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RESEARCH NOTE

COMPARING PLATFORM OWNERS' EARLY AND LATE ENTRY INTO COMPLEMENTARY MARKETS[1]

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Research on platform owners' entry into complementary markets points in divergent directions. One strand of the literature reports a squeeze on post-entry complementor profits due to increased competition, while another observes positive effects as increased customer attention and innovation benefit the complementary market as a whole. In this research note, we seek to transcend these conflicting views by comparing the effects of the early and late timing of platform owners' entry. We apply a difference-in-differences design to explore the drivers and effects of the timing of platform owners' entry using data from three entries that Amazon made into its Alexa voice assistant's complementary markets. Our findings suggest that early entry is driven by the motivation to boost the overall value creation of the complementary market, whereas late entry is driven by the motivation to capture value already created in a key complementary market. Importantly, our findings suggest that early entry, in contrast to late entry, creates substantial consumer attention that benefits complementors offering specialized functionality. In addition, the findings also suggest that complementors with more experience are more likely to benefit from the increased consumer attention. We contribute to platform research by showing that the timing of the platform owner's entry matters in a way that can potentially reconcile conflicting findings regarding the consequences of platform owners' entry into complementary markets.

Keywords: Complementary markets, complements, functional diversity, platform owner, platforms, timing of entry, value creation

Introduction

Platform complements are add-on services that enhance the usefulness of a platform's core offering (Cennamo & Santaló, 2019; Hukal et al., 2020; Tiwana, 2018). They add specific functionalities that otherwise would be difficult for the platform owner[2] to offer (Adner, 2017; Jacobides et al., 2018). For instance, in 2015, the Google Play Store hosted more than 1,200 photography applications that extended the platform's photo-taking, editing, and sharing features

[1] Sunil Mithas was the accepting senior editor for this paper. Jui Ramaprasad served as the associate editor.

[2] We define a platform owner as the focal actor that mediates the value exchange between platform complementors and users (Rietveld & Schilling, 2020) through the platform's governance framework (Tiwana et al., 2010).

(Foerderer et al., 2018). Such clusters of complements typically form highly competitive markets on popular platforms (Boudreau, 2012). We define platform complementors as actors that offer an application (or other type of complement) that brings additional value to platform users when used in combination with the platform (Jacobides et al., 2018; Teece, 2018). Since platform businesses are premised on mutual benefit between platform owners and platform complementors, platform owners need to govern complementary markets to satisfy both their own interests and the interests of the complementors (Hukal et al., 2020; Tiwana et al., 2010). However, platform owners sometimes disrupt their relationship with the complementors in a specific complementary market by launching their own applications or by acquiring one of the complementors.

Research on platform owners' entry into complementary markets points in divergent directions. One stream of research emphasizes the contentiousness of platform owners' entry as it puts owners in direct competition with their complementors (Cennamo et al., 2016; Jiang et al., 2011; Lan et al., 2019; Zhu, 2019; Zhu & Liu, 2018). The platform owner's entry can leave less room for existing complementors to make profits (Zhu & Liu, 2018) and may reduce complementors' level of innovation (Lan et al., 2019; Wen & Zhu, 2019), forcing complementors to adapt to an increasingly competitive environment (Edelman & Lai, 2016) or even exit the market (Cennamo et al., 2016). This stream of literature rests on the assumption that complementary markets exhibit stable customer demand from which value can be extracted. Another stream of literature emphasizes the positive impact of platform owners' entry. This perspective suggests that platform owners' entry increases the popularity of a complementary market among consumers (Li & Agarwal, 2017), stimulates complementor participation by further opening platform resources (Gawer & Henderson, 2007), and improves consumer retention on the platform (Li & Agarwal, 2017). This stream of literature rests on the assumption that the complementary market will grow because of the platform owner's entry.

In this research note, we propose that the timing of entry is a significant factor in explaining the differences manifested in the literature. In early-stage markets, there is typically little immediate value to appropriate, as the markets exhibit "extreme ambiguity about opportunities and customer demand" (McDonald & Eisenhardt, 2020, p. 485). Early entry, defined here as occurring when the ratio between the current and the eventual complementary market size is low,[3] is therefore likely motivated by an ambition to grow the market and the value created on the platform instead of capturing value in the short term. For instance, the platform owner may try to signal its commitment to a complementary market by entering the market (Hukal et al., 2020) and thus stimulate its growth by showing that the platform owner is determined to secure the long-term viability of the market. In contrast, late entry into a relatively mature complementary market is different and may involve a squeeze on complementor profits due to increased competition. We thus argue that the timing of the entry may affect how complementors should perceive the entry and respond to it.

We designed an empirical study that examines the following research question: *How does the timing of platform owners' entry into a complementary market influence value creation?* We refer to value creation as the activities geared toward increasing the perceived attractiveness of the platform ecosystem among customers and measure it as changes to complement popularity among customers. We use complement popularity among customers as a proxy for measuring changes in value creation. We collected panel data from Amazon's Alexa platform and harnessed two early entries and one late entry by Amazon into Alexa Smart Home complementary markets as natural experiments using a difference-in-differences design. The three selected entries are suitable for answering our research question because the category of Smart Home complements was new (as opposed to, for instance, games), as it largely emerged along with the introduction of Echo smart speakers to consumers. The findings show that Amazon's early entry into the Home Surveillance subcategory is associated with increasing complement popularity and that it supports value creation in the market. The increasing popularity seems to benefit complements with specialized functionality, which is typically associated with easy configuration and adoption of the complement. The findings also suggest that complementors with more experience are more likely to benefit from the increased consumer attention.

This research note contributes to platform research by showing that the timing of platform owners' entry into complementary markets matters and that complementors offering specialized functionality are in a good position to benefit from the platform owner's early entry. As such, the results suggest a way to reconcile conflicting findings regarding the consequences of platform owners' entry into complementary markets (cf. Rietveld & Schilling, 2020).

[3] For the purposes of empirical research, a researcher must determine what qualifies as low in a particular case.

Literature Review

Platform Owners' Entry into Complementary Markets

Market entry is a central topic in the management and strategy literature. A decision to enter a new market is often a deliberate way to diversify the firm (see, e.g., Mayer et al., 2015; Teece, 1982) by using excess resources that are "surplus to current operations" (Chatterjee & Wernerfelt, 1991, p. 33). Such use of excess resources for establishing a firm's presence in another market is typically realized through internal product development or acquisitions (Lee & Lieberman, 2010; Miric et al., 2021). However, in platform business, a platform owner's success rests critically on the viability and quality of complements from complementors who are neither owned nor directly controlled by the platform owner (see, e.g., Ghazawneh & Henfridsson, 2013; Karhu et al., 2018; Parker et al., 2017; Teece, 1986; Tiwana et al., 2010). It is therefore important for the platform owner to ensure that complementors continue to operate and thrive on the platform; consequently, the owner's entry into a complementary market can disrupt the relationship between the platform and its complementors. The entry can call into question the mutually beneficial relationship between the platform owner and the complementors in the specific complementary market, also potentially sending a negative signal to complementors in other markets (Hukal et al., 2020; Zhu & Liu, 2018). Entering a complementary market can result in the redistribution of the value captured in the market at the expense of complementors, but it may also speed up market growth and thus benefit both the platform owner and the complementors.

A review of the literature[4] reveals that a significant proportion of the existing research on platform owners' entry focuses on the competition between platform owners and complementors. The literature predominantly examines how the platform owner can appropriate value from the market by launching offerings similar to those of complementors (Cennamo et al., 2016; Edelman & Lai, 2016; Jiang et al., 2011; Lan et al., 2019; Wen & Zhu, 2019; Zhu & Liu, 2018). In doing so, the owner is typically in a good position to appropriate value, as the owner can, for instance, exploit its privileged position to identify the most promising complementary markets to enter and imitate successful complementors, which often allows the platform owner to quickly gain market share and to generate profits (Priem, 2007; Zhu & Liu, 2018). The process is often supported by the platform owner's capacity to shape the governance of the platform ecosystem to benefit its own complements (Edelman & Lai, 2016; Priem, 2007). For example, complements controlled by the platform owner may receive prioritized display, competitive bundle pricing, or add-on services that help them compete with other complements (Zhu & Liu, 2018). In sum, this stream of literature posits that the platform owner's entry typically increases competition in the complementary market and thus squeezes complementors' profits, which, in turn, reduces complementors' investments in the market (Zhu & Liu, 2018). Furthermore, the more predatory the approach that the owner takes, the more the impact of the entry can spill over to other complementary markets, jeopardizing the trust between the platform owner and complementors in general (Rietveld et al., 2019; Wareham et al., 2013).

Another smaller body of literature recognizes the value creation aspects of a platform owner's entry into a complementary market. The owner's participation in the market can increase its appeal to consumers and stimulate quality improvements, innovation, and positive co-specialization among complementors (Gawer & Cusumano, 2002; Gawer & Henderson, 2007; Priem, 2007). First, the platform owner's participation can improve the reputation of the platform among consumers (Cennamo & Santaló, 2019), and the existence of complements controlled by the platform owner can positively influence consumers' perceptions of the overall viability of complements in a particular category (Roger & Vasconcelos, 2014). In this regard, improved platform reputation may benefit all platform participants (Cusumano et al., 2019; Hagiu & Spulber, 2013; Rietveld et al., 2019). Second, reputation improvement can drive market growth as the platform owner's presence in the complementary market stimulates the curiosity of potential

[4] We followed Levy and Ellis's (2006) input-processing-output approach to conduct the literature review. First, we initiated our search in the journals included in the AIS Basket of Eight and the ABS Information Management division lists. We performed a keyword search to identify studies using the phrases "platform owner's entry," "platform entry," and "platform enter complementary market" in their title. We then narrowed down the selection to papers focusing on the platform owner's entry into a complementary market by analyzing the research questions and datasets used in the papers (Booth et al., 2022). Second, we summarized the remaining papers along multiple dimensions such as the studied platform context, entry mode, target market characteristics, and the consequences and implications of entry (Webster & Watson, 2002). Two key observations emerged from the summaries that motivated our research. First, we found that past studies have mainly focused on pure digital innovation platforms (e.g., Android, iOS) or retail platforms (e.g., Amazon Marketplace), while little attention has been given to platforms that engage the innovation of both physical and digital artifacts. Second, studies have shown conflicting findings regarding whether the platform owner's entry motivates complementor innovation or discourages complementors from investing in the market. This triggered us to speculate that the discrepancies in results might be due to the timing of entry. Therefore, we decided to use Amazon Alexa, an IoT platform, as the empirical context and to focus on examining the effects of early and late entry conducted by the platform owner.

consumers and complementors (Li & Agarwal, 2017). Together, the platform and the entered complementary market may become more visible and viable in the eyes of consumers. The increased consumer attention, in turn, boosts the growth of the complementary market, benefiting complementors by increasing the total size of the market.

The Timing of Entry into Complementary Markets

Extant research has primarily examined platform owners' entry into and competition in relatively mature complementary markets (e.g., Cennamo et al., 2016; Edelman & Lai, 2016; Foerderer et al., 2018; Jiang et al., 2011; Wen & Zhu, 2019; Zhu, 2019; Zhu & Liu, 2018). Such markets have an established portfolio of available products and, as a result, consumers are often well informed about the available complements and their key features. For instance, in Zhu and Liu's (2018) study of Amazon Marketplace, the sample included 163,853 incumbent products in 22 product categories. In Foerderer et al.'s (2018) study, the sample consisted of 1,266 available complements in Android's photography category. Given the platform owner's privileged position and access to information about complementary markets, entering such mature markets can be a relatively predictable endeavor for the owner.

At the same time, there are fewer studies examining the early timing of platform owners' entry (Gawer & Henderson, 2007; Lan et al., 2019), that is, an entry when the market represents a new form of complementary activity (Aldrich & Fiol, 1994; Santos & Eisenhardt, 2009). Such markets typically exhibit fleeting market structures accompanied by a low level of institutionalization and a high degree of ambiguity (Aldrich & Fiol, 1994; Eisenhardt, 1989; Rindova & Fombrun, 2001). Because products are untested (Tushman & Anderson, 1986), early complementors face challenges, such as a lack of a clear and coherent identity of their complements (Navis & Glynn, 2011). Furthermore, there are few exemplars that complementors wishing to make an early entry to the market can learn from, meaning that there is often "extreme ambiguity about opportunities and customer demand" (McDonald & Eisenhardt, 2020, p. 485) in the early stage of the complementary market development. Given the high ambiguity and uncertainty that complementors may face at an early stage, early entry by a platform owner can improve market viability in the eyes of complementors and thus accelerate the instantiation of market novelty (McDonald & Eisenhardt, 2020). The speed with which the platform can achieve this goal affects how fast the novel platform services can be recognized and adopted by consumers.

Complementors may initially hesitate to invest in a market due to the lack of consumer attention and knowledge about consumer preferences. The platform owner may therefore want to draw consumer attention to the emerging complementary market and feed user data to complementors to encourage complementors to enter the market (Bingham & Eisenhardt, 2011; Chen et al., 2010; Gregory et al., 2021). The platform owner's presence in the market could improve the reputation of the complementary market in the eyes of consumers and provide promotional spillover effects. This effect may then also enhance complements' popularity among consumers and consequently signal the viability of the market to other complementors considering entering it (Hukal et al., 2020).

Early entry by the platform owner can motivate complementors to enter the market for several reasons. First, news about a platform owner's entry draws consumer attention to the new type of complementary services (Assaad & Gómez, 2011). This, in turn, can trigger an attention spillover effect as consumers may try out novel complementary products beyond the platform owner's offering (Li & Agarwal, 2017; Liu et al., 2015). Second, the adoption of complements often relies on expectations of usefulness and quality (Cennamo & Santaló, 2019). To this end, the platform owner's participation in the complementary market lends its complements increased credibility as useful services and reduces potential worries about sudden discontinuation of the market. Third, given the lack of institutionalized market structure and dominant design(s), it is unlikely that the platform owner's complement alone can satisfy the variety of consumer preferences in the market. Therefore, the platform owner's promotion of its own product does not necessarily result in a zero-sum game in the early stage of market development. Instead, the existing complements in the market may benefit from the increased and more varied consumer demand and the promotional activities related to the market.

However, a platform owner's early entry may not impact complementors equally. First, we propose that more experienced complementors are more likely to benefit from early entry. Factors such as development capability, financing, and innovation rates are generally important to the success of individual complements on the market (Casadesus-Masanell & Yoffie, 2007), and the increased consumer attention resulting from early entry by the platform owner may be more readily exploited by experienced complementors. Second, we propose that functional diversity, that is, the degree of heterogeneity between the subfunctions of a complement (Tiwana, 2018), may moderate the effect of the platform owner's early entry.

Complements with specialized functionality should benefit (compared with complements with broad functionality) from the increased customer attention resulting from an early entry of the platform owner because a specialized complement should be easier for a consumer to understand. This quality might be important in nascent markets due to consumers' lack of prior experience using novel types of complements. In contrast, functionally diverse complements offer a range of different functionalities, which makes them more difficult to grasp for early adopters. Additionally, the adoption of such complements typically requires more configuration effort. For example, a camera app offers a focused core functionality of taking photos, complementing a smartphone in an easy-to-understand way. It may incorporate some additional features, such as panorama mode, night view, and filters, but these are easy to comprehend within the overall scope of photo taking. In this regard, the app offers synergistic specificity (Schilling, 2000) in that its subfunctionality achieves synergy with the main function. In contrast, a social media app such as Snapchat may have photo taking as one of its many features, supporting various modifications, such as adding cartoon elements and different photo frames, while having another layer of diverse functions related to sharing content on social media or even launching paid advertisements for business purposes.

In view of the (1) divergent directions in the extant literature and (2) the reasons supporting entry timing as a significant factor, we designed an empirical study that examines the effect of early entry by the platform owner on the popularity of complements among customers.

Research Design

We investigate three entries by Amazon into its Alexa voice assistant's Smart Home complementary market. The Alexa voice assistant enables consumers to use voice commands to control various home appliances and digital services. For example, users can say "Alexa, dim the bedroom light" to remotely control their bedroom lighting or say "Alexa, play Spotify" to turn on their playlist while cooking. Alexa Skills are complements created by developers to extend Alexa's capabilities in performing various tasks such as ordering groceries, checking the front door, turning on home entertainment devices, and controlling connected smart furniture. At the end of 2020, Alexa Skills had connected one million smart home gadgets for Alexa users worldwide.[5] However, given the novelty of smart home interactions to both developers and consumers, Amazon initially saw slow growth in its complementary markets. At the end of 2015, there were only 130 active complements available in the overall market, which grew to 10,000 by the end of 2017 and to over 50,000 by 2021. In addition, the demand for different types of complements grew at an uneven pace.

Games & Trivia was initially the fastest-growing complementary market on Alexa. In June 2018, it accounted for 18.5% of all available complements, followed by Education, Music & Audio, Movies, and Lifestyle, which each accounted for approximately 12% of complements. However, the release of complements into these categories often represented adaptations from other platforms rather than novel inventions specific to Alexa (Ghazawneh & Henfridsson, 2015). In contrast, complements related to smart home appliances and services grew at a much slower pace, with only 3.5% of complements falling into this category at the end of 2018. The category was new, largely born out of the Amazon Echo smart speakers themselves, and many emerging consumer products related to the category, such as cleaning robots, surveillance gadgets, furniture, and utility controls, were still in the early stages of development. As a result, Amazon experienced relatively slow growth in the complementary market that would seem central to the Alexa platform's long-term success.

Data

We used data collected from the Smart Home category of Alexa Skills in Amazon's U.S. and U.K. stores between June 2017 and September 2019. During this period, there were three entry events by Amazon: the acquisitions of Blink Home in December 2017, Ring in February 2018, and Eero in February 2019.[6] We identify the first two entries as early entries because of the low ratio between the number of complements in the market at the time of entry and the eventual size of the market in 2021. Consider that until 2017, smart speakers had very low market penetration among consumers according to analysts,[7] and the Smart Home category represented the smallest of all Alexa complementary markets, with just 3.5% of all complements

[5] https://ir.aboutamazon.com/annual-reports-proxies-and-shareholder-letters/default.aspx

[6] To ensure that there were no other major acquisitions made by Amazon in its Alexa ecosystem, we cross-checked Amazon's business activities from December 2015 to November 2021 using multiple sources such as Wikipedia (list of mergers and acquisitions by Amazon), MICROACQUIRE (Amazon Acquisitions), and Crunchbase (Amazon, Amazon Alexa Fund, The Alexa Accelerator).

[7] https://voicebot.ai/wp-content/uploads/2018/11/voice-assistant-consumer-adoption-report-2018-voicebot.pdf

in 2018. The category grew substantially over time, representing approximately 6.7% of all complements by 2019 and 10.3% by 2021, leading us to consider the third entry to be a late entry. We only used data on complements that were available in the Alexa store at least six months before the entry event. Complements that joined after the entry were excluded to avoid overestimating the impact of the entry.

Dependent Variable

To investigate the impact of platform owners' early entry on the popularity of complements, we followed a common approach in the literature and used *the number of reviews* submitted by users on each complement as a proxy for the popularity of complements among consumers (Barlow et al., 2019; Foerderer et al., 2018; Halckenhaeusser et al., 2020; Yin et al., 2014). We excluded complements that had an unchanged number of reviews for more than four months, as this indicated that the complement had likely become dormant. The dependent variable was log-transformed due to its skewed distribution.

Independent and Control Variables

In addition to standard treatment and time-period indicators used for difference-in-differences estimation, we included two independent variables in our model that enable in-depth analysis of the heterogeneous effects of platform owner's entry (functional specificity and the age of complementor) and a few other variables used as controls or to find a balanced match between treatment and control group complements.

First, *functional specificity* measures the heterogeneity of a complement based on the complexity of services offered by the complement. Functional specificity uses a scale consisting of three mutually exclusive categories: specialized, suite, and integration. Starting from the simplest, "specialized" complements control a single (set of) device(s). For instance, the Avatar smart light allows users to manipulate one or several Avatar light bulbs with Alexa. "Suite" indicates that the complement is designed to operate multiple types of devices from the same manufacturer, typically from the complementor itself. For instance, TP-Link KASA can control different devices, such as lights, security cameras, switches, sockets, and wireless routers, from the same brand. Finally, "integration" indicates that the complement can control devices from multiple manufacturers, which makes it the most functionally diverse category. For instance, Harmony is essentially an integration system that enables Alexa to be connected to lights, speakers, and smart TVs regardless of the manufacturer.

Second, we accounted for platform-specific investments (Zhu & Liu, 2018) by measuring *interface coupling*, which indicates the degree to which the complement is specifically connected with the platform core (i.e., Echo smart speakers). "Tight coupling" indicates that the complement is directly and solely connected to Echo. For instance, Avatar and TP-Link are tightly coupled to Echo as a central command station. In contrast, "loose coupling" indicates that an intermediary technology exists between the complement and the platform core. Using a middleware device, Harmony belongs to this category.

Third, we accounted for the varying difficulty in developing smart home services by categorizing complements into 12 *service subcategories* (see Table 1). In doing so, we used the functional description of each complement to identify the purpose of the complement in the same way an Alexa user would. We complemented this examination with information from the complementors' (i.e., developers') websites when needed. Furthermore, for complements with vague descriptions, we installed the complement and tested it with Alexa ourselves. We lastly determined the complement's subcategory by analyzing the descriptions and clustering complements with a focus on functionality (e.g., Lights and Plugs) or purpose in the smart home environment (e.g., Entertainment).

Fourth, we included the complement's average *rating score* (1 to 5), which controls for the innovation quality of the complement (Foerderer, 2020; Foerderer et al., 2018; Wen & Zhu, 2019). We used the number of *languages* of a complement to control for the broadness of the potential market. The number of *helpful votes* given to consumer reviews indicates the quality of consumers' contributions and interactions with the complement. On the complementor level, we used the complementor's *portfolio*, which is the number of complements released by the same company (Li et al., 2013), together with *the age of the complementor* as proxies for the complementor's technological experience (Foerderer, 2020). Complementor age is calculated by subtracting the year the complementor firm was established from 2018, that is, the year Amazon first entered the market (the variable was log-transformed by adding 1 to the calculated age). Finally, we included complementor *size*, measured as the number of employees, the geographic *region* of the complementor, and *IPO status*, which indicates whether the company is public or private. The variables used for the study are summarized in Table 2.

Table 1. Alexa Smart Home Subcategories

Subcategory	Description	Complement examples
Climate control	Thermostats, fans, air conditioning, air quality monitors and purifiers	tado, ecobee plus, Midea Air, Awair Glow
Electric appliances (i)	Indoor home appliances such as ovens, kettles, and cookers	LaundaryNFC, Appkettle, Coffee Machine
Electric appliances (ii)	Outdoor appliances such as irrigation and water controllers	Rachio, Eco watering, RainCloud
Entertainment and communication	Entertainment devices such as TV, audio, speakers, and telecom devices	TV Remote, Polycom, play-Fi, Vizio SmartCase
Furniture	Indoor furniture such as shades, beds, sofas, and mirrors	MySmartBlinds, SOMA Smart Shades
Garage	Remote and smart garage controllers	Mighty Mule, Tailwind, Garageio
Home assistance	Utility monitors, location trackers, situational advice, and pet care devices	Flo, tracMo, Baby sleep coaching, How to Geek, Petnet SmartFeeder
Home integration	Hybrid integration of comprehensive smart home environment	Smart life, Yonomi
Home surveillance	Cameras, sensors, and alarm systems	Blink smart home, Alarm.com, Scout Alarm
Lights and plugs	Lightning, sockets, switches, and plugs	Hue, Wemo, Vivitar, eFamilyCloud
Robotics	Cleaning robots and massage robots	iRobot Home, Roborock home
Wireless connection	WiFi systems and routers	Luma WiFi, ASUS router

Table 2. The Description of Study Variables

Variable	Description
Dependent variable	
Number of reviews	The number of reviews received by a complement per month (natural log-transformed)
Complement-related variables	
Functional specificity	The complexity of services enabled by a complement
Interface coupling	The degree of interface specificity between a complement and the platform core
Service subcategory	The type of home services enabled by a complement
Rating score	The average rating score (1-5) per month (natural log-transformed)
Languages	The number of languages that the complement is available in (natural log-transformed)
Helpful votes	The number of helpful votes that the reviews of the complement received per month (natural log-transformed)
Complementor-related variables	
Portfolio	The number of complements offered by the complementor on the Alexa smart home complementary market
Age of complementor	The number of years the complementor has been in operation in January 2018 (we track the earliest time the complementor created an online presence via Twitter and LinkedIn) (natural log-transformed)
Size	The number of people employed by the complementor
Region	The geographic location of the complementor
IPO status	The IPO status of the complementor

Research Model

To analyze the impact of Amazon's early entries into the Smart Home complementary market on its Alexa platform, we estimated a difference-in-differences (DID) model with two-way fixed effects using panel data on 332 complements at the individual complement level. The main analysis focused on the 12-month time window ranging from six months before to six months after the platform owner's entry into the target complementary market—that is, a subcategory of Smart Home complements (cf. Foerderer et al., 2018). To facilitate the DID estimation, we created two indicator variables: $Treated$ is set to 1 if the complement belongs to the entered subcategory and is otherwise 0. $After$ is set to 1 if the observation is from the post-treatment period ($t > 6$) and is otherwise 0. Note that we omitted the main effects of the $Treated$ and $After$ variables in the model due to collinearity with complement and time-period fixed effects (Beck et al., 2010). Equation (1) shows the model specification used for the estimation.

$$Reviews_{it} = \alpha + \beta Treated_i \times After_t + \delta Controls_{it} + C_i + T_t + \varepsilon_{it} \quad (1)$$

In the model, $Reviews_{it}$ is the number of reviews received by complement i at time t, and α is a common intercept for all complements in the treatment and control groups. Our interest is on the interaction term parameter β that captures the average treatment effect on the affected complements. $\delta Controls_{it}$ is a set of time-varying complement-level variables that include the complement's rating score and helpful votes. We assume that the one-year observation window keeps constant the influence of factors such as the evolving development capability of a complementor or the accumulated knowledge of the platform, which could vary both over time and complement, and we control for any remaining unobserved heterogeneity using complement (C_i) and time-period (T_t) fixed effects (Bertrand et al., 2004; Foerderer et al., 2018; Wing et al., 2018). ε_{it} is the error term.

Results

To explore whether the entry decision can be considered exogenous, we first confirm that the number of reviews accumulated by the complements did not seem to influence Amazon's decision to enter a particular subcategory using a logit regression. We then present the results of the DID estimation on the impact of the entry on complement popularity.

The Exogeneity of Amazon's Entry

To assess the exogeneity of Amazon's entry into specific complementary markets, we conducted a logit regression analysis using the number of reviews received by complements to predict Amazon's entry into the Home Surveillance and Wireless Connection subcategories.[8] We used the data on complements covering six months before the announcement of entry to observe any overall pattern describing the entries. The dependent variable indicates whether the complement belongs to the entered subcategory, which is not explained by the number of reviews if the entry is exogenous.

The results are shown in Table 3. Models 1-4 present the results for complements from the Home Surveillance subcategory and other complements, and Models 5-8 present the results for complements from the Wireless Connection subcategory and other complements. The six-month period provides a reasonable time window during which platform owners can assess entry market options. The information captured in the independent variables used in this analysis is readily available to the platform owner and can thus be considered to be a potentially influential factor in the evaluation of a target market for entry.

Table 3 shows the results on the potential factors that may have influenced Amazon's entry decision. First and most importantly, the number of reviews received by complements did not seem to influence either Amazon's early entry or late entry into the target complementary markets. The finding is consistent with the assumption that platform owner's entries are exogenous in our main analysis, which examines the entry's effect on the number of complements' reviews. Second, the complement's average rating score has a significant but opposite impact on Amazon's entry decision in the early and late entry scenarios. Model 4 reveals that a 1% increase in complements' rating score reduced the likelihood of Amazon's early entry over nonentry by a factor of 6, while Model 8 shows the opposite by increasing this ratio by 2.5 for late entry. Regarding the functional specificity of complements, the target of the platform owner's early entry (i.e., Home Surveillance) revealed a greater possibility for developers to release suite-type complements where profits can be captured by having several in-house physical devices connected to Amazon Echo. In contrast, the market targeted by late entry (i.e., Wireless Connection) did not show such potential because complements in this subcategory mostly have only a router or booster connected to the platform core.

[8] We provide a model specification in the online transparency materials.

Table 3. Amazon's Early and Late Entry Patterns

	Home surveillance				Wireless connection			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Early entry	Early entry	Early entry	Early entry	Late entry	Late entry	Late entry	Late entry
Number of reviews	0.030 (0.10)	-0.216 (0.13)	-0.369 (0.34)	-0.243 (0.36)	-0.170* (0.08)	-0.134 (0.08)	0.067 (0.08)	0.304 (0.19)
Rating score		-2.864*** (0.48)	-6.016*** (0.33)	-6.062*** (0.33)		0.697 (0.36)	0.944* (0.39)	2.491*** (0.61)
Functional specificity								
Suite			3.974*** (0.99)	4.085*** (1.03)				
Integration			1.342 (0.96)	1.646 (0.98)				
Interface coupling								
Loose coupling			4.745*** (0.89)	5.440*** (0.82)			-1.211* (0.58)	-2.241 (1.24)
Languages			-1.743* (0.73)	-1.821** (0.60)			-0.199 (0.19)	-0.219 (0.33)
Helpful votes			0.874*** (0.23)	0.822** (0.27)			-0.427*** (0.10)	-0.883*** (0.18)
Portfolio				-1.114* (0.45)				3.844*** (0.99)
Age of complementor				-0.062 (0.39)				-1.406*** (0.27)
Intercept	-2.729* (1.27)	0.506 (1.40)	0.097 (1.79)	0.940 (2.90)	-3.560** (1.27)	-4.547*** (1.17)	-4.690*** (1.23)	-7.639** (2.79)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	504	504	504	504	732	732	732	732
Pseudo-R^2	0.103	0.221	0.590	0.593	0.081	0.099	0.120	0.400

Note: Standard errors are clustered on the subcategories of complements and are reported in parentheses. All estimations use an observation window starting six months prior to the platform owner's entry. The baseline is specialized complements (functional diversity) with tight coupling to the platform core (interface coupling). For the sake of brevity, the size, region, and IPO status of complementor are not shown. Time fixed effects include monthly dummies. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The findings suggest that it is unlikely that Amazon's early entries into the Home Surveillance subcategory were motivated by value capture, as it had not yet become a reputable category of complements among consumers. Together with the potential of the home surveillance complements to enable the suite of services and its diverse links to consumers' domestic needs, it makes sense that Amazon's early entries were aimed at boosting the popularity of the subcategory among complementors and at drawing consumer attention to it. This inference is further supported by anecdotal evidence. For example, Amazon disclosed to *The Verge* magazine that they bought Blink because "we already know customers love their home security cameras and monitoring systems. We are excited to welcome their (i.e., Blink) team and invent together on behalf of customers."[9] In contrast, the Wireless Connection subcategory targeted by Amazon's late entry suggests a much clearer opportunity to capture value and enhance the platform's control of a critical intermediate market. In the case of the Eero acquisition, deemed here as a late entry, the media widely discussed the importance of gaining consumers' data and improving the overall experience of a connected home. As a critical connector between Amazon Echo and a variety of other devices, the mesh WiFi system could serve as a valuable control point in Alexa's competition with Google Nest WiFi and the Google-led smart home ecosystem.[10]

The Impact of Early Entry on Complement Popularity

We applied propensity score matching (PSM) and coarsened exact matching (CEM) methods to find appropriate control complements to those affected by Amazon's entry. As an equal percent bias-reducing model (Rubin, 1976), PSM helps to correct the estimation effects by using similar treated and control observations upon controlling for confounding factors

[9] https://www.theverge.com/circuitbreaker/2017/12/22/16810516/amazon-blink-acquisition-smart-camera-doorbell-company

[10] https://www.buzzfeednews.com/article/nicolenguyen/amazon-acquisition-eero-routers-privacy

(Becker & Ichino, 2002; Rosenbaum & Rubin, 1983; Rosenbaum & Rubin, 1985). Following Michalopoulos et al. (2004), we matched the treatment and control group complements based on the following covariates: functional specificity, interface coupling, rating score, languages, helpful votes, portfolio, and the age of the complementor (Stuart & Rubin, 2008). Figure 1 shows that the distribution of the propensity score between the matched treated and control group complements is very similar. This indicates a similar likelihood of becoming an entry target (cf. Garrido et al., 2014), while the bias between the matched samples across most covariates is reduced to below 10% (details available upon request). The CEM method employs an alternative logic with no assumptions or prior knowledge about the entry pattern (Iacus et al., 2011), and it has been suggested that it may be superior when the observed dataset is relatively small (Bapna et al., 2016). Following Bapna et al. (2016), we implemented the coarsening procedure based on functional specificity, interface coupling, languages, size, region, and IPO status, which together yielded the lowest L1 multivariate distance (0.1389) compared to other combinations of covariates (details available upon request).

Table 4 reports the result of the DID estimation using the PSM dataset (Columns 1 to 4) and the CEM dataset (Columns 5 to 7). Column 1 shows a 36% increase in the number of reviews received by Home Surveillance complements after Amazon's early entry into the subcategory. The estimated popularity improvement is slightly higher with the CEM matched data, as shown in Column 5. Importantly, the effect is significant and of similar magnitude regardless of the type of matching used. The results with respect to the heterogeneous impact of complements' functional specificity are reported in Columns 2 to 4 for the PSM dataset and in Columns 6 to 7 for the CEM dataset. Columns 2 and 6 show that complements that offer consumers specialized functionality gained a similar degree of additional reviews (popularity). At the same time, the extra improvement in complement popularity is not significant for complements offering broader functionality.

Further Analysis and Robustness Checks

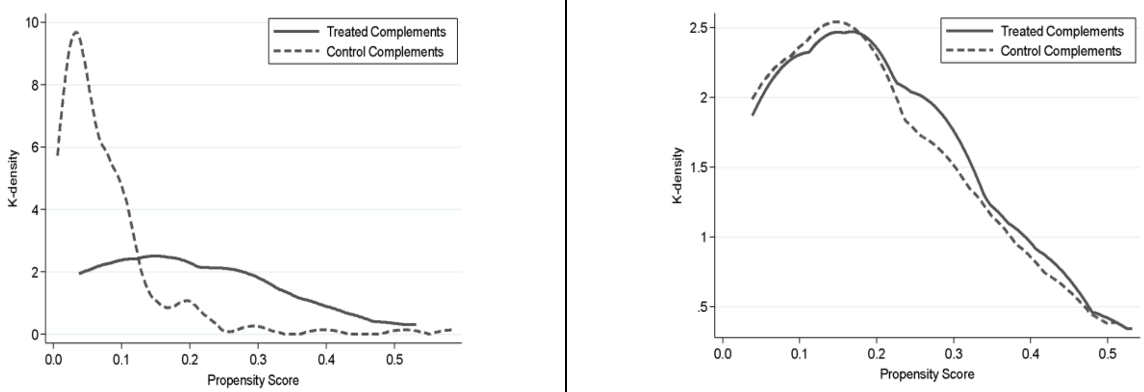
To extend our results and check their robustness, we first compared the observed impact of early entry to the platform owner's late entry into a complementary market to assess whether the latter is associated with a different type of impact. We then reestimated the results using semi-random control groups and a manipulated treatment window as a placebo test, and studied how the age of the complementor moderated the impact of entry.

Late Entry

To explore the impact of Amazon's late entry into the Wireless Connection subcategory, we compared the changes in the number of reviews received by complements in the category to the complements in the Climate Control subcategory. We used the latter as the control group because the two subcategories showed very similar patterns in terms of the number of reviews, rating score, helpful votes, portfolio, and size. Nearly all complements in both subcategories showed a high level of functional specificity. The only discernible difference between the Wireless Connection subcategory and the Climate Control subcategory was found in the complements' languages (diff = 0.857, *SE* = 0.385) and the age of complementors (diff = -27.875, *SE* = 5.623). We estimated the model presented in Equation (1) using data from the two subcategories six months before and after Amazon's late entry and found that the popularity improvement on the affected complements is not statistically significant in the case of late entry (details available upon request).

Semi-Random Control Group and Manipulated Treatment Window

To extend our main analysis where the treated and control complements were matched following the fully blocked randomization with pruned pretreatment imbalances, we harnessed the idea of having a control group similar to one that would be generated in a randomized experiment (Singh & Masuku, 2014). This method entails fewer restrictions on the pretreatment balances and model dependence and can be used as an alternative way to explore the validity of our main findings (King & Nielsen, 2019). Among the pool of 323 Smart Home complements, excluding the entered subcategory (Home Surveillance with 36 complements and Wireless Connection with 17 complements), we allowed the control group to include half (50%) and three quarters (75%) of complements randomly selected from the pool. We again estimated the model in Equation (1) to observe the impact of the platform owner's entry. The results are reported in Table 6, Panel A. Columns 1 and 2 show that the improved popularity gained by the Home Surveillance complements from early entry is approximately 44% to 35%. The coefficients are largely consistent with the main estimation using the pure PSM and the CEM control groups (see Table 3). Columns 3 and 4 again show that the impact of late entry on complement popularity is not significant, which is again consistent with the robustness check above. Finally, we combined the randomly selected control group with a manipulated treatment window where we set the entry event to three months before and after the actual entry time as a placebo test. Panel B in Table 5 shows that the early entry effect on complements' popularity is no longer significant once we changed the treatment period. In the case of late entry, forward and backward analysis again did not reveal any significant impact on the popularity of complements.



Unmatched Complements | **Matched Complements**

Note: We applied PSM with nearest-neighbor matching using complements that have been active since June 2017. The logit model behind Table 3 was applied to predict the propensity score. Matching reduced the standard percent bias across all variables to below or around 10%, and no covariate displays significant differences between the matched treated and control group after the matching.

Figure 1. Propensity Score Distributions

Table 4. Impact of Platform Owner's Early Entry on Complements' Popularity

	PSM				CEM		
	(1) ALL	(2) Specialized	(3) Suite	(4) Integration	(5) ALL	(6) Specialized	(7) Suite
Treated × After	0.357** (0.11)	0.368** (0.10)	0.172 (0.12)	1.166 (0.30)	0.417*** (0.09)	0.419** (0.10)	0.904 (0.30)
Intercept	2.863*** (0.29)	2.855*** (0.49)	3.296** (0.50)	2.726 (0.66)	4.289*** (0.31)	4.183*** (0.31)	-0.715 (0.76)
Complement FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.533	0.578	0.603	0.449	0.764	0.762	0.828
N	1152	504	348	300	252	240	35

Note: All models control for time-varying variables, including the complement's rating score and helpful votes. Model 1 and Model 5 are the baseline analyses, using all the matched complements. Models 2, 3, 4, 6, and 7 are grouped regressions based on different levels of functional specificity. The integration group under CEM is dropped due to the lack of a sufficient number of observations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5. Entry Impact with Semi-Random Control Groups and Manipulated Entry Time

Panel A: Semi-Random Control Groups				
	Early entry		Late entry	
	(1) Half random	(2) Three quarters random	(3) Half random	(4) Three quarters random
Treated × After	0.442** (0.14)	0.353* (0.14)	-0.027 (0.08)	-0.054 (0.07)
Intercept	3.033*** (0.51)	2.296*** (0.42)	2.118*** (0.40)	2.238*** (0.34)
Complement FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R^2	0.537	0.496	0.316	0.339
N	888	1272	1628	2557

Panel B: Manipulated Treatment Window				
	Early entry		**Late entry**	
	(1) 3 months backward	**(2) 3 months forward**	**(3) 3 months backward**	**(4) 3 months forward**
Treated × After	0.227 (0.16)	0.149 (0.08)	-0.130 (0.07)	-0.110 (0.08)
Intercept	1.120** (0.41)	2.225*** (0.41)	2.417*** (0.27)	1.926*** (0.38)
Complement FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R^2	0.455	0.291	0.439	0.298
N	815	1271	1470	1589

Note: All models control for time-varying variables, including the complement's rating score and helpful votes. Models 1 to 4 in Panel B use a 50% random selection method. Robust standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6. Impact of Complementor Age on Complement Popularity in Early Entry

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	All complements				**Functionally specialized complements**			
Age	(0,4]	(4,7]	(7,17]	(17,118)	(0,4]	(4,6]	(6,17]	(17,118)
Treated × After	0.049 (0.19)	0.077 (0.21)	0.382 (0.41)	0.457*** (0.13)	-0.061 (0.39)	0.176 (0.18)	0.712 (0.71)	0.306*** (0.08)
Intercept	0.825 (0.50)	2.867*** (0.80)	1.368 (0.70)	1.921*** (0.31)	0.436 (0.57)	3.369* (1.26)	1.070 (0.80)	1.479* (0.57)
Complement FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.415	0.462	0.367	0.549	0.392	0.498	0.468	0.574
N	855	484	639	609	464	335	336	377

Note: Models 1 to 4 are applied to all eligible complements for early entry analysis where the sectioning of the age factor is gained from the 25th, 50th, and 75th percentile of all complements. Models 5 to 8 are applied to functionally specialized complements only. All models control for service subcategories, complement's rating score, and helpful votes. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The Age of the Complementor

To further extend our knowledge of platform owners' early entry, Table 6 shows the analysis results with respect to four complementor age brackets. The findings in Columns 1 to 4 are consistent with the received wisdom that developers with more years of operation are often better positioned to benefit from increased consumer attention resulting from the platform owner's entry. Such a premium gained by older firms also applies to complementors whose complements are specialized in terms of their functionality. The magnitude of the entry's effects shown by the coefficients is consistent with what we observed in the previous analysis, which further enhances the confidence in our results.

Discussion and Implications

In this paper, we set out to study platform owners' early entry into complementary markets by comparing the impact of early entry to the impact of late entry. Our analysis of Amazon's early entries into the Home Surveillance subcategory of the Alexa Smart Home complementary market suggests that the timing of platform owners entering complementary markets matters. As distinct from late entry, early entry into a complementary market draws considerable consumer attention to the market, which benefits complementors that offer specialized functionality regardless of how long the complementor has been in the market.

Table 7 summarizes our key findings. First, compared to its late entry, a platform owner's early entry is associated with more consumer attention to a complementary market and thus increases the market's perceived viability among early adopters. This, in turn, may trigger more complementors to enter the market, enabling the complementary market to prosper since more services enable more consumers to find complements that are useful to them and become adopters. While this may seem to contradict Wen and Zhu (2018), who found that platform owners' entry disincentivizes complementors from participating in the complementary market, we surmise that the early timing of entry in our case explains the contradictory results.

Table 7. Key Findings

Finding	Early entry	Late entry	Interpretation
Platform owner's entry into a complementary market increases complements' popularity among consumers in the post-entry period.	True	False	Complementary markets are initially driven by a value-creation logic for which the entry may be a positive catalyst for both complementors and consumers, as it reduces uncertainty associated with novel markets.
Functionally specialized complements are more likely to benefit from increased consumer attention after the platform owner's entry.	True	N/A	Consumers are initially drawn to complements that are easy to understand and require little configuration; developing such complements is typically within the reach of startup companies.
Established complementors are more likely to benefit from increased consumer attention after the platform owner's entry.	True	N/A	Developers with more experience have the capacity to seize the opportunity as they can harness broader development, financing, and innovation resources.

Our study suggests that when consumers have limited experience, the platform owner's entry serves as an important source of customer enthusiasm about the novel category of complementary services (cf. Anthony et al., 2016; McDonald & Eisenhardt, 2020). In this regard, nascent market growth is driven by a value creation logic rather than the logic of capturing value that is present in mature markets. The timing of the platform owner's entry thus defines whether the entry should incentivize or disincentivize complementors to participate in the market (cf. Mitchell, 1989). A platform owner entering a complementary market at an early stage can be a positive signal to complementors, whereas its entry at a later stage suggests an intention to capture value that would otherwise be captured by complementors.

Second, our analysis of heterogeneous entry effects suggests that the functional specificity of complements significantly influences whether the complementor can benefit from the increased attention of early adopters in the complementary market (cf. Tiwana, 2018). At an early stage, complementary markets present not only considerable novelty but also unfamiliarity and uncertainty about the value of individual complements to consumers. Consequently, early adopters are likely to first try out functionally specialized complements that revolve around an easy-to-understand main function and require little configuration effort (Schilling, 2000). Moreover, our results are consistent with earlier findings that complementors with more years of experience are favored by consumers when the platform owner enters the market early, probably because more experienced complementors can better adapt to the unfolding market structure (King & Tucci, 2002). Importantly, however, our results show that young developer firms can mitigate this effect if their offerings are functionally specialized, aligning with similar findings in prior work (e.g., Coad et al., 2016; Czarnitzki & Kraft, 2004). Even small, innovative complementors may thus not need to view the platform owner's entry into a nascent market as threatening and can instead take it as a signal of the market's viability.

Overall, this research note offers important insights regarding the timing of platform entry into complementary markets. We provide a first step in reconciling divergent views in prior studies of platform owners' entry into complementary markets (Rietveld & Schilling, 2020) by exploring the effects of early and late entry timing. Rooted in the platform owner's power over its ecosystems, one stream of literature characterizes the platform's entry into complementary markets as a competitive threat to complementors (Jiang, 2011; Wen & Zhu, 2019; Zhu & Liu, 2018). This line of research recognizes the platform owner's capabilities in estimating the complementary market's demand ex ante. Such capabilities can assist in the development and release of complementary products that may become "blockbusters" in the entered market because the platform owner benefits from its privileged access to consumer data and platform resources (Adner et al., 2019). However, another strand of studies on platform owners' entry into complementary markets sheds light on the innovation spurred among complementors after platform entry (Foerderer et al., 2018) and on how platform owners motivate value co-creation through shared platform resources (Gawer & Henderson, 2007).

In this regard, our research reflects the notion that a platform's entry strategy should be reflective of the developmental stage of its ecosystem (cf. Rietveld & Schilling, 2020). At an early stage, the platform owner's entry can signal a commitment to growing the prosperity and popularity of the entered market, thus incentivizing the release of more complements into the market. Moreover, the platform owner's participation attracts consumer attention to the new market, which further provides complementors with richer consumer knowledge and a more vigorous developmental environment. Importantly, our results reveal an opportunity for young complementors to gain competitive advantage from the platform owner's early entry by offering functionally specialized complements in a new market.

Finally, no study is without limitations. In what follows, we highlight two limitations of our study. First, although we made significant efforts to rule out an association between the timing of the platform owner's entry and the popularity of complements in the entered market, we cannot fully confirm that the entry is exogenous. The results also assume that Amazon, as a leading player in the smart home sector, had a similar level of interest in both early- and late-entered markets and used its entry timing strategically to influence market growth, which would seem to be difficult to prove econometrically. For these reasons, we find it prudent to avoid making claims about causal identification (Mithas et al., 2022a, 2022b). However, nothing in our results suggests otherwise; as such, the results point to a distinct opportunity to validate and further specify the potential causal impact of entry timing on complementors. Future studies could, for instance, address the question of whether platform owners' entry into complementary markets should be regulated and, if so, whether the regulation should consider the timing of the entry. The second limitation of our study emerges from the fact that the unique nature of the Alexa platform may limit the generalizability of our results. Unlike previous research that has mainly investigated the impact of platform owners' actions on purely digital innovation platforms, the selection of Amazon's Alexa as our empirical setting responds to Rietveld and Schilling's (2020) call for a diversity of empirical contexts in platform research. The smart home environment epitomizes an emergent type of complementary market and provides a relevant and distinct hybrid setting for platform research (Chung et al., 2017; Sciuto et al., 2018). However, our results would need to be replicated and further theorized in other settings to establish their generalizability. Despite the limitations of causal identification and external validity, our results advance the idea that platform owners can use the timing of their entry into a complementary market as a strategic tool to accelerate the growth of complements in that market.

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Appendix

Logit Regression Model Specification

To assess the exogeneity of Amazon's entry into specific complementary markets, we estimated the following model using logit regression:

$$Entry_{it} = \alpha + \beta_1 Number\ of\ Reviews_{it} + \beta_2 C_{it} + \beta_3 D_i + \gamma + \varepsilon_{it}$$

In the model, $Entry_{it}$ equals 1 if the complement i belongs to the entered complementary market at month t, and 0 if the complement i does not belong to the entered complementary market at month t. β_1 is the coefficient of interest that estimates the endogenous impact of the number of reviews received by the complement on platform owner's entry decision. β_2 captures time-variant complement-level control factors. β_3 captures the impact of complementor-level controls. γ represents time dummies. α is the intercept and ε_{it} is the error term.