The Entry-Deterring Effects of Synergies in Complementor Acquisitions: Evidence from Apple's Digital Platform Market, the iOS App Store

Forthcoming at *Strategic Management Journal*

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ABSTRACT

Acquisitions can shift the market structure of a digital platform in ways that affect subsequent entries and hence the platform's base of complementors. Synergies that complementor acquirers accrue can be entry-deterring. We develop a two-by-two typology of acquisition synergies in a multisided platform based on the two sides of a platform market (user side or complementary-technology side) and two sources of synergies (scale or scope economies). We then leverage over 279 thousand app developers' entry decisions into product categories in Apple's iOS App Store, over 71 million customer reviews, and over 12 thousand unique software development kits to construct measures of synergies. Our paper contributes to the platform literature by demonstrating the entry-deterring effects of synergies that complementor acquirers can exploit. (Word count: 121)

RESEARCH SUMMARY

We develop the following typology of four types of acquisition synergies by integrating the multisidedness feature of digital platforms with the mainstream strategy research: complementary-technology-side economies of scope, complementary-technology-side economies of scale, user-side economies of scope, and user-side economies of scale. We show that (1) acquisition synergies are entry-deterring, (2) synergies derived from economies of scope have stronger effects than those derived from economies of scale, and (3) synergies derived from the technology side have stronger effects than those derived from the user side. We highlight the significant competitive and regulatory implications of our findings. For example, one standard-deviation increase in technology-side economies of scope is associated with 55 deterred entries in one month or a $2.80 million potential loss in annual revenue. (Word count: 123.)

1. INTRODUCTION

Complementors are crucial for value creation in a platform market. While the platform owner creates the infrastructure and plays an orchestrator role, complementors offer complementary products, services, and functionalities, influencing the quantity, quality, and diversity of experience that a platform can provide to consumers (Cennamo, 2018; Miric, Ozalp, & Yilmaz, 2023; Rietveld, Seamans, & Meggiorin, 2021). Recent platform literature has increasingly emphasized the role of complementors and especially factors that affect complementors' population dynamics (Agarwal, Miller, & Ganco, 2023; Rietveld & Ploog, 2022; Rietveld, Ploog, & Nieborg, 2020; Rietveld, Schilling, & Bellavitis, 2019). We contribute to this growing body of literature by investigating the relationship between two fundamental processes that shape the dynamics of a platform's complementor base: *acquisitions* and *market entries*. Whereas acquisitions of complementors can significantly change the industry structure through consolidation of market power, market entries contribute to the addition of new capacity.[1] However, if synergies derived through acquisitions deter market entries, then researchers and policymakers should pay serious attention to the anti-competitive implications of acquisitions of complementors in platform markets.

Acquisitions of complementors are economically significant. There were 872 acquisitions of complementors in Apple's iOS App Store alone between 2008 and 2015. According to available information in Securities Data Company (SDC) Platinum, the average total assets of acquirers was $24.18 billion while the corresponding average of the targets was $2.86 billion. A particularly visible example, Facebook's $22 billion acquisition of Whatsapp in 2014 (Economist, September 17, 2016) has been under the scrutiny of the U.S. Federal Trade Commission for several years.

[1] We thank the SMJ editor for an insight related to this point.

After Activision Blizzard's $5.9 billion acquisition of the mobile game development company King, the Activision CEO, Bobby Kotick, noted that the deal "solidifie[s] [the company's] position as the largest, most profitable, standalone company in interactive entertainment" (BBCNews, 2015). And, of course, Activation was subsequently acquired by Microsoft in 2023, a deal valued at $69 billion (Forbes). The deal provoked yet another debate on underlying antitrust concerns for (or against) tightening the regulatory scrutiny of technological firms' acquisitions (Economist, July 15, 2023).

While acquisitions of complementors can lead to the consolidation of complementors in a platform and ultimately influence the platform's vibrancy, innovativeness, and long-term growth, extant research on acquisitions in platform markets has primarily focused on those initiated by *platform owners*. These are either between-platform acquisitions (e.g., Correia-da-Silva, Jullien, Lefouili, & Pinho, 2019; Farronato, Fong, & Fradkin, 2023; Ivaldi & Zhang, 2022; Song, 2021) or a platform owner's acquisitions of its complementors (e.g., Khan, 2017; Wen & Zhu, 2019). Platform owners differ substantially from complementors. Platform owners are large and dominant, but few in number. While their high-profile acquisitions can attract substantial public attention, acquisitions by complementors are much more frequent. Attending only to platform owners may result in oversight of an important source of the anti-competitive behaviors in platform markets. In addition, because complementor acquirers are more abundant, studying them makes it more empirically feasible to unpack acquirer heterogeneities in market power. Therefore, the lack of research on the effect of *acquisitions of complementors* on subsequent *entries* constitutes a critical literature gap. We hence ask the following research question: *When do acquisitions of complementors in a platform's product categories deter future entries?*

We address this important gap by studying the impact of acquisitions of complementors in a given product category on potential entrants' decisions to enter this category. We go beyond the traditional literature's approach of anchoring on the number of acquisitions (e.g., Berger, Bonime, Goldberg, & White, 2004) (which we control for). We instead unpack the detailed *synergies* from different sides of a platform that complementor acquirers can derive, and we then examine the associations between each type of synergy and future market entries in a product category. In particular, as shown in Figure 1, we develop a typology of synergies from complementor acquirers' multisidedness in interacting with both *the user side* (i.e., individual customers who use complementors' product offerings) (Hagiu & Wright, 2015; Ozalp, Cennamo, & Gawer, 2018; Rietveld & Eggers, 2018; Rochet & Tirole, 2006) and *the complementary-technology side* (i.e., software development kits, or SDKs, that enable complementors to develop and integrate product features) (Agarwal & Kapoor, 2023; Agarwal et al., 2023; Chen, Tong, Tang, & Han, 2022; Hukal, Kanat, & Ozalp, 2022; Miric et al., 2023). Moreover, for each side, we further separate synergies that originate from *economies of scale* (abbreviated as EOSL) from those that originate from *economies of scope* (abbreviated as EOSP). EOSL-type synergies come from the lower marginal costs through aggregated demand and production (Argote & Epple, 1990; Feldman, 2022; Karim & Capron, 2016) and usually accrue when acquirers and targets have overlapping product categories. By contrast, EOSP-type synergies arise when a firm exploits its fungible resources in product markets other than the current one to increase the productivity of its otherwise idle or under-utilized resources (Feldman, 2022; Helfat & Eisenhardt, 2004; Karim & Mitchell, 2000; Levinthal & Wu, 2010; Rumelt, Schendel, & Teece, 1994) and usually accrue when acquirers and targets are located in different product categories. We develop novel empirical measures for each type of synergy—*the user-side EOSL*, *the user-side EOSP*, *the technology-side EOSL*, and *the technology-side EOSP*—and demonstrate the usefulness of leveraging large-scale text analyses for developing computational measures of synergies in the platform market.

[Figure 1 goes about here]

Our research contributes to the platform strategy literature and informs the debate on antitrust policy in this important market. First, we document how complementor acquirers' synergies are *negatively* related to market entries. Specifically, we build on the unique multisided feature of the platform market (Armstrong, 2006; Hagiu & Wright, 2015; Ozalp et al., 2018) and the classic concepts of EOSL and EOSP in strategic management (Farronato et al., 2023; Feldman, 2022; Karim & Capron, 2016; Ozalp et al., 2018; Parker, Petropoulos, & Van Alstyne, 2021; Rumelt et al., 1994) to develop a theory-based typology of complementor acquisition synergies, construct detailed empirical measures for each type of synergy, and provide nuanced evidence regarding the entry-deterring effects of each type of synergy. Our second contribution to the platform literature is to shift the focus from platform-owner-initiated acquisitions to acquisitions of complementors in general. By doing so, our study sheds light on a neglected aspect of acquisitions in platform markets and answers the call from platform strategy scholars for more research on complementor dynamics (Boudreau, 2012; Cennamo, 2018; Rietveld et al., 2020). Finally, our paper has important policy implications. As researchers and regulators have become increasingly concerned about how consolidation of a platform market can stifle innovation and hinder competition (Khan, 2017; Parker et al., 2021; Zhu & Liu, 2018), there is an increased need for a better understanding of the underlying mechanisms through which acquisitions can deter future entries. For example, one of our key findings is that increasing complementary-technology-side economies of scope by one standard deviation is associated with 55 deterred entries in a month or a $2.80 million potential loss in annual revenue.

2. THEORY AND HYPOTHESES

Complementor Acquirers' Synergies in a Multisided Platform

We describe the mechanisms through which acquisitions of complementors affect entries by integrating prior mergers and acquisitions research with the unique multisidedness feature of a platform market (Hagiu, 2014; Hagiu & Wright, 2015; Ozalp et al., 2018; Parker et al., 2021; Rietveld et al., 2020). According to classic economics and strategy literature, economies of scale and scope are the two basic channels through which acquisitions can deter entry: they allow an acquisition to create more value than the simple sum of the parts, resulting in a higher competitive advantage over other firms and, in turn, deterring future entrants (Feldman, 2022; Puranam & Vanneste, 2016). Yet these two concepts were mostly developed in traditional industries characterized by linear value chains, which differ from the platform settings where multisidedness plays a central role (Cennamo, 2021; Farronato et al., 2023; Li & Agarwal, 2017; Miric, Pagani, & El Sawy, 2021; Ozalp et al., 2018; Parker et al., 2021; Zhu & Liu, 2018). This fundamental difference requires us to reconceptualize economies of scale and scope in the context of platforms.

EOSL arises when an acquisition occurs in the same market and the combined entity can leverage the increased scale to lower cost or increase willingness to pay (Argote & Epple, 1990; Feldman, 2022; Karim & Capron, 2016). EOSP arises when an acquisition spans different markets, across which the acquirer gains advantage through sharing or reallocating resources (Feldman, 2022; Helfat & Eisenhardt, 2004; Karim & Mitchell, 2000; Levinthal & Wu, 2010; Rumelt et al., 1994). We interact these two economies with the two sides of a platform to develop the following typology: *the user-side EOSL*, *the user-side EOSP*, *the complementary-technology-side EOSL*, and *the complementary-technology-side EOSP*.

	Economies of Scale (EOSL)	**Economies of Scope (EOSP)**
User Side	Quadrant 1. When the products and services of the acquirer and of the target serve overlapping product categories such that the scale of the user base will increase.	Quadrant 2. When a common user base can be potentially leveraged across the acquirer's and the target's non-overlapping product categories.
Complementary-Technology Side	Quadrant 3. When the acquirer's set of complementary technologies can be applied in overlapping product categories with the target.	Quadrant 4. When the acquirer's set of complementary technologies can be applied across non-overlapping product categories with the target.

Complementor Acquirers' Economies on the User Side

We first focus on economies from the user side (as shown in Figure 1). We define users as the ultimate consumers that purchase and utilize the final products or services provided by complementors; users are critical sources from which complementor acquirers can derive synergies (Agarwal et al., 2023; Clough & Wu, 2022; Gregory, Henfridsson, Kaganer, & Kyriakou, 2021; Ozalp et al., 2018; Rietveld, 2018). While some complementor acquirers (such as those that offer social networking apps) achieve user-side EOSL by gaining a larger base of engaged users in the same market (Farronato et al., 2023), others achieve user-side EOSP by serving a common set of users that have correlated preferences across different product categories (Schmidt, Makadok, & Keil, 2016; Ye, Priem, & Alshwer, 2012). Below, we distinguish between these two types of economies.

User-side EOSL (Quadrant 1) arise when an acquirer and its target serve overlapping product categories such that the acquirer's value proposition can be amplified over the increased user base post-acquisition. Fundamental to user-side EOSL are positive direct network effects, a key source of competitive advantage in digital platform markets (Agarwal et al., 2023; Cennamo, 2021; Farronato et al., 2023; Hukal et al., 2022; Ozalp et al., 2018; Parker et al., 2021; Rietveld &

Eggers, 2018; Rietveld & Ploog, 2022; Shapiro & Varian, 1999).[2] For instance, when game players can connect with other players in massive multi-players games, they can communicate, collaborate, and compete with each other, deriving utilities from these social interactions (Agarwal et al., 2023; Cennamo & Santaló, 2019; Farronato et al., 2023; Rietveld & Ploog, 2022). Acquiring more users can enhance network effects by creating more interaction opportunities in the enlarged user network (e.g., Afuah, 2013; Dhebar, 2016; Iansiti, 2021; Lee, Song, & Yang, 2016). Moreover, since information-based products (such as video games, movies, mobile apps) exhibit high fixed cost yet close to zero marginal costs, the aggregated user base enables the acquirer to amortize the fixed costs, increase product offerings, and scale up with hyper speed (Giustiziero, Kretschmer, Somaya, & Wu, 2023; Parker et al., 2021; Shapiro & Varian, 1999). User-side EOSL can be illustrated by Zynga's acquisition of Rising Tide Games, a social casino game company. The acquisition served to "further its commitment to Social Casino games" (Zynga, 2015) and enabled it to leverage Rising Tide's user base to create additional other *social* games, rapidly increasing performance gains (Takahashi, 2015). Overall, when acquisitions on the user side solidify complementor acquirers' economies of scale, they reduce the ability of a new entrant to achieve a critical mass of users and, consequently, deter its entry.

Hypothesis 1a. *Complementor acquirers' economies of scale on the user side will be negatively associated with the likelihood of subsequent entry into the product category.*

User-side EOSP (Quadrant 2) occurs when a common user base can be potentially leveraged across an acquirer's and its target's non-overlapping but related product categories

[2] Extant literature has proposed and studied various types of network effects—for instance, (1) same-side (direct) versus cross-side (indirect) network effects, where the scholarly interest lies in the externalities from one side of platform participants to the other side; (2) positive versus negative network effects, where the interest lies in whether the externalities of affected participants are positive or negative; and (3) the four possible scenarios that can be defined based on the two dimensions (e.g., see Eisenmann (2007) for the fundamentals). Here we focus on positive user-side network effects (e.g., Iansiti, 2021) to reflect the mechanism of user-side economies of scale.

(Miric et al., 2021; Ozalp et al., 2018; Parker et al., 2021; Rietveld et al., 2020; Schmidt et al., 2016; Ye et al., 2012). When the markets are non-overlapping, an acquisition expands the complementor acquirer's product portfolio, thus offering users a richer set of experiences. However, these markets need to be related in the sense that user preferences are correlated across them, ensuring that existing users are likely to try the new products or services (though in a different product category) offered by the merged entity (Miric et al., 2021; Schmidt et al., 2016; Ye et al., 2012).[3] Research at the platform level shows that exploiting correlated user preferences across markets is a key rationale behind platforms' envelopments into adjacent markets (Condorelli & Padilla, 2020; Eisenmann, Parker, & Van Alstyne, 2011).

Acquisitions enable an acquirer to integrate a target's features in the adjacent product categories and bundle those with its own core products (Chao & Derdenger, 2013; Ye et al., 2012). Leveraging correlated user preferences across product categories facilitates users' one-stop shopping, increases their utilities of adopting one product and their stickiness to it, and, consequently, forecloses potential rivals' access to such users (Parker et al., 2021). An acquirer can further enhance user experience by making the acquirer's and target's markets interoperable (Cennamo, Ozalp, & Kretschmer, 2018; Jacobides, Cennamo, & Gawer, 2018; Kretschmer & Claussen, 2016). An example at the complementor level in the mobile app market is Facebook's acquisition of Branch, a company that specialized in facilitating users' conversations and news

[3] In traditional industry contexts relatedness across markets has been theorized based on the product market and technologies. In the multisided digital platform that we conceptualize (shown in Figure 1), we distinguish relatedness between two product categories in terms of *user-side relatedness* and *complementary-technology-side relatedness*. For details of complementor acquirers' user-side relatedness to the target's product categories, please refer to the user-side measures based on "comentioning" later in the manuscript and the "correlated user preferences" section in Appendix B; and, for details of acquirers' technology-side relatedness to the target's product categories, please refer to complementary-technology-side measures based on "technological fungibility" later in the manuscript and measures in Appendix C based on "technology cosharing."

sharing. The acquisition not only enabled Facebook to "improve its News Feed"[4] but also expand from its core market (social networking) to an adjacent market (news) with a standalone product.[5] Acquisitions like this will make it harder for a new complementor to compete with Facebook when it comes to news sharing among users. Hence, when acquirers are in a position to leverage EOSP on the user side, such acquisitions will be negatively associated with future entries.

Hypothesis 1b. *Complementor acquirers' economies of scope on the user side will be negatively associated with the likelihood of subsequent entry into the product category.*

Complementor Acquirers' Economies on the Complementary-Technology Side

Complementary technologies here refer to technologies in a platform that can be deployed by complementors to enhance the value or functionalities of their products and services (e.g., Agarwal & Kapoor, 2023; Hukal et al., 2022; Teece, 1986). While the platform owner can provide complementary technologies, such as software development kits (SDKs) that enable developers to realize basic app functionalities (e.g., UIKit[6] to display objects on screen for users to interact with), third-party providers can also offer such technologies that can be used to integrate and enhance additional features (e.g., Open Graphics Libraries, or OpenGL,[7] for rendering graphs, for instance, in mobile games).[8] We argue that EOSL and EOSP can exist on the side of complementary technologies in digital platform markets (Ganco, Kapoor, & Lee, 2020).

Complementary-Technology-Side EOSL (Quadrant 3) occurs when an acquirer's set of complementary technologies can be applied in overlapping product categories with the target to

[4] Source: https://www.theverge.com/2014/1/13/5303702/facebook-acquires-link-sharing-app-branch-for-15-million, accessed on November 28, 2023.
[5] Source: https://laughingsquid.com/potluck-2-0-an-iphone-app-for-reading-curated-news-and-discussing-it-with-friends/, accessed on November 28, 2023.
[6] Please find at Apple's Developer Documentation at https://developer.apple.com/documentation/uikit/about_app_development_with_uikit.
[7] Please find additional information at https://en.wikipedia.org/wiki/OpenGL.
[8] We provide in Appendix D each product category's top-ten used SDKs and their frequency of usage.

reduce the cost and effort of developing, maintaining, or scaling its product or service. When an acquirer and the target operate in overlapping product categories, the acquirer can integrate the technological features from both entities, strip away redundancies, and amortize costs over aggregated demand (Capron, Dussauge, & Mitchell, 1998; Rabier, 2017; Rumelt, 1982; Teece, 1986). For product development, complementary technologies provide standardized tools and libraries so that complementors do not have to "reinvent the wheel" for common functionalities. Such standardization makes it faster and more efficient to develop multiple applications or iterations (Miric et al., 2023; Parker et al., 2021). For product maintenance and updates, complementary technologies with a common set of tools or libraries help streamline the processes. An update or patch can be applied across all products using the same complementary technology and thus reduce time and fragmentation. For product scaling, complementary technologies help ensure that complementors' products run smoothly even as the user base or data volume grows. The shared tools or libraries ensure connectivity, caching, and optimized queries, which can handle larger data volumes and more concurrent users. Repetitive usage of technologies for scaling purposes also avoids high adjustment costs, which is a main reason for digital companies' hyper scalability (Giustiziero et al., 2023).

The potential advantage that acquirers may accrue translate into competitive disadvantages for potential entrants, thereby reducing their entry motivations. For example, Veeva, a cloud computing provider for life science industries, acquired Selligy, which specializes in customer relationship management (CRM). The acquisition makes the target (Selligy) part of their "many CRM products and services, which can be used in a variety of commercial applications,"[9] hence strengthening the acquirer's (Veeva) position in the overlapping product category (business).

[9] Source: https://www.10bestcrm.com/software/systems/2017/february/selligy/, accessed on November 28, 2023.

In sum, acquirers' enhanced economies of scale on the complementary-technology side of the platform market are likely to deter potential entrants.

Hypothesis 2a. *Complementor acquirers' economies of scale on the complementary-technology side will be negatively associated with the likelihood of subsequent entry into the product category.*

Complementary-Technology-Side EOSP (Quadrant 4) occurs when a common set of complementary technologies can be applied across non-overlapping product categories of an acquirer and its target so that the acquirer can more efficiently produce multiple products, services, or functionalities. While non-overlapping, these markets are related in terms of complementary technologies (as explained in greater detail in Appendix C), meaning that they are fungible across markets of the acquirer and the target (Jacobides et al., 2018; Levinthal & Wu, 2010; Sakhartov & Folta, 2014). Fungible digital technologies are akin to general purpose technologies that have a wide range of applications (Agarwal & Kapoor, 2023; Hukal et al., 2022; Parker et al., 2021; Shapiro & Varian, 1999). Specifically, when the shared complementary technologies can be applied across multiple markets, technology fungibility allows complementors to expand the variety of their offerings without proportional increases in costs.

Furthermore, when complementary technologies are fungible in related markets across the acquirer and the target, the post-merger integration of the two entities' technologies is smoother and the acquirer is able to provide more coherent experiences to customers (across its own and the target's markets), increase their utilities, and hence increase their stickiness to its products. The shared complementary technologies may support plug-ins or extensions, which allow an acquirer to directly integrate its target's products and services. This capability helps the acquirer quickly add diverse features or integrations to its existing products or services. Doing so allows users to conduct one-stop-shopping in the companies' products that they have already used and, consequently, reduces the need to promote a completely new functionality. After users start to use the added functionality, the shared complementary technology can further ensure they have a consistent experience due to the common design principles and user experience guidelines. Together, complementary-technology-side EOSP eases the process for an acquirer to leverage user familiarity and create a unified experience across diverse product offerings.

We illustrate our argument with an example: in 2013, Yandex, a major European internet company operating in multiple app categories, including search engines, e-commerce, and online advertising, acquired KinoPoisk, a movie database company. Through this acquisition, Yandex could leverage the complementarity between its search technologies, machine learning, and personalization algorithms with the target's extensive database (from the Entertainment app category) to develop personalized movie recommendation systems for users.[10] Besides, Yandex was also able to bundle movie streaming with its other services offered to users.

In sum, acquirers' enhanced economies of scope on the complementary-technology side of the platform market are likely to deter potential entrants.

Hypothesis 2b. *Complementor acquirers' economies of scope on the complementary-technology side will be negatively associated with the likelihood of subsequent entry into the product category.*

Ex ante we expect that the four sources of synergies accrued from acquisitions will each deter future complementors' entries. We do not have a theoretical basis to expect that one type of synergy will be more strongly associated with entry deterrence than another and thus leave their individual strengths to empirical testing.

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[10] Source: https://yandex.com/company/press_center/press_releases/2013/2013-10-15, accessed on November 28, 2023.

3. EMPIRICAL ANALYSES

3.1 Sample and data

Our empirical context is the App Store of Apple's iOS mobile platform from 2008 to 2015, which includes 279,184 app developers' potential decisions to enter 23 primary product categories (as of November 2015). Apple's App Store is an economically significant market, and its revenue reached $46.6 billion in 2018.[11] We obtained product-category information for the U.S. App Store from Apple's iTunes website as of October 2015; we release history and other information from an app analytics company that derives data from Apple's Enterprise Partner Feed Program. We obtained proprietary data from 71,752,510 app reviews to capture information on the user side and data from a total of 12,545 SDKs adopted by 441,947 apps to capture information on the side of complementary technologies.

We collected the data on acquisition events that occurred in Apple's App Store from *Crunchbase* and the *AngelList* database. We identified all acquisitions that had occurred in the App Store through cross-checking companies' websites, app developer pages, news reports, and the Internet Archive (internetarchive.org) to match event companies to app developers and corresponding product categories. In all, we were able to identify 872 completed acquisitions in this market between July 2008 and November 2015.

We then used this sample of acquisition events to create the study variables. For the measures of user-side synergies, we collected reviews for every app included in acquirers' app portfolios before the time of each acquisition's announcement. For the measures of complementary-technology-side synergies, we used the information compiled from acquirers' app portfolios at the time of acquisition announcements and were able to construct the acquirers'

[11] The source is sensortower.com, an analytics company: https://sensortower.com/blog/app-revenue-and-downloads-2018, accessed on February 2, 2020.

product-portfolio information for 746 acquisitions. We then collected SDKs for all apps in acquirers' app portfolios that adopted SDKs. Our unit of analysis is an app developer's decision to enter a product category in a month (i.e., developer-month-category); the advantage of the developer-month-category-level analysis is that it enables us to control for developer-month fixed effects to mitigate concerns of developer heterogeneities (due to fixed attributes) and time trends (e.g., due to economy- or platform-specific attributes) in entry decisions and to control for category fixed effects.

3.2 Variables

3.2.1 Dependent variable: Entry Likelihood

A developer's entry into a product category was measured as a dichotomous variable that equals 1 in the month that the developer first released app product(s) in the focal product category. For the same developer-month, we coded all of the other categories the developer could have entered but did not as 0.

3.2.2 Measures of complementor acquirers' user-side synergies

We used the target's product category(ies) when accounting for acquisition events because target companies tend to have a more focused business scope, which may better reflect the strategic intention of acquisitions (e.g., Chatterjee, 1986; Miric et al., 2021).[12] Following prior studies in the platform literature (Karim & Capron, 2016; Karim & Mitchell, 2000; Miric et al., 2021), we measure EOSL by counting only acquisitions in which the acquirer and the target have overlapping product category(ies) and EOSP by counting only acquisitions in which the acquirer and the target do not have any overlapping product category. The rationale is that when an acquirer and a target share a product category, the merged entity is more likely to serve similar products or services to

[12] Because a target may have apps in multiple product categories at the time of acquisition, the number of category months affected by acquisition events is greater than the number of sampled acquisitions.

a larger user base and hence achieve user-side economies of scale, whereas when an acquirer and a target do not share a product category, the merged entity is more likely to serve the same user base with different products and services and hence achieve user-side economies of scope. We visualize these measures in Figure 2. The distribution of overlapping versus non-overlapping acquisitions in our sample is 51 percent versus 49 percent.

To construct the user-side measures, we exploited the extent to which the acquirer's user-reviewers comentioned the features of the target's product category(ies), essentially tapping into correlated user preferences (e.g., Chao & Derdenger, 2013; Parker et al., 2021; Schmidt et al., 2016; Ye et al., 2012). The comentioning is reflected by the red dashed line in Figure 2 linking the acquirer's user base to the target's category(ies). The first step of measure construction is to capture the unique features of a product category. In order to do so, we pooled all user reviews (71,752,510) during the studied time window and applied natural language processing (NLP) techniques to extract the top 100 unique (noun) keywords of each category.[13] Then, for each acquisition event, we calculated the total number of occurrences where an acquirer's user reviews comentioned the top keywords of the target's category(ies) (i.e., $comention_i$, where i denotes an acquisition). We then calculated comentioning as a percentage—that is, an acquisition's comentioning score divided by the maximum across all sampled acquisitions (i.e., $comention_i/\max(comention_i)$). We then averaged across non-overlapping acquisitions (where the acquirer and the target do not have any overlapping category) in a three-month moving time window leading up to (and including) the focal month in a category to construct the measure: *user-side EOSP*. We used the same approach to calculate the average of overlapping acquisitions (where the acquirer and target have overlapping product category(ies)) to construct the corresponding

[13] The specific NLP procedure is described in Appendix E.

measure: *user-side EOSL*.

[Figure 2 goes about here]

3.2.3 Measures of complementor acquirers' complementary-technology-side synergies

We used SDKs, software tools, and libraries that developers use to create applications and integrate functionalities to measure complementary technology. Again, we operationalized EOSL by counting only acquisitions in which the acquirer and the target have overlapping product category(ies) and EOSP by counting only acquisitions in which the acquirer and the target have no overlapping product category.

To construct the complementary-technology-side measures, we exploit SDK heterogeneities in terms of their fungibility—whereas some SDKs are general-purpose technologies that can be widely applied across product categories, other SDKs are special-purpose technologies with more restricted range of category applications (e.g., Agarwal & Kapoor, 2023; Jacobides et al., 2018; Levinthal & Wu, 2010; Sakhartov & Folta, 2014). To gauge the fungibility of each individual SDK, we pooled all SDKs adopted by all apps in Apple's App Store during the studied time window (2008–2015) and constructed an SDK-to-category matrix. Each cell of the matrix represents an SDK's (s) percentage of usage in a category (c) (denoted as P_s^c). We then developed a composite measure by taking into account (1) the acquirer's frequency of usage of an SDK (n_s) and (2) said SDK's percentage of usage in the target's category, then summed across all SDKs of the acquirer and all categories of the target (i.e., $\sum_c \sum_s (n_s * P_s^c)$). A greater value of the measure means an acquirer adopts more technologies that can be applied in the target's market category(ies) and therefore has a greater ease of applying these SDKs to the category(ies). We then aggregated to the category level by averaging across the non-overlapping acquisitions to build the variable, *complementary-technology-side EOSP*, and averaged across the overlapping acquisitions in the same three-month moving time window to construct the variable, *complementary-technology-side EOSL*. We scaled down the measures by 1000 for ease of interpretation.

[Figure 3 goes about here]

3.3 Control variables

At the category level, we controlled for *acquisition intensity* as the cumulative number of acquisitions in the three months leading up to (and including) a focal month in a category. To consider the effects of competition, we controlled for *category size* (measured as the number of developers) in each product category. Additionally, we added *category fixed effects* to account for category-specific time-invariant unobservables.

We also controlled for the growth of a product category to address the concern that market expansion may influence both entries and acquisitions. Specifically, we used a flow variable—the number of apps released in a category month—as the building block to construct the measure of *category growth in app products*. Based on Dess and Beard (1984), we first regressed the flow variable (i.e., number of released apps in a category month) on year dummy variables in a random-coefficient maximum likelihood model, where each coefficient has its own mean and standard deviation and can vary across categories. The year 2008 was set as the baseline. We then obtained the estimated coefficients for each category; for instance, the "Games" category has a set of predicted regression coefficients. Following this, we used the predicted coefficients to divide the average value of the variable, monthly app releases, during the entire study period, which spanned from 2008 to 2015. Thus, the annual growth measure is in the form of a predicted regression coefficient divided by a corresponding average value.

Finally, in the fixed-effects models, *developer-month fixed effects* were accounted for through group specification. It is important to note that the fine-grained developer-month fixed effects absorb *month fixed effects* (because there was no within-group variation for months), *developer fixed effects* (such as whether the developer is an incumbent or a new entrant to the platform), and *developer-month-specific attributes* (such as developer experiences that vary over time but do not vary across categories).

Table 1 provides the descriptive statistics (i.e., number of observations, mean, standard deviation, minimum, median, and maximum) and correlations of the dependent variable, the four theorized synergy measures, and control variables.

[Insert Table 1 about here]

4. ESTIMATION APPROACH

4.1 Developer-month fixed-effects linear probability models to estimate entry likelihood

To test the hypotheses, we constructed a developer-month-category panel, with each observation reflecting a $Developer_d$'s decision at a $Month_t$ to enter a $Category_i$. That is, the unit of analysis is a developer-month-category. Apple's App Store included 23 primary categories as of 2015.[14] We applied ordinary least square models to estimate the linear probability (e.g., Starr, Frake, & Agarwal, 2019) of an app developer's decision in a month to enter a category. With the developer-month fixed-effects model specification, the interest lies in within-group effects—that is, an entry decision into a certain product category is rendered conditional on the existence of alternative product categories. Thus, we followed the logic of case-control designs to differentiate realized entry events from a set of control cases that could have happened but were not realized (e.g., Carnabuci, Operti, & Kovács, 2015; Rogan & Sorenson, 2014). For the realized case group, we extracted all developer-month-categories in which an entry occurred. Control cases included all of

[14] The app economy follows industry dynamics with emergence and evolution of product categories over time. For instance, because our studied time window and main data collection ended before the end of the year 2015 when a new category, "Lifestyle," was opened, this new category is not included in our sample.

the other categories a focal developer could have entered in the month but did not (i.e., all $Developer - Month - Category_i$ observations in which an entry did not occur). The final sample consisted of 8,767,477 developer-month-category observations.

The developer-month fixed-effects linear probability models take the following form:

$$Prob(Entry_{dit}) = F(\beta_0 + \tilde{\beta} * Complementor\_Acquirers\_Synergies_{it}$$
$$+\gamma_1 * Acquisition\_Intensity_{it} + Z_{it}{'} * \tilde{\gamma} + \lambda_{dt} + u_i + \varepsilon_{dit}) \quad (1)$$

where the dependent variable, $Entry_{dit}$, is a dummy variable that takes a value of 1 when $Developer_d$ enters $Category_i$ at $Month_t$, and 0 otherwise; β_0 is the intercept, which captures the baseline entry probability; the coefficient vector, $\tilde{\beta}$, relates to the measures for the four hypothesized synergies; γ_1 denotes the effect of the control variable $Acquisition\_Intensity_{it}$ on entry probability; $Z_{it}{'}$ is the vector of time-variant category control variables, and $\tilde{\gamma}$ denotes their coefficients; λ_{dt} represents the developer-month fixed effects; u_i denotes category fixed effects; and ε_{dit} is the error term.

4.1.1 Collinearity tests. We checked for multicollinearity via two approaches. First, we calculated the variance inflation factor (VIF) for each of the models in Table 2 and obtained an average VIF of 2.69 and a maximum of 7.26, all below the suggested threshold of 10 (Belsley, Kuh, & Welsch, 1980; Cennamo & Santaló, 2019). In the second approach, we applied the test suggested by Belsley, Kuh, & Welsch et al. (1980), which combines the condition index and variance decomposition. We found that all of the models are well below the suggested threshold (30), with an average conditional index of 3.87 and a maximum of 17.47 (Intriligator, Bodkin, & Hsiao, 1996). With respect to variance-decomposition proportions at relatively large conditional index values, the theorized variables all have proportions lower than 50 percent (Belsley et al., 1980). Hence, multicollinearity is not a concern.

4.1.2 Regression results. As shown in Table 2, we first ran a baseline model without any acquisition-related measures (Model 1), then entered *user-side economies of scale* and *user-side economies of scope* in Model 2, *complementary-technology-side economies of scale* and *complementary-technology-side economies of scope* in Model 3, and finally entered all four theorized measures in Model 4. Because the dependent variable (entry) is binary, we need to report McFadden's pseudo-R-squared which can be calculated based on the log likelihood of an estimated model and the log likelihood of the intercept-only model (Cameron & Trivedi, 2005; McFadden, 1973). All models in Table 2 exhibit high goodness of fit (i.e., when pseudo-R-squares are between 0.2 and 0.4 according to McFadden (1979)). Additionally, we conducted likelihood ratio tests (Cameron & Trivedi, 2005: p.234) to assess model improvements and report test statistics following prior research that also used binary outcome variables (e.g., Zhou, 2011). Note that the baseline entry probability, as reflected by the intercept, is low, ranging from 0.88 percent (in Model 1) to 0.90 percent (in Model 3), which is typical for market entry research and sets a benchmark for us to later gauge effect sizes of our theorized relations.

[Table 2 goes about here]

Hypothesis 1a predicted that acquirers' user-side economies of scale will be negatively associated with entry likelihood. As shown in Models 2 and 4 in Table 2, the coefficients on the variable, *user-side EOSL*, are positive but not statistically significant. The hypothesis was therefore not supported by the coefficient on the main measure (based on comentioning). A possible explanation is that aspiring potential entrants perceived the scale of user base (involved in the acquisition deal) as a positive signal about market potential, a force that may offset the entry-deterring effects. In a supplementary analysis where we used alternative user-side measures to capture the occurrence of social interactions among users,[15] we found that the coefficient on user-

[15] We focused on the user-side direct network effects (Iansiti, 2021). We developed a dictionary of keywords that indicate "social" functionalities and calculated keyword frequency in a review text (r) of an app as K_r. We utilized a

side EOSL is negative and significant (Model 2 in Table B.1 of Appendix B: $\beta = -0.0005, p = 0.000$). Hence, our nuanced finding is that the entry-deterring effect of user-side EOSL is significant when social interactions (that likely enable the merged entity to better lock in the user base) are present.

Hypothesis 1b predicted that acquirers' user-side economies of scope will be negatively related to the entry likelihood. As can be seen, the coefficients on the variable, *user-side EOSP*, are negatively associated with the entry likelihood (Model 2: $\beta = -0.0149, p = 0.000$; Model 4: $\beta = -0.0120, p = 0.000$), thus providing strong support for Hypothesis 1b.

Moving to the complementary-technology side, Hypothesis 2a predicted a negative relationship between acquirers' economies of scale on the side of complementary technologies and the likelihood of future entry. This hypothesis is tested by the coefficients on the variable, *complementary-technology-side EOSL*, in Models 3 and 4, which are consistently negative (Model 3: $\beta = -0.0091, p = 0.000$; Model 4: $\beta = -0.0100, p = 0.000$), thus supporting the hypothesis (H2a). Finally, Hypothesis 2b predicted a negative association between acquirers' economies of

combination of both inductive and deductive approaches. First, we derived keywords from the literature on network effects (e.g., Afuah, 2013; Eisenmann, Parker, & Van Alstyne, 2011; Iansiti, 2021; Katona, Zubcsek, & Sarvary, 2011; McIntyre & Srinivasan, 2017). We then derived keywords by closely examining a subset of user reviews (using the linguistic research software AntConc) in order to bridge the gap between theory and reality. The resulting dictionary included the following keywords: "social network," "social networking," "networking," "social," "social life," "social apps," "social media," "social sports," "friends," "friend," "family," "buddies," "buddy," "players," "group," and "network marketing." We standardized the keyword frequency (K_r) with the length of the review text (N_r), which provided the standardized frequency ($\frac{K_r}{N_r}$). To account for the fact that positive reviews are better indicators that an app possesses desirable "social" functionalities from consumers' perspectives, we then used the rating scale (R_r) (from 1 to 5) associated with the review. The product of this variable with the standardized keyword frequency (i.e., $\left(\frac{K_r}{N_r}\right) \cdot R_r$) captures the extent to which consumers communicated positive impressions of an app product's "social" functionalities. Next, we calculated the sum of the scores across all reviews of an app (a) at the time of an acquisition, and then calculated the total across all apps in an acquirer's portfolio at the time of the acquisition announcement. The resulting measure captures whether social interactions are present, and it can be expressed as $\sum_a \sum_r \left(\frac{K_r}{N_r}\right) \cdot R_r$. We again aggregated the measure to the category level by averaging it across the overlapping acquisitions in the same three-month moving window to derive the variable, *user-side EOSL (social interactions)*, and averaged it across the non-overlapping acquisitions to generate the variable, *user-side EOSP (social interactions)*. We then scaled down the variables (i.e., dividing by 1,000) to ease the interpretation of regression coefficients.

scope on the complementary-technology side and a potential entrant's entry probability. The hypothesis is tested via coefficients on the variable, *complementary-technology-side EOSP*, which, as shown, are consistently negative (Model 3: $\beta = -0.2934, p = 0.000$; Model 4: $\beta = -0.2531, p = 0.000$). Thus, Hypothesis 2b is supported.

It is worthwhile to point out that, while three of the four types of acquisition synergies significantly reduce a new entrant's likelihood of entering a market product, acquisition intensity is instead positively associated with entry likelihood. The reason is perhaps that the sheer number of acquisitions may indicate the hotness of a market and therefore attract new entrants as in traditional industry settings (e.g., Berger et al., 2004). In contrast, our findings on synergy measures' entry-deterring effects suggest that simply counting the number of acquisitions as in traditional industrial organization research may not be sufficient. We instead emphasize each individual acquisition event's underlying synergies from a strategic management perspective[16] and thus reveal the loci where entry-deterring effects stem from.

4.1.3 Effect sizes. Based on regression estimates in Model 4 of Table 2, we interpreted effect sizes in four ways (as shown in the header of Table 3): (1) percentage point change in entry likelihood (e.g., Starr, 2019; Starr et al., 2019), (2) percentage of the effect in proportion to the baseline entry probability, (3) number of entries, and (4) estimated dollar value. All effect sizes are in terms of the change in the outcome variable (e.g., percentage change in entry likelihood) from one standard deviation increase of the corresponding independent variable. We illustrate our approach with one of the four hypothesized synergy measures: *user-side EOSP*. A one standard

[16] Though our synergy measures are at the product-category level, they are aggregated from each acquisition event when we unpack them across the four types of theorized economies. We provide a visual aid of how individual acquisitions are distributed across the measures in Appendix F, in which one figure (Figure F.1) shows the distribution of non-overlapping acquisitions across user-side EOSP and complementary-technology-side EOSP, and the other figure (Figure F.2) visualizes overlapping acquisitions as distributed across user-side EOSL and technology-side EOSL.

deviation increase in acquirers' *user-side EOSP* corresponds to (1) a 0.09 percent decrease in a potential entrant's entry probability, (2) an 11 percent decline relative to the baseline entry probability, (3) 40 deterred entries, or (4) a $2.07 million potential loss of annual revenue for the *would-have-been entrants had they entered the affected product category*.[17]

A comparison of the magnitude of potential loss of annual revenues from a one standard deviation increase in each of the four synergy measures suggests the following ranking (from highest to lowest magnitude of effect): (1) complementary-technology-side EOSP ($2.80 million), (2) complementary-technology-side EOSL ($2.41 million), and (3) user-side EOSP ($2.07 million). Another interesting pattern is that, for both the user side as well as the complementary-technology side, the corresponding effect sizes of scope economies are consistently larger than those of scale economies. We discuss the implications of our findings in the concluding section.

[Table 3 goes about here]

4.1.4. Robustness checks and supplementary analyses. Besides the main results presented in the paper, we report in online appendices the following robustness checks and supplementary analyses. First, whereas for each of the four types of economies we only described one operational measure in the manuscript due to space constraints, we provide in the online appendix additional measures, descriptions, and results to provide additional validation (please see Appendix B for user-side alternative measures, and Appendix C for alternative complementary-technology-side measures). Second, to address the potential endogeneity of acquisitions, as a robustness check we implemented an instrumental variable approach (Angrist & Pischke, 2008, p.203; Starr et al., 2019) and two-stage least square estimation (with details shown in Appendix G). We acknowledge that it was challenging to find an ideal instrument to capture the cross-

[17] Please see the detailed notes under Table 3 regarding how the four types of effect sizes were calculated.

category variation within the relatively closed system of Apple's App Store and caution that we are not able to draw strict causal inferences (all our hypotheses and interpretations are hence worded as associations rather than causal effects). Third, we conducted a robustness check by controlling for month fixed effects in modified model specifications (i.e., with developer fixed effects instead of developer-month fixed effects), to absorb the potential confounding effects of macro factors, such as platform generational transitions, macroeconomic factors, behaviors of the competing platform Android, technological trends, and regulatory changes. The results are shown in Appendix H. Fourth, we conducted tests on the impact of potential confounding variables (Frank, 2000; Xu, Frank, Maroulis, & Rosenberg, 2019) and concluded that our estimated effects are not confounded by other unobserved variables (Appendix I). Fifth, as a supplementary analysis (Appendix J), we compared regression coefficients based on the full model (Model 4) in Table 2 in order to evaluate which aspect of complementor acquirers' synergies is more or less entry-deterring. Finally, to account for acquirers with more abundant resources (i.e., cash or investment from financial markets) as an alternative explanation, in a robustness check (Appendix K) we controlled for acquirers' total assets, number of employees, and whether publicly listed.[18] Results remain qualitatively the same.

5. DISCUSSION AND CONCLUSION

The rise of digital platforms has attracted increasing scrutiny from academic scholars and regulatory agencies due to potential anti-competitive behaviors by dominant firms. And yet most of the attention has been focused on platform owners and how they build market power at the expense of complementors and consumers (Khan, 2017; Parker et al., 2021; Zhu & Liu, 2018). We add to this line of inquiry by extending the focus from platform-owner-initiated acquisitions

[18] We thank a reviewer for this insight.

(Correia-da-Silva et al., 2019; Farronato et al., 2023; Khan, 2017; Song, 2021; Thatchenkery & Katila, 2022; Wen & Zhu, 2019) to all acquisitions of complementors. Rather than only looking at the number or the intensity of acquisitions as in the traditional industrial organization literature, our study emphasizes firm heterogeneities and unpacks potential synergies that acquirers can accrue through acquisitions. Specifically, we build on the multisided nature of platform markets to distinguish between four sources of synergies—economies of scale and scope on the user side, and economies of scale and scope on the complementary-technology side.

We find consistent entry-deterring effects for user-side economies of scope (H1b), complementary-technology-side economies of scale (H2a), and complementary-technology-side economies of scope (H2b). However, we find entry-deterring effects for user-side economies of scale (H1a) only in the presence of social interactions in the user base. These findings support prior research that recognizes demand-side factors as crucial sources of competitive advantage in platform markets (Rietveld & Eggers, 2018; Rietveld et al., 2020) while extending this line of work by showing which specific user-side factors are associated with lower market entries (Khan, 2017).

Overall, our results indicate that user-side scope economies are stronger than scale economies and the technology-side synergies are stronger than the user-side synergies when it comes to deterring future entries. The specific ranking of effect sizes, when increasing the corresponding synergy measure by one standard deviation, is as follows: (1) *complementary-technology-side EOSP* (55 deterred entries or a $2.80 million potential loss in annual revenue for would-have-been entrants), (2) *complementary-technology-side EOSL* (47 deterred entries or a $2.41 million potential loss in annual revenue), and (3) *user-side EOSP* (40 deterred entries or a $2.07 million potential loss in annual revenue). The stronger effects of scope economies compared to scale economies may reflect the fact that the ecosystem-like structure in which multiple categories of products interact and complement each other can offer an acquirer stronger competitive advantages than a structure based on a single category of service offerings in a platform market (e.g., Agarwal & Kapoor, 2023; Kapoor & Agarwal, 2017). Customers using multiple products from the same complementor may find more seamless connections and better user experiences, and thus can be more loyal and stickier. In contrast, the product offering in a single category may not be as protected and may be more susceptible to imitation and, consequently, offer opportunities for market entrants.

We also noted that the effects of technology-side synergies were stronger than user-side synergies, and this may indicate that having a stronger technological foundation may yield more significant and longer-lasting competitive advantages than merely having a larger user base. Technological capabilities can lead to features, efficiencies, or services that competitors find hard to replicate. By contrast, due to users' multi-homing tendency (Cennamo et al., 2018; Chung, Zhou, & Ethiraj, 2022; Li & Zhu, 2021), competitive advantages afforded by the scale of a larger user base, without other competitive moats, can be more transient, especially if competitors offer similar or better features. Moreover, superior technology often translates to faster load times, better personalization, fewer glitches, and a more seamless user experience. Even with a smaller user base, this can lead to higher user engagement, loyalty, and word-of-mouth referrals. The competition between Apple's iOS and Google's Android in the mobile operating system market illustrates that technological strengths have granted Apple significant competitive advantages in areas like profitability, user engagement, and brand loyalty, even though Google has a far larger user base.

The above conjectures are also consistent with a comparison between Uber and Lyft. The large user base afforded by the ride-hailing business has not allowed Uber to achieve superior performance due to the competition from Lyft. Instead, what has given Uber a competitive edge over Lyft is the addition of Uber Eats. Uber's competitive advantage can be attributed to economies of scope and the underlying ability to integrate unique technologies across two distinct business lines (food and beverage delivery and ride hailing). Nevertheless, we acknowledge that our study only provides initial evidence in an important yet understudied domain. We hope future research can use our findings as a steppingstone to gain a deeper understanding of our conjectures.

Contributions

First and foremost, our study helps deepen our understanding of the mechanisms through which complementor acquisitions influence subsequent complementor entries. The important influence of economies of scale and scope have been well-documented in the mainstream strategy literature (e.g., Feldman, 2022; Karim & Capron, 2016; Rumelt et al., 1994) and have been recently highlighted in the platform literature as well (e.g., Farronato et al., 2023; Miric et al., 2021; Ozalp et al., 2018; Parker et al., 2021). However, to the best of our knowledge, our study is the first empirical attempt to tease apart economies of scale and economies of scope on both the user side and the complementary-technology side in a digital platform market. Our study thus contributes conceptually as well as methodologically to the literature by developing a typology that distinguishes between four difference sources of acquisition synergies and operationalizing each of the four theoretical constructs with multiple measures. Based on this typology we are able to compare the relative (entry-deterring) strengths of different synergy sources. We find that the synergies derived from economies of scope have stronger entry-deterring effects than those from economies of scale, and that synergies derived from the technology side have a stronger entry-deterring effect than their counterparts on the user-side. (Please see online Appendix J for related details.)

Relatedly, our paper extends the acquisition literature, in particular the research stream on acquisition synergies (Devos, Kadapakkam, & Krishnamurthy, 2009; Feldman & Hernandez, 2021; Rabier, 2017), from traditional industries to digital platforms. We do this by directly recognizing the multisided nature of a platform market in developing and testing our hypotheses. In the spirit of cross-side network effects (Eisenmann, 2007; Zhu & Iansiti, 2012), our user-side hypotheses (H1a and H1b) link the synergies derived from the *user side* to the entry decisions on the *developer side*; similarly, our complementary-technology hypotheses (H2a and H2b) link the synergies derived from the *complementary-technology side* to the entry decisions on the *developer side*. Moreover, whereas the traditional research on acquisition synergies has been primarily focused on the input (or supply) side of synergies (akin to the complementary-technology side in a digital platform), our paper responds to calls for a more balanced view by conceptualizing (and measuring) the demand (or user) side (e.g., Adner & Levinthal, 2001; Mawdsley & Somaya, 2018). User-side synergies arise primarily because interactions with one another improve users' utilities or users can ex post enjoy lower search and transaction costs through one-stop shopping (Ye et al., 2012).

Our work also contributes to the emerging research stream that examines competitive and regulatory implications of acquisitions in platform markets (Khan, 2017; Miric et al., 2021; Parker et al., 2021; Thatchenkery & Katila, 2022; Wen & Zhu, 2019). Our findings can provide useful new insights to inform the current debate around antitrust concerns. On one side of the debate, proponents call for regulating technology giants and their acquisitions in order to curtail their growing market power, whereas an opposing view regards regulators' tightened scrutiny on technological firms' acquisitions as misguided (Economist, July 15 2023). Our findings suggest a more nuanced and balanced view of acquisitions in that some acquisitions, but not all of them, are potentially anti-competitive and that this heterogeneity stems from underlying synergies that accrue differentially to different acquirers. Additionally, our study complements prior work, which has primarily focused on platform-owner-initiated acquisitions (Correia-da-Silva et al., 2019; Farronato et al., 2023; Khan, 2017; Song, 2021; Thatchenkery & Katila, 2022; Wen & Zhu, 2019), by examining acquisitions of complementors in general. Thus, we not only identify an omitted and potentially anti-competitive force on the platform market, but we also unpack acquirer heterogeneities in market power that accrue from each of the four types of acquisition synergies. Our research thus contributes to a more complete understanding of the loci of market power in a digital platform market. We nevertheless encourage future studies that are more amenable to causal inferences to offer stronger policy prescriptions.

Our study also makes methodological contributions. We developed novel measures of synergies by exploiting the multisided feature of platforms. For instance, the user-side-synergy measures integrate information from the developer side (i.e., acquirers' and targets' products and the corresponding categories) as well as information from the user side of the platform (i.e., acquirers' user bases). Similarly, the complementary-technology-side synergy measures combine information from the complementary-technology side of the platform market (i.e., SDKs) with information from the developer side (i.e., acquirers' and targets' products and the corresponding categories). Moreover, we applied natural language processing techniques to process the data of millions of user reviews. Future research can build on the dictionary of keywords we developed to study social network effects and adopt our keyword-ranking approach to capture category-specific user preferences and cross-category correlations of user preferences.

Limitations and Directions for Future Research

We acknowledge some limitations and related directions for future research. First, we admit that our explanations for why certain type of synergies (e.g., EOSP) have stronger effect than others (e.g., EOSL) can be speculative. In the absence of any compelling theoretical arguments, we did not theorize on the stronger effect of scope versus scale economies or the stronger effect from the technology side than the user side. Instead, our primary contribution lies in carefully measuring the four sources of potential synergies and showing their empirical relationships with subsequent market entries. Future researchers can use our typology (and related findings) to investigate whether and the conditions under which scope economies are stronger than scale economies and, similarly, whether and under what conditions technology-side synergies dominate user-side synergies. Second, our research design does not permit us to draw causal inferences. In spite of our careful empirical design (e.g., case-control panels with developer-month fixed effects and category fixed effects), it is reasonable to argue that there might be unobserved factors that may affect both acquisitions and entries. However, we developed multiple robustness checks and supplementary analyses (as described in Section 4.1.4) to mitigate major concerns around endogeneity (Appendix G), confounding variables (Appendices H and I), and alternative explanations (Appendix K). We nevertheless encourage future research to use other identification strategies, such as difference-in-differences that exploits exogenous shocks (e.g., Chung et al., 2022; Farronato et al., 2023; Wen & Zhu, 2019), to draw direct causal inferences. Third, we acknowledge boundary conditions that may limit the generalizability of our results. Our empirical findings are based on one digital platform market—Apple's iOS App Store—where multiple sides coexist: complementors, complementary technologies, and users. Hence, our findings may only be generalizable to other digital platform markets and especially to contexts that mimic the characteristics of our empirical context, such as the presence of complementors on one side and at least one of the other two sides of the market. For example, the enterprise software industry (e.g., Angeren & Karunakaran, 2023; Thatchenkery & Katila, 2022) is another digital platform context where our findings could apply. Fourth, while we were able to obtain comprehensive information of acquirers' app products, user bases, and SDKs, the corresponding information for targets was not as comprehensive for reasons such as "killer acquisitions," situations in which targets' products were withdrawn from the App Store post-acquisition (e.g., Cunningham, Ederer, & Ma, 2021).

Conclusion

It is well-recognized in the strategy literature that acquisitions are often used by firms to shape market structure and enhance their own competitive advantages. The synergies that acquirers derive can serve as powerful deterrents to future entries and thus have long-lasting effects on competitive dynamics. Digital platform markets have garnered increasing attention, both from strategy scholars as well as regulatory agencies concerned with the anti-competitive effects of acquisitions by powerful firms. Research on acquisitions in digital platform markets has, however, focused mainly on platform owners even though significant acquisition activity can be attributed to complementor acquisitions more generally. To address this critical gap, we leverage the unique multisided nature of a digital platform market to conceptualize four different types of synergies that complementor acquirers can accrue. We develop multiple measures for each of these synergies to examine their associations with entry likelihood in a sample of hundreds of acquisitions that took place between 2008 and 2015 in a prominent digital platform market, Apple's iOS App Store. We discuss the implications of our findings for both research as well as policy and hope that our study can serve as a bridge between platform strategy scholars and the mainstream strategy literature as well as a foundation for work by future scholars interested in studying other digital platform contexts.

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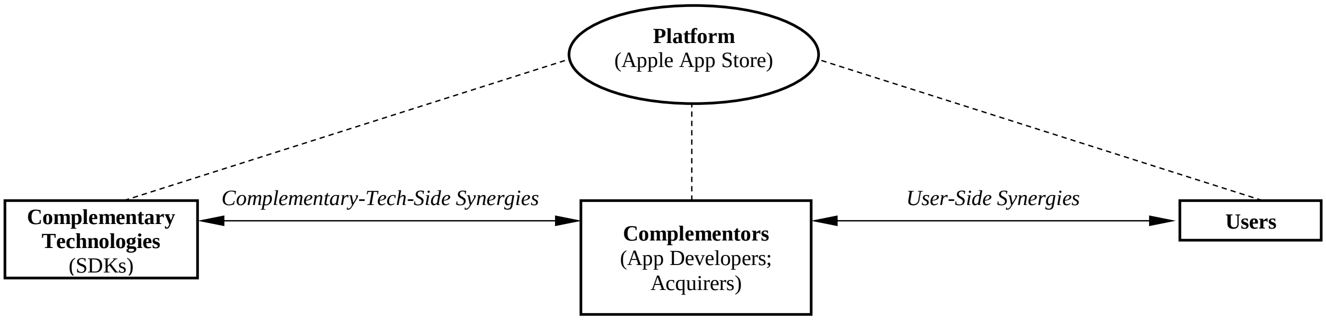

Figure 1: A Stylized Diagram of the Multisided Platform Market of Apple's iOS App Store

Notes: We developed this diagram by building on prior platform studies (e.g., Hagiu, 2014; Hagiu & Wright, 2015; Kapoor & Agarwal, 2017; Rietveld, Ploog, & Nieborg, 2020; Cennamo, 2021; Ozalp, Cennmo, & Gawer, 2018) to reflect the multisidedness of the platform market (Apple App Store). In the diagram, dotted lines show the different sides affiliated with the multisided platform; double-arrowed solid lines describe the second unique feature of a platform market where, unlike a traditional industry, the different sides interface directly with each other because the platform enables these interfaces. The three affiliated sides that our study focuses on include complementors (app developers, which also include acquirers), users, and complementary technologies (SDKs). Depicted by the double-arrowed lines, app developers interface directly with complementary technologies (SDKs) when adopting them and users (by providing them mobile apps).

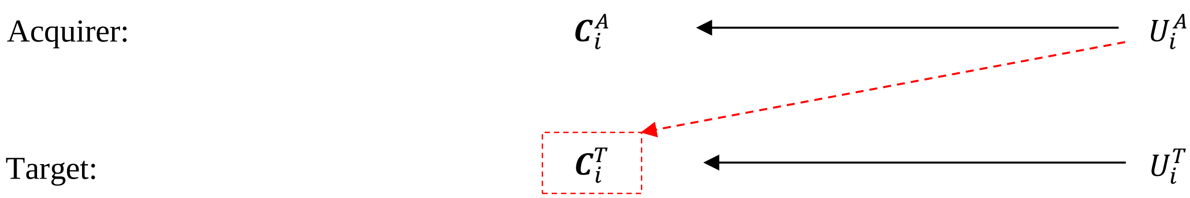

Figure 2: User-Side Synergies When Taking into Account the Two Sides of Complementors and Users

Notes: In the diagram depicting a single acquisition event (i), $\boldsymbol{C}_i^A$ is a vector of categories denoting that the acquirer's (A) products are in certain category(ies) of the category vector; U_i^A refers to users of said acquirer's product(s). Similar notations are adopted for the target by replacing A with T. The solid black lines show existing users' usage of the respective company's product(s) before the acquisition announcement. The key is to show the dashed red line, which links the acquirer's users (U_i^A) to the target's product category(ies). When the acquirer and the target share the same product category(ies) (i.e., when the acquirer's category vector ($\boldsymbol{C}_i^A$) and the target's category vector ($\boldsymbol{C}_i^T$) have positive values on the same category(ies)), the underlying mechanism stems from *user-side economies of scale*; however, when they do not overlap in product categories (i.e., when the vectors $\boldsymbol{C}_i^A$ and $\boldsymbol{C}_i^T$ do not simultaneously have positive values in any same category(ies)), the underlying mechanism stems from *user-side economies of scope*.

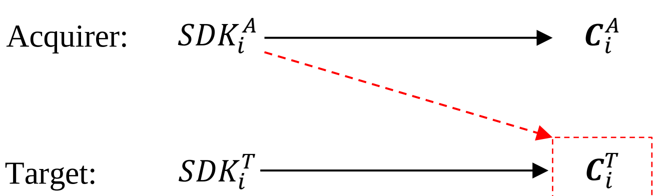

Figure 3: Complementary-Technology-Side Synergies When Taking into Account the Two Sides of Complementors and Complementary Technologies

Notes: In a similar vein as Figure 2 above, the diagram (Figure 3) reflects economies of scale (i.e., when $\boldsymbol{C}_i^A$ and $\boldsymbol{C}_i^T$ have positive values on the same category(ies)) and economies of scope (i.e., when $\boldsymbol{C}_i^A$ and $\boldsymbol{C}_i^T$ do not simultaneously have positive values on any same category(ies)) on the side of complementary technologies (SDKs), where SDK_i^A denotes the complementary technologies (SDKs) of the acquirer's products, andSDK_i^T that of the target.

Table 1: Descriptive Statistics and Correlations

		Observations	Mean	Standard Deviation	Minimum	Median	Maximum
(1)	Entry	8767477	0.079	0.269	0	0	1
(2)	User-Side Economies of Scope	8767477	0.037	0.078	0	0	0.537
(3)	User-Side Economies of Scale	8767477	0.150	0.168	0	0.098	0.702
(4)	Complementary-Technology-Side Economies of Scope	8767477	0.001	0.005	0	0	0.063
(5)	Complementary-Technology-Side Economies of Scale	8767477	0.041	0.109	0	0.001	1.015
(6)	Acquisition Intensity	8767477	2.720	2.959	0	2	17
(7)	Category Size	8767477	29.320	32.269	0.020	18.903	173.620
(8)	Category Growth in App Products	8767477	1.694	0.918	-2.791	1.607	4.700

Note: The unit of analysis is a developer-month-category.

Table 1 (continued): Descriptive Statistics and Correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Entry	1.000							
(2)	User-Side Economies of Scope	0.028	1.000						
(3)	User-Side Economies of Scale	0.084	0.206	1.000					
(4)	Complementary-Technology-Side Economies of Scope	0.037	0.248	0.072	1.000				
(5)	Complementary-Technology-Side Economies of Scale	0.045	-0.007	0.463	0.036	1.000			
(6)	Acquisition Intensity	0.111	0.344	0.710	0.201	0.228	1.000		
(7)	Category Size	0.135	0.136	0.493	0.237	0.515	0.521	1.000	
(8)	Category Growth in App Products	-0.085	-0.003	0.060	-0.054	0.093	-0.028	-0.012	1.000

Table 2: Developer-Month Fixed-Effects OLS Linear Probability Models Testing Acquirers' Economies of Scale and Economies of Scope on User- and Complementary-Technology Sides

	(1) Baseline	(2) User Side	(3) Complementary-Technology Side	(4) Full Model
User-Side Economies of Scope		-0.0149		-0.0120
		(0.000)		(0.000)
User-Side Economies of Scale		0.0006		0.0014
		(0.520)		(0.191)
Complementary-Technology-Side Economies of Scope			-0.2934	-0.2531
			(0.000)	(0.000)
Complementary-Technology-Side Economies of Scale			-0.0091	-0.0100
			(0.000)	(0.000)
Acquisition Intensity	0.0004	0.0005	0.0005	0.0005
	(0.000)	(0.000)	(0.000)	(0.000)
Category Size	-0.0004	-0.0004	-0.0004	-0.0004
	(0.000)	(0.000)	(0.000)	(0.000)
Category Growth in App Products	0.0239	0.0240	0.0235	0.0236
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0089	0.0088	0.0090	0.0089
	(0.000)	(0.000)	(0.000)	(0.000)
Developer-Month Fixed Effects	Yes	Yes	Yes	Yes
Category Fixed Effects	Yes	Yes	Yes	Yes
Developer-Month-Categories	8767477	8767477	8767477	8767477
Developer-Months	430479	430479	430479	430479
Log Likelihood	-683198	-683133	-683068	-683027
Log Likelihood of Intercept-Only Model	-879606	-879606	-879606	-879606
McFadden's Pseudo R-Squared	0.2233	0.2234	0.2234	0.2235
Model Comparison Likelihood Ratio Test		$\chi2(2)$ vs. Model 1 = 129.81	$\chi2(2)$ vs. Model 1 = 260.83	$\chi2(4)$ vs. Model 1 = 343.02
Model Comparison Likelihood Ratio Test p-value		(0.000)	(0.000)	(0.000)

Notes: (1) *p*-values are in parentheses (two-sided). (2) The group of fixed effects was set at the developer-month level. (3) The *developer-month fixed effects* absorb developer attributes and month fixed effects. (4) The *category fixed effects* absorb time-invariant category attributes. (5) Multicollinearity was not an issue in any model according to results of two approaches of collinearity tests (the average VIF is 2.69; the average conditional index is 3.87).

Table 3: Effect Sizes Based on Regression Estimates in Model 4 of Table 2

Complementor Acquirers' Synergies	Percentage-Point Change	Percentage Relative to Baseline Entry Probability	Number of Entries	Dollar Value (Million USD)
User-Side Economies of Scope	-0.09	-11%	-40	-2.07
User-Side Economies of Scale	0.02	3%	10	0.52
Complementary-Technology-Side Economies of Scope	-0.13	-14%	-55	-2.80
Complementary-Technology-Side Economies of Scale	-0.11	-12%	-47	-2.41

Notes: Each cell reports effect size based on estimates from Model 4 of Table 2. The first two types of effect size—percentage-point change and percentage relative to baseline entry probability—can be derived directly from the regression estimates, whereas the last two—number of entries and dollar value—rely on certain assumptions that we explain here. The number of entries was calculated based on the assumption that the average number of entries in a category-month in our data (i.e., 384.56) corresponds to the baseline entry probability (i.e., intercept in each regression model). The effect size in terms of dollar values was calculated based on the annual revenue in the Apple App Store from 2014 to 2015 (i.e., $14.28 billion)[19] and the total number of app developers in our sample (279,184) (which owned about 95 percent of apps in the store). The estimated dollar value represents the total annual revenue by the "would-have-been" entrant developers if they "had entered the affected market." The estimated dollar values are likely to be conservative and will be larger with a stricter assumption (e.g., not all app developers earn positive revenues).

[19] Source: https://sensortower.com/blog/app-store-revenue-update, accessed on July 13, 2023.