro	2017	Human curated recommendations of selected freelancers, exact selection criteria not fully disclosed
Spotify	Music streaming	Spotify Editorial Playlists	2018	Human curated recommendations of songs, exact selection criteria not fully disclosed
Sony PlayStation	Video game consoles	Essentials ⁴⁵	1997	Human curated recommendations of games, exact selection criteria not fully disclosed
Kickstarter	Crowdfunding	Projects we love	2016	Human curated recommendations of selected projects, exact selection criteria not fully disclosed
SAP	B2B software apps	SAP Spotlight Partner Apps	2020	Human curated recommendations of software apps, exact selection criteria not fully disclosed

Sources: Official platform websites, accessed March 2021.

⁴⁵ Formerly “Platinum Games”, see also Rietveld et al. (2019) for a study of complement certification in the context of video game consoles.

Table 13: List of Journals Included in the Literature Review

Field	Journals
<i>Management</i>	Strategic Management Journal Organization Science Academy of Management Journal Academy of Management Review Academy of Management Annals Academy of Management Perspectives Administrative Science Quarterly Journal of Management Organization Studies Journal of Management Studies Strategic Organization Management Science Journal of International Business Studies Research Policy Long Range Planning
<i>Economics</i>	American Economic Review Journal of Economics RAND Journal of Economics
<i>Practitioner research</i>	Harvard Business Review California Management Review MIT Sloan Management Review

Notes: All journals were reviewed from their inception until June 2021.

A.2 Appendix for Chapter 3

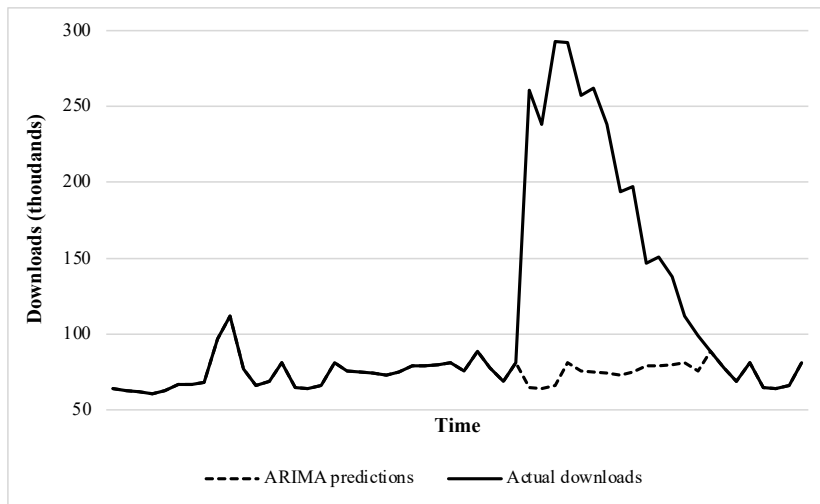
Indicative Estimation of App Featuring on Download Performance

As several other studies of the App Store (e.g., Kang, 2018; Kapoor & Agarwal, 2017), my main dataset includes only monthly ranking data to estimate app performance in terms of number of downloads. This makes estimating the performance effects of certification on app performance relatively difficult in my data as ranks do not have equal spaces between them (for example, rank 1 could equal 100k downloads, rank 2 50k downloads, and rank 3 15k downloads). Thus, to indicatively estimate the effects of app certification on app performance, I retrieved additional, more granular daily download data for a small subsample of about 100 apps. This additional data complements the rank data with additional download ranges (for example, 50k to 100k downloads, 100 to 150k downloads, etc.).⁴⁶ Methodologically, I followed the approach from the market leading app analytics firm AppAnnie (AppAnnie, 2016) to estimate the effects of Apple's certification on app performance. First, treating each app as a separate instance, I constructed a time-series panel. Second, for each of these instances, I fit a window of an app's prior downloads using an ARIMA model (Nielsen, 2019). This model allows me to estimate the downloads of the apps in my subset that would have occurred had the app not been featured. Third, I compare these predictions against the actual downloads to calculate the estimated download effects from the app certification. I find that, *on average*, certification increases app download performance by approximately 175%⁴⁷ in the subsample.⁴⁸ See Figure 4 for a visualization of the estimated indicative uplift effect of certification on app downloads.

⁴⁶ As noted in Chapter 3, app download numbers (like other variables included in the analysis) are not actual reported values but estimated values by app analytics providers.

⁴⁷ This indicative result is comparatively low compared to estimates from mobile analytics firms that analyzed download effects of app featuring at large scale and found download uplifts for apps of more than 1,700% and more than 700% for games (Source: https://guce.techcrunch.com/copyConsent?sessionId=3_cc-session_e0a6ab05-c9ef-4b0c-bd91-a1950e99f245&lang=en-US).

⁴⁸ ARIMA models were estimated using the *statsmodels* module.

Figure 4: Estimated Effects of Certification on App Download Performance

Note: Indicative ARIMA predictions are averaged.

A.3 Appendix for Chapter 4

Table 14: Robustness Tests – Alternative Algorithms for Feature Selection

	Model 8: Extra Trees Classifier			Model 9: XGBoost Classifier			Model 10: Logistic Regression with RFE		
	Run 1	Run 2	Run 3	Run 1	Run 2	Run 3	Run 1	Run 2	Run 3
Overall model metrics									
Logistic loss	-0.33	-0.33	-0.33	-0.34	-0.34	-0.34	-0.38	-0.38	-0.38
Accuracy (in sample I)	0.88	0.88	0.88	0.89	0.89	0.89	0.82	0.82	0.82
Precision	0.90	0.90	0.90	0.90	0.90	0.90	0.80	0.80	0.80
Recall	0.90	0.90	0.99	0.90	0.90	0.99	0.82	0.81	0.82
F1-score	0.89	0.89	0.89	0.89	0.89	0.89	0.80	0.80	0.80
True positives	2332	2332	2331	2331	2331	2331	2263	2263	2262
True negatives	388	388	388	388	388	388	220	220	221
False positives	277	277	277	277	277	277	444	444	444
False negatives	29	29	30	30	30	30	99	99	99

Notes: Precision, Recall, and F1 scores are calculated using the weighted average method. All models were tuned using 10-fold cross-validation. *Extra Trees Classifier:* Optimal hyperparameters: n_trees (number of decision trees in the ensemble) = 500, min_samples_split (number of samples in a node of the decision tree before adding a split) = 7. *XGBoost Classifier:* Optimal hyperparameters: n_estimators (number of sequential trees to be modeled) = 500, learning_rate (impact of each tree on the final outcome) = 0.1, max_depth (maximum depth of the tree) = 4. *Logistic regression with RFE:* Optimal hyperparameters: n_features_to_select (number of features to be selected) = 4, penalty (regularization term) = L1, C (inverse of regularization strength) = 0.1.

Table 15: Robustness Tests – Features Identified by Different Algorithms

<i>Predictors</i>	<i>Top 4 selected features</i>				
	Gradient Boosting	Random Forest	Lasso Regression	Extra Trees Classifier	XGBoost Classifier
New app (x ₁)	X	X	X	X	X
Apps per developer (x ₂)					
Popular developer (x ₃)					
App quality (x ₄)					
Adaption speed (x ₅)	X	X	X	X	X
App size (x ₆)					
iPad version (x ₇)					
In-app purchases avg value (x ₈)					
In-app purchase options (x ₉)	X	X	X	X	X
Update frequency (x ₁₀)	X	X	X	X	X
Top rank (x ₁₁)					

Notes: X indicates that the variable was identified among the top 4 selected features across all three model runs. Gradient Boosting and XGBoost classifier select variables based on gain, Random Forest and Extra Trees Classifier based on impurity, and Logistic Regression with recursive feature elimination based on coefficient sizes. All algorithms were tuned as described in the notes section for Table 6 (for Gradient Boosting, Random Forest, and Lasso Regression) and Table 14 (for Extra Trees, XGBoost, and Logistic Regression with RFE).

Table 16: Robustness Tests – Two-way Interactions among Predictor Variables

	Model 11: Lasso Regression
<i>Predictors</i>	<i>Coefficients</i>
New app (x_1)	1.6073
Adaption speed (x_5)	-2.0689
In-app purchase options (x_9)	1.5715
Update frequency (x_{10})	4.5522
Adaption speed (x_5) * In-app purchase options (x_9)	0.0000
Adaption speed (x_5) * Update frequency (x_{10})	0.0021
In-app purchase options (x_9) * Adaption speed (x_5)	0.0000
In-app purchase options (x_9) * Update frequency (x_{10})	0.0018

Notes: A model with all two-way interactions among the selected continuous variables $\{x_5, x_9, x_{10}\}$ was build and then fed into a Lasso regression (Tibshirani, 1996) using 10-fold cross-validation and model the following optimal hyperparameters: C (inverse of regularization strength) = 0.1.

Table 17: Robustness Tests – Alternative Variable Computations

<i>DV: Featured</i>	Model 12	Model 13	Model 14	Model 15	Model 16
Update frequency	7.9145*** (2.5417)	5.6523*** (0.7581)			6.0155*** (1.4313)
Update frequency (performance)			13.5397*** (3.3182)		
Update frequency (content)				6.8843*** (2.3049)	
In-app-purchase options	1.2329*** (0.1004)	1.2493*** (0.0998)	1.1914*** (0.1003)	1.2733*** (0.0996)	1.2543*** (0.0998)
Adaption speed	-3.1139*** (0.2474)	-3.0013*** (0.2507)	-3.0147*** (0.2494)	-3.0378*** (0.2495)	-3.0338*** (0.2498)
New app			1.2157*** (0.1153)	1.5383*** (0.0989)	1.4110*** (0.1021)
New app (six months)	0.9152*** (0.1061)				
App age (continuous measure)		-2.6838*** (0.1749)			
App quality	1.5658*** (0.5652)	1.6499** (0.5775)	1.5643*** (0.5667)	1.6610*** (0.5685)	1.7346*** (0.5791)
Top rank (500)	-0.3296** (0.0976)	-0.1953* (0.0973)	-0.2326* (0.0978)	-0.3089** (0.0974)	
Top rank (250)					-0.2741** (0.0074)
Constant	-1.1614** (0.5599)	0.6188 (0.5700)	-1.2926** (0.5632)	-1.3736** (0.5646)	-1.4024** (0.5632)
Population FE	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	4,323	4,323	4,323	4,323	4,323
Log-likelihood	-1811.0	-1752.1	-1761.9	-1783.4	-1771.7
McFadden's Pseudo R ²	0.20	0.22	0.22	0.21	0.22

Notes: Robust standard errors reported in parentheses. ***p < 0.01; **p < 0.05; *p < 0.10.

A.4 Appendix for Chapter 5

Table 18: Robustness Tests – Alternative Variable Computations

	Model 9	Model 10	Model 11	Model 12
<i>Dependent variable</i>	<i>Log(Updates)</i>	<i>Log(Updates)</i>	<i>Log(Updates)</i>	<i>Log(Updates)</i>
Featured	0.211*** (0.042)		0.219*** (0.032)	
Featured rival		0.102** (0.008)		0.081** (0.004)
Category competition			-0.009* (0.001)	-0.041** (0.003)
Featured * Category competition			-0.012** (0.002)	-0.012** (0.000)
App age	-0.036** (0.003)	-0.063*** (0.004)	-0.038*** (0.014)	-0.061*** (0.003)
Version age	0.005* (0.002)	-0.091*** (0.001)	0.106*** (0.000)	0.006** (0.000)
Platform age	-0.001 (0.000)	-0.005* (0.000)	0.006* (0.001)	-0.001 (0.000)
Constant	1.984*** (0.069)	1.781*** (0.078)	1.699*** (0.101)	1.788*** (0.034)
App FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Number of apps	807	807	3,399	3,399
Observations	4,842	4,842	20,394	20,394
Adjusted R ²	0.25	0.21	0.26	0.22

Notes: Robust standard errors in parentheses and clustered at the app level. The dependent variable *Updates* is calculated for a 60-day time window (see Section 5.7 for details). Model 9 tests H1a, Model 10 tests H2a, Model 11 tests H3a, and Model 12 tests H4a, respectively. ***p < 0.01; **p < 0.05; *p < 0.10.

Table 19: Robustness Tests – Alternative Variable Computations

	Model 13	Model 14	Model 15	Model 16
<i>Dependent variable</i>	<i>Log(App price)</i>	<i>Log(App price)</i>	<i>Log(App price)</i>	<i>Log(App price)</i>
Featured	0.077*** (0.012)		0.049*** (0.019)	
Featured rival		-0.099**		0.009** (0.002)
Category competition			-0.081*** (0.008)	0.077*** (0.014)
Featured * Category competition			-0.014** (0.005)	0.002 (0.000)
App size	0.037*** (0.006)	0.019*** (0.004)	0.101*** (0.009)	0.103*** (0.012)
Constant	1.999*** (0.078)	2.190*** (0.121)	1.981*** (0.065)	2.193*** (0.131)
App FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Number of apps	807	807	3,399	3,399
Observations	4,842	4,842	20,394	20,394
Adjusted R ²	0.19	0.17	0.21	0.19

Notes: Robust standard errors in parentheses and clustered at the app level. The dependent variable *app price* is calculated as the median value of an app's in-app-purchase-options (see Section 5.7 for details). Model 13 tests H1b, Model 14 tests H2b, Model 14 tests H3b, and Model 12 tests H4b, respectively. ***p < 0.01; **p < 0.05; *p < 0.10.

References

- Adner, R. (2017). Ecosystem as Structure: An Actionable Construct for Strategy. *Journal of Management*, 43(1), 39–58.
- Agarwal, S., & Kapoor, R. (2018). Two faces of value creation in business ecosystems: Leveraging complementarities and managing interdependencies. *Working Paper*.
- Aguiar, L., & Waldfogel, J. (2018). *Platforms, Promotion, and Product Discovery: Evidence from Spotify Playlists* (National Bureau of Economic Research, Working Paper No. 24713).
- Akerlof, G. A. (1970). The Market for “Lemons”: Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, 84(3), 488–500.
- Albano, G. L., & Lizzeri, A. (2001). Strategic certification and provision of quality. *International Economic Review*, 42(1), 267–283.
- AppAnnie. (2016). *The Value of an App Store Feature*. Retrieved from <https://go.appannie.com/report-impact-app-store-feature>
- Apple. (2017). Introducing the New App Store. Retrieved from <https://developer.apple.com/videos/play/wwdc2017/301/?time=2927>
- Armstrong, M. (2006). Competition in two-sided markets. *The Rand Journal of Economics*, 37(3), 668–691.
- Arora, S., Ter Hofstede, F., & Mahajan, V. (2017). The implications of offering free versions for the performance of paid mobile apps. *Journal of Marketing*, 81(6), 62–78.
- Askalidis, G. (2015). The Impact of Large Scale Promotions on the Sales and Ratings of Mobile Apps: Evidence from Apple’s App Store. Retrieved from <http://arxiv.org/abs/1506.06857>
- Athey, S. (2018). The impact of machine learning on economics. In *The economics of artificial intelligence: An agenda* (pp. 507–547). University of Chicago Press.
- Bakos, Y., & Halaburda, H. (2020). Platform Competition with Multihoming on Both Sides: Subsidize or Not? *Management Science*, 66(12), 5599–5607.

- Barach, M. A., Kaul, A., Leung, M. D., & Lu, S. (2019). Strategic Redundancy in the Use of Big Data: Evidence from a Two-Sided Labor Market. *Strategy Science*, 4(4), 298–322.
- Barlow, M. A., Verhaal, J. C., & Angus, R. W. (2019). Optimal distinctiveness, strategic categorization, and product market entry on the Google Play app platform. *Strategic Management Journal*, 40(8), 1219–1242.
- Bell, R. M., Koren, Y., & Volinsky, C. (2008). The bellkor 2008 solution to the netflix prize. *Statistics Research Department at AT&T Research*, 1(1). Retrieved from <http://signallake.com/innovation/Bellkor2008.pdf>
- Belloni, A., Chernozhukov, V., & Hansen, C. (2014). High-Dimensional Methods and Inference on Structural and Treatment Effects. *The Journal of Economic Perspectives: A Journal of the American Economic Association*, 28(2), 29–50.
- Benjamin, B. A., & Podolny, J. M. (1999). Status, Quality, and Social Order in the California Wine Industry. *Administrative Science Quarterly*, 44(3), 563–589.
- Biglaiser, G., & Li, F. (2018). Middlemen: the good, the bad, and the ugly. *The Rand Journal of Economics*, 49(1), 3–22.
- Biglaiser, G., Li, F., Murry, C., & Zhou, Y. (2020). Intermediaries and product quality in used car markets. *The Rand Journal of Economics*, 51(3), 905–933.
- Binken, J. L. G., & Stremersch, S. (2009). The effect of superstar software on hardware sales in system markets. *Journal of Marketing*, 73(2), 88–104.
- Boudreau, K. J. (2010). Open Platform Strategies and Innovation: Granting Access vs. Devolving Control. *Management Science*, 56(10), 1849–1872.
- Boudreau, K. J. (2012). Let a thousand flowers bloom? An early look at large numbers of software app developers and patterns of innovation. *Organization Science*, 23(5), 1409–1427.
- Boudreau, K. J. (2017). Platform Boundary Choices & Governance: Opening-Up While Still Coordinating and Orchestrating☆. In *Advances in Strategic Management: Vol. 37. Entrepreneurship, Innovation, and Platforms* (pp. 227–297). Emerald Publishing Limited.

- Boudreau, K. J., & Hagiu, A. (2009). Platform rules: Multi-sided platforms as regulators. *Platforms, Markets and Innovation*, 1, 163–191.
- Boudreau, K. J., & Jeppesen, L. B. (2015). Unpaid crowd complementors: The platform network effect mirage. *Strategic Management Journal*, 36(12), 1761–1777.
- Boudreau, K. J., Jeppesen, L. B., & Miric, M. (2019). Competing on Free (mium): Digital Competition with Network Effects. *Working Paper*. Available at SSRN 2984546.
- Brandenburger, A. M., & Nalebuff, B. J. (1996). *Co-opetition: A revolutionary mindset that combines competition and cooperation in the marketplace*. Boston, MA: Harvard Business School Press.
- Bresnahan, T., Orsini, J., & Yin, P.-L. (2014). Platform choice by mobile app developers. *NBER Working Paper*. Retrieved from <https://www.nber.org/conferences/2014/EoDs14/multihoming%20BOY.pdf>
- Brink, H., Richards, J., & Fetherolf, M. (2016). *Real-world machine learning*. Simon and Schuster. New York, NY: Manning Publications Co.
- Brownlee, J. (2016). Overfitting and underfitting with machine learning algorithms. *Machine Learning Mastery*. <https://machinelearningmastery.com/overfitting-and-underfitting-with-machine-learning-algorithms/>.
- Brunswicker, S., Almirall, E., & Majchrzak, A. (2019). Optimizing and satisficing: The interplay between platform architecture and producers' design strategies for platform performance. *The Mississippi Quarterly*, 43(4), 1249–1277.
- Burtch, G., He, Q., Hong, Y., & Lee, D. (2021). How Do Peer Awards Motivate Creative Content? Experimental Evidence from Reddit. *Management Science*. *Forthcoming*.
- Caillaud, B., & Jullien, B. (2003). Chicken & Egg: Competition among Intermediation Service Providers. *The Rand Journal of Economics*, 34(2), 309–328.
- Casadesus-Masanell, R., & Halaburda, H. (2014). When does a platform create value by limiting choice? *Journal of Economics & Management Strategy*, 23(2), 259–293.

- Ceccagnoli, M., Forman, C., Huang, P., & Wu, D. J. (2011). Co-creation of value in a platform ecosystem: The case of enterprise software. *MIS Quarterly*, 263-290.
- Cennamo, C., Gu, Y., & Zhu, F. (2018). Value co-creation and capture in platform markets: Evidence from a creative industry. *Working Paper. Harvard Business School*.
- Cennamo, C.. (2018). Building the value of next-generation platforms: the paradox of diminishing returns. *Journal of Management*, 44(8), 3038–3069.
- Cennamo, C. (2021). Competing in digital markets: A platform-based perspective. *Academy of Management Perspectives*, 35(2), 265-291.
- Cennamo, C., & Santalo, J. (2013). Platform competition: Strategic trade-offs in platform markets: Platform Competition. *Strategic Management Journal*, 34(11), 1331–1350.
- Cennamo, C., & Santaló, J. (2019). Generativity Tension and Value Creation in Platform Ecosystems. *Organization Science*, 30(3), 617–641.
- Chen, L., Yi, J., Li, S., & Tong, T. W. (2021). Platform Governance Design in Platform Ecosystems: Implications for Complementors' Multihoming Decision. *Journal of Management*, *Forthcoming*.
- Chen, T., & Guestrin, C. (2016). Xgboost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International*.
- Chen, Y., & Xie, J. (2005). Third-Party Product Review and Firm Marketing Strategy. *Marketing Science*, 24(2), 218–240.
- Choi, J., Menon, A., & Tabakovic, H. (2021). Using machine learning to revisit the diversification–performance relationship. *Strategic Management Journal*. *Forthcoming*.
- Choudhury, P., Allen, R. T., & Endres, M. G. (2021). Machine learning for pattern discovery in management research. *Strategic Management Journal*, 42(1), 30–57.
- Choudhury, P., Starr, E., & Agarwal, R. (2020). Machine learning and human capital complementarities: Experimental evidence on bias mitigation. *Strategic Management Journal*, 41(8), 1381–1411.

- Choudhury, P., Wang, D., Carlson, N. A., & Khanna, T. (2019). Machine learning approaches to facial and text analysis: Discovering CEO oral communication styles. *Strategic Management Journal*, 40(11), 1705–1732.
- Chu, L. Y., & Wu, B. (2021). Designing online platforms for customized goods and services: A market-frictions based perspective. *Academy of Management Review*. *Forthcoming*.
- Claussen, J., Essling, C., & Kretschmer, T. (2015). When less can be more-Setting technology levels in complementary goods markets. *Research Policy*, 44(2), 328–339.
- Claussen, J., Kretschmer, T., & Mayrhofer, P. (2013). The Effects of Rewarding User Engagement: The Case of Facebook Apps. *Information Systems Research*, 24(1), 186–200.
- Clements, M. T., & Ohashi, H. (2005). Indirect network effects and the product cycle: Video games in the U.S., 1994-2002. *The Journal of Industrial Economics*, 53(4), 515–542.
- Comino, S., Manenti, F. M., & Mariuzzo, F. (2019). Updates management in mobile applications: iTunes versus Google Play. *Journal of Economics & Management Strategy*, 28(3), 392-419.
- Cox, V. (2017). Exploratory Data Analysis. In V. Cox (Ed.), *Translating Statistics to Make Decisions : A Guide for the Non-Statistician* (pp. 47–74). Berkeley, CA: Apress.
- Cusumano, M. A., Gawer, A., & Yoffie, D. B. (2019). The Business of Platforms: Strategy in the Age of Digital Competition. *Innovation, and Power*. *HarperCollins Publishers*.
- Cusumano, M. A., Gawer, A., & Yoffie, D. B. (2021). *Can Self-Regulation Save Digital Platforms*. Working Paper.
- Cusumano, M. A., Yoffie, D. B., & Gawer, A. (2020). The Future of Platforms. *MIT Sloan Management Review*; 61(3), 46–54.
- Cutolo, D., Hargadon, A., & Kenney, M. (2021). Competing on Platforms. *Sloan Management Review*. *Forthcoming*.

- Dash, M., & Liu, H. (1997). Feature selection for classification. *Intelligent Data Analysis*, 1(1), 131–156.
- D'Aveni, R. A., Dagnino, G. B., & Smith, K. G. (2010). The age of temporary advantage. *Strategic Management Journal*, 31(13), 1371–1385.
- de Chaisemartin, C., & D'Haultfœuille, X. (2020). Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *The American Economic Review*, 110(9), 2964–2996.
- DellaVigna, S., & Hermle, J. (2017). Does conflict of interest lead to biased coverage? Evidence from movie reviews. *The Review of Economic Studies*, 84(4), 1510–1550.
- Dexheimer, M. (2020). Complement certification in platform-based markets: An empirical analysis of Amazon.de. *Working Paper*.
- Dhanaraj, C., & Parkhe, A. (2006). Orchestrating Innovation Networks. *Academy of Management Review*, 31(3), 659–669.
- Dinerstein, M., Einav, L., Levin, J., & Sundaresan, N. (2018). Consumer Price Search and Platform Design in Internet Commerce. *The American Economic Review*, 108(7), 1820–1859.
- Dranove, D., & Jin, G. Z. (2010). Quality Disclosure and Certification: Theory and Practice. *Journal of Economic Literature*, 48(4), 935–963.
- Dranove, D., Kessler, D., McClellan, M., & Satterthwaite, M. (2003). Is More Information Better? The Effects of “Report Cards” on Health Care Providers. *The Journal of Political Economy*, 111(3), 555–588.
- Eaton, B., Elaluf-Calderwood, S., Sørensen, C., & Yoo, Y. (2015). Distributed tuning of boundary resources. *The Mississippi Quarterly*, 39(1), 217–244.
- Eckhardt, J. T. (2016). Welcome contributor or no price competitor? The competitive interaction of free and priced technologies. *Strategic Management Journal*, 37(4), 742–762.
- Eisenhardt, K. M. (1989). Building Theories from Case Study Research. *Academy of Management Review*, 14(4), 532–550.

- Eisenhardt, K. M., & Graebner, M. E. (2007). Theory Building From Cases: Opportunities And Challenges. *Academy of Management Journal*, 50(1), 25–32.
- Eisenmann, T., Parker, G., & Van Alstyne, M. (2011). Platform envelopment. *Strategic Management Journal*, 32(12), 1270–1285.
- Eisenmann, T., Parker, G., & Van Alstyne, M. W. (2006). Strategies for two-sided markets. *Harvard Business Review*, 84(10), 92.
- Eisenmann, T. R., Parker, G., & Van Alstyne, M. (2009). Opening platforms: how, when and why? *Platforms, Markets and Innovation*, 6, 131–162.
- Elfenbein, D. W., Fisman, R., & McManus, B. (2015). Market Structure, Reputation, and the Value of Quality Certification. *American Economic Journal: Microeconomics*, 7(4), 83–108.
- Eliashberg, J., & Shugan, S. M. (1997). Film Critics: Influencers or Predictors? *Journal of Marketing*, 61(2), 68–78.
- Evans, D. S., Hagiu, A., & Schmalensee, R. (2006). *Invisible engines: how software platforms drive innovation and transform industries*. MIT Press: Cambridge, MA.
- Evans, David S. (2003). Some Empirical Aspects of Multi-Sided Platform Industries. *Review of Network Economics* 2, 191-209.
- Fang, L., & Peress, J. (2009). Media coverage and the cross-section of stock returns. *The Journal of Finance*, 64(5), 2023–2052.
- Lu, S. (2012). Multitasking, information disclosure, and product quality: Evidence from nursing homes. *Journal of Economics & Management Strategy*, 21(3), 673–705.
- Foerderer, J. (2020). Interfirm exchange and innovation in platform ecosystems: Evidence from Apple’s Worldwide Developers Conference. *Management Science*, 66(10), 4772–4787.
- Foerderer, J., Kude, T., Mithas, S., & Heinzl, A. (2018). Does platform owner’s entry crowd out innovation? Evidence from Google photos. *Information Systems Research : ISR*, 29(2), 444–460.

- Foerderer, J., Lueker, N., & Heinzl, A. (2021). And the winner is ...? The desirable and undesirable effects of platform awards. *Information Systems Research*, *Forthcoming*.
- Forbes, S. J., Lederman, M., & Tombe, T. (2015). Quality Disclosure Programs and Internal Organizational Practices: Evidence from Airline Flight Delays. *American Economic Journal: Microeconomics*, *7*(2), 1–26.
- Frank, R. G., & Salkever, D. S. (1997). Generic entry and the pricing of pharmaceuticals. *Journal of Economics & Management Strategy*, *6*(1), 75–90.
- Furman, J. L., & Teodoridis, F. (2020). Automation, research technology, and researchers' trajectories: Evidence from computer science and electrical engineering. *Organization Science*, *31*(2), 330–354..
- Gao, G., Gopal, A., & Agarwal, R. (2010). Contingent Effects of Quality Signaling: Evidence from the Indian Offshore IT Services Industry. *Management Science*, *56*(6), 1012–1029.
- Gawer, A. (2009). *Platforms, Markets and Innovation*. Edward Elgar Publishing: Northampton, MA.
- Gawer, A. (2014). Bridging differing perspectives on technological platforms: Toward an integrative framework. *Research Policy*, *43*(7), 1239–1249.
- Gawer, A., & Cusumano, M. A. (2002). *Platform Leadership: How Intel, Microsoft and Cisco Drive Industry Innovation*. Harvard Business School Press: Boston, MA.
- Gawer, A., & Cusumano, M. A. (2014). Industry platforms and ecosystem innovation. *Journal of Product Innovation Management*, *31*(3), 417–433.
- Gawer, A., & Henderson, R. (2007). Platform owner entry and innovation in complementary markets: Evidence from Intel. *Journal of Economics & Management Strategy*, *16*(1), 1–34.
- Geurts, P., Ernst, D., & Wehenkel, L. (2006). Extremely randomized trees. *Machine Learning*, *63*(1), 3–42.

- Ghazawneh, A., & Henfridsson, O. (2013). Balancing platform control and external contribution in third-party development: the boundary resources model. *Information Systems Journal*, 23(2), 173–192.
- Glaser, B. G., & Strauss, A. L. (1967). *The discovery of grounded theory: Strategies of qualitative research*. London: Wiedenfeld and Nicholson.
- Godes, D., Ofek, E., & Sarvary, M. (2009). Content vs. Advertising: The Impact of Competition on Media Firm Strategy. *Marketing Science*, 28(1), 20–35.
- Gómez-Losada, Á., & Duch-Brown, N. (2019). Competing for Amazon's buy box: A machine-learning approach. In *Lecture Notes in Business Information Processing. Business Information Systems Workshops* (pp. 445–456). Cham: Springer International Publishing.
- Graffin, S. D., & Ward, A. J. (2010). Certifications and Reputation: Determining the Standard of Desirability Amidst Uncertainty. *Organization Science*, 21(2), 331–346.
- Greve, H. R., & Song, S. Y. (2017). Amazon warrior: How a platform can restructure industry power and ecology. *Entrepreneurship, Innovation, and Platforms*, 37: 299-335..
- Gu, G., & Zhu, F. (2020). Trust and disintermediation: Evidence from an online freelance marketplace. *Management Science*. 67(2), 794-807.
- Gurun, U. G., & Butler, A. W. (2012). Don't believe the hype: Local media slant, local advertising, and firm value. *The Journal of Finance*, 67(2), 561–598.
- Guyon, I., & Elisseeff, A. (2003). An introduction to variable and feature selection. *Journal of machine learning research*, 3(Mar), 1157-1182.
- Hadi, A. S., & Chatterjee, S. (2015). *Regression Analysis by Example*. John Wiley & Sons.
- Hagiu, A., & Wright, J. (2015). Marketplace or reseller? *Management Science*, 61(1), 184-203.
- Hagiu, A. (2006). Pricing and commitment by two-sided platforms. *The Rand Journal of Economics*, 37(3), 720–737.
- Hagiu, A. (2011). *Quantity vs. quality: Exclusion by platforms with networks effects*. Harvard Business School, HBS Working Paper Number: 11-125.

- Hagiu, A. (2014). Strategic Decisions for Multisided Platforms. *MIT Sloan Management Review*;55(2), 71–80.
- Hagiu, A., & Spulber, D. (2013). First-Party Content and Coordination in Two-Sided Markets. *Management Science*, 59(4), 933–949.
- Hannah, D. P., & Eisenhardt, K. M. (2018). How firms navigate cooperation and competition in nascent ecosystems. *Strategic Management Journal*, 39(12), 3163–3192.
- Hannah, D. P., Tidhar, R., & Eisenhardt, K. M. (2021). Analytic models in strategy, organizations, and management research: A guide for consumers. *Strategic Management Journal*, 42(2), 329–360.
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). Unsupervised Learning. In T. Hastie, R. Tibshirani, & J. Friedman (Eds.), *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (pp. 485–585). New York, NY: Springer New York.
- Haviv, A., Huang, Y., & Li, N. (2020). Intertemporal Demand Spillover Effects on Video Game Platforms. *Management Science*, 66(10), 4788–4807.
- He, V. F., Puranam, P., Shrestha, Y. R., & Krogh, G. (2020). Resolving governance disputes in communities: A study of software license decisions. *Strategic Management Journal*, 41(10), 1837–1868.
- Helfat, C. E., & Raubitschek, R. S. (2018). Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems. *Research Policy*, 47(8), 1391–1399.
- Hey, T. (2010). The next scientific revolution. *Harvard Business Review*, 88(11), 56–63.
- Ho-Dac, N. N., Kumar, M., & Slotegraaf, R. J. (2020). Using product development information to spur the adoption of continuous improvement products. *Journal of the Academy of Marketing Science*, 48(6), 1156–1173.
- Houde, S. (2018). How consumers respond to product certification and the value of energy information. *The Rand Journal of Economics*, 49(2), 453–477.

- Hsu, G. (2006). Jacks of All Trades and Masters of None: Audiences' Reactions to Spanning Genres in Feature Film Production. *Administrative Science Quarterly*, 51(3), 420–450.
- Hsu, G., Roberts, P. W., & Swaminathan, A. (2012). Evaluative Schemas and the Mediating Role of Critics. *Organization Science*, 23(1), 83–97.
- Huang, P., Ceccagnoli, M., Forman, C., & Wu, D. J. (2013). Appropriability mechanisms and the platform partnership decision: Evidence from enterprise software. *Management Science*, 59(1), 102–121.
- Hui, X., Liu, M., & Chan, T. (2020). *Targeted Incentives, Broad Impacts: Evidence from an E-commerce Platform*. Working Paper.
- Hui, X., Saeedi, M., Shen, Z., & Sundaresan, N. (2016). Reputation and regulations: Evidence from eBay. *Management Science*, 62(12), 3604–3616.
- Hui, X., Saeedi, M., Spagnolo, G., & Tadelis, S. (2018). *Certification, Reputation and Entry: An Empirical Analysis*. National Bureau of Economic Research, No. 24916).
- Hukal, P., Henfridsson, O., Shaikh, M., & Parker, G. (2020). Platform signaling for generating platform content. *The Mississippi Quarterly*, 44(3), 1177–1205.
- Hwang, I., Radhakrishnan, S., & Su, L. (2006). Vendor Certification and Appraisal: Implications for Supplier Quality. *Management Science*, 52(10), 1472–1482.
- Iansiti, M., & Levien, R. (2004). *The Keystone Advantage: What the New Dynamics of Business Ecosystems Mean for Strategy, Innovation, and Sustainability*. Harvard Business School Press: Boston, MA.
- Ifrach, B., & Johari, R. (2014). The Impact of Visibility on Demand in the Market for Mobile Apps. Working Paper.
- Imai, K., & Kim, I. S. (2021). On the Use of Two-Way Fixed Effects Regression Models for Causal Inference with Panel Data. *Political Analysis: An Annual Publication of the Methodology Section of the American Political Science Association*, 29(3), 405–415.
- Iyer, G., & Singh, S. (2018). Voluntary Product Safety Certification. *Management Science*, 64(2), 695–714.

- Jacobides, M. G., Cennamo, C., & Gawer, A. (2018). Towards a theory of ecosystems. *Strategic Management Journal*, 39(8), 2255–2276.
- Jacobides, M. G., Cennamo, C., & Gawer, A. (2020). *Distinguishing between Platforms and Ecosystems: Complementarities, Value Creation, and Coordination Mechanisms*. Working paper.
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning: With applications in R*. New York, NY: Springer.
- Jiang, R. J., & Bansal, P. (2003). Seeing the need for ISO 14001. *The Journal of Management Studies*, 40(4), 1047–1067.
- Jin, G. Z., & Leslie, P. (2003). The effect of information on product quality: Evidence from restaurant hygiene grade cards. *The Quarterly Journal of Economics*, 118(2), 409–451.
- Jin, G. Z., & Leslie, P. (2009). Reputational Incentives for Restaurant Hygiene. *American Economic Journal: Microeconomics*, 1(1), 237–267.
- Jullien, B., & Pavan, A. (2018). Information Management and Pricing in Platform Markets. *The Review of Economic Studies*, 86(4), 1666–1703.
- Jung, J., Concannon, C., Shroff, R., Goel, S., & Goldstein, D. G. (2017). Creating simple rules for complex decisions. *Harvard Business Review*.
- Kang, H. Y. (2018). *Essays on within-platform competitive dynamics*. Dissertation. Retrieved from <https://open.bu.edu/handle/2144/30067>
- Kapoor, R., & Agarwal, S. (2017). Sustaining superior performance in business ecosystems: Evidence from application software developers in the iOS and Android smartphone ecosystems. *Organization Science*, 28(3), 531–551.
- Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. *The American Economic Review*, 75(3), 424–440.
- Kesler, R., Kummer, M., & Schulte, P. (2017). User data, market power and innovation in online markets: Evidence from the mobile app industry. Working Paper.
- Kim, J.-H., Prince, J., & Qiu, C. (2014). Indirect network effects and the quality dimension: A look at the gaming industry. *International Journal of Industrial Organization*, 37, 99–108.

- King, A. A., Lenox, M. J., & Terlaak, A. (2005). The Strategic Use of Decentralized Institutions: Exploring Certification With the ISO 14001 Management Standard. *Academy of Management Journal*, 48(6), 1091–1106.
- Koo, W. W., & Eesley, C. E. (2021). Platform governance and the rural–urban divide: Sellers’ responses to design change. *Strategic Management Journal*, 42(5), 941–967.
- Kovács, B., & Sharkey, A. J. (2014). The Paradox of Publicity: How Awards Can Negatively Affect the Evaluation of Quality. *Administrative Science Quarterly*, 59(1), 1–33.
- Kretschmer, T., & Claussen, J. (2016). Generational transitions in platform markets—The role of backward compatibility. *Strategy Science*, 1(2), 90–104.
- Kretschmer, T., Leiponen, A., Schilling, M., & Vasudeva, G. (2021). Platform ecosystems as meta-organizations: Implications for platform strategies. *Strategic Management Journal*, Forthcoming.
- Kulchina, E. (2014). Media coverage and location choice. *Strategic Management Journal*, 35(4), 596–605.
- Landsman, V., & Stremersch, S. (2011). Multihoming in Two-Sided Markets: An Empirical Inquiry in the Video Game Console Industry. *Journal of Marketing*, 75(6), 39–54.
- Lanzolla, G., Lorenz, A., Miron-Spektor, E., Schilling, M., Solinas, G., & Tucci, C. L. (2020). Digital Transformation: What is New if Anything? Emerging Patterns and Management Research. *Academy of Management Discoveries*, 6(3), 341–350.
- Lau, J. H., & Baldwin, T. (2016). An Empirical Evaluation of doc2vec with Practical Insights into Document Embedding Generation. Retrieved from <http://arxiv.org/abs/1607.05368>
- Lawrence, J., Park, J., Budzynska, K., Cardie, C., Konat, B., & Reed, C. (2017). Using Argumentative Structure to Interpret Debates in Online Deliberative Democracy and eRulemaking. *ACM Transactions on Internet Technology*, 17(3), 1–22.

- Le, Q., & Mikolov, T. (2014). Distributed Representations of Sentences and Documents. In E. P. Xing & T. Jebara (Eds.), *Proceedings of the 31st International Conference on Machine Learning* (pp. 1188–1196). Beijing, China: PMLR.
- Leavitt, K., Schabram, K., Hariharan, P., & Barnes, C. M. (2020). Ghost in the Machine: On Organizational Theory in the Age of Machine Learning. *Academy of Management Review*. In press.
- Li, Z., & Agarwal, A. (2016). Platform integration and demand spillovers in complementary markets: Evidence from Facebook's integration of Instagram. *Management Science*, 63(10), 3438–3458.
- Liang, C., Shi, Z., & Raghu, T. S. (2019). The Spillover of Spotlight: Platform Recommendation in the Mobile App Market. *Information Systems Research*, 30(4), 1296–1318.
- linearmodels. (2017). linearmodels. Models for panel data, system regression, instrumental variables and asset pricing. Retrieved from <https://bashtage.github.io/linearmodels/index.html>
- Liu, C. Z., Au, Y. A., & Choi, H. S. (2014). Effects of freemium strategy in the mobile app market: An empirical study of google play. *Journal of Management Information Systems*, 31(3), 326–354.
- Malter, D. (2014). On the Causality and Cause of Returns to Organizational Status: Evidence from the Grands Crus Classés of the Médoc. *Administrative Science Quarterly*, 59(2), 271–300.
- Mantere, S., & Ketokivi, M. (2013). Reasoning in Organization Science. *Academy of Management Review*, 38(1), 70–89.
- Marinovic, I., Skrzypacz, A., & Varas, F. (2018). Dynamic Certification and Reputation for Quality. *American Economic Journal: Microeconomics*, 10(2), 58–82.
- Markovich, S., & Moenius, J. (2009). Winning while losing: Competition dynamics in the presence of indirect network effects. *International Journal of Industrial Organization*, 27(3), 346–357.

- Maslova, N., & Potapov, V. (2017). Neural Network Doc2vec in Automated Sentiment Analysis for Short Informal Texts. *Speech and Computer*, 546–554. Springer International Publishing.
- McIntyre, D. P., & Srinivasan, A. (2017). Networks, platforms, and strategy: Emerging views and next steps. *Strategic Management Journal*, 38(1), 141–160.
- McIntyre, D. P., Srinivasan, A., & Chintakananda, A. (2020). The persistence of platforms: The role of network, platform, and complementor attributes. *Long Range Planning*, 101987.
- McIntyre, D. P., & Subramaniam, M. (2009). Strategy in Network Industries: A Review and Research Agenda. *Journal of Management*, 35(6), 1494–1517.
- McIntyre, D., Srinivasan, A., Afuah, A., Gawer, A., & Kretschmer, T. (2020). Multi-sided platforms as new organizational forms. *Academy of Management Perspectives*. In press.
- Miric, M., Boudreau, K. J., & Jeppesen, L. B. (2019). Protecting their digital assets: the use of formal & informal appropriability strategies by app developers. *Research Policy*, 103738.
- Miric, M., & Jeppesen, L. B. (2020). Does piracy lead to product abandonment or stimulate new product development?: Evidence from mobile platform-based developer firms. *Strategic Management Journal*, 41(12), 2155–2184.
- Mullainathan, S., & Spiess, J. (2017). Machine Learning: An Applied Econometric Approach. *The Journal of Economic Perspectives: A Journal of the American Economic Association*, 31(2), 87–106.
- Nambisan, S., & Sawhney, M. (2011). Orchestration Processes in Network-Centric Innovation: Evidence From the Field. *Academy of Management Perspectives*, 25(3), 40–57.
- Nielsen, A. (2019). *Practical Time Series Analysis: Prediction with Statistics and Machine Learning*. O'Reilly Media. Newton, MA, USA.
- Oestreicher-Singer, G., & Sundararajan, A. (2012). Recommendation Networks and the Long Tail of Electronic Commerce. *The Mississippi Quarterly*, 36(1), 65–83.

- Olson, D. M., & Waguespack, D. M. (2020). Strategic behavior by market intermediaries. *Strategic Management Journal*, 41(13), 2474–2492.
- Ozalp, H., Cennamo, C., & Gawer, A. (2018). Disruption in Platform-Based Ecosystems. *Journal of Management Studies*, 55(7), 1203–1241.
- Panico, C., & Cennamo, C. (2020). User preferences and strategic interactions in platform ecosystems. *Strategic Management Journal*. In press.
- Parker, G. G., & Van Alstyne, M. W. (2005). Two-sided network effects: A theory of information product design. *Management Science*, 51(10), 1494–1504.
- Parker, G. G., & Van Alstyne, M. W. (2018). Innovation, Openness, and Platform Control. *Management Science*, 64(7), 3015–3032.
- Parker, G., Van Alstyne, M., & Choudary, S. P. (2016). *Platform revolution: how networked markets are transforming the economy - and how to make them work for you*. W.W. Norton & Company.
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., and Others. (2011). Scikit-learn: Machine learning in Python. *The Journal of Machine Learning Research*, 12, 2825–2830.
- Polidoro, F. (2013). The Competitive Implications of Certifications: The Effects of Scientific and Regulatory Certifications on Entries into New Technical Fields. *Academy of Management Journal*, 56(2), 597–627.
- Pollock, T. G., & Gulati, R. (2007). Standing out from the crowd: the visibility-enhancing effects of IPO-related signals on alliance formation by entrepreneurial firms. *Strategic Organization*, 5(4), 339–372.
- Pollock, T. G., & Rindova, V. P. (2003). Media Legitimation Effects in the Market for Initial Public Offerings. *Academy of Management Journal*, 46(5), 631–642.
- Raj, M. (2021). Friends in High Places: Demand Spillovers and Competition on Digital Platforms. Working Paper.
- Rao, H. (1994). The social construction of reputation: Certification contests, legitimation, and the survival of organizations in the American automobile industry: 1895–1912. *Strategic Management Journal*, 15(S1), 29–44.

- Řehůřek, R., Sojka, P., & Others. (2011). *Gensim—statistical semantics in python*. Retrieved from <https://www.fi.muni.cz/usr/sojka/posters/rehurek-sojka-scipy2011.pdf>
- Reinstein, D. A., & Snyder, C. M. (2005). The influence of expert reviews on consumer demand for experience goods: A case study of movie critics. *The Journal of Industrial Economics*, 53(1), 27–51.
- Rietveld, J., Seamans, R., & Meggiorin, K. (2021). Market Orchestrators: The Effects of Certification on Platforms and Their Complementors. *Strategy Science*. Forthcoming.
- Rietveld, J. (2018). Creating and capturing value from freemium business models: A demand-side perspective. *Strategic Entrepreneurship Journal*, 12(2), 171–193.
- Rietveld, J., & Eggers, J. P. (2018). Demand heterogeneity in platform markets: Implications for complementors. *Organization Science*, 29(2), 304–322.
- Rietveld, J., Ploog, J. N., & Nieborg, D. B. (2020). Coevolution of Platform Dominance and Governance Strategies: Effects on Complementor Performance Outcomes. *Academy of Management Discoveries*, 6(3), 488–513.
- Rietveld, J., & Schilling, M. A. (2020). Platform Competition: A Systematic and Interdisciplinary Review of the Literature. *Journal of Management*, 47(6), 1528–1563.
- Rietveld, J., Schilling, M. A., & Bellavitis, C. (2019). Platform strategy: Managing ecosystem value through selective promotion of complements. *Organization Science*, 30(6), 1232–1251.
- Rochet, J.-C., & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, 1(4), 990–1029.
- Rochet, J.-C., & Tirole, J. (2006). Two-sided markets: a progress report. *RAND Journal of Economics*, 37, 645–667.
- Rothaermel, F. T., & Deeds, D. L. (2004). Exploration and exploitation alliances in biotechnology: a system of new product development. *Strategic Management Journal*, 25(3), 201–221.

- Rysman, M., Simcoe, T., & Wang, Y. (2020). Differentiation Strategies in the Adoption of Environmental Standards: LEED from 2000 to 2014. *Management Science*, 66(9), 4173–4192.
- Safadi, H., Boudreau, M.-C., & Faraj, S. (2021). *One Picture to Study One Thousand Words: Visualization for Qualitative Research in the Age of Digitalization*. Working Paper.
- Salganik, M. J., Dodds, P. S., & Watts, D. J. (2006). Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, 311(5762), 854–856.
- Sampler, J. L. (2018). Platforms That Grow Are More Than Matchmakers. *MIT Sloan Management Review*; 60(1), 1–5.
- Schilling, M. A. (2002). Technology success and failure in winner-take-all markets: The impact of learning orientation, timing, and network externalities. *Academy of Management*, 45(2), 387–398.
- Seabold, S., & Perktold, J. (2010). Statsmodels: Econometric and statistical modeling with python. *Proceedings of the 9th Python in Science Conference*, 57, 61. Austin, TX.
- Seamans, R., & Zhu, F. (2014). Responses to Entry in Multi-Sided Markets: The Impact of Craigslist on Local Newspapers. *Management Science*, 60(2), 476–493.
- Seamans, R., & Zhu, F. (2017). Repositioning and Cost-Cutting: The Impact of Competition on Platform Strategies. *Strategy Science*, 2(2), 83–99.
- Shi, X., Li, F., & Chumnumpan, P. (2020). Platform Development: Emerging Insights From a Nascent Industry. *Journal of Management*, In press.
- Shrestha, Y. R., He, V. F., Puranam, P., & von Krogh, G. (2020). Algorithm Supported Induction for Building Theory: How Can We Use Prediction Models to Theorize? *Organization Science*. Forthcoming.
- Simcoe, T., & Watson, J. (2019). Forking, Fragmentation, and Splintering. *Strategy Science*, 4(4), 283–297.

- Sine, W. D., David, R. J., & Mitsuhashi, H. (2007). From plan to plant: Effects of certification on operational start-up in the emergent independent power sector. *Organization Science*, 18(4), 578–594.
- Spence, M. (1974). Competitive and optimal responses to signals: An analysis of efficiency and distribution. *Journal of Economic Theory*, 7(3), 296–332.
- Stahl, K., & Strausz, R. (2017). Certification and Market Transparency. *The Review of Economic Studies*, 84(4), 1842–1868.
- Stuart, T. E., Hoang, H., & Hybels, R. C. (1999). Interorganizational Endorsements and the Performance of Entrepreneurial Ventures. *Administrative Science Quarterly*, 44(2), 315–349.
- Sufi, A. (2009). The real effects of debt certification: Evidence from the introduction of bank loan ratings. *The Review of Financial Studies*, 22(4), 1659–1691.
- Sun, M. (2012). How Does the Variance of Product Ratings Matter? *Management Science*, 58(4), 696–707.
- Tae, C. J., Luo, X., & Lin, Z. (2020). Capacity-constrained entrepreneurs and their product portfolio size: The response to a platform design change on a Chinese sharing economy platform. *Strategic Entrepreneurship Journal*, 14(3), 302–328.
- Taeuscher, K., & Rothe, H. (2021). Optimal distinctiveness in platform markets: Leveraging complementors as legitimacy buffers. *Strategic Management Journal*, 42(2), 435–461.
- Tajedin, H., Madhok, A., & Keyhani, M. (2019). A Theory of Digital Firm-Designed Markets: Defying Knowledge Constraints with Crowds and Marketplaces. *Strategy Science*, 4(4), 323–342.
- Tan, D. (2016). Making the news: Heterogeneous media coverage and corporate litigation. *Strategic Management Journal*, 37(7), 1341–1353.
- Tavalaei, M. M., & Cennamo, C. (2020). In search of complementarities within and across platform ecosystems: Complementors' relative standing and performance in mobile apps ecosystems. *Long Range Planning*, 101994.
- Teodorescu, M. (2017). Machine Learning methods for strategy research. *Harvard Business School Research Paper Series*, No. 18-011).

- Thomas, L. A. (1999). Incumbent firms' response to entry: Price, advertising, and new product introduction. *International Journal of Industrial Organization*, 17(4), 527–555.
- Thomas, L. D. W., Autio, E., & Gann, D. M. (2014). Architectural Leverage: Putting Platforms in Context. *Academy of Management Perspectives*, 28(2), 198–219.
- Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society*, 58(1), 267–288.
- Tidhar, R., & Eisenhardt, K. M. (2020). Get rich or die trying... finding revenue model fit using machine learning and multiple cases. *Strategic Management Journal*, 41(7), 1245–1273.
- Tiwana, A. (2015). Evolutionary competition in platform ecosystems. *Information Systems Research*, 26(2), 266–281.
- Van Alstyne, M. W., Parker, G. G., & Choudary, S. P. (2016). Pipelines, platforms, and the new rules of strategy. *Harvard Business Review*, 94(4), 54–62.
- Varian, H. R. (2014). Big Data: New Tricks for Econometrics. *The Journal of Economic Perspectives: A Journal of the American Economic Association*, 28(2), 3–28.
- Venkatraman, N., & Lee, C.-H. (2004). Preferential linkage and network evolution: A conceptual model and empirical test in the US video game sector. *Academy of Management Journal*, 47(6), 876–892.
- von Krogh, G., Ben-Menahem, S., & Shrestha, Y. R. (2021). *Artificial Intelligence in Strategizing: Prospects and Challenges*. Working Paper.
- Voss, G. B., Sirdeshmukh, D., & Voss, Z. G. (2008). The Effects of Slack Resources and Environmental Threat on Product Exploration and Exploitation. *Academy of Management Journal*, 51(1), 147–164.
- Wager, S., & Athey, S. (2018). Estimation and Inference of Heterogeneous Treatment Effects using Random Forests. *Journal of the American Statistical Association*, 113(523), 1228–1242.
- Waguespack, D. M., & Sorenson, O. (2011). The Ratings Game: Asymmetry in Classification. *Organization Science*, 22(3), 541–553.

- Wang, Q., Li, B., & Singh, P. V. (2018). Copycats vs. original mobile apps: A machine learning copycat-detection method and empirical analysis. *Information Systems Research*, 29(2), 273–291.
- Wang, R. D., & Miller, C. D. (2020). Complementors' engagement in an ecosystem: A study of publishers' e-book offerings on Amazon Kindle. *Strategic Management Journal*, 41(1), 3–26.
- Wareham, J., Fox, P. B., & Cano Giner, J. L. (2014). Technology ecosystem governance. *Organization Science*, 25(4), 1195–1215.
- Wen, W., & Zhu, F. (2019). Threat of platform-owner entry and complementor responses: Evidence from the mobile app market. *Strategic Management Journal*, 40(9), 1336–1367.
- Weyl, E. G. (2010). A Price Theory of Multi-sided Platforms. *The American Economic Review*, 100(4), 1642–1672.
- Wimmer, B. S., & Chezum, B. (2003). An empirical examination of quality certification in a “lemons market.” *Economic Inquiry*, 41(2), 279–291.
- Xue, L., Song, P., Rai, A., Zhang, C., & Zhao, X. (2019). Implications of application programming interfaces for third-party new app development and copycatting. *Production and Operations Management*, 28(8), 1887–1902.
- Yin, P.-L., Davis, J. P., & Muzyrya, Y. (2014). Entrepreneurial innovation: Killer apps in the iPhone ecosystem. *The American Economic Review*, 104(5), 255–259.
- Yin, R. K. (2009). *Case study research: Design and methods (applied social research methods)*. London and Singapore: Sage.
- Yoffie, D. B., & Kwak, M. (2006). With friends like these: the art of managing complementors. *Harvard Business Review*, 84(9), 88–98, 157.
- Yoo, Y., Boland, R. J., Jr, Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization Science*, 23(5), 1398–1408.
- Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). Research commentary—the new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research*, 21(4), 724–735.

- Yoo, Y., Lyytinen, K. J., Boland, R. J., & Berente, N. (2010). *The next wave of digital innovation: Opportunities and challenges. A report on the research workshop "Digital Challenges in Innovation Research"*. Working Paper.
- Yu, Y., Tang, S., Raposo, F., & Chen, L. (2019). Deep Cross-Modal Correlation Learning for Audio and Lyrics in Music Retrieval. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, 15(1), 1-16.
- Zapechelnyuk, A. (2020). Optimal Quality Certification. *American Economic Review: Insights*, 2(2), 161–176.
- Zhang, Y., Li, J., & Tong, T. W. (2020). Platform governance matters: How platform gatekeeping affects knowledge sharing among complementors. *Strategic Management Journal*, In Press.
- Zhao, W., & Zhou, X. (2011). Status Inconsistency and Product Valuation in the California Wine Market. *Organization Science*, 22(6), 1435–1448.
- Zhou, W., & Duan, W. (2016). Do Professional Reviews Affect Online User Choices Through User Reviews? An Empirical Study. *Journal of Management Information Systems*, 33(1), 202–228.
- Zhou, Z., Zhang, L., & Van Alstyne, M. W. (2020). How Users Drive Platform Value. Working Paper.
- Zhu, F. (2019). Friends or foes? Examining platform owners' entry into complementors' spaces. *Journal of Economics & Management Strategy*, 28(1), 23–28.
- Zhu, F., & Liu, Q. (2018). Competing with complementors: An empirical look at Amazon. com. *Strategic Management Journal*, 39(10), 2618–2642.
- Zhu, F., & Zhang, X. (2010). Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics. *Journal of Marketing*, 74(2), 133–148.

Curriculum Vitae

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Education

2018 – 2021	University of St. Gallen (HSG), St. Gallen, Switzerland Ph.D. in Management
2015 – 2017	University of St. Gallen (HSG), St. Gallen, Switzerland Master of Arts (M.A. HSG) in Management
2011 – 2014	Johann W. Goethe University, Frankfurt am Main, Germany Bachelor of Science (B.Sc.) in Economics & Business Administration

Experience

2018 – Present	Institute of Management and Strategy, St. Gallen, Switzerland Research Associate, Full Time
2017/2018	Lazard & Co., Frankfurt am Main, Germany M&A, Internship (3 months)
2016/2017	Gauly Advisors, Frankfurt am Main, Germany Strategy Consulting, Internship (4 months)
2015/2016	Institute of Insurance Economics, St. Gallen, Switzerland Research, Student Assistant (8 months)
2014	UBS Investment Bank, Frankfurt am Main, Germany Equity Derivatives Sales, Internship (5 months)
2013	BWM Group, Berlin, Germany Marketing & Sales, Internship (2 months)

Publications

- | | |
|-------------------|--|
| Conference Papers | <ul style="list-style-type: none"> - Dexheimer, Maximilian Jakob & Lechner, Christoph: <i>How to stand out from the crowd: Detecting patterns in app endorsements on the App Store</i> (2021). Strategic Management Society Conference, Toronto, Canada - Dexheimer, Maximilian Jakob & Lechner, Christoph: <i>A competitive dynamics view on complementor commitment</i> (2019). Strategic Management Society Conference, Minneapolis, USA |
| Research Articles | <ul style="list-style-type: none"> - Lang, Nikolaus; Lechner, Christoph; Wurzer, Charline & Dexheimer, Maximilian Jakob: <i>Four Strategies to Orchestrate a Digital Ecosystem</i> (2021). The Boston Consulting Group. - Dexheimer, Maximilian Jakob & Lechner, Christoph (2019) <i>Ökosystem-basierte Wettbewerbsstrategien</i>. Die Unternehmung, 4 308. - Lechner, Christoph & Dexheimer, Maximilian Jakob (2019) <i>Ökosysteme: Eine neue Strategie im digitalen Zeitalter?</i> OrganisationsEntwicklung, 3 38-43. |
| Case Studies | <ul style="list-style-type: none"> - Hettich, Erwin & Dexheimer, Maximilian Jakob: <i>FIFA and the eSports Ecosystem: From Lean Back to Lean In</i>. Case Study and Teaching Note. 2021. - Lechner, Christoph & Dexheimer, Maximilian Jakob: <i>Clariant (A): Steering Through Turbulent Waters (2008-2010)</i>. Case Study and Teaching Note. 2020. - Lechner, Christoph & Dexheimer, Maximilian Jakob: <i>Clariant (B): On the Route to Profitable Growth (2011-2016)</i>. Case Study and Teaching Note. 2020. |

- Lechner, Christoph & Dexheimer, Maximilian Jakob: *Clariant (C): Merger Talks and New Investors (2017-2019)*. Case Study and Teaching Note. 2020.
- Reiter, Thorsten; Stonig, Joachim; Dexheimer, Maximilian Jakob & Lechner, Christoph: *Shaping a Mobility Ecosystem: The Case of Car2go in China*. Case Study and Teaching Note. 2019.