Information Systems Research

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Strategic Drivers of Core Expansion on Software Platforms: Evidence from Apple iOS

André Halckenhaeusser, Jens Forderer, Armin Heinzl, Ola Henfridsson

INFORMATION SYSTEMS RESEARCH
Articles in Advance, pp. 1–20
https://pubsonline.informs.org/journal/isre
ISSN 1047-7047 (print), ISSN 1526-5536 (online)

Strategic Drivers of Core Expansion on Software Platforms: Evidence from Apple iOS

André Halckenhaeusser,[a] Jens Forderer,[a,*] Armin Heinzl,[a] Ola Henfridsson[b]

[a] Business School, University of Mannheim, 68161 Mannheim, Germany; [b] Miami Herbert Business School, University of Miami, Coral Gables, Florida 33146

*Corresponding author

Contact: halckenhaeusser@uni-mannheim.de, https://orcid.org/0000-0001-5258-4560 (AnH); jens.foerderer@uni-mannheim.de, https://orcid.org/0000-0002-3090-4559 (JF); heinzl@uni-mannheim.de, https://orcid.org/0000-0001-9886-9596 (ArH); ohenfridsson@miami.edu, https://orcid.org/0000-0003-1605-5180 (OH)

Received: June 16, 2023
Revised: March 20, 2024; January 19, 2025; June 23, 2025
Accepted: August 12, 2025
Published Online in Articles in Advance: November 12, 2025

https://doi.org/10.1287/isre.2023.0347

Abstract. Software platforms are extensible systems built on a core-periphery model, where the platform owner provides a foundational code base that third-party developers can leverage for complementary apps. This model incentivizes software platform owners to enlarge the overall value generated by the ecosystem, thereby increasing their share of the revenues, rather than competing directly with third-party developers by offering apps themselves. As part of this strategy, platform owners nevertheless intermittently expand their core to cover functionality that has once resided in the periphery. What are the drivers behind such core expansion into ecosystem niches? We meticulously assembled a large-scale data set of all Apple's core expansions on the iOS platform from 2012 to 2020, encompassing both stand-alone apps and features integrated into the core, to examine these drivers. The findings support our hypotheses that niches characterized by low user satisfaction, low levels of innovation efforts, and higher market concentration are more likely to be targets for core expansion. Core expansion through stand-alone apps manifests in niches with low levels of innovation efforts, whereas core expansion through integration of features into the platform core manifests in niches with low user satisfaction and high market concentration. Our study extends the software platform literature by hypothesizing and testing the drivers behind a platform owner's core expansion into ecosystem niches.

History: Anandasivam Gopal, Senior Editor; Yuliang Yao, Associate Editor.

Funding: J. Forderer acknowledges funding from the Deutsche Forschungsgemeinschaft [Grant 453186120].

Supplemental Material: The online appendix is available at https://doi.org/10.1287/isre.2023.0347.

Keywords: platform ecosystems • core-periphery • Apple iOS • platform competition • gatekeeper

1. Introduction

Software platforms are extensible systems built on a core-periphery model, where the platform owner provides a foundational code base (*core*) that third-party developers can leverage to design, build, and monetize complementary apps (*periphery*) (Tiwana et al. 2010, Yoo et al. 2010, Constantinides et al. 2018, Fuerstenau et al. 2023). The core-periphery model emphasizes a notion of mutual prosperity, where both the platform owner and third-party developers benefit from maintaining a vibrant and ideally expanding[1] platform ecosystem. Mutual success is critical for software platform owners as their revenue derives from commissions charged for third-party apps. This creates a strong incentive to support value creation within the ecosystem.

At the same time, platform owners intermittently engage in a behavior that appears at odds with the notion of mutual prosperity; they expand the platform core to incorporate functionalities previously offered by third-party developers. Apple, for instance, has expanded the iOS operating system with features, such as flashlight utilities, screen-time tracking, or password managers, that had already been provided in the periphery. These core expansions raise the theoretical question of how such behavior aligns with the notion of mutual prosperity that underpins the core-periphery structure of software platforms.

Surprisingly, extant research into this question is limited, despite substantial studies exploring the boundary between the core and the periphery. These studies include the resource provision at the boundary between the core and periphery (e.g., Ghazawneh and Henfridsson 2013, Eaton et al. 2015, Karhu et al. 2018, Ye and Kankanhalli 2018), the design of the core to enable peripheral contributions (e.g., Brunswicker et al. 2019, Meng et al. 2022, Zhang et al. 2022), and strategies to encourage contributions to the periphery (e.g., Huang et al. 2013, Liang et al. 2019, Hukal et al. 2020). Several qualitative studies suggest that platform owners strategically manage relationships with third-party developers to foster ecosystem growth (Gawer and Henderson 2007, Sarker et al. 2012, Eaton et al. 2015, Huber et al. 2017). However, in understanding platform owners' decisions to expand the platform core, prior work has predominantly focused on the effects of such expansions on complementors rather than the drivers behind them (Foerderer et al. 2018, Wen and Zhu 2019).

Beyond its theoretical relevance, understanding the drivers of core expansions is also important from public policy and managerial perspectives. Expansions, like those undertaken by Apple, have become the subject of a public policy debate about the role of dominant platforms in relation to peripheral innovation (Nicas 2019, Romm 2020), particularly in light of recent regulatory developments, such as the European Union's Digital Markets Act (Cabral et al. 2021, Crémer et al. 2023). Furthermore, peripheral developers face uncertainty about when their niches may experience core expansion. For these theoretical and practical reasons, it is diligent to better understand what drives software platform owners' decision to expand the core with peripheral functionality.

We seek to address this research gap by investigating the drivers of core expansion. Drawing on the conceptualization of software platforms based on the core-periphery model and with the idea of mutual prosperity in mind,[2] we surmise that core expansions are primarily driven by the need to address weaknesses in the ecosystem. We argue that core expansions seek to increase the overall value of the ecosystem, enabling platform owners to profit indirectly—for instance, through increased adoption rates and higher commissions generated from a larger number of apps—rather than relying solely on direct monetization of the core expansions. We develop hypotheses concerning the level of ecosystem niches in terms of functionally distinct areas of user demand and third-party development. We propose that platform owners are likely to target niches characterized by low user satisfaction, stagnating innovation efforts, and high market concentration. In addition, we examine the drivers that lead core expansions to take different forms, either as integrated features embedded directly into the platform core or as stand-alone apps distributed alongside third-party offerings.

To test these hypotheses, we assembled a unique data set that includes all 62 of Apple's core expansions on the iOS platform from 2012 to 2020, encompassing both stand-alone apps and features integrated into the core. To identify the ecosystem niche that is affected by a core expansion, we relied on the Apple App Store's category system, which groups apps into functionally similar domains, such as *Health and Fitness*, *Navigation*, or *Finance*. We constructed a monthly panel data set comprising data on app ratings, updates, and other relevant metrics across all categories in the store. Employing a panel fixed-effects logit model, we analyzed the relationship between user satisfaction, innovation efforts, and market concentration within each category and the likelihood of a subsequent core expansion. Our results confirm the hypotheses, providing robust empirical evidence that Apple's expansions have systematically targeted underperforming niches in concordance with the hypothesized drivers.

We conduct an extensive set of robustness checks, particularly to address concerns over endogeneity and ensure the validity of our results. To mitigate concerns about omitted variable bias, we implement an approach in the spirit of matching techniques, a control function approach, and perform a sensitivity analysis using robustness of inference procedures. To account for possible measurement errors, we vary the time window used to assess niche characteristics, account for the potential reclassification of apps across categories, and demonstrate that the results remain consistent with alternative measures of niche characteristics. In addition, we address multicollinearity concerns and rule out key rival explanations to further strengthen our conclusions.

The paper is structured as follows. The next section outlines the core-periphery model of software platforms, reviews relevant literature, and develops the hypotheses. This is followed by a description of the empirical setting, methodology, and data. We then present the results of the hypotheses tests alongside descriptive evidence and dedicate a separate section to an extensive set of robustness checks. Subsequently, we discuss the findings before concluding the paper.

2. Conceptual Foundation and Hypotheses

2.1. The Core-Periphery Model of Software Platforms

Software platforms constitute an extensible software product system with core functionality that serves as a foundation for third-party complementary software (Tiwana et al. 2010, Yoo et al. 2010, Gawer and Cusumano 2014, Fuerstenau et al. 2023, Vial 2023, Leong et al. 2024). For the purpose of this paper, we define a software platform as "the extensible codebase of a software-based system that provides core functionality shared by the modules that interoperate with it and the interfaces through which they interoperate" (Tiwana et al. 2010, p. 657). As an entity responsible for the governance and development of the software platform while also profiting indirectly from a healthy ecosystem, the platform owner typically seeks to enlarge the overall value generated by the ecosystem. To achieve this, the platform owner enables independent third-party developers to commercialize the platform's periphery by creating ancillary software, known as complements, that augments the platform's functionality and features (Brandenburger and Nalebuff 1996). At the same time, software platforms operate as multisided markets, offering third-party developers access to users through app stores or similar marketplace mechanisms (Parker and Van Alstyne 2005, Constantinides et al. 2018).

The definition of software platforms (see above) of Tiwana et al. (2010) manifests a core-periphery model. The platform core consists of foundational, highly reusable functionality developed by the platform owner, whereas the periphery comprises functionality contributed by third-party developers (Baldwin and Woodard 2009, Yoo et al. 2010, Eaton et al. 2015, Wang 2021). The platform core components constitute a foundation upon which the periphery is built, facilitated by resources and interfaces provided at the boundary, such as Application Programming Interfaces, software development kits, and standards (Ghazawneh and Henfridsson 2013, Foerderer et al. 2019). The core and the periphery are interdependent, a mutual relationship underscored by network effects; the value of the platform to consumers increases with the availability of third-party apps, whereas the attractiveness of the platform to third-party developers depends on the size of the consumer base that can purchase their apps. The periphery consists of niches, which we define as functionally distinct areas of user demand and third-party development.

Extensive research focuses on various decisions made by platform owners regarding the core and the periphery, including the provision of resources at the core-periphery boundary (e.g., Ghazawneh and Henfridsson 2013, Eaton et al. 2015, Karhu et al. 2018, Ye and Kankanhalli 2018), the design of the core to facilitate reuse (e.g., Brunswicker et al. 2019, Meng et al. 2022, Um et al. 2023), and strategies to encourage contributions to the periphery (e.g., Huang et al. 2013, Liang et al. 2019, Foerderer 2020, Hukal et al. 2020). However, less attention, if any, has been devoted to understanding and explaining decisions of platform owners to expand the platform core.

2.2. Platform Core Expansion

Several studies have documented that platform owners intermittently expand the platform core to encompass functionality that previously resided in the periphery, spanning a wide array of software platforms, including mobile apps (Foerderer et al. 2018, Kang et al. 2019, Wen and Zhu 2019), enterprise software (Sarker et al. 2012, Huang et al. 2013), voice assistants (Shi et al. 2023), and social media (Li and Agarwal 2017). We define platform core expansion as the strategic decision of a platform owner to incorporate new functionalities into the platform core that were previously provided by third-party developers in the platform periphery.

Platform core expansions typically focus on two types of software objects: stand-alone applications and features. Stand-alone applications are executable pieces of software that are offered as native apps to end users of the platform and distributed alongside third-party apps (cf. Ghazawneh and Henfridsson 2013). For example, Apple has expanded the core of its iOS platform by introducing Apple Maps as a stand-alone app. In contrast, features are "distinguishing characteristic[s] of a system" that permit new actions or behaviors (IEEE 2008, p. 9) and are integrated into the platform core, enhancing its capabilities. An example of a core expansion through a feature is Apple's integration of flashlight functionality into iOS, enabling users to use the camera light as an electric torch.

Aligned with the core-periphery logic, the owner of a software platform has significant incentives to maximize the overall value generated by the ecosystem. To achieve this, fostering an environment that supports third-party developer creativity and innovation is essential (Yoo et al. 2010, Eaton et al. 2015, Um et al. 2023). Given the complementarity between the core and the periphery in generating platform value, it is critical for platform owners to nurture a symbiotic relationship between these two components (Boudreau 2012, Sarker et al. 2012, Wareham et al. 2014, Eaton et al. 2015). Numerous studies, often based on qualitative research involving software platform managers, have highlighted the deliberate efforts that platform owners make to cultivate relationships with third-party developers based on mutual prosperity (Sarker et al. 2012, Wareham et al. 2014, Huber et al. 2017, Hurni et al. 2021). For example, Sarker et al. (2012) describe how the owner of an enterprise platform carefully engages in relationships with third-party developers to create or even cocreate value. This dynamic forms a delicate interplay that can easily be disrupted by poorly considered decisions regarding engagement at the core-periphery boundary. Early work by Gawer and Henderson (2007) based on longitudinal fieldwork with Intel found that Intel strategically avoided competing with third-party developers to maintain ecosystem stability. Subsequent studies corroborate these findings, observing that when third-party developers anticipate competition with a platform owner, they refrain from joining a platform or safeguard against imitation—thus creating a counter-incentive to contribute value to the software platform ecosystem (Ceccagnoli et al. 2012, Huang et al. 2013, Song et al. 2018).

2.3. Hypotheses

Core expansions enable platforms to increase their overall value by addressing and improving underperforming areas of the periphery. We, therefore, posit that core expansions will concentrate on underperforming niches—aligning with platform owners' intent to develop these areas—while focusing less on well-performing niches.

One strategic driver of value creation arises when ecosystem niches show low user satisfaction. User satisfaction is crucial to platform value as it directly influences user retention and the adoption of the platform by new users (e.g., Xie et al. 2016, Lee et al. 2023). A platform's appeal to users is, to a large extent, determined by users' satisfaction with third-party apps (Yoo et al. 2010, Ghazawneh and Henfridsson 2013). However, managing user satisfaction with third-party apps poses challenges for platform owners given the highly distributed and decentralized nature of development (Eaton et al. 2015), the large number of complements (Coughlan 2004, Boudreau 2012), and the arm's length relationships with third-party developers (Tiwana et al. 2010, Wareham et al. 2014).

One cause of low user satisfaction is a lack of complement quality, which can stem from issues such as erroneous, fraudulent, or low-quality copycat products (Coughlan 2004, Wang et al. 2018). These issues undermine the platform's functionality and user perception, but they can be difficult to detect during app review processes (Lahiri and Dey 2013, Xie et al. 2016, Zhang et al. 2022). Another contributor to low user satisfaction is a lack of understanding. It might take considerable time for complementors to identify user demand for specific features, organize required resources within their constraints, develop the complement, and bring it to the market (Song et al. 2018).

We expect that platform owners are more likely to expand into niches with low levels of user satisfaction for several reasons. First, such expansions provide a clear incentive for users who may have been previously dissatisfied along specific dimensions of the platform to re-engage. By addressing these deficiencies, the platform owner's presence directly improves the perceived quality of the platform, offering a more compelling proposition to potential and existing users. Moreover, the adoption of complements often relies on expectations of usefulness (Cennamo and Santaló 2019). To this end, the platform owner's expansion serves as a credible signal, reducing user uncertainty and enhancing trust in the platform's ability to meet their needs (Hukal et al. 2020). Qualitative evidence supports this notion. For example, Gawer and Cusumano (2014) find how Intel's expansion into the ecosystem niche for Universal Serial Bus (USB) connectors was driven by the need to enhance quality. Intel identified the niche as underdeveloped and lacking value for users, which then drove the decision to intervene.

When platform owners expand into niches with low user satisfaction, they are more likely to do so by introducing a feature into the platform core rather than stand-alone apps. This is because integrated features enhance the platform's existing functionality and therefore, can improve the user experience without requiring additional effort to discover, download, or install a separate app (e.g., Ray et al. 2012). Unlike stand-alone apps, which must be discovered and installed, features can be rolled out to users through platform updates, thus allowing the platform to immediately address unmet needs. This also signals the platform owner's commitment to proactively improving the quality of the ecosystem to users. A further reason is that integrated features enable platform owners to leverage their existing user base more effectively. By embedding solutions directly into the platform, the owner avoids requiring users to engage with additional products. For instance, Intel's enhancement of USB compatibility through platform functionality demonstrates how addressing dissatisfaction through integrated solutions can elevate the perceived value of the platform (Gawer and Henderson 2007). Based on these arguments, we propose Hypothesis 1.

Hypothesis 1. *Software platform owners are more likely to expand into ecosystem niches characterized by low user satisfaction, and these expansions are more likely to be implemented through integrated platform features rather than stand-alone apps.*

Because of network effects—and the resulting importance of a large variety of complements—it is a strategic imperative for platform owners to encourage innovation efforts. Owners of software platforms are concerned with expanding the platform's application spectrum to offer functional advantages over competing platforms (Boudreau 2012, Parker et al. 2017, Hukal et al. 2020). Furthermore, success in emerging technology markets is often based on trial and error and on experimentation (Brown and Eisenhardt 1995). This necessitates encouraging complementors to engage in ongoing development to increase the potential for novel breakthroughs (Tiwana 2015). In other words, it is crucial for platform owners to ensure that complementors frequently enhance their existing third-party apps with new features as well as release entirely new apps.

We propose that software platform owners are more likely to expand into ecosystem niches where the innovation efforts of third-party developers are low. First, core expansion can stimulate greater innovation efforts by triggering competitive responses of complementors

(Tiwana 2015). After all, the platform's expansion into a niche alters the competitive environment, encouraging third-party developers to intensify their innovation efforts to stand out from the platform and capture user attention (e.g., Derfus et al. 2008). Second, the platform's core expansion sets a new standard for users, serving as a reference point against which to judge their apps and further compelling complementors to enhance their products. Finally, platform core expansions can amplify the visibility of a niche, from which both the platform and third-party developers benefit (Li and Agarwal 2017, Foerderer et al. 2018, Song et al. 2018, He et al. 2020). Such attention spillovers also provide third-party developers with valuable feedback for improvement and innovation. For example, Foerderer et al. (2018) observe that the release of Google's first-party app Google Photos increased the overall attention for photo apps, ultimately fostering an environment conducive to innovation by providing user feedback and stimulating demand.

When software platform owners expand into niches with low innovation efforts, they are more likely to do so by releasing stand-alone apps rather than integrating features. First, stand-alone apps allow the platform owner to establish a distinct product in the targeted niche, creating a direct competitor that can serve as a catalyst for competitive responses from complementors. By introducing a stand-alone app, the platform owner sets a new benchmark for quality in the niche, especially when the stand-alone app provides a clear solution to user needs. Second, stand-alone apps act as focal points for user attention as they are presented as independent solutions that are highly visible to users. This increased visibility enables the aforementioned spillover effects. By contrast, we expect that platform owners avoid feature-based core expansions. Features are part of the platform core and will not be able to generate the attention spillovers necessary to stimulate innovation as they lack distinct presence. Furthermore, features, which are integrated into the platform core, do not create the same competitive dynamic. Third-party developers are unlikely to compete directly with built-in features, and users are less motivated to seek third-party alternatives when the functionality is already embedded within the platform. Thus, we formulate Hypothesis 2.

Hypothesis 2. *Software platform owners are more likely to expand into ecosystem niches characterized by low levels of innovation efforts, and these expansions are more likely to be implemented through stand-alone apps rather than integrated platform features.*

The relationship between the platform owner and third-party developers is characterized by asymmetric organizational interdependencies, enabling them to cocreate value through two types of complementarities (Sarker et al. 2012, Huber et al. 2017, Jacobides et al. 2018). First, unique complementarities arise from the functional reliance of complements on the platform core (Baldwin and Woodard 2009). This complementarity is unidirectional as the platform can function without complements, whereas the complements depend on the platform to operate. Second, supermodular complementarities exist when the presence of complements enhances the overall value of the platform ecosystem to its users, creating network effects (Parker and Van Alstyne 2005, Jacobides et al. 2018). Maintaining both complementarities requires preserving the inherent power asymmetry between the platform owner and third-party developers.

Preserving this power asymmetry is crucial for sustaining value creation within the software platform ecosystem (Wareham et al. 2014, Eaton et al. 2015, Leong et al. 2019, Hurni et al. 2022). A shift in power in favor of certain complementors can disrupt this balance and jeopardize value creation (cf. Liu et al. 2025). For example, Eaton et al. (2015) describe how Apple's decision to prohibit Adobe Flash on iOS was driven by the need to prevent a complementor from gaining excessive influence, which could compromise Apple's control over the platform. Platform owners are, therefore, likely to expand into ecosystem niches characterized by high market concentration where one or a few third-party developers dominate. Such expansions allow platform owners to restore power asymmetry, preventing a transition from supermodular to unique complementarities, which could undermine the broader value of the ecosystem (Jacobides et al. 2018).

To address these highly concentrated niches, we expect that platform owners expand the core using features and avoid releasing stand-alone apps for that purpose for three reasons. First, stand-alone apps face adoption barriers. Users must first discover an app before they install it, which is particularly challenging to accomplish in high-concentration niches where attention is concentrated on a few well-established apps. A novel stand-alone app must compete for visibility (e.g., in an app store) and convince users to download the app (e.g., Ray et al. 2012). In contrast, integrated features are available natively and require no discovery, download, or installation. In markets dominated by a few peripheral apps, this seamless access can be a powerful mechanism to erode their market share. Second, even beyond discovery, a stand-alone app faces barriers to adoption in the form of user inertia. Users prefer known workflows, even when alternatives exist (e.g., Polites and Karahanna 2012). Integrated features can subtly redirect behavior without requiring users to actively switch. For example, when Apple embedded Quick Response code scanning into the iOS camera, users no longer needed to open a new app because the function became part of what they were already using. Overcoming user inertia is much harder with a stand-alone app as compared with integrating or adapting a feature. Third, in contrast to stand-alone apps, integrated features are less likely to signal appropriation. Stand-alone apps may be interpreted by developers as a sign that the platform owner is competing directly with third-party offerings as they appear in the store as separate products, carry their own branding, and directly vie for user attention. In contrast, features are embedded into the platform core and typically introduced as part of system updates, subtly reducing reliance on powerful complementors without requiring overt, head-to-head competition. This distinction matters because complementors may reduce their innovation efforts if they perceive a platform owner's expansions as a threat (Ceccagnoli et al. 2012, Huang et al. 2013). Based on these arguments, we propose Hypothesis 3.

Hypothesis 3. *Software platform owners are more likely to expand into ecosystem niches with higher concentration, and these expansions are more likely to be implemented through integrated platform features rather than stand-alone apps.*

3. Empirical Context, Method, and Data

3.1. Empirical Context: Mobile Platform Ecosystem Apple iOS

We test the hypotheses using the Apple iOS software platform as our empirical context. Apple iOS is a mobile operating system for various devices of Apple (e.g., iPhone and iPad). It was released in June 2007 together with the first-generation iPhone. In July 2008, Apple opened iOS to third-party developers, allowing them to develop add-ons for the operating system in the form of *apps*. The apps are distributed and sold over the Apple App Store. Since then, Apple has occasionally expanded the core of its platform either by releasing stand-alone apps or by integrating new features into the operating system iOS. Since September 2019, iOS refers exclusively to the iPhone operating system, as Apple separated the iPad version.

The Apple iOS platform is well suited as an empirical context to test our hypotheses for several reasons. First, Apple iOS is one of the largest and most influential software platforms and comprises thousands of developers around the globe, therefore representing a highly relevant setting (e.g., Qiu et al. 2017). For example, in 2022, third-party apps generated over U.S. $1.1 trillion in total billings, matching the Netherlands' gross domestic product (Apple 2023). Second, the platform provides a distinct advantage in terms of data availability. Given that iOS was introduced in 2007, we are able to observe a reasonable number of core expansions. Moreover, we have access to monthly panel data over a multiyear period on all niches of the iOS app ecosystem, which enables a comprehensive analysis. Third, Apple iOS has been frequently studied in previous research, which allows for incorporating established measures and data filtering procedures and eases comparability (e.g., Wang et al. 2018, Foerderer 2020).

3.2. Identifying Core Expansions

We begin by compiling a list of Apple's core expansions for the iOS platform between 2012 and 2020.[3] As core expansions, we consider all apps and features that Apple released for the iOS platform. As a first step, we identified Apple's app releases using data from AppMonsta, an analytics company for mobile app stores. We obtained a list of all apps released by Apple and its subsidiaries together with further information, such as the release date. Next, we collected data on platform features by manually analyzing the official release notes of each update of the iOS platform. The release notes list all changes made to the platform, including the addition of new features. We condensed the release notes into a list of distinct changes that were made to the platform. We then removed any changes that represented bug fixes, maintenance updates of existing features, or modifications targeting first-party apps. This procedure resulted in a list of all core expansions by Apple.

To identify the ecosystem niche that is affected by a core expansion, we use the App Store's category system following prior research (Foerderer et al. 2018, Wen and Zhu 2019). The App Store classifies apps according to their functionality into different categories (e.g., *Business*, *Music*, and *Weather*). This approach seems to be well suited for the following reasons. First, apps within the same category are highly similar in terms of their functionality and compete against each other for visibility (e.g., Wen and Zhu 2019, Li et al. 2022). Also, within categories, development requirements are similar (e.g., regarding hardware use and data access), whereas they vary considerably across categories (Ghose and Han 2014, Li et al. 2022). Second, this approach is in line with extant research, which has extensively relied on the category system of the App Store to facilitate comparison or to create peer groups (e.g., Foerderer et al. 2018, Zhu and Liu 2018, Wen and Zhu 2019, He et al. 2020). Finally, categories are accurate in terms of reflecting an app's functionality. App developers are required to assign a unique category that best describes the purpose and main features for each app. Although app developers initially decide on the category for their app, Apple checks whether the classification is accurate and has the final word.[4] Technically, an app can set a primary category and a secondary category. We use the primary app category because it is considered by both the developer and Apple to exhibit the highest fit with regard to the app's characteristics and functionality.

To map Apple's core expansions to categories, we proceed as follows. For Apple apps, determining the category is straightforward because they are assigned to a category, similar to third-party apps. We obtained the information about Apple apps' categories from AppMonsta as well. For features, a more elaborate process is necessary. We began by manually analyzing Apple's description of the platform feature in the release notes. In particular, we compared the feature description with Apple's official developer guidelines for choosing the appropriate category for their app (Apple 2024). Through reading, comparing, distinguishing, and interpreting, we assigned the category that shows the closest content fit. For example, we assigned the feature battery health, which provides information about an iPhone's battery capacity and usage, to the category *Utilities*, which comprises apps that "enable the user to solve a problem or complete a specific task" (Apple 2024). Another example is *Audio recognition service via Siri (Shazam Support)*, which provides users with information on a song currently playing. We assigned this feature to the category *Music*, which labels apps "for discovering, listening to, recording, performing, or composing music, and that are interactive in nature" (Apple 2024). The full mapping as well as empirical examples of the coding are in Tables A.1 and A.2 in the Online Appendix. The resulting variables are *Core expansion (app)*, which is one if the expansion manifested in the form of an app release by Apple and zero otherwise, and *Core expansion (feature)*, which is one if the expansion manifested in the form of a platform feature and zero otherwise.

Table 1 shows Apple's core expansions by category.[5] In total, we identified 62 core expansions between 2012 and 2020, comprising 34 app releases and 28 feature releases. Of the 21 relevant categories, 15 experienced a core expansion. Most often affected was the niche *Utilities*, which contains apps that provide additional basic functionality for users, such as calculators, flashlights, or password managers. This is followed by *Productivity* and *Health and Fitness*. The core expansions are spread out over time, a favorable characteristic for our forthcoming statistical analysis approach.

3.3. Measurement of Niche Characteristics

Next, we collected the data on the niche characteristics (i.e., *User satisfaction*, *Innovation efforts*, and *Concentration*). The raw data set contains weekly snapshots of all apps in the Apple App Store between 2012 and 2020, which we obtained from AppMonsta. It comprises all information displayed in the App Store on these apps, including their rating, price, and updates.

We filtered the data as follows. First, we excluded games from the sample to increase comparability. In contrast to other apps, games are an artistic creation as well as an entertainment product. Games have different development costs, audiences, and revenue models, which hinder a comparison with apps; additionally, Apple has never expanded into this category. We also excluded apps from the kids category because it was more a curated collection than a traditional category and exhibited overlaps with games, education, and entertainment. Second, to further increase comparability, we solely retained English-language apps in the sample (i.e., as determined by the user language attribute and the language of the app description).

Table 1. Core Expansions Between 2012 and 2020 by Category

Category	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total
Books										0
Business		x				x	x	x		4
Education					x		x			2
Entertainment	x		x		x	x				4
Finance	x									1
Food and drink										0
Health and fitness			x	x		xx		x	x	6
Lifestyle					x		xx			3
Medical										0
Music			x	x			x	x		4
Navigation	x									1
News	x			xx			x			4
Photo and video										0
Productivity			xx	x		x	x	x		6
Reference										0
Shopping										0
Social networking					xxxx					4
Sports	x									1
Travel				x		x				2
Utilities		xxx	xx	xxxxx	xx	xx	xx	xxx		19
Weather									x	1
Total	5	4	7	11	9	8	9	7	2	62

Notes. Apple's core expansions between 2012 and 2020 are given by App Store category. Each x denotes one core expansion.

Third, we aggregated apps from categories *Developer Tools* with *Utilities*, *Graphics and Design* with *Photo and Video*, and *Magazines and Newspapers* with *News*. These categories show relatively few apps, and therefore, to ensure comparability with the rest of the categories, we merged them. Fourth, we removed nonprofessional apps from the sample. The App Store also lists nonprofessional apps (for instance, those developed by hobbyists or students), and the behavior of these developers differs considerably from that of professional developers (Qiu et al. 2017, Boudreau 2018). To remove nonprofessional apps, we followed existing research and dropped apps with zero ratings (Kang et al. 2019, Lueker et al. 2022). In addition, a very brief app description hinted at nonprofessional apps, and therefore, we dropped apps with descriptions shorter than 250 characters (D'Heureuse et al. 2012, Harman et al. 2012, Boudreau 2018).

We then collapsed the data at the category level and created the variables.[6] To measure *User satisfaction*, we followed extant research in our context and used the valence of user ratings (e.g., Wen and Zhu 2019). The App Store allows users to rate apps on a five-star scale, with more stars indicating a better rating. The variable *User satisfaction* holds the average user rating of apps in category i. For *Innovation efforts*, we followed extant research that has inferred innovation from app update behavior (e.g., Tiwana 2015, Foerderer et al. 2018, Wen and Zhu 2019). The decision to innovate an app is a strategic one and should not be determined by behavior at one single point in time. We, therefore, followed existing research and use the frequency of app updates (e.g., Tiwana 2015, Wen and Zhu 2019). The variable *Innovation efforts* contains the average number of updates of apps (since their release) in category i. We normalized the app update frequency by an app's age in months to adjust for older apps having more time to release updates. We log transformed the variable to account for skewness. Regarding *Concentration*, there exist no prior measures readily available for our empirical context. We, therefore, turned to research that sought to understand the concentration of industries, where the dominant measure has been the four-firm concentration ratio in terms of the market share of the four largest firms in an industry (Cohen and Levin 1989, Scherer and Ross 1990). We transferred this logic to our context and defined *Concentration* as the market share of the top four apps in a category. Because neither market shares nor download statistics were publicly available, we followed existing research and approximated the market share from the total number of times that an app had been rated by users in terms of the quantity of ratings (e.g., Ghose and Han 2014, Foerderer 2020, Deng et al. 2023). Based on this, *Concentration* of category i is the total count of ratings of the top four apps divided by the total count of ratings of all other apps in a niche. To address skewness, we log transformed the variable.

Relating niche characteristics at time t to core expansion at the very same time t could be invalid because it does not account for the fact that Apple likely decided to enter the niche before t. This is because core expansion requires time: for example, for defining the requirements, developing the user interface and logic, testing, and rollout. Although Apple does not disclose details about its product development process, information from market observers and news websites suggests a cycle between 6 and 12 months given a major update release cycle of around one year (MacWorld 2024), which also corresponds to typical industry estimates for app development (e.g., Forbes 2022). In addition, given the extensive network of suppliers, partners, and employees involved in Apple's development, there is the possibility of information leakage. Rumors and speculations often circulate within tech circles and media outlets (e.g., Economist 2012, TechCrunch 2023). These leaks can influence the behavior of app developers; for instance, they might reduce their investments into their apps, which further distorts the estimation. To overcome, we measured *User satisfaction*, *Innovation efforts*, and *Concentration* long before the actual core expansion took place. We measured niche characteristics over a 5-month window, which starts 11 months before the core expansion (i.e., the release date of the app or feature) and ends 7 months before the expansion (see Figure A.1 in the Online Appendix for an illustration). In Section 5, we demonstrate that the results of the hypotheses tests are consistent when varying the time window. We used a window of several months instead of a snapshot in order to avoid biases from a one-time observation and in order to use fixed effects to control for unobserved confounders as we explain in the following. For observations that experienced a core expansion, we coded the niche characteristics for the next five months as unobserved (missing) in order to avoid carryover effects to subsequent core expansions. The final sample contained 2,324 category-month observations.

Table 2 shows the descriptive statistics. Table A.3 in the Online Appendix reports the correlation matrix.

3.4. Estimation Model

We tested the hypotheses by relating characteristics of the ecosystem niche (i.e., measured before the expansion) to the fact of whether the niche experienced a core expansion (Angrist and Pischke 2009):

$$Y_{i,t} = \beta_0 + \beta_1 X_{i,t\ (pre)} + \beta_k Controls_{i,t\ (pre)} + \vartheta_i + \phi_t + \epsilon_{i,t}, \tag{1}$$

where $Y_{i,t}$ is the dependent variable in terms of *Core expansion (app)* and *Core expansion (feature)* observed for category i in month t. X refers to the particular

Table 2. Variables and Descriptive Statistics

	Variable	Description	Mean	SD	Min	Median	Max
1	Core expansion (app)	1 if category *i* is affected by a core expansion via app release and otherwise 0	0.06	0.23	0.00	0.00	1.00
2	Core expansion (feature)	1 if category *i* is affected by a core expansion via feature integration and otherwise 0	0.04	0.20	0.00	0.00	1.00
3	User satisfaction	Average user rating of apps in category *i*	3.60	0.23	0.29	3.59	4.78
4	Innovation efforts	Average update frequency defined as the count of updates of apps normalized by *Age* in category *i*	5.80	0.23	0.00	4.90	22.65
5	Concentration	Number of user ratings of the top 4 apps divided by the total number of ratings of all apps in category *i*	0.31	0.14	0.07	0.28	1.00
6	Number of apps	Number of apps in category *i*	7,408.86	4,416.91	1.00	6,209.50	23,988.00
7	Firm size	Average number of total apps published by developers in category *i*	27.14	24.72	3.80	21.23	280.29

Notes. Summary statistics are based on the sample ($N = 2{,}324$). SD, standard deviation.

independent variable associated with Hypothesis 1, Hypothesis 2, and Hypothesis 3 (i.e., *User satisfaction*, *Innovation efforts*, and *Concentration*, respectively), whereby the coefficient of interest is $ß_1$. We included control variables to account for potential time-varying confounders but also, to increase the accuracy of the obtained estimates as represented by the term *Controls*. Our choice of the control variables seeks to account for theoretically relevant relationships and at the same time, to avoid multicollinearity with the predictors of the hypotheses. We controlled for the number of apps (*Number of apps*) in category *i* to adjust the estimates for growth or decline in categories (Xue et al. 2019). We also controlled for firm size, which we inferred from the average number of apps published by developers in category *i* (*Firm size*). Further, we controlled for unobserved heterogeneity within categories (υ_i) and time (Φ_t) by including fixed effects. Category fixed effects mitigate static variations within categories over time, ensuring that category-specific differences, such as development costs or revenue models, do not confound estimations. For instance, they help to account for variations in development costs between categories, like *Utilities* (relatively lower development costs) versus *Medical* (relatively higher development costs). Further, category fixed effects help account for differences in revenue models. In some categories, revenue models are mostly based on advertisement (e.g., *Social Networking*), whereas others predominantly rely on subscriptions (e.g., *Music*). Moreover, by incorporating time-unit fixed effects, we controlled for static variations within these temporal units. They, for instance, mitigate demand spikes around events like Christmas or variations across years. Consequently, the inclusion of time fixed effects provided additional control over the drivers of core expansion.

We estimated the model using two separate conditional logit models. Conditional logistic analysis differs from regular logistic regression in that the data are grouped and the likelihood is calculated relative to each group; that is, a conditional likelihood is used (Greene 2018, chapter 18). This modeling choice closely maps our theoretical conceptualization in terms of integrated features and stand-alone apps representing two distinct forms of core expansion rather than mutually exclusive choices among a single set of options. Moreover, the conditional logit estimator allows for the accounting of the binary structure of the dependent variable, and it can incorporate unit and time fixed effects.[7] We estimated the regressions with Stata 17. We used the Stata package clogit to estimate the conditional logit models, which is identical in our case to using the standard Stata command but computationally more efficient. Category fixed effects were implemented via the group attribute; time fixed effects were implemented by adding dummies.[8]

4. Results

4.1. Descriptive Evidence

Our main argument laid out in the hypothesis development is that core expansion is targeted toward underperforming niches and helps to increase the overall health of the ecosystem. Before delving into the hypothesis tests, we seek to build intuition for the subsequent hypothesis tests and to ground our interpretation of the results in observable patterns by reporting descriptive evidence.

First, software platforms usually earn a considerable share of their revenue from a commission model, where the commission rates are much higher than on pure transaction platforms. For example, during our observation period, Apple charged a commission of 30% on all app sales or in-app transactions. In some cases, such as for small developers, a reduced rate of 15% has been applied in recent years. Moreover, Apple earned through brokering in-app advertisement as well as sponsored search results in the App Store. This provides software platforms, such as Apple, an incentive to enlarge the overall pie of value (and take a share) rather than focusing on directly selling complements. Supporting this argument is the fact that as of 2020, the App Store was home to about 2 million apps. The overall revenue generated by apps in the App Store has more than tripled in size between 2015 (U.S. $21 billion) and 2020 (U.S. $64 billion) as measured by estimates of total billings from third-party developers (Caminade and von Wartburg 2022). Because Apple takes a share of this revenue, the firm's revenues from the App Store have likely risen over that period correspondingly. Second, Apple has not expanded into particularly profitable niches as one would expect if the core expansions were not driven by the goal to enhance the ecosystem. For example, Apple decided to abstain from entering the gaming app market, despite its substantial profitability and the company's capacity to do so. The gaming market has been the most lucrative segment of the App Store, accounting for 62% of global App Store spending (Statista 2023). For several further markets, Apple's core expansions have directly supported third parties in creating value. For example, in *Books* (comprising 2% of the global App Store spending), Apple has supported e-book collection, reading, and purchases with its *Apple Books* app. For several further profitable markets, no Apple app existed. For example, Apple has not expanded into the *Dating* (e.g., Tinder and Bumble), *Travel* (e.g., Booking and Kayak), or *Food* (e.g., NYT Cooking and BBC Good Food) category. Finally, complementary hardware sales (iPhone, iPad, Watch, and Mac) benefitted from the availability of third-party apps. For example, Apple's iPhone revenues have more than doubled over the observation period, rising from U.S. $23 billion in 2012 (quarter 1) to U.S. $55 billion in 2020 (quarter 1) (Statista 2024).

4.2. Hypotheses Tests

Table 3 summarizes the results of the hypotheses tests as estimated from Equation (1). Column (1) in Table 3 indicates the results for core expansion through the release of a stand-alone app, and column (2) in Table 3 indicates the results for core expansion through the integration of a platform feature. To ease readability and for reasons of logical consistency, we invert the coefficients for *User satisfaction* (Hypothesis 1) and *Innovation efforts* (Hypothesis 2). This means that for these predictors, a more positive coefficient corresponds to a lower value of the predictor in our model. Moreover, to ease readability, we mark the coefficients corresponding to the hypotheses in bold in Table 3.

We begin with the test for Hypothesis 1. We begin with column (2) in Table 3 because it reports the hypothesized association between *User satisfaction* and *Core expansion (feature)*. In column (2) in Table 3, we observe a statistically significant positive coefficient on *(inverted) User satisfaction*. The positive coefficient on *(inverted) User satisfaction* suggests that lower user satisfaction in a niche is associated with higher odds of core expansion through a feature, which is in line with Hypothesis 1. More specifically, a one-standard-deviation-lower *User satisfaction* increases the odds of a core expansion with a feature by a factor of $e^{4.081} = 59.204$. Moreover, in line with Hypothesis 1, we observe a positive but insignificant coefficient on *(inverted) User satisfaction* in column (1) in Table 3. Taken together, this evidence confirms Hypothesis 1.

We proceed with the test for Hypothesis 2. We begin with column (1) in Table 3, which shows the hypothesized association between *Innovation efforts* and *Core expansion (app)*. In column (1) in Table 3, we observe a statistically significant positive coefficient on *(inverted) Innovation efforts*. The positive coefficient on *(inverted) Innovation efforts* suggests that lower innovation efforts in an ecosystem niche are associated with higher odds of a core expansion with an app, which confirms what Hypothesis 2 had suggested. In particular, a one-standard-deviation-lower *Innovation efforts*

Table 3. Results of the Hypotheses Tests

	DV = *Core expansion (app)*	DV = *Core expansion (feature)*
	(1)	(2)
(inverted) User satisfaction	1.291	**4.081*****
	(0.704)	**(0.954)**
(inverted) Innovation efforts	**3.683***	−4.333**
	(1.584)	(1.431)
Concentration	−1.564***	**1.901*****
	(0.457)	**(0.506)**
Controls		
Number of apps	−0.500	−0.279
	(1.050)	(0.978)
Firm size	−0.287	1.015**
	(0.396)	(0.383)
Fixed effects		
Unit (category)	x	x
Time (month)	x	x
Log likelihood	−223.8	−133.8

Notes. Coefficients for *User satisfaction* and *Innovation efforts* are inverted to align the interpretation with regard to the formulation of the hypotheses. For example, in column (2), the lower the *User satisfaction* is, the more likely a core expansion is. Conditional coefficients corresponding to the variables tested in Hypotheses 1–3 are presented in bold to facilitate interpretation. Conditional logit estimates are given. Standardized coefficients in log-odds notation are shown. Standard errors are in parentheses. Observations are in category-months. Parameters are estimated using the sample of $N = 2{,}324$ category-months, with 1,189 category-months effectively entering the estimation in column (1) and 814 category-months effectively entering the estimation in column (2). DV, dependent variable. "x" indicates that the respective fixed effects have been included.

*Significance at the 5% level; **significance at the 1% level; ***significance at the 0.1% level.

increases the odds of a core expansion with an app by a factor of $e^{3.683} = 39.766$. In column (2) in Table 3, we detect a statistically significant negative coefficient on *(inverted) Innovation efforts*. The negative coefficient on *(inverted) Innovation efforts* suggests that lower user satisfaction in a niche is associated with lower odds of core expansion through a feature, which further confirms Hypothesis 2. A one-standard-deviation-lower *Innovation efforts* decreases the odds of a core expansion with a feature by a factor of $e^{-4.333} = 0.013$ on average. We conclude that Hypothesis 2 is supported.

Finally, we test for Hypothesis 3. We begin with column (2) in Table 3 because it reports the hypothesized association between *Concentration* and *Core expansion (feature)*. In column (2) in Table 3, we observe a positive coefficient on *Concentration*. The coefficient is statistically significant. The positive coefficient on *Concentration* suggests that higher concentration in a niche is associated with higher odds of core expansion through a feature, which confirms Hypothesis 3. More specifically, a one-standard-deviation-higher *Concentration* increases the odds of a core expansion with a feature by a factor of $e^{1.901} = 6.693$ on average. In line, in column (1) in Table 3, we observe a negative and statistically significant coefficient on *Concentration*. The negative coefficient on *Concentration* suggests that the higher the concentration is in an ecosystem niche, the lower the odds are of a core expansion with an app, which is also in line with Hypothesis 3. More precisely, a one-standard-deviation-higher *Concentration* decreases the odds of a core expansion with an app by a factor of $e^{-1.564} = 0.209$. Taken together, we conclude that the data support Hypothesis 3.

5. Robustness

5.1. Endogeneity

5.1.1. Omitted Variable Bias. We conducted several robustness checks to rule out endogeneity biasing our estimates. The primary potential source of endogeneity is the presence of omitted variables (Rutz and Watson 2019). If our model omits important variables that are correlated with the probability of a core expansion in a category and the included variables, then there is the possibility of omitted variable bias, which would render our hypotheses tests potentially spurious. To meet this challenge, our model included fixed effects for the panel unit and time to account for time-invariant omitted variables and further control variables suggested by the literature (e.g., Xue et al. 2019).

We conducted several additional tests to approach this issue. In a first test, we sought to reduce omitted variable bias through enhancing the comparability between categories before a core expansion using an approach in the spirit of matching techniques.[9] We compare only those categories that have not experienced a core expansion at the time of observation. By doing so, we strived to enforce similar levels of an unknown confounder that might correlate with a category not having experienced a core expansion yet. The results are reported in columns (1) and (2) in Table 4, where we enforce that a category is not used for comparison if it has seen an expansion within the past two years. The analysis corroborates the results of the hypotheses tests. In further analyses, not reported for the sake of brevity, the results were

Table 4. Checks on Omitted Variable Bias

	Matching		Control function approach	
	DV = *Core expansion (app)*	DV = *Core expansion (feature)*	DV = *Core expansion (app)*	DV = *Core expansion (feature)*
	(1)	(2)	(3)	(4)
(inverted) User satisfaction	2.328	**3.321****	−2.215*	**−5.320*****
	(1.319)	**(1.038)**	(0.905)	**(1.245)**
(inverted) Innovation efforts	**15.987*****	−6.491**	**−1.085**	−5.891***
	(3.533)	(1.840)	**(2.264)**	(1.662)
Concentration	−5.322***	**2.164****	−1.802***	**2.271*****
	(1.186)	**(0.661)**	(0.500)	**(0.590)**
Controls	x	x	x	x
Fixed effects	x	x	x	x
Log likelihood	−103.3	−91.8	−210.8	−121.0

Notes. Coefficients for *User satisfaction* and *Innovation efforts* are inverted to ease interpretation with regard to the formulation of the hypotheses. The coefficients corresponding to the hypotheses are marked in bold to ease readability. Conditional logit estimates are given. Standardized coefficients in log-odds notation are shown. Standard errors are in parentheses. Observations are in category-months. Parameters are estimated using the sample of $N = 2{,}324$ category-months, with 1,189 category-months effectively entering the estimation in columns (1) and (3) and 814 category-months effectively entering the estimation in columns (2) and (4). DV, dependent variable. "x" indicates that controls and fixed effects have been included.

*Significance at the 5% level; **significance at the 1% level; ***significance at the 0.1% level.

consistent when setting the threshold for longer periods (four years).[10]

In a second test and in the absence of an instrumental variable estimator for logit models with endogenous continuous regressors, such as ours, we follow the recommendation of the methodological literature and implement the control function method to further account for endogeneity (Blundell and Powell 2004, Petrin and Train 2010). We follow prior research in information systems (e.g., Benaroch and Chernobai 2017, Saldanha et al. 2020, Wu et al. 2021) and construct the control function using lags of the regressors. The idea is that these lagged variables create exogenous variation by separating the cumulative effects of past category characteristics from immediate unobserved factors that might align with Apple's expansion. For example, past *User satisfaction* captures established consumer preferences and app quality, which influence current levels of that variable within a category (for instance, through repeated use or loyalty) yet will only influence Apple's expansion decisions through their influence on current *User satisfaction*. Crucially, these lagged variables introduce exogenous variation by isolating the cumulative impact of prior category dynamics from immediate, unobserved factors that could correlate with Apple's expansion.[11] The results using the control function approach are reported in columns (3) and (4) in Table 4. The resulting coefficients are consistent in direction, although the coefficient on *Innovation efforts* drops below the significance level. We alternatively estimated the model using the same regressors and instruments using Stata's instrumental variable probit estimator (ivprobit), which likewise confirms the hypotheses. The results are reported in Table A.4 in the Online Appendix.

Last, we conducted a sensitivity analysis to quantify how endogeneity—manifested through an unobserved confounding variable—could turn the hypotheses tests insignificant. We follow the so-called robustness of inference to replacement (RIR) approach (Frank et al. 2013, Xue et al. 2019, Busenbark et al. 2022). RIR estimates how much of a data set had to be altered to hypothetically invalidate the inference, and it is analogous to the impact threshold for a confounding variable analysis adapted for dichotomous dependent variables (Frank et al. 2013, Huang et al. 2018, Whitaker et al. 2019).

The results of the procedure demonstrate that for Hypothesis 1, an omitted variable would need to overturn the relationship in 54.10% of the cases (i.e., more than half of the data set), which seems unlikely. For Hypothesis 2, an omitted variable would have to overturn 35.17% of the cases, and for Hypothesis 3, an omitted variable would have to overturn 47.70% of the cases. Taken together, an omitted confounder would need to overturn between one third and one half of the data set to invalidate the results. Few studies can currently serve as benchmarks; among them, Gleasure (2024) reports values ranging from 20.26% to 50.99% for its Ordinary Least Squares (OLS) models, and Wang et al. (2023) report values between 27.90% and 53.60%. Our values fall within the range of these and therefore, appear sufficiently robust.

5.1.2. Functional Form. Another source of endogeneity bias can arise from the incorrect specification of a model because of the use of an inappropriate functional form. The literature recommends constructing this relationship on the basis of a logit model, which we have followed. We also estimated the results using OLS (i.e., resulting in a so-called linear probability model).[12] The outcome of this exercise is reported in Table 5. The hypotheses tests are consistent concerning the direction of the coefficients, but the coefficients associated with Hypothesis 1 (*User satisfaction*) and Hypothesis 3 (*Concentration*) fall below statistical significance.

5.1.3. Measurement Error. Aside from omitted variable bias, another source of endogeneity arises when the explanatory variables of a model exhibit measurement errors, which we assessed in four robustness checks.

First, measurement error could arise from developers changing the categories of their apps. Apple validates developers' changes to ensure that they are appropriate. Given the large number of apps within

Table 5. Alternative Estimation Using a Linear Probability Model

	DV = *Core expansion (app)*	DV = *Core expansion (feature)*
	(1)	(2)
(inverted) User satisfaction	0.160 (0.305)	**0.361** **(0.259)**
(inverted) Innovation efforts	**0.158***** **(0.057)**	−0.042 (0.050)
Concentration	−0.089*** (0.024)	**0.022** **(0.020)**
Controls	x	x
Fixed effects	x	x
Estimator	LPM	LPM
Adjusted R^2	0.0379	0.0381

Notes. Coefficients for *User satisfaction* and *Innovation efforts* are inverted to ease interpretation with regard to the formulation of the hypotheses. The coefficients corresponding to the hypotheses are marked in bold to ease readability. Fixed-effects OLS estimates are given. Standard errors are in parentheses. Observations are in category-months. Parameters are estimated using the sample of $N = 2{,}324$ category-months, with 1,189 category-months effectively entering the estimation in column (1) and 814 category-months effectively entering the estimation in column (2). DV, dependent variable; LPM, linear probability model. "x" indicates that controls and fixed effects have been included.

***Significance at the 0.1% level.

each category, the impact of a small number of apps changing categories is likely negligible for our estimation. Nevertheless, we assessed the impact of this possibility. We created a second data set, departing from the data on the app level as before but excluding apps from the sample that change their category. Using this data set, we re-estimated the model. Columns (1) and (2) in panel A of Table 6 document the results. The coefficients are consistent in direction and significance with our main results. Second, we assessed the sensitivity of our results to variations in the pre-event window used for measuring niche characteristics. We re-estimated the model using alternative windows (from 12 to 8 months before the core expansion and from 11 to 6 months). The results are reported in columns (3)–(6) in panel A of Table 6. The results are consistent with the hypotheses tests in terms of the direction of the coefficients. However, for Hypothesis 2 (*Innovation efforts*), the coefficient falls below the level of statistical significance. Third, we explored variations in the measure for *Concentration* by calculating it based on the top 8 and top 20 apps within a category. The results are reported in columns (1)–(4) in panel B of Table 6. We conclude that our hypotheses tests are consistent across these variations. This provides further support for the robustness of our findings across different variations of *Concentration* based on this measure. Last, to bolster our choice of the four-firm concentration ratio as a measure of *Concentration*, we used the widely adopted Herfindahl–Hirschman

Table 6. Tests for Measurement Error

Panel A: Measurement of niche characteristics						
	Apps that change categories excluded		Alternative time window [−11, −6]		Alternative time window [−12, −8]	
	DV = *Core expansion (app)*	DV = *Core expansion (feature)*	DV = *Core expansion (app)*	DV = *Core expansion (feature)*	DV = *Core expansion (app)*	DV = *Core expansion (feature)*
	(1)	(2)	(3)	(4)	(5)	(6)
(inverted) User satisfaction	1.541*	**3.690***	1.028	**2.911***	1.358	**2.891**
	(0.640)	**(0.905)**	(0.653)	**(0.819)**	(0.782)	**(0.982)**
(inverted) Innovation efforts	**2.967***	−3.046**	**2.094**	−3.800**	**0.919**	−3.872**
	(1.276)	(1.121)	**(1.503)**	(1.221)	**(1.893)**	(1.419)
Concentration	−1.664***	**1.934***	−1.343***	**1.831***	−1.385**	**1.947***
	(0.460)	**(0.511)**	(0.397)	**(0.470)**	(0.456)	**(0.529)**
Controls	x	x	x	x	x	x
Fixed effects	x	x	x	x	x	x
Log likelihood	−223.4	−134.4	−284.8	−178.7	−234.1	−145.4
Panel B: Alternative measurement of *Concentration*						
	Measurement of *Concentration* based on top 8 apps		Measurement of *Concentration* based on top 20 apps		Measurement of *Concentration* using Herfindahl–Hirschman Index	
	DV = *Core expansion (app)*	DV = *Core expansion (feature)*	DV = *Core expansion (app)*	DV = *Core expansion (feature)*	DV = *Core expansion (app)*	DV = *Core expansion (feature)*
	(1)	(2)	(3)	(4)	(5)	(6)
(inverted) User satisfaction	1.266	**3.951***	1.176	**3.934***	1.232	**4.454***
	(0.721)	**(0.964)**	(0.693)	**(0.962)**	(0.719)	**(0.972)**
(inverted) Innovation efforts	**3.933***	−4.631**	**4.059**	−4.370**	**3.724***	−4.195**
	(1.609)	(1.455)	**(1.562)**	(1.462)	**(1.590)**	(1.431)
Concentration	−2.227***	**2.189***	−2.231***	**2.070***	−1.510**	**2.325***
	(0.565)	**(0.511)**	(0.608)	**(0.574)**	(0.470)	**(0.556)**
Controls	x	x	x	x	x	x
Fixed effects	x	x	x	x	x	x
Log likelihood	−221.3	−131.7	−222.6	−135.5	−224.4	−130.1

Notes. Predictors for *User satisfaction* and *Innovation efforts* are inverted to ease interpretation with regard to the formulation of the hypotheses. The coefficients corresponding to the hypotheses are marked in bold to ease readability. Conditional logit estimates. Standardized coefficients in log-odds notation. Standard errors in parentheses. Observations are category-months. Panel A estimations use the sample of $N = 2{,}324$ category-months, with 1,189 category-months effectively entering the estimation in Column (1), 814 in Column (2), 1,271 in Column (3), 954 in Column (4), 1,242 in Column (5), and 925 in Column (6). Panel B estimations use the sample of $N = 2{,}324$ category-months, with 1,189 category-months effectively entering the estimation in Columns (1), (3), (5), and 814 in Columns (2), (4), (6). DV, dependent variable. "x" indicates that controls and fixed effects have been included.

*Significance at the 5% level; **significance at the 1% level; ***significance at the 0.1% level.

Index (HHI) as an alternative (Scherer and Ross 1990, Mithas et al. 2013, Pan et al. 2018). The HHI assesses concentration by accounting for the market share distribution across all competitors rather than focusing solely on the top firms. Using the HHI, we re-estimated the models. Columns (5) and (6) in panel B of Table 6 report the results, which are consistent with the hypotheses and therefore, further corroborate the measurement of niche concentration.[13]

5.2. Multicollinearity

The levels of *User satisfaction*, *Innovation efforts*, and *Concentration* could be correlated, causing multicollinearity. High multicollinearity can inflate standard errors, making it difficult to discern the individual effects of these variables on core expansion. To assess this issue, we followed the standard procedure in the literature and calculated variance inflation factors (VIFs) (Cohen et al. 2003, Hair et al. 2006). Multicollinearity is considered present when the VIF exceeds a value of 10 (Cohen et al. 2003, Hair et al. 2006). The VIFs for the variables in our model are far below that threshold: $VIF_{User\ satisfaction} = 1.74$, $VIF_{Innovation\ efforts} = 1.77$, and $VIF_{Concentration} = 1.17$. Thus, multicollinearity is not biasing our estimates. In a complementary test reported in Table A.5 in the Online Appendix, we further assess concerns over multicollinearity by reporting a stepwise test of the hypotheses. The coefficients are consistent in direction and significance, further refuting concerns over multicollinearity biasing our tests.

5.3. Falsification Checks

A few rival explanations exist that we sought to exclude in a series of falsification checks. First, the results could be driven by an imbalance in the number of expansions across categories. As evident from Table 1, the category *Utilities* was most affected by core expansions. One concern, consequently, could be that the findings are driven by an overrepresentation of these core expansions in our sample. In a further check, we, therefore, excluded core expansions into the category *Utilities* from the data entirely and re-estimated the model. Columns (1) and (2) in Table 7 report the results. We find that the hypotheses are confirmed; thus, the results are not driven by core expansions into the category *Utilities* alone but reflect a larger underlying relationship present in the data.

Another rival explanation could be that the results are distorted by carryover effects in terms of past core expansions influencing the likelihood that a niche experiences a core expansion in the future. To assess it, we included a control that considers prior core expansions in a category. More specifically, *Core expansion*$_{pre}$ is a binary variable indicating whether category i was affected by a core expansion—app or feature—within the last two years. Columns (3) and (4) in Table 7

Table 7. Falsification Checks

	Core expansions into *Utilities* excluded		Control for carryover effects	
	DV = *Core expansion (app)*	DV = *Core expansion (feature)*	DV = *Core expansion (app)*	DV = *Core expansion (feature)*
	(1)	(2)	(3)	(4)
(inverted) User satisfaction	1.027 (0.750)	**2.795**** **(1.050)**	1.545* (0.731)	**4.089***** **(0.956)**
(inverted) Innovation efforts	**4.539**** **(1.701)**	−6.081*** (1.684)	**1.810** **(1.705)**	−4.326** (1.431)
Concentration	−1.716*** (0.471)	**2.243***** **(0.595)**	−1.225** (0.457)	**1.906***** **(0.508)**
Core expansion$_{pre}$			−7.251 (392.226)	0.039 (0.267)
Controls	x	x	x	x
Fixed effects	x	x	x	x
Log likelihood	−204.0	−107.2	−207.3	−133.8

Notes. Predictors for *User satisfaction* and *Innovation efforts* are inverted to ease interpretation with regard to the formulation of the hypotheses. The coefficients corresponding to the hypotheses are marked in bold to ease readability. There are smaller numbers of observations in columns (1) and (2) because of excluding the category *Utilities*. Conditional logit estimates are given. Standardized coefficients in log-odds notation are shown. Standard errors are in parentheses. Observations are category-months. The coefficients in columns (1) and (2) are estimated using the sample of $N = 2{,}213$ category-months, with 1,143 category-months effectively entering the estimation in column (1) and 766 category-months effectively entering the estimation in column (2). The coefficients in columns (3) and (4) are estimated using the sample of $N = 2{,}324$ category-months, with 1,189 category-months effectively entering the estimation in column (1) and 814 category-months effectively entering the estimation in column (2). DV, dependent variable. "x" indicates that controls and fixed effects have been included.

*Significance at the 5% level; **significance at the 1% level; ***significance at the 0.1% level.

report the results. The thereby obtained coefficients are consistent in direction and significance, with the exception of the test for Hypothesis 2, which falls below the significance level.

Last, there could be the concern that two core expansions occur in close succession and therefore, cause attribution issues for the estimation.[14] We, therefore, conducted a robustness check, in which we excluded the small number of core expansions that temporally overlap and re-estimated the regression models. Table A.6 in the Online Appendix reports the results, which are consistent to our main findings. To conclude, prior core expansions do not distort the results of our hypotheses tests.

5.4. Unit of Analysis

To validate the robustness of our approach in aggregating app-level data to the category level, we conducted an additional robustness check using the raw app-level data prior to its aggregation. Specifically, we re-estimated the model at the app level using the same independent and dependent variables as specified in the primary analysis but measured directly at the level of the app. The results from the app-level estimation, which are reported in Table A.7 in the Online Appendix, are consistent with those obtained using the aggregated category-level data. The coefficients retain similar directions, magnitudes, and statistical significance. To conclude, the aggregation process did not distort the analysis and supports the validity of our category-level analysis.

6. Discussion

6.1. Theoretical Contributions and Implications

The core-periphery model of software platforms combined with commission-based revenue generation incentivizes platform owners to maximize the overall value generated by their ecosystem. With these incentives, it becomes crucial for platform owners to develop strategies by which the platform ecosystem can grow and generate more value. Prior research on the growth of software platform ecosystems has primarily focused on providing resources for third-party developers at the core-periphery boundary of the platform (Ghazawneh and Henfridsson 2013, Eaton et al. 2015, Karhu et al. 2018, Ye and Kankanhalli 2018), designing the platform core to promote reuse (Brunswicker et al. 2019, Meng et al. 2022, Um et al. 2023), and encouragement mechanisms (Huang et al. 2013, Liang et al. 2019, Foerderer 2020, Hukal et al. 2020). The research reported in this paper complements this stream of research by investigating the drivers behind software platform owners' decisions to expand their platform core into ecosystem niches. Core expansion aims at addressing underperforming niches within the ecosystem that fail to contribute meaningfully to the platform's overall value.

We propose the hypotheses that platforms are more likely to expand into ecosystem niches characterized by low user satisfaction, reduced innovation efforts, and high market concentration. To test these hypotheses, we constructed a novel and comprehensive data set capturing Apple's core expansions on the iOS platform between 2012 and 2020, comprising both stand-alone apps and features integrated into the core. Testing these hypotheses presents significant challenges as it requires an empirical setting with variation in core expansions, a meticulous and labor-intensive process to identify these core expansions, and robust measures to accurately characterize the affected niches.

Our research offers several contributions. First, on a general level, the findings statistically evaluate and extend the qualitative insights of prior research on software platforms (Gawer and Henderson 2007, Sarker et al. 2012, Wareham et al. 2014, Eaton et al. 2015, Huber et al. 2017), which all in one way or another highlight the platform owner's management of third-party developer relationships in increasing the overall value of the platform ecosystem. Our findings confirm the overarching hypothesis that software platforms strategically expand into underperforming ecosystem niches. We extend this hypothesis by finding that expansions are driven by low user satisfaction, reduced innovation efforts, and high market concentration. By systematically linking platform core expansions to measurable niche deficiencies, our study moves beyond anecdotal evidence to establish a robust statistical association. This association has been rigorously validated through extensive robustness checks, including tests for endogeneity regarding omitted variable bias, measurement error, and functional form specification, as well as by ruling out important rival explanations. Second, our work situates platform core expansion into the broader framework of platform governance mechanisms. We demonstrate that platform owners actively engage with the periphery, moving beyond the traditional reliance on interfaces, rules, and quality control mechanism for managing third-party contributions as suggested in early work (Tiwana et al. 2010, Yoo et al. 2010). Our research resonates well with the more recent understanding that platform governance manifests in complex behaviors (Song et al. 2018, Hukal et al. 2020, Wang 2021, Alhauli et al. 2023, Leong et al. 2024). Third, our findings offer new insights into the balance of power within platform ecosystems (Wareham et al. 2014, Parker et al. 2017, Hurni et al. 2022, Hunt et al. 2025, Liu et al. 2025). By demonstrating that high market concentration drives platform core expansions aimed at preserving power asymmetry, it highlights how software platform owners strategically safeguard supermodular complementarities in their ecosystems. This perspective reframes platform core expansions not as moves that disrupt competition but rather, as deliberate strategies to maintain a healthy balance of power. Finally, our findings not only highlight *where* software platform owners intervene with core expansions but also, *how* these interventions take shape. We introduced the notion of core expansions implemented through stand-alone apps versus integrated features, advancing prior research that has not differentiated between these forms (e.g., Gawer and Henderson 2007, Foerderer et al. 2018, Wen and Zhu 2019). Our results show that the choice of the expansion form is systematically linked to the characteristics of ecosystem niches. This confirms that the distinction is a significant factor in platform owners' decisions regarding the boundary between the platform core and the periphery. Moreover, our findings highlight that the form of platform core expansion is chosen depending on specific ecosystem deficiencies. This distinction provides a deeper understanding of why platform core expansions take different forms and emphasizes the strategic considerations underlying these decisions.

6.2. Managerial and Policy Implications

There are at least four managerial implications of our research. First, third-party developers or complementors must recognize that underperformance in their niche—manifested as low user satisfaction, reduced innovation efforts, or high market concentration—may prompt platform core expansions. To mitigate potential risks that can arise from that, third-party developers should prioritize continuous innovation, enhance competitive differentiation, and proactively address user satisfaction to maintain their relevance within the ecosystem. Second, platform owners should view expansion into underperforming niches as a strategy to enhance the overall ecosystem rather than as a short-term opportunity for rent extraction. By addressing issues, such as low user satisfaction, stagnating innovation, and high market concentration, platform owners can strengthen network effects and foster ecosystem growth. The case of Apple—a leading software platform owner—illustrates this approach. Apple's focus on expanding its core into underperforming niches rather than extracting immediate rents highlights the strategic importance of fostering long-term value creation. This observation is particularly significant as it demonstrates that even dominant platforms prioritize ecosystem development over short-term revenue generation from selling complements. Third, platform owners need to align the form of core expansion—stand-alone apps or features—with specific ecosystem deficiencies. They must recognize that not all underperforming niches require the same type of expansion. High market concentration is best addressed through feature integration as it helps limit the influence of dominant complementors. Conversely, stagnant innovation in niches is more effectively addressed by introducing stand-alone apps to stimulate competitive responses and drive innovation. Tailoring these strategies ensures that expansions are well suited to the unique challenges of each niche. Finally, regulators should reconsider the prevailing assumption that core expansions primarily serve as a means for platform owners to extract rents. Our findings demonstrate that core expansions often target underperforming niches in an apparent attempt to develop these areas. This insight suggests that core expansions play a constructive role, which calls for a more nuanced perspective that moves beyond blanket assumptions of anticompetitive moves.

6.3. Future Research

Although our findings provide support for the hypotheses, they also raise an important question for future research. Do platform core expansions achieve their intended objectives? Likely, the actual outcome of core expansion will depend on a variety of factors, including the degree of functional overlap between the platform's core expansion and existing peripheral complements, platform owner's communication, and prior expansion activities. For example, under some conditions, developers might interpret core expansions as an appropriation and reduce their innovation efforts (Ceccagnoli et al. 2012, Huang et al. 2013). However, if a platform owner clearly signals that its expansion is intended to complement rather than replace third-party innovation, it has the potential to mitigate fears of appropriation and can be very effective. In line, core expansions could have unintended consequences. For example, when Apple introduced Apple Maps in 2012, the move was likely intended to restore power asymmetry in the niche for navigation apps on iOS, which had become heavily concentrated around Google Maps (e.g., Forbes 2012). However, the launch of Apple Maps was plagued by technical issues and inaccuracies, leading to widespread criticism and a loss of user trust, whereas Google Maps retained its dominance and even fortified it by acquiring and integrating Waze. This example illustrates how various conditions and counteractions can affect the outcomes of the core expansion. Studying whether and under what conditions core expansions achieve their objectives was infeasible because it requires a research design capable of accounting for the preexisting differences observed here and identifying counterfactual niches that can serve as control benchmarks for those affected by core expansions. This challenge is underscored by the fact that prior research on the consequences of platform core expansions has been limited to the investigation of one or few individual cases (Foerderer et al. 2018, Wen and Zhu 2019, Kang and Suarez 2023). Future research would benefit from systematically studying postexpansion outcomes to understand under which conditions the objectives are achieved.[15]

In addition, future research is needed to comprehend when platform owners treat the two forms of core expansion modes (i.e., features versus stand-alone app) as substitutes in terms of actively choosing one form while avoiding the other. Understanding this distinction logic behind not only whether to expand but how and when to refrain from a particular form has the potential to offer valuable insights into considerations, such as ecosystem stability or avoiding regulatory attention.[16]

6.4. Limitations

Understanding the patterns that drive platform core expansions is empirically challenging as researchers must rely solely on observational data. The motives behind these expansions cannot be directly observed, and even with access to decision makers, the reliability of their statements may be questionable, especially given the heightened regulatory scrutiny in this domain (e.g., Bhargava et al. 2022, Li and Wang 2024). To address this empirical challenge, we adopt an indirect approach by statistically testing for associations between the hypothesized drivers and core expansions. Importantly, these associations should be interpreted as evidence of statistical consistency with the theorized mechanisms rather than implying that every individual expansion complies with the theorized mechanisms. To ensure the robustness of these findings, we implemented a series of tests for endogeneity bias, including an approach in the spirit of matching techniques, which is a control function approach; performed a sensitivity analysis using robustness of inference procedures; assessed measurement errors in a series of tests; and varied the functional form. We tested for multicollinearity and ruled out key rival explanations. However, as with any nonexperimental study, we cannot fully rule out the possibility of omitted variable bias. We, therefore, refrain from framing our study as causal and instead, interpret our results as predictive and whether they are consistent with the hypothesized theoretical drivers.

7. Conclusion

This study advances our understanding of the strategic drivers behind core expansions initiated by software platform owners, providing valuable results into both the *where* and *how* of core expansions. Through an analysis of Apple's core expansions on its iOS platform, we have been able to demonstrate that platform owners target underperforming niches—characterized by low user satisfaction, reduced innovation efforts, and high market concentration of complementor offerings—as a strategy to address ecosystem weaknesses. Furthermore, we have revealed that the form of these expansions varies systematically, with stand-alone apps and integrated features tailored to specific ecosystem conditions.

Acknowledgments

The authors thank the senior editor, the associate editor, and three anonymous reviewers for their thoughtful and constructive feedback throughout the review process. The authors are grateful for the insightful comments received from participants at research seminars hosted by the University of Mannheim, Germany; the Technical University of Munich, Germany; and the University of Bern, Switzerland. The authors also appreciate the valuable suggestions provided by attendees at the International Conference of Information Systems. Their perspectives helped to refine and strengthen the arguments presented in this paper.

Endnotes

[1] Extension and expansion are oftentimes used interchangeably. We use expansion to capture the fact that over time, the platform core will not only be enhanced within the confines of the original scope of the platform but also, be expanded with entirely new functionalities (e.g., Apple Health was not envisioned in the original platform core of iOS).

[2] It should be mentioned that the literature on the economics of platforms presents an alternative explanation. For instance, the theoretical work by Farrell and Katz (2000) suggests that firms, like Apple, have an incentive for expanding the core to extract rents—either by charging a higher price for the platform itself or by creating additional revenue streams through the sale of complements. Platforms have the advantage of access to valuable information about successful complements, the capability to imitate them, and the market power to effectively sell them.

[3] Our data provider covers historical data on the Apple App Store only from 2012 onward.

[4] We considered but discarded alternative approaches to using the category system. One approach had been to analyze the app description either through manual coding or through a machine learning classification. However, manual coding proved to be impractical because of the large volume of apps to be analyzed. A machine learning approach necessitated a sizable training data set that relied heavily on the accuracy of the app descriptions. Another option considered was leveraging the App Store's *similar apps* recommendations (e.g., Mayya and Viswanathan 2025), but the limited number of suggestions available did not suffice for an analysis in our very setting.

[5] We use *niche* to denote the theoretical concept and *category* to represent the measure.

[6] The category level is the intuitive data structure given the hypotheses and the measures. The app level, on the other hand, allows for utilizing the complete information available for each app within a niche without the need for averaging. We appreciate the guidance by the review team to conduct the analysis at the category level.

[7] We considered two alternatives: a multinomial model and a nested logit model. We discarded the multinomial logit because it assumes independence of irrelevant alternatives across expansion modes, an assumption unlikely to hold in our setting where the choice between "integrated feature" and "stand-alone app" likely depends on whether the platform chooses to expand at all (Cameron and Trivedi 2010, chapter 18). Although the nested logit model relaxes this assumption by modeling the expansion decision hierarchically, no fixed-effects estimator was available at the time of our study. We, therefore, opted for conditional logit estimation.

[8] Note that all categories were included in the data set, even if they do not experience any core expansion throughout the observation period. However, the conditional logit estimator used for our analysis excludes these niches from the estimation because the outcome variables (i.e., *Core expansion (app)* and *Core expansion (feature)*) do not vary over time for these categories (i.e., they are always zero). This is a characteristic of the estimator as it relies on variation within groups (in this case, categories) to estimate the coefficients.

[9] Classical matching (e.g., propensity score matching and coarsened exact matching) is usually applied for achieving balanced comparison groups before an intervention: for instance, the treatment and control groups in a difference-in-differences design. Such an approach is not applicable in our case because we predict the likelihood of a core expansion; matching on niche characteristics would eliminate the differences across niches that our hypotheses tests aim to uncover. We thank an anonymous reviewer for suggesting this discussion.

[10] We cannot exclude a category permanently from the analysis once it has been affected as it would reduce the sample size to a level where no estimation is possible.

[11] Aside from the lags, suitable instruments are limited in our case because there exist few isolated sources of exogenous variation that are correlated with individual categories and their levels of *User satisfaction*, *Innovation efforts*, and *Concentration* and not immediately correlated with platform owners' propensity for core expansion. As part of this, we considered but discarded, for instance, using Google's core expansions as an instrument because prior research has documented a direct influence of core expansions across platforms (Wen and Zhu 2019). We also discarded activities of large complementors because they are indirectly captured already in our measure of *Concentration* and *Innovation efforts*, which would cause a spurious correlation.

[12] This estimator allows us to include category and time fixed effects without potential bias arising from the incidental parameter problem that can affect nonlinear fixed effects models, like logit, when the number of groups is large relative to the number of observations (Greene 2018, chapter 18). Moreover, although conditional logit drops all categories that exhibit no within-group variation in the outcome variable, a linear probability model allows us to utilize the full sample.

[13] We thank an anonymous reviewer for the idea to use the Herfindahl–Hirschman Index.

[14] Note also that we coded observations as missing for categories that had experienced an expansion for the five months after a core expansion to prevent any given data point from influencing more than one window within the same category (see Section 3.3). We thank an anonymous reviewer for suggesting investigating this issue.

[15] We thank an anonymous reviewer for suggesting this idea.

[16] We are grateful to a reviewer for prompting this line of thought.

References

Alhauli A, Elmaghraby WJ, Gopal A (2023) Impressionable or immune? Examining the influence of marquee sellers in B2B secondary market platforms for IT products. *Inform. Systems Res.* 34(2):570–589.

Angrist JD, Pischke J-S (2009) *Mostly Harmless Econometrics: An Empiricist's Companion* (Princeton University Press, Princeton, NJ).

Apple (2023) App Store developers generated $1.1 trillion in total billings and sales in the App Store ecosystem in 2022. Accessed March 22, 2024, https://www.apple.com/newsroom/2023/05/developers-generated-one-point-one-trillion-in-the-app-store-ecosystem-in-2022.

Apple (2024) Choosing a category. Accessed March 25, 2024, https://developer.apple.com/app-store/categories/.

Baldwin CY, Woodard CJ (2009) The architecture of platforms: A unified view. Gawer A, ed. *Platforms, Markets and Innovation* (Edward Elgar Publishing, Cheltenham, UK), 19–44.

Benaroch M, Chernobai A (2017) Operational IT failures, IT value destruction, and board-level IT governance changes. *MIS Quart.* 41(3):729–762.

Bhargava HK, Wang K, Zhang X (2022) Fending off critics of platform power with differential revenue sharing: Doing well by doing good? *Management Sci.* 68(11):8249–8260.

Blundell RW, Powell JL (2004) Endogeneity in semiparametric binary response models. *Rev. Econom. Stud.* 71:655–679.

Boudreau KJ (2012) Let a thousand flowers bloom? An earlier look at large numbers of software app developers and patterns of innovation. *Organ. Sci.* 23(5):1409–1427.

Boudreau KJ (2018) Amateurs crowds & professional entrepreneurs as platform complementors. NBER Working Paper No. 24512, National Bureau of Economic Research, Cambridge, MA.

Brandenburger A, Nalebuff B (1996) *Co-opetition: A Revolutionary Mindset that Redefines Competition and Cooperation* (Currency Doubleday, New York).

Brown SL, Eisenhardt KM (1995) Product development: Past research, present findings, and future directions. *Acad. Management Rev.* 20(2):343–378.

Brunswicker S, Almirall E, Majchrzak A (2019) Optimizing and satisficing: The interplay between platform architecture and producers' design strategies for platform performance. *MIS Quart.* 43(4):1249–1277.

Busenbark JR, Yoon HE, Gamache DL, Withers MC (2022) Omitted variable bias: Examining management research with the impact threshold of a confounding variable (ITCV). *J. Management* 48(1):17–48.

Cabral L, Haucap J, Parker G, Petropoulos G, Valletti TM, Van Alstyne MW (2021) The EU Digital Markets Act: A report from a panel of economic experts. Report, Publications Office of the European Union, Luxembourg.

Cameron AC, Trivedi PK (2010) *Microeconometrics Using Stata*, 2nd ed. (Stata Press, College Station, TX).

Caminade J, von Wartburg M (2022) The success of third-party apps on the App Store. Accessed January 8, 2025, https://www.apple.com/newsroom/pdfs/the-success-of-third-party-apps-on-the-app-store.pdf.

Ceccagnoli M, Forman C, Huang P, Wu DJ (2012) Cocreation of value in a platform ecosystem! The case of enterprise software. *MIS Quart.* 36(1):263–290.

Cennamo C, Santaló J (2019) Generativity tension and value creation in platform ecosystems. *Organ. Sci.* 30(3):617–641.

Cohen WM, Levin RC (1989) Empirical studies of innovation and market structure. Schmalensee R, Willig R, eds. *Handbook of Industrial Organization*, vol. 2 (Elsevier, Amsterdam), 1059–1107.

Cohen J, Cohen P, West SG, Aiken LS (2003) *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*, 3rd ed. (Routledge, New York).

Constantinides P, Henfridsson O, Parker GG (2018) Introduction—Platforms and infrastructures in the Digital Age. *Inform. Systems Res.* 29(2):381–400.

Coughlan PJ (2004) The golden age of home video games: From the reign of Atari to the rise of Nintendo. Harvard Business School Case Study No. 9-704-487, Harvard Business School, Boston.

Crémer J, Crawford GS, Dinielli D, Fletcher A, Heidhues P, Schnitzer M, Morton FMS (2023) Fairness and contestability in the Digital Markets Act. *Yale J. Regulation* 40(3):973–999.

Deng Y, Lambrecht A, Liu Y (2023) Spillover effects and freemium strategy in the mobile app market. *Management Sci.* 69(9):5018–5041.

Derfus PJ, Maggitti PG, Grimm CM, Smith KG (2008) The red queen effect: Competitive actions and firm performance. *Acad. Management J.* 51(1):61–80.

D'Heureuse N, Huici F, Arumaithurai M, Ahmed M, Papagiannaki K, Niccolini S (2012) What's app? A wide-scale measurement study of smart phone markets. *Mobile Comput. Comm. Rev.* 16(2):16–27.

Eaton B, Elaluf-Calderwood S, Sørensen C, Yoo Y (2015) Distributed tuning of boundary resources: The case of Apple's iOS service system. *MIS Quart.* 39(1):217–243.

Economist (2012) You've been sherlocked. (July 13), https://www.economist.com/babbage/2012/07/13/youve-been-sherlocked.

Farrell J, Katz ML (2000) Innovation, rent extraction, and integration in systems markets. *J. Indust. Econom.* 48(4):413–432.

Foerderer J (2020) Interfirm exchange and innovation in platform ecosystems: Evidence from Apple's Worldwide Developers Conference. *Management Sci.* 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. *Inform. Systems Res.* 29(2):444–460.

Foerderer J, Kude T, Schuetz SW, Heinzl A (2019) Knowledge boundaries in enterprise software platform development: Antecedents and consequences for platform governance. *Inform. Systems J.* 29(1):119–144.

Forbes (2012) Why Apple had to release its terrible maps app now. (September 29), https://www.forbes.com/sites/shelisrael/2012/09/29/apples-maps-strategy-china-today-tomorrow-the-world/.

Forbes (2022) Software development time estimation: How long should it take to develop a product? (December 2), https://www.forbes.com/sites/forbesbusinesscouncil/2022/12/02/software-development-time-estimation-how-long-should-it-take-to-develop-a-product/?sh=f62784a76cee.

Frank KA, Maroulis SJ, Duong MQ, Kelcey BM (2013) What would it take to change an inference? Using Rubin's causal model to interpret the robustness of causal inferences. *Ed. Evaluation Policy Anal.* 35(4):437–460.

Fürstenau D, Baiyere A, Schewina KAI, Schulte-Althoff M, Rothe H (2023) Extended generativity theory on digital platforms. *Inform. Systems Res.* 34(4):1686–1710.

Gawer A, Cusumano MA (2014) Industry platforms and ecosystem innovation. *J. Product Innovation Management* 31(3):417–433.

Gawer A, Henderson R (2007) Platform owner entry and innovation in complementary markets: Evidence from Intel. *J. Econom. Management Strategy* 16(1):1–34.

Ghazawneh A, Henfridsson O (2013) Balancing platform control and external contribution in third-party development: The boundary resources model. *Inform. Systems J.* 23(2):173–192.

Ghose A, Han SP (2014) Estimating demand for mobile applications in the new economy. *Management Sci.* 60(6):1470–1488.

Gleasure R (2024) Contrasting the response to past and future oriented appeals for help on donation-based crowdfunding platforms. *Eur. J. Inform. Systems* 33(6):953–974.

Greene WH (2018) *Econometric Analysis*, 8th ed. (Pearson, Munich, Germany).

Hair JF, Tatham R, Anderson R, Black W (2006) *Multivariate Data Analysis*, 7th ed. (Pearson, Munich, Germany).

Harman M, Jia Y, Zhang Y (2012) App Store mining and analysis: MSR for app stores. *Proc. 9th IEEE Working Conf. Mining Software Repositories (MSR '12) (Zurich)*, 108–111.

He S, Peng J, Li J, Xu L (2020) Impact of platform owner's entry on third-party stores. *Inform. Systems Res.* 31(4):1467–1484.

Huang P, Tafti A, Mithas S (2018) Platform sponsor investments and user contributions in knowledge communities: The role of knowledge seeding. *MIS Quart.* 42(1):213–240.

Huang P, Ceccagnoli M, Forman C, Wu DJ (2013) Appropriability mechanisms and the platform partnership decision: Evidence from enterprise software. *Management Sci.* 59(1):102–121.

Huber TL, Kude T, Dibbern J (2017) Governance practices in platform ecosystems: Navigating tensions between cocreated value and governance costs. *Inform. Systems Res.* 28(3):563–584.

Hukal P, Henfridsson O, Shaikh M, Parker GG (2020) Platform signaling for generating platform content. *MIS Quart.* 44(3):1177–1205.

Hunt RA, Townsend DM, Simpson JJ, Nugent R, Stallkamp M, Bozdag E (2025) Digital battlegrounds: The power dynamics and governance of contemporary platforms. *Acad. Management Ann.* 19(1):265–297.

Hurni T, Huber TL, Dibbern J (2022) Power dynamics in software platform ecosystems. *Inform. Systems J.* 32(2):310–343.

Hurni T, Huber TL, Dibbern J, Krancher O (2021) Complementor dedication in platform ecosystems: Rule adequacy and the moderating role of flexible and benevolent practices. *Eur. J. Inform. Systems* 30(3):237–260.

IEEE (2008) IEEE standard for software test documentation. IEEE Standard No. 829-2008, IEEE, New York.

Jacobides MG, Cennamo C, Gawer A (2018) Towards a theory of ecosystems. *Strategic Management J.* 38(8):2255–2276.

Kang HY, Suarez FF (2023) Platform owner entry into complementor spaces under different governance modes. *J. Management* 49(5):1766–1800.

Kang C, Aaltonen A, Henfridsson O (2019) The impact of platform entry strategies on the quality of complements in multihoming. *Proc. 40th Internat. Conf. Inform. Systems (Munich, Germany)*.

Karhu K, Gustafsson R, Lyytinen K (2018) Exploiting and defending open digital platforms with boundary resources: Android's five platform forks. *Inform. Systems Res.* 29(2):479–497.

Lahiri A, Dey D (2013) Effects of piracy on quality of information goods. *Management Sci.* 59(1):245–264.

Lee MH, Han SP, Park S, Oh W (2023) Positive demand spillover of popular app adoption: Implications for platform owners' management of complements. *Inform. Systems Res.* 34(3):961–995.

Leong C, Lin S, Tan F, Yu J (2024) Coordination in a digital platform organization. *Inform. Systems Res.* 35(1):363–393.

Leong C, Pan SL, Leidner DE, Huang JS (2019) Platform leadership: Managing boundaries for the network growth of digital platforms. *J. Assoc. Inform. Systems* 20(10):1531–1565.

Li Z, Agarwal A (2017) Platform integration and demand spillovers in complementary markets: Evidence from Facebook's integration of Instagram. *Management Sci.* 63(10):3438–3458.

Li Z, Wang G (2024) Regulating powerful platforms: Evidence from commission fee caps. *Inform. Systems Res.* 36(1):126–140.

Li M, Han Y, Goh KY, Cavusoglu H (2022) Mobile app portfolio management and developers' performance: An empirical study of the Apple App Store. *Inform. Management* 59(8):103716.

Liang C, Shi Z, Raghu TS (2019) The spillover of spotlight: Platform recommendation in the mobile app market. *Inform. Systems Res.* 30(4):1296–1318.

Liu S, Henfridsson O, Hummel JT, Nandhakumar J (2025) The complementor's dilemma: Navigating growth ambitions and the dependency on focal actors in platform ecosystems. *MIS Quart.* 49(3):1123–1152.

Lueker N, Foerderer J, Heinzl A (2022) Competing with superstars: Does exclusive third-party content discourage complementary innovation? Bjørn-Andersen N, ed. *Proc. 43rd Internat. Conf. Inform. Systems* (AIS Electronic Library (AISeL), Atlanta).

MacWorld (2024) iOS versions: Every version of iOS from the oldest to the newest. Accessed October 10, 2025, https://www.macworld.com/article/1659017/ios-versions-list.html.

Mayya R, Viswanathan S (2025) Delaying informed consent: An empirical investigation of mobile apps' upgrade decisions. *Management Sci.* 71(8):7113–7135.

Meng T, Ng E, Tan B (2022) Digital attrition: The negative implications of the sharing economy for the digital options of incumbent firms. *Inform. Systems J.* 32(5):1005–1033.

Mithas S, Tafti A, Mitchell W (2013) How a firm's competitive environment and digital strategic posture influence digital business strategy. *MIS Quart.* 37(2):511–536.

Nicas J (2019) Apple cracks down on apps that fight iPhone addiction. *New York Times* (April 27), https://www.nytimes.com/2019/04/27/technology/apple-screen-time-trackers.html.

Pan Y, Huang P, Gopal A (2018) Board independence and firm performance in the IT industry: The moderating role of new entry threats. *MIS Quart.* 42(3):979–999.

Parker GG, Van Alstyne MW (2005) Two-sided network effects: A theory of information product design. *Management Sci.* 51(10):1494–1504.

Parker G, Van Alstyne M, Jiang X (2017) Platform ecosystems: How developers invert the firm. *MIS Quart.* 41(1):255–266.

Petrin A, Train K (2010) A control function approach to endogeneity in consumer choice models. *J. Marketing Res.* 47(1):3–13.

Polites GL, Karahanna E (2012) Shackled to the status quo: The inhibiting effects of incumbent system habit, switching costs, and inertia on new system acceptance. *MIS Quart.* 36(1):21–42.

Qiu Y, Gopal A, Hann IH (2017) Logic pluralism in mobile platform ecosystems: A study of indie app developers on the iOS App Store. *Inform. Systems Res.* 28(2):225–249.

Ray S, Kim SS, Morris JG (2012) Research note—Online users' switching costs: Their nature and formation. *Inform. Systems Res.* 23(1):197–213.

Romm T (2020) Amazon, Apple, Facebook and Google grilled on Capitol Hill over their market power. *Washington Post* (July 29), https://www.washingtonpost.com/technology/2020/07/29/apple-google-facebook-amazon-congress-hearing/.

Rutz OJ, Watson GF (2019) Endogeneity and marketing strategy research: An overview. *J. Acad. Marketing Sci.* 47:479–498.

Saldanha TJ, Sahaym A, Mithas S, Andrade-Rojas MG, Kathuria A, Lee HH (2020) Turning liabilities of global operations into assets: IT-enabled social integration capacity and exploratory innovation. *Inform. Systems Res.* 31(2):361–382.

Sarker S, Sarker S, Sahaym A, Bjørn-Andersen N (2012) Exploring value cocreation in relationships between an ERP vendor and its partners: A revelatory case study. *MIS Quart.* 36(1):317–338.

Scherer F, Ross D (1990) *Industrial Market Structure and Economic Performance* (Houghton Mifflin Company, Boston).

Shi R, Aaltonen A, Henfridsson O, Gopal R (2023) Comparing platform owners' early and late entry into complementary markets. *MIS Quart.* 47(4):1727–1744.

Song P, Xue L, Rai A, Zhang C (2018) The ecosystem of software platform: A study of asymmetric cross-side network effects and platform governance. *MIS Quart.* 42(1):121–142.

Statista (2023) Distribution of worldwide mobile app revenues in the Apple App Store store from 2021 to 2027, by category. Accessed January 8, 2025, https://www.statista.com/statistics/1401233/apple-app-store-revenue-share-by-category/.

Statista (2024) Apple's iPhone revenue from 3rd quarter 2007 to 4th quarter 2024. Accessed January 8, 2025, https://www.statista.com/statistics/263402/apples-iphone-revenue-since-3rd-quarter-2007/.

TechCrunch (2023) All the things Apple sherlocked at WWDC 2023. Accessed October 2025, https://tcrn.ch/3oZkfU1.

Tiwana A (2015) Evolutionary competition in platform ecosystems. *Inform. Systems Res.* 26(2):266–281.

Tiwana A, Konsynski B, Bush AA (2010) Platform evolution: Coevolution of platform architecture, governance, and environmental dynamics. *Inform. Systems Res.* 21(4):675–687.

Um S, Zhang B, Wattal S, Yoo Y (2023) Software components and product variety in a digital platform ecosystem: A dynamic network analysis of WordPress. *Inform. Systems Res.* 34(4):1339–1374.

Vial G (2023) A complex adaptive systems perspective of software reuse in the Digital Age: An agenda for IS research. *Inform. Systems Res.* 34(4):1728–1743.

Wang P (2021) Connecting the parts with the whole: Towards an information ecology theory of digital innovation ecosystems. *MIS Quart.* 45(1):397–422.

Wang Q, Li B, Singh PV (2018) Copycats vs. original mobile apps: A machine learning copycat-detection method and empirical analysis. *Inform. Systems Res.* 29(2):273–291.

Wang D, Zhu Q, Avolio BJ, Shen W, Waldman D (2023) Do employees' views matter in corporate governance? The relationship between employee approval and CEO dismissal. *Strategic Management J.* 44(5):1328–1354.

Wareham J, Fox PB, Cano Giner JL (2014) Technology ecosystem governance. *Organ. Sci.* 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 J.* 40(9):1336–1367.

Whitaker J, Mithas S, Liu CW (2019) Beauty is in the eye of the beholder: Toward a contextual understanding of compensation of information technology professionals within and across geographies. *Inform. Systems Res.* 30(3):892–911.

Wu J, Zhao H, Chen H (2021) Coupons or free shipping? Effects of price promotion strategies on online review ratings. *Inform. Systems Res.* 32(2):633–652.

Xie Z, Zhu S, Li Q, Wang W (2016) You can promote, but you can't hide: Large-scale abused app detection in mobile app stores. *Proc. 32nd Annual Conf. Comput. Security Appl.* (Association for Computing Machinery, New York), 374–385.

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 Oper. Management* 28(8):1887–1902.

Ye H, Kankanhalli A (2018) User service innovation on mobile phone platforms. *MIS Quart.* 42(1):165–192.

Yoo Y, Henfridsson O, Lyytinen K (2010) The new organizing logic of digital innovation: An agenda for information systems research. *Inform. Systems Res.* 21(4):724–735.

Zhang Y, Li J, Tong TW (2022) Platform governance matters: How platform gatekeeping affects knowledge sharing among complementors. *Strategic Management J.* 43(3):599–626.

Zhu F, Liu Q (2018) Competing with complementors: An empirical look at Amazon.com. *Strategic Management J.* 39(10):2618–2642.