Smart timing for smart products?
Complementor multihoming in nascent platform markets

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ABSTRACT

Complementor multihoming is becoming pervasive in platform-mediated markets populated by multiple platforms. In a study of the nascent “smart home” industry, we use a novel dataset to examine complementor strategies regarding timing of entry and timing of multihoming, with their corresponding performance implications. We find that early entrants to a platform market multihome faster than later entrants. While early entrants achieve lower performance than later entrants, this negative performance effect is mitigated for complementors that multihome fast. This implies that multihoming is an effective hedging strategy for early entrants in multi-platform markets characterized by high uncertainty. Also, multihoming scope (number of platforms a complementor joins) is associated with higher complementor performance and shorter time to the next platform adoption.

Keywords: platforms, complementor multihoming, entry timing, time to multihome, nascent markets

INTRODUCTION

Research on platform-mediated markets and business models has proliferated over the past decade. Many of today's products and services, such as video games, social media, or smartphones, are organized around platforms that facilitate interactions and transactions among firms and individuals (Eisenmann, Parker and Van Alstyne, 2006: Gawer, 2014; Hagiu, 2005; McIntyre and Srinivasan, 2017; Rochet and Tirole, 2006). Platform scholars use the term "sides of the platform" to indicate the types of actors in a given platform. Platforms typically serve different sides: for example, Facebook serves end users, complementors and advertisers. Complementors are actors that provide complementary products or services that run on a platform (Bresnahan, Orsini and Yin, 2015; Gawer and Cusumano, 2002). They have been shown to be crucial to a platform's success because complementors are the source of "indirect network effects" (Rochet and Tirole, 2006).

Despite the importance of complementors, much of the platform literature has adopted the perspective of the platform owner, concerned with how owners can create or maintain competitive advantage in the market against competing platforms (Armstrong, 2006; Gawer and Henderson, 2007; Kapoor and Lee, 2013; Schilling, 2002). This literature focuses on the role of complementors as a source of indirect network effects that help a platform attract more users (Evans, 2003; Rochet and Tirole, 2003). The lack of attention to complementors' competitive dynamics is rather surprising given the size and importance of many complementor markets today; these entrepreneurial ecosystems have a significant impact on economic growth and employment (Audretsch, Keilbach and Lehmann, 2006; Baumol and Strom, 2007; Jacobides, Cennamo and Gawer, 2016).

Our study builds upon an emerging body of work focusing on the competitive strategies of platform complementors (Ceccagnoli *et al.*, 2012; Cennamo, Ozalp and Kretschmer, forthcoming; Kapoor and Agarwal, 2017; Venkataraman, Ceccagnoli and Forman, 2017). For instance, authors have studied the conditions under which participation in a platform is most favorable for complementors (Venkatraman and Lee, 2004), and examined the impact of complementors' possession of intellectual property (IP) protection and downstream capabilities on their platform adoption decisions (Huang *et al.*, 2013). Other authors have investigated how participation in a platform affects complementor performance (Ceccagnoli *et al.*, 2012) and studied complementors' market entry strategies (Corts and Lederman, 2009; Landsman and Stremersch, 2011).

We contribute to and expand on this literature by focusing on key strategies available to complementors competing in industries transformed by the emergence of platforms. Such transformations have challenged incumbents used to compete in "pipeline" industries[1] (Parker, Van Alstyne and Choudary, 2016) that must now compete in platform-mediated industries (Bresnahan *et al.*, 2015; Hagiu and Altman, 2017). This transformation comes with great uncertainty for incumbents, not only for the novelty of the new business model, but also because typically several platforms compete for dominance in the new space. Complementors in industries with multiple platforms face two critical decisions: when to enter the new platform-mediated space (i.e. join a first platform) and when to "multihome" to other platforms. Multihoming occurs when a complementor offers its product or service in more than one competing platform – a phenomenon that has become common as platforms proliferate. Complementors multihome to access non-overlapping user bases, spread fixed costs, or reduce

[1] Traditional value chain model, where businesses create value by arranging their activities in a linear fashion.

dependence on any one platform (Clements and Ohashi, 2005; Kretschmer and Claussen, 2016; Corts and Lederman, 2009).

Multihoming has been comprehensively examined through formal models (Armstrong, 2006; Rochet and Tirole, 2003, 2006; Armstrong and Wright, 2007) but empirical research on the topic has been scant. A recent review of the platform literature lamented the lack of attention paid to complementors' strategies, particularly whether and when they should adopt multiple platforms (McIntyre and Srinivasan, 2017). We argue that multihoming can be an effective hedging strategy for complementors, particularly in the early stage of a platform-mediated market characterized by high technological and market uncertainty.

We first study the relationship between a complementor's strategic decision to enter a new platform-mediated market (by joining any one of the competing platforms) and time to multihome (i.e. time to join a second platform after having joined the first one). Specifically, we examine whether early entrants to the new platform-mediated market will also tend to multihome faster. Second, we explore the relationship between multihoming scope (number of platforms a complementor has joined) and the time it takes to multihome again. Third, we investigate whether multihoming scope is related to complementor performance. Fourth, we test how entry timing, and the time that complementors take to join existing platforms, interact to influence complementor performance. We found that early entry in a platform-mediated market is associated with shorter time to multihome. Further, our results suggest that multihoming scope is correlated with shorter time to the next multihoming event and better complementor performance. We also found that the early-entry disadvantage common in fast-moving industries (Suarez and Lanzolla, 2007) can be mitigated by multihoming faster, a result that lends support to our argument that multihoming can be used as a hedging strategy.

The empirical setting for our study is the ecosystem of complementors, which has emerged around several competing "smart home" platforms, a market still in its infancy and therefore rife with technological and market uncertainty (Balta-Ozkan *et al.*, 2013). The entry of large technology firms, such as Google (Nest), Amazon (Alexa), and Samsung (SmartThings), which espouse platform strategies, has rapidly changed the landscape of what only a few years ago was a traditional pipeline industry. With the emergence of these new platform firms, traditional producers of home products, such as thermostats, lighting, locks, and smoke detectors, must decide whether to join the new platforms, how many to join, and how fast. The smart home market has been experiencing considerable and accelerating growth (Begovic, 2013), making our study timely and relevant.

THEORY AND HYPOTHESES

The phenomenon of multi-homing in two-sided platforms was first studied from the end user perspective, and thus defined accordingly: "[multihoming occurs when] end users of one or two sides connect to several platforms" (Rochet and Tirole, 2003: p. 991). This body of research argues that end users may benefit from adopting several competing platforms (Evans, 2003; Rysman, 2007). We extend this research by focusing on complementors' strategic decisions related to multihoming, i.e. joining two or more competing platforms. An example of multihoming occurs in the smartphone industry when a complementor (independent software vendor) develops an app that is offered in more than one of the competing platforms, such as Apple's iPhone/iOS, Google Android, and Windows Mobile.

Time to Multihoming

In many industries, the advent of platform-mediated markets was preceded by a period in which product categories competed in traditional pipeline markets. For instance, participants in the taxi industry can now join cab-ride platforms, such as Arro, Way2ride, or Curb.[2] The transition from product markets to one where different products or services are part of a platform is often referred to as a move "from pipelines to platforms" (Hagiu and Altman, 2017; Parker *et al.*, 2016). When platforms emerge, complementors that used to compete in traditional markets must now decide whether to enter the platform-mediated market or remain a standalone offering. If there are multiple platforms, complementors also must decide when to multihome.

Industries transformed by the emergence of platforms are characterized by a fast pace of technological and market change. During the last decade or so, researchers have tried to determine the conditions that activate or disable the "isolating mechanisms" through which early entry advantages materialize: technological leadership, preemption of scarce assets, and switching costs (Lieberman and Montgomery, 1988; 1998). Particularly relevant for our purposes here is the stream of research that explores entry-timing advantages in nascent industries characterized by high levels of technological uncertainty and market dynamism. Christensen, Suarez, and Utterback (1998) reported that the notion of first-mover advantage was "not applicable" in the dynamic disk drive industry. Similarly, Bohlmann, Golder, and Mitra (2002) found that entry-timing advantages were hard to sustain in the presence of "vintage effects," that is, situations where product quality was rapidly improving over time. Suarez and Lanzolla (2007) proposed that early-entry advantages are "disabled" in highly dynamic markets where technology advances rapidly and the market grows fast. Moreover, a related body of literature has also posited that early entrants may be at a disadvantage due to lack of categorical legitimacy, especially in an industry's early stages (Dobrev and Gotsopoulos, 2010), rapid technological change in an industry (Fosfuri, Lanzolla and Suarez, 2013), and a local search

[2] See http://www.govtech.com/dc/articles/Boston-Taxis-Take-Ride-Hailing-Apps-Head-On.html

process that retards the transition to the dominant design (Dowell and Swaminathan, 2006). In addition, learning from the failure experiences of early entrants gives later entrants advantage over early entrants (Yang, Li and Delios, 2015).

All in all, the existing literature suggests that complementors entering the platform-mediated market early face higher risk of failure. We argue that multihoming represents a hedging strategy that complementors can use to cope with the high risk of failure. A hedging strategy can be conceptualized as having two different components: a *speed* component, which captures how fast a complementor multihomes; and a *scope* component that captures how many platforms to which a complementor multihomes. The speed component will be most effective in the earliest stage of the new platform-mediated market, when both technology and market uncertainty are highest. Complementors that enter early cannot accurately predict which platform will end up dominating the market. And, given that complementors' success is intrinsically tied to the success of the platform, fast multihoming allows early entrants to lower the risk of being stranded in a losing platform. To the extent of our knowledge, this study is first to identify hedging strategy in the context of multihoming. Following our arguments, we expect that early entrants in an emerging platform-mediated market would pursue a hedging strategy and multihome fast,

Hypothesis 1: The earlier a complementor enters a platform-mediated market, the faster it will multihome.

We also posit that the scope component of the hedging strategy through multihoming influence the time elapsed from one multihoming event to the next. As a complementor joins more platforms, it will generate more experiential learning that can be used to shorten the time that it will take for the complementor to join another platform.

Multihoming across multiple platforms consists of a series of tasks that need to be completed, some similar and others differentiated due to the need to integrate with different platforms that use unique architectures and technologies. Learning theory suggests that executing similar tasks repeatedly yields specialization benefits that help complete the task faster (Argote, 1999; Newell and Roosenbloom, 1981; Huckman and Pisano, 2006). Knowledge gained about the specific set of steps to follow, specialized (programming) tools, and customers served may all yield time savings (Staats and Gino, 2012). Similarly, repeating the tasks across platforms may allow a complementor not only to gain mastery of the individual steps in performing the task, but also may provide ideas for task innovation or improvements that lead to additional time savings (Bohn and Lapre, 2011). Replicating codified knowledge (Zollo and Winter, 2002) can be done fast and with precision (Zander and Kogut, 1995). Product design methodology has shown that modular design approaches that use standardized component interfaces render the product development process loosely coupled (Sanchez and Mahoney, 1996). This allows for product variations by substituting some components without the need to redesign others (Garud and Kumaraswamy, 1993), which in turn enables rapid development of product variations, as illustrated by studies on aircraft, automobiles, consumer electronics, and software (Cusumano and Nobeoka, 1992).

The evolution of technology in platform-mediated markets has provided additional tools to facilitate the portability of a complementor's product into other platforms. This is in large part due to the conscious efforts of platform owners to create middleware (e.g. application programming interfaces (API)) that exempt complementors from having to customize from scratch for each platform (Eisenmann *et al.*, 2006; Ohrt and Turau, 2012). For instance, Corts and Lederman (2009: p. 125), in their study of the U.S. home videogame market, argue that “middleware allows specific technical aspects of the game—for example, 3-D animation—to be developed within a programming tool that can provide output usable by the operating systems of more than one platform.” Thus, the more platforms for which a complementor firm already produces, the more likely it will have the necessary sub-systems and skills to port its product to another platform. While there are some differences among platform architectures, some of the subsystems will still be common to two or more platforms, giving a speed advantage to complementors that already produce for several platforms.

We therefore posit that,

Hypothesis 2: The more a complementor multihomes, the shorter the time to the next multihoming event.

Multihoming and Complementor Performance

As noted earlier, the scope component of a hedging strategy through multihoming (producing for several platforms) helps complementors expand their potential market (Clements and Ohashi, 2005; Kretschmer and Claussen, 2016) and spread out fixed costs of production. Complementors may also multihome to reduce the dependency on any given platform and mitigate the risk of holdup (Hagiu, 2005; Hagiu and Yoffie, 2009). A large installed base gives a complementor the possibility of collecting data from multiple types of users, which can be used to improve the product. Complementors can reutilize sub-systems or other resources across platforms to reduce production costs. Multihoming to several platforms may provide complementors with additional strategic levers to compete against single-platform complementors. For instance, a multi-platform complementor could subsidize its products in the platform where a single-platform complementor operates.

Early research on platforms held that the cost associated with cross-platform software development and integration to enable successful multihoming was not trivial (Armstrong and Wright, 2007; Tiwana, Konsynski and Bush, 2010). Multihoming requires investment of time and resources in learning the technological requirements of a new platform, such as different programming languages and architectures (Claussen, Kretschmer and Mayrhofer, 2013; Claussen, Kretschmer and Stieglitz, 2015). Maintaining and regularly updating a complementor product and ensuring consistency in user experience across platforms also adds costs and technological complexity (Anderson, Parker and Tan, 2014; Schilling, 2000; Sanchez and Mahoney, 1996). However, several recent studies have pointed out that multihoming costs have declined over the past decade, due to the emergence of middleware (e.g. APIs), which allows software code to be less platform-specific (Corts and Lederman, 2009; Eisenmann *et al*., 2006; Ohrt and Turau, 2012). These changes in technology have made multihoming significantly easier and more cost-effective, suggesting that the most likely scenario is one where the performance benefits of multihoming exceed the cost of multihoming. This implies that multihoming should now be ultimately associated with higher market performance (Landsman and Stremersch, 2011). We hypothesize that,

Hypothesis 3: The more a complementor multihomes, the higher its performance.

Entry Timing and Complementor Performance from Multihoming

Our theorizing about multihoming complementors argues that the speed component of this hedging strategy is most important in the early stages of the platform-mediated markets. As prior research has shown, later entrants into a market space characterized by fast-moving technology can outcompete early movers with more sophisticated products using the latest technology (Bohlmann *et al*., 2002; Kretschmer and Claussen 2016). Similarly, fast-growing platform-mediated markets attract resources that allow later entrants to operate and grow (Suarez and Lanzolla, 2007), undercutting the effectiveness of resource preemption as an isolating mechanism that favors early entrants. Switching costs may also be negatively affected by high rates of market growth in the platform-mediated market because the proportion of total users in the market 'locked-in' by early entrants is decreasing (Gomez, Lanzolla and Maicas, 2016). In light of these arguments, we expect that complementors entering a nascent and fast-growing platform-mediated market would tend to underperform relative to complementors entering the platform later.

By multihoming fast, an early-entry complementor in an uncertain platform-mediated market can not only hedge its bets on multiple platforms, but also mitigate the negative performance effects expected in uncertain contexts with fast-moving technology. Fast multihoming is a hedging strategy that helps early-entry complementors in many ways. First, multihoming fast places early entrants in a better position to prevent their being locked out of the 'winning' platform(s): rapidly hedging their bets on several platforms through multihoming lowers the complementors' market risk. Second, multihoming fast at an early stage helps a complementor speed up the growth of its user base, which can help the early-entry complementor to create customer lock-in, particularly in the presence of network effects. Moreover, a presence in several platforms may give the early-entry complementor greater legitimacy with users, which can help them better compete with later entrants. Third, fast multihoming gives the early-entry complementor the ability to compete more effectively through sharing resources across platforms. In sum, we expect that,

Hypothesis 4: The negative performance effect of a complementor's early entry into a platform-mediated market is mitigated by fast complementor multihoming.

Figure 1 summarizes our hypotheses in the theoretical model.

Figure 1 about here

THE SMART HOME MARKET

A smart home is defined as a residence "equipped with computing and information technology which anticipates and responds to the needs of the occupants, working to promote their comfort, convenience, security and entertainment through the management of technology within the home and connections to the world beyond" (Aldrich, 2003: p. 17). The emergence of the smart home market has been enabled by developments in Internet of Things (IoT) and machine learning technologies. The Economist (2016) described a scenario in a smart home as "coffee pots that turn on when the alarm clock rings, lighting and blinds that adjust to the time of the day, and fridges that send an alert when the milk runs out."[3] Although the smart home market is in its infancy, by 2017 it had already reached a worldwide household penetration rate of 2.4 % and is expected to hit 15.6 % by 2021.[4] In the United States alone, the revenue from smart home devices amounts to US$14.6 billion in 2017 and is expected to register an annual growth rate (CAGR 2017-2021) of 21.8 % resulting in a market potential of US$32.2 billion by 2021.[5]

The concept of a "smart home" is not new. It was introduced in 1984 by the National Association of Home Builders (NAHB). However, early technologies largely failed because they were closed solutions with scant customization capabilities, resulting in fragmented and

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[3] The Economist (June 2016) "Where the smart is" available at: https://www.economist.com/news/business/21700380-connected-homes-will-take-longer-materialise-expected-where-smart

[4] Source: Statista Digital Market Outlook (February 2017).

[5] Smart Home Market Report available at: https://www.statista.com/outlook/279/109/smart-home/united-states#

incompatible systems that gained little traction (Van Berlo *et al*., 1999; Heimer, 1995). Starting in the 2010s and taking advantage of advances in broadband communication and microprocessors, a new generation of smart home systems have emerged, espousing platform architectures and business models. Some of the key players in this new space are Google-Nest, Samsung-SmartThings, and Amazon-Alexa. These and other companies have introduced middleware software solutions (e.g. APIs) that make it easier for third party complementors to join the platform. These changes have transformed the traditional home products categories from several independent markets of stand-alone products into a platform-mediated market where the producers in the different product categories became complementors to various platforms.

The smart home context is highly appropriate for testing our multihoming-related hypotheses. First, there are several competing platforms, and complementors may adopt more than one. Second, unlike existing research on multihoming that has focused on mature industries (e.g. video games, mobile apps), the smart home market is nascent, which allows us to observe complementor strategies during the uncertain, ferment stage of the industry (Utterback and Abernathy, 1975; Anderson and Tushman, 1990). Finally, given the recent inception of this market, we can track complementor entry from the very beginning.

Our study focuses on the four leading smart home platforms: Google-Nest, Samsung-Smartthings, Amazon-Alexa, and Wink.[6] In 2011, Nest was the first to enter the market with a programmable, self-learning, and sensor-driven thermostat. In 2013, Nest launched a smoke and carbon monoxide detector, followed by indoor and outdoor cameras in 2014. Nest's fast growth drew much industry attention, and the startup was acquired by Alphabet-Google for US$3.2 billion in January 2014. Soon after, Google opened its Nest platform to allow complementors to

[6] A fifth platform, HomeKit by Apple was not considered because it was a slow-mover, late entrant: only a limited number of complementors had joined the platform by 2016.

offer their products on the platform by releasing APIs, in a program labeled “Works with Nest.” SmartThings was founded in 2012; unlike Nest, SmartThings had a platform strategy from the start, releasing APIs in 2013 to attract complementors. In 2014, Samsung acquired SmartThings. Amazon entered the smart home market in 2014 with a platform strategy linked to its Alexa/Echo technology.[7] In 2015, Amazon launched their “Alexa Skills Kit” to add functionality to its voice-control assistant, and then released their “SmartHome Skills APIs” in 2016 to allow different home products to connect to the Alexa/Echo in a program labeled “Works with Alexa.” Wink was launched in 2014 by a startup and offered broad connectivity through several protocols. The company was acquired by Flex (Flextronics) in 2015.

The smart home market can be divided into several product categories, such as thermostats, smoke detectors, lighting, appliances, and security systems (e.g. cameras, locks, doorbells). Complementors competing in these categories range from “analog” incumbents dating back to the pre-platform stage of industry (e.g. Philips, Whirlpool, Honeywell), to diversifying entrants from the electronics industry (e.g. LG, Motorola, Logitech), to “digital” startups with no prior experience in a particular home product category (e.g. Ecobee, LIFX, Canary).

DATA AND METHODS

We created a unique dataset of complementors in the global smart home market that captures the industry from its inception. We focus on five large product categories that are common to all four platforms: lights, appliances, smoke detectors, security systems, and thermostats. We gathered data on global smart device manufacturers from a market research company that tracks

[7] Echo is the voice-controlled device that customers purchase, while Alexa is the imaginary AI-powered virtual assistant.

the performance of products in the smart home market. In this study, a device is considered "smart" if it has an app-controlled interface; some of these products are offered in one or more platforms, while others still operate as stand-alone products (only app-controlled). Our panel dataset includes 151 firm-category observations over 33 months, between September 2014 and May 2017. There are 136 unique firms (some firms produce for more than one category) in our dataset. Our unit of analysis is complementor-category-month, and the total number of firm-category-month observations is 4,983.

Variables

Dependent Variables

Time to First Multihome: This dichotomous variable takes the value of 1 if the smart device firm produces for two or more platforms at month *t* and 0 otherwise.[8] We gathered the data on complementor multihoming event by collecting it directly from each platform's "works with" program website. Through news releases, we identified the date when a complementor joined a platform by announcing its compatibility with that platform.

Complementor Performance: Prior research on complementor performance is scant. Some of the recent studies on platforms measure the construct by the rate of consumer demand for the complementor's products (e.g. the number of times each product is acquired by consumers, as in Ozer, 2017), while others use sales (Ceccagnoli, *et al*., 2012) and the number of transactions (e.g. downloads, as in Wen, Ceccagnoli and Forman, 2015). Following Ceccagnoli *et al.* (2012), we measure complementor performance using monthly product sales revenue. We log-transform this variable to address skewness in the data.

[8] Starting in 2014, there were two or more platforms available for complementors to consider. Our data was available from September 2014 onwards, just three months after a second platform (Google-Nest) came to the industry. While Samsung-SmartThings was the first platform to announce its developer program API (May 2013), Google-Nest platform announced its developer program API in June 2014.

Independent Variables

Multihoming Scope: This variable counts the number of platforms a firm is a complementor of at time *t*.

Entry Timing: This variable captures the time of entry of complementor firms to the nascent platform-mediated markets that began with the entry of Nest. We count the number of months elapsed from the Nest entry to the date in which a focal firm becomes a complementor of any of the competing platforms.

Average Multihoming Time: This variable counts the average time (in months) between consecutive platform adoptions for a given complementor. Since the hedging strategy argument relies on the speed of multiple platform adoptions, we consider the average time between consecutive platform adoptions as the measure of multihoming time.

Control Variables

Complementor Resources: This control variable accounts for the potential impact of a complementor's resources on its decision to multihome and on its sales performance. We measure complementor resources using the cumulative number of active trademarks the complementor owns at month *t*. The stock of trademarks has been used in previous studies to account for a firm's complementary assets (Ceccagnoli and Jiang, 2013), marketing capabilities (Fosfuri, Giarratana and Luzzi, 2008), intangible marketing assets (Seethamraju, 2003), and advertising capabilities (Fosfuri and Giarratana, 2009). The data on complementor trademarks was retrieved from the United States Patent and Trademark Office (USPTO) trademark database for a period of 33 months. We lagged this variable by one month.

Complementor Product Quality: A smart device's quality may also affect a complementor's performance and ability to multihome. We control for smart device quality using the average review scores for a complementor's smart device app, computed monthly for both Apple iOS and Android apps. We lagged this variable by one month.

Market Share: This variable measures the market share of a complementor in a focal product category. We also control for the potential impact of market share on complementor performance. We constructed the market share measure as follows: in each product category, we take the sales revenue of a smart device producer, divide it by the total sales revenue of the category in that month and multiply this number by 100. Hence, we get a percentage measure of how much of the total sales revenue in that product category at month *t* accrues to the focal complementor. We lagged this variable by one month.

Within-Category Complementors: To control for the extent of potential competition in a product category, this variable measures the number of within-category complementors in each category per month. We repeated this for all platforms.

Complementor Type: This construct was measured using dummy variables for each complementor type. The *Denovo* variable takes the value of 1 if the complementor is a startup (we used a 10-year cut-off point: startups are founded in 2008 or later, such as LIFX, August, or Netatmo, in our sample), 0 otherwise. The *Dealio* variable takes the value of 1 if the complementor is an established firm in another industry and diversifies into the smart home market (e.g. LG, Motorola, Logitech), and 0 otherwise. Finally, the *Incumbent* variable takes the value of 1 if the complementor is an established company in home devices (such as, Philips, Whirlpool, or Belkin), 0 otherwise.

Smart Device Category: We controlled for category effects by creating dummy variables for each category in our dataset, namely: lighting, appliances, smoke detectors, security systems, and thermostats.

Model Specifications

We use two types of model specifications in the analysis to examine two different types of questions. The first type focuses on the determinants of how fast complementors multihome (time to multihome). Because of the "time to event" nature of our dependent variable, we test our first two hypotheses (H-1 and H-2) using Cox survival analysis. We measure the time to the multihoming event, where the multihoming event is taken as the hazard, as done in several prior studies (e.g. Lee, Mun and Park, 2015; Leone and Reichstein, 2012; Suarez and Utterback, 1995). To test H-1, which links the timing of entry to the platform-mediated market with time to multihome, we only consider a complementor's first multihoming decision (time elapsed from the beginning of the platform-mediated market to a complementor's first multihoming event). Thus, we conduct our survival analysis as a single event per subject study. The failure event in our study is the complementor's multihoming event and the time is measured in months. Letting x_i be the row vector of covariates for the time interval $(t_{0i}, t_i]$ for the *i*th observation in the dataset $i = 1, \ldots, N$. We obtain parameter estimates, $\hat{\beta}$, by maximizing the partial log-likelihood function (Cox, 1972):

$$\log L = \sum_{j=1}^{D}\left[\sum_{i \in D_j} x_i\beta - d_j \log\left\{\sum_{k \in R_j} exp(x_k\beta)\right\}\right]$$

where j indexes the ordered failure times $t_{(j)}$, $j = 1, \ldots, D$; D_j is the set of d_j observations that fail at $t_{(j)}$; d_j is the number of failures at $t_{(j)}$; and R_j is the set of observations k that are at risk at time $t_{(j)}$ (that is, all k such that $t_{0k} < t_{(j)} \leq t_k$).

In testing H-2, we allow for multiple multihoming events per subject, i.e. the time elapsed between the last platform that a complementor adopted and the next. We use ordered failure event method with Efron ties; in particular, the conditional risk set model on "time from the previous event" (Prentice, Williams and Peterson, 1981), which is considered an appropriate model for recurrent event data analysis (Kelly and Lim, 2000).

The second model specification type tests how multihoming-related strategies affect complementor performance. We examine (a) the relationship between *multihoming scope* and *complementor performance*, and (b) how the interaction of *entry timing* and *average multihoming time* affect *complementor performance*. The dependent variable *complementor performance* is specified as a continuous variable. Given that some of our explanatory variables are time-invariant, we use random-effects generalized least squares (GLS) regression model for testing hypotheses H-3 and H-4 as done in previous studies (Jiang, Tao and Santoro, 2010; Kor and Mahoney, 2005).

$$Y_{it} = \alpha + x_{it}\,\beta_1 + (K)_{it}\beta_k + \varepsilon_{it}$$

$i = 1,\ldots, N$ and $t = 1,\ldots,T_i$ where K is the vector of control variables and x is *multihoming scope* variable for complementor i at time t, β_1 is the coefficient we are interested in for testing H-3.

$$Y_{it} = \alpha + y_{it}\,\beta_1 + z_{it}\,\beta_2 + (y_{it} * z_{it})\,\beta_3 + (K)_{it}\beta_k + \varepsilon_{it}$$

where K is the vector of control variables and y is *entry timing* variable for complementor i at time t, z is *average multihoming time* variable for complementor i at time t, β_3 is the coefficient of the interaction term that we are interested in for testing H-4.

RESULTS

Descriptive Statistics

Table 1 presents the descriptive statistics of our variables. *Complementor performance* had a mean of US$3.42 million per month, ranging between 0 and US$75.7 million per month. *Time to first multihome* dummy had a mean of 0.59. Our *entry timing* variable was equal to 0 for the first entrant into the smart home platform-mediated market. The latest entrant in our dataset entered the market 58 months after the first entrant, with an average entry time across complementors of 40.41 months. Nearly half the complementors in our dataset have multihomed, the maximum number of multihoming events per complementor is 4 (i.e. complementors that adopt all platforms in the sample), with an average of 1.79 platforms adopted. *Average multihoming time* ranged between 0 and 53 months, with a mean of 9.03 months. *Complementor product quality* ranged from 0.8 to 4.9, with an average of 3.02 (out of 5). On average, a complementor held 8% of the market share in its product category. The category breakdown was as follows: 5% of all complementors in our data set were in *smoke detectors*, 16% in *lighting*, 26% in *thermostats*, and 48% in *security systems*. About 31% of complementors were startups; 14% were diversifying firms and 55% were incumbents. In terms of within-category complementor competition, the maximum number of competitors in a category by platform were: Alexa with 22 competitors, followed by SmartThings with 16, Wink with 13, and Nest with 10. The correlation matrix of our variables can be found in Table 2.

Table 1 about here

Table 2 about here

Empirical Results

Table 3 presents the result for H-1 and H-2. Model 1 shows the results of a baseline model, which only includes control variables. The results indicated that *complementor product quality* and the number of *within-category complementors* have a positive and significant relationship with the hazard to multihome. Shorter time to multihome was associated with firms that have higher product quality, and with those that have higher number of competitors in the same product category. Model 2 tests H-1: the *entry timing* variable had a negative and significant effect on the hazard to multihome. In other words, the longer it takes a complementor to enter the platform-mediated smart home market, the less likely it will switch from single-homing to multihoming in a given time period.[9] For each month that a complementor delays entry into the platform-mediated market, its hazard of multihoming decreased by 8%. This provides support for H-1. We tested for the proportional hazard assumption in our models by running the test based on Schoenfeld residuals using the estat phtest command in STATA. The results of the test suggest that the proportional hazard assumption was not violated in our analyses (Table 4).

Table 3 about here

Table 4 about here

In Table 3, Model 3 and Model 4 test H-2. Model 3 presents the baseline analysis of the conditional risk set model that takes “time from the previous event.” This model showed that the number of *within-category complementors* is positively associated with the hazard of

[9] We also tested the probability of multihoming with a logit model (not shown) and found that the longer it takes for a complementor to enter the platform-mediated smart home market, the less likely it is to multihome (marginal effect size = -0.006, p-value = 0.000).

multihoming. In Model 4, we introduced the *multihoming scope* variable and found that it is positively and significantly associated with the hazard to multihome. This suggests that a complementor that has multihomed before is faster to multihome again. Specifically, for each unit increase in multihoming scope, a focal complementor was six times more likely to multihome again. This result lends support to H-2. We also tested for the proportional hazards assumption for these models and found no violation for our independent variable (Table 5).

Table 5 about here

In Table 6, we present the estimation results of H-3. Hypothesis H-3 suggests that greater the number of platforms adopted, the higher the complementor performance. Model 1 is the baseline model and includes control variables only. In Model 2, we included a complementor's *multihoming scope* and found that it had a positive and significant relationship with *complementor performance*. One unit increase in multihoming scope increased complementor performance by 37%. This finding supports H-3. As for the control variables, *complementor product quality* had a positive and significant relationship with complementor performance and complementor's *market share* in the previous month appear to have a positive and significant relationship with complementor performance.

Table 6 about here

Next, we analyze how *entry timing* and *average multihoming time* interact to affect complementor performance. H-4 posits that fast complementor multihoming can mitigate the negative performance effect of early entry into a platform-mediated market. Table 7 shows the results of this analysis. Model 1 is the baseline model that includes only the control variables.

Model 2 and 3 present the direct effects of *average multihoming time* and *entry timing.* The direct effects of *average multihoming time* and *entry timing* were not significant in our analyses. Model 4, the full model, contains the interaction effects between *entry timing* and *average multihoming time*. We found a negative and significant effect for the interaction term, suggesting that companies that enter the platform-mediated industry early and multihome fast are better off. This lends support to H-4. The marginal effects analysis indicated that the negative performance effect of entry timing can be mitigated if a complementor multihomes, on average, in less than ten months (Table 8). Regarding control variables, *complementor resources* and *market share* had a positive and significant relationship with complementor performance.

Table 7 about here

Table 8 about here

DISCUSSION

The emergence of platform-mediated markets in traditional pipeline industries where products used to be sold as stand-alone offerings represents a major change in the existing competitive dynamics. This change is accentuated when several platforms coexist and compete for dominance, presenting additional challenges and opportunities for new entrants and existing firms (incumbents). In this situation, complementors face two important timing decisions: how fast to enter the platform-mediated market (i.e. offer their products through a platform, becoming a complementor), and how fast to multihome (i.e. offer their products in more than one platform concurrently). We study the implications of these timing decisions in the context of the smart home market – that is, a set of technologies that allow various smart home products to be connected with each other through a platform. The smart home context is a good example of a nascent platform-mediated market, populated with several platforms competing for market and technological dominance, such as Amazon-Alexa, Samsung-SmartThings, and Google-Nest.

We found that a complementor's timing of entry into a platform-mediated market is related to its timing of multihoming. Specifically, early entrants in a platform-mediated market multihome faster than late entrants. Our results also indicated that multihoming scope (number of platforms a complementor has already joined) shortens the time to a complementor's next multihoming event. This is due to the emergence of middleware solutions that facilitate the easy porting of applications to different platforms. In addition, we found that multihoming scope is positively related to complementor performance as complementors can effectively leverage economies of scale and scope in several platforms. Finally, while existing theory (Bohlman, Golder and Mitra, 2002; Suarez and Lanzolla, 2007) posits that early entry may be disadvantageous in fast-moving markets, our analyses indicate that early entrants in a platform-mediated market can mitigate the performance penalty of entering early if they multihome fast. Therefore, our results suggest that multihoming can act as a hedging strategy in nascent spaces characterized by technological and market uncertainty. Complementors that enter early and multihome fast reduce uncertainty through hedging, while simultaneously taking advantage of the synergies (e.g. brand recognition, legitimacy) coming from non-overlapping user bases to drive performance growth.

Our research contributes to the literatures on entry timing strategies and platform-mediated markets. We test and extend entry-timing arguments by considering them in the context of a nascent platform-mediated market fraught by uncertainty. Moreover, we theorize on the importance of the time to multihome decision, and its relationship with entry timing. Entry timing scholars have argued that early entrants in fast-moving markets are likely to be displaced by later entrants (Franco *et al*., 2009, Christensen *et al*., 1998). We show that early entrants can use fast multihoming as a hedging strategy to minimize the disadvantages of early entry into these markets. Multihoming helps complementors cope with the uncertainty of nascent markets by providing them with the ability to hedge their bets into different, non-overlapping markets, in much the same way as early venture capitalists invest across several promising startups in a context of high market and technological uncertainty (Sahlman, 1990).

We also contribute to the platform literature (Eisenmann *et al*., 2006; Boudreau, 2012; Boudreau and Jeppesen, 2015; Venkatraman and Lee, 2004), particularly to the small but growing body of literature that takes a complementor-centric perspective (Ceccagnoli *et al.*, 2012; Cennamo *et al.*, forthcoming; Huang *et al.*, 2013; Kapoor and Agarwal, 2017). While few studies have focused on complementor market entry strategies (Ceccagnoli *et al*., 2012; Cennamo *et al*., forthcoming; Corts and Lederman, 2009; Hung *et al.*, 2013; Kapoor and Agarwal, 2017), they have considered only single-platform settings (Ceccagnoli *et al.,* 2012; Kapoor and Agarwal, 2017). Studies in multi-platform settings are scant, and empirical studies on these settings are even rarer (e.g. Cennamo *et al.*, forthcoming; Venkataraman *et al.*, 2017). To our knowledge, we provide the first empirical evidence of the performance implications of complementor multihoming. Our study is also the first to investigate the relationship between time to multihome and entry timing in platform-mediated markets.

Our empirical context is unique in that it pertains to a nascent industry characterized by significant levels of market uncertainty and technological change. Therefore, our findings might not necessarily extend to other contexts, such as mature platform-mediated markets. Likewise, our study only considers multihoming from the complementor’s perspective; future empirical studies may explore situations where both complementors and users multihome. Other areas for future research are how complementors should organize internally to successfully manage multihoming, and what type of platform characteristics facilitate or impede complementor multihoming.

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Figure 1 Theoretical Model

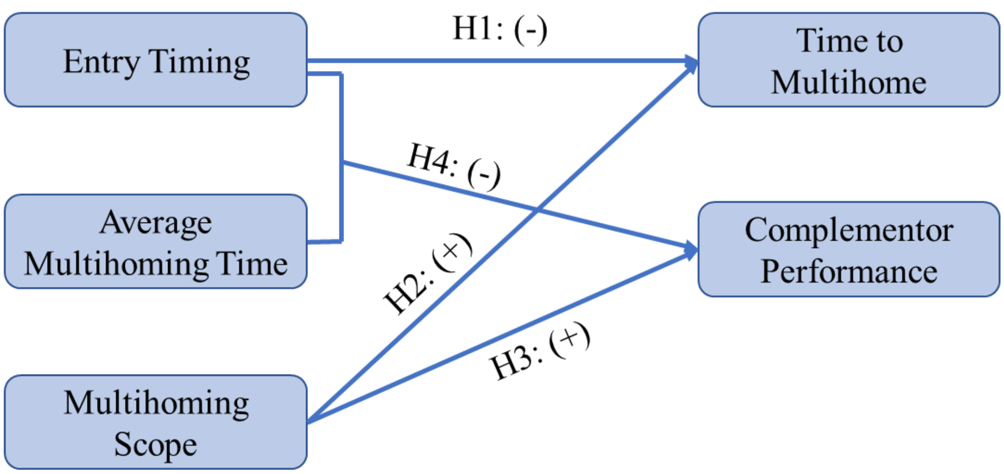

Table 1 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Complementor performance (US $)	1,145	3,416,869.00	6,748,969.00	0.00	75,700,000.00
Time to first multihome (dummy)	1,145	0.59	0.49	0.00	1.00
Entry timing (in months)	1,145	40.41	11.33	0.00	58.00
Multihoming scope	1,145	1.79	1.20	0.00	4.00
Average multihoming time (in months)	1,145	9.03	9.53	0.00	53.00
Complementor product quality (on a range of 1-5)	1,145	3.02	0.84	0.80	4.90
Complementor resources	1,145	160.05	281.95	0.00	1258.00
Market share	1,145	0.08	0.14	0.00	0.74
Lights	1,145	0.16	0.36	0.00	1.00
Appliances	1,145	0.04	0.20	0.00	1.00
Smoke detectors	1,145	0.05	0.23	0.00	1.00
Security systems	1,145	0.48	0.50	0.00	1.00
Thermostats	1,145	0.26	0.44	0.00	1.00
Denovo	1,145	0.31	0.46	0.00	1.00
Dealio	1,145	0.14	0.34	0.00	1.00
Incumbent	1,145	0.55	0.50	0.00	1.00
Within-category complementors Nest	1,145	1.69	3.25	0.00	10.00
Within-category complementors Alexa	1,145	6.28	8.09	0.00	22.00
Within-category complementors SmartThings	1,145	4.43	5.93	0.00	16.00
Within-category complementors Wink	1,145	2.55	3.95	0.00	13.00

Table-2 Correlation Matrix

		1	2	3	4	5	6	7	8	9	10
1	Time to first multihome	1.0000									
2	Complementor revenue	0.1704	1.0000								
3	Multihoming scope	0.8753	0.1327	1.0000							
4	Entry timing	-0.1729	-0.1137	-0.3313	1.0000						
5	Average multihoming time	-0.2251	0.0239	-0.1272	-0.6932	1.0000					
6	Complementor product quality	0.0119	0.4034	-0.0046	-0.1486	0.2181	1.0000				
7	Complementor resources	0.1017	0.1411	0.0386	-0.0173	-0.0839	-0.1917	1.0000			
8	Market share	0.1217	0.4681	0.1811	-0.3935	0.2345	0.2361	0.1500	1.0000		
9	Lights	0.2420	-0.0380	0.3771	-0.3240	-0.1196	-0.1817	0.1014	0.1738	1.0000	
10	Appliances	-0.0090	-0.0085	-0.0234	-0.0397	0.1166	-0.2583	0.5702	0.0572	-0.0887	1.0000
11	Smoke	-0.0657	-0.0573	-0.0802	-0.1627	0.3057	-0.0296	-0.1046	0.3235	-0.1037	-0.0490
12	Security	0.0868	0.0617	-0.0183	0.4786	-0.5397	-0.0009	-0.2571	-0.3124	-0.4188	-0.1977
13	Thermostats	-0.2607	-0.0053	-0.2395	-0.1731	0.5016	0.2815	0.0072	0.0188	-0.2599	-0.1227
14	Denovo	-0.0469	0.0703	-0.0239	-0.1573	0.2104	0.2418	-0.3471	0.0902	-0.1284	-0.1385
15	Dealio	-0.0753	-0.0546	-0.1594	0.1887	-0.0397	-0.1556	0.3659	-0.0457	-0.1721	0.3336
16	Incumbent	0.0957	-0.0279	0.1322	0.0167	-0.1690	-0.1184	0.0716	-0.0527	0.2385	-0.1007
17	Within-category complementors Nest	0.3705	0.0265	0.4057	-0.0043	-0.1489	0.1525	-0.2077	-0.0410	0.0535	-0.0928
18	Within-category complementors Alexa	0.5749	0.0890	0.5587	0.0920	-0.1746	0.1028	-0.0391	-0.1057	-0.0568	-0.1490
19	Within-category complementors SmartThings	0.5386	0.0410	0.5849	0.0886	-0.2895	-0.1344	-0.0820	-0.1473	-0.0186	-0.1528
20	Within-category complementors Wink	0.4727	0.1658	0.5101	0.0178	-0.1995	0.1514	-0.1136	-0.0064	-0.1202	-0.1322

		11	12	13	14	15	16	17	18	19	20
11	Smoke	1.0000									
12	Security	-0.2313	1.0000								
13	Thermostats	-0.1435	-0.5798	1.0000							
14	Denovo	0.1040	0.0984	0.0031	1.0000						
15	Dealio	0.2425	0.0186	-0.1517	-0.2690	1.0000					
16	Incumbent	-0.2642	-0.1046	0.1017	-0.7477	-0.4385	1.0000				
17	Within-category complementors Nest	-0.1055	0.3036	-0.2927	0.0071	-0.2067	0.1359	1.0000			
18	Within-category complementors Alexa	-0.1859	0.1820	0.0025	0.0293	-0.0657	0.0179	0.1709	1.0000		
19	Within-category complementors SmartThings	-0.1787	0.4527	-0.3378	-0.0219	0.0054	0.0167	0.1957	0.5785	1.0000	
20	Within-category complementors Wink	-0.1332	0.2672	-0.0762	0.0211	-0.0738	0.0312	0.2787	0.3911	0.4174	1.0000

Table 3 Results of Survival Analyses (Cox Hazard Model)

	Single Event per Subject		Multiple Event per Subject	
	(1)	(2)	(3)	(4)
VARIABLES	_Multihome	_Multihome	_Multihome	_Multihome
Multihoming scope				1.783
				(0.199)
				[0.000]
Entry timing		-0.0834		
		(0.0162)		
		[0.000]		
Complementor product quality	0.439	0.243	0.303	0.337
	(0.219)	(0.217)	(0.187)	(0.260)
	[0.045]	[0.263]	[0.105]	[0.194]
Complementor resources	0.00102	0.00137	0.000557	0.000191
	(0.000508)	(0.00117)	(0.000419)	(0.000633)
	[0.045]	[0.242]	[0.184]	[0.762]
Market share	2.728	1.428	0.528	-1.709
	(1.636)	(1.477)	(1.113)	(1.130)
	[0.095]	[0.333]	[0.635]	[0.130]
Lights	-0.413	-0.616	-0.243	-2.670
	(0.832)	(0.917)	(0.758)	(1.032)
	[0.619]	[0.502]	[0.748]	[0.010]
Appliances	0.422	1.029	0.825	0.593
	(1.098)	(1.170)	(0.934)	(0.972)
	[0.701]	[0.379]	[0.377]	[0.541]
Security	-1.570 ^{t}	-1.694	-0.802	-0.997
	(0.908)	(1.159)	(0.796)	(0.754)
	[0.084]	[0.144]	[0.313]	[0.186]
Thermostats	-0.879	-1.905	-0.340	-0.860
	(0.894)	(0.908)	(0.763)	(0.796)
	[0.326]	[0.036]	[0.656]	[0.280]
Incumbent	0.407	0.735	0.359	-0.167
	(0.600)	(1.039)	(0.488)	(0.626)
	[0.498]	[0.479]	[0.462]	[0.789]
Denovo	0.536	0.0520	0.109	-0.559
	(0.581)	(1.243)	(0.585)	(0.749)
	[0.356]	[0.967]	[0.853]	[0.456]
Within-category complementors Nest	0.338	0.307	0.167	0.0202
	(0.0989)	(0.101)	(0.0454)	(0.0572)
	[0.001]	[0.002]	[0.000]	[0.725]
Within-category complementors Alexa	0.309	0.357	0.177	0.0776
	(0.0852)	(0.0785)	(0.0442)	(0.0385)
	[0.000]	[0.000]	[0.000]	[0.044]
Within-category complementors SmartThings	0.317	0.267	0.0861	-0.0415
	(0.0520)	(0.0523)	(0.0326)	(0.0410)
	[0.000]	[0.000]	[0.008]	[0.312]
Within-category complementors Wink	0.240	0.300	0.121	-0.0587
	(0.120)	(0.101)	(0.0470)	(0.0485)
	[0.045]	[0.003]	[0.010]	[0.226]
Observations	3,215	1,390	3,865	3,865

Robust standard errors in parentheses
p-values in brackets

Table 4 Test of Proportional Hazards Assumption for H1

	rho	chi2	df	Prob>chi2
Entry timing	-0.00922	0	1	0.9700
Complementor product quality	-0.14276	0.57	1	0.4486
Complementor resources	-0.10998	1.57	1	0.2101
Market share	-0.09429	0.3	1	0.5814
Lights	-0.20395	3.27	1	0.0704
Appliances	-0.15008	2.17	1	0.1405
Security	-0.23664	6.49	1	0.0108
Thermostats	-0.21026	3.82	1	0.0505
Incumbent	-0.10522	1.62	1	0.2034
Denovo	-0.14891	3.55	1	0.0596
Within-category complementors Nest	0.09713	0.57	1	0.4520
Within-category complementors Alexa	-0.08745	0.9	1	0.3418
Within-category complementors SmartThings	0.06037	0.31	1	0.5754
Within-category complementors Wink	0.04194	0.16	1	0.6881
Global test		12.26	14	0.5851

Table 5 Test of Proportional Hazards Assumption for H2

	rho	chi2	df	Prob>chi2
Multihoming scope	0.12830	1.57	1	0.2098
Complementor product quality	-0.23323	7.47	1	0.0063
Complementor resources	0.00053	0	1	0.9956
Market share	-0.21639	3.95	1	0.0470
Lights	-0.21149	5.65	1	0.0175
Appliances	-0.08353	0.51	1	0.4739
Security	-0.15571	1.37	1	0.2425
Thermostats	-0.11998	1.14	1	0.2850
Incumbent	0.00370	0	1	0.9634
Denovo	-0.06138	0.69	1	0.4068
Within-category complementors Nest	-0.07625	0.72	1	0.3958
Within-category complementors Alexa	0.09670	0.87	1	0.3515
Within-category complementors SmartThings	-0.11749	1.42	1	0.2341
Within-category complementors Wink	0.11588	1.02	1	0.3115
Global test		23.28	14	0.0558

Table 6 Results of Random Effects Generalized Least Square Analysis (H3)

VARIABLES	(1) Complementor Revenue	(2) Complementor Revenue
Multihoming scope		0.370
		(0.0795)
		[0.000]
Complementor product quality	0.298	0.299
	(0.0944)	(0.0935)
	[0.002]	[0.001]
Complementor resources	0.00234	0.00219
	(0.00135)	(0.00130)
	[0.082]	[0.091]
Market share	5.766	5.457
	(1.456)	(1.396)
	[0.000]	[0.000]
Lights	0.453	0.303
	(0.587)	(0.576)
	[0.440]	[0.599]
Appliances	0.884	0.881
	(1.055)	(1.068)
	[0.402]	[0.410]
Smoke	-1.288	-1.392
	(0.961)	(0.959)
	[0.180]	[0.147]
Security	2.535	2.502
	(0.445)	(0.444)
	[0.000]	[0.000]
Incumbent	0.655	0.539
	(0.498)	(0.501)
	[0.189]	[0.282]
Denovo	-0.505	-0.556
	(0.612)	(0.604)
	[0.410]	[0.357]
Within-category complementors Nest	0.0533	0.00605
	(0.0360)	(0.0367)
	[0.139]	[0.869]
Within-category complementors Alexa	0.0317	0.00959
	(0.00687)	(0.00842)
	[0.000]	[0.255]
Within-category complementors Wink	0.0292	-0.00576
	(0.0218)	(0.0246)
	[0.181]	[0.815]
Constant	9.036	9.054
	(0.583)	(0.581)
	[0.000]	[0.000]
Observations	3,833	3,833
Number of compid1	142	142

Standard errors in parentheses, p-values in brackets

Table 7 Results of Random Effects Generalized Least Square Analysis (H4)

VARIABLES	(1) Complementor Revenue	(2) Complementor Revenue	(3) Complementor Revenue	(4) Complementor Revenue
Entry timing * Average multihoming time				-0.00279
				(0.000977)
				[0.004]
Entry timing			-0.0451	-0.0444
			(0.0384)	(0.0415)
			[0.240]	[0.284]
Average multihoming time		-0.0226		0.00187
		(0.0236)		(0.00779)
		[0.337]		[0.811]
Complementor product quality	0.0337	0.0497	0.0324	0.0689
	(0.151)	(0.150)	(0.152)	(0.150)
	[0.824]	[0.740]	[0.831]	[0.647]
Complementor resources	0.00619	0.00621	0.00621	0.00626
	(0.00288)	(0.00289)	(0.00290)	(0.00290)
	[0.032]	[0.032]	[0.033]	[0.031]
Market share	6.507	6.326	6.472	6.108
	(1.416)	(1.407)	(1.420)	(1.398)
	[0.000]	[0.000]	[0.000]	[0.000]
Lights	-0.622	-0.839	-0.896	-1.618
	(1.038)	(1.049)	(1.007)	(1.107)
	[0.549]	[0.424]	[0.374]	[0.144]
Appliances	-3.973	-3.969	-4.083	-3.755
	(2.208)	(2.227)	(2.183)	(2.214)
	[0.072]	[0.075]	[0.061]	[0.090]
Smoke	0.130	0.268	-0.177	0.421
	(1.410)	(1.449)	(1.266)	(1.315)
	[0.927]	[0.854]	[0.889]	[0.749]
Security	0.936	0.649	1.298	0.518
	(0.973)	(0.998)	(1.065)	(1.209)
	[0.336]	[0.516]	[0.223]	[0.668]
Incumbent	1.372	1.433	1.119	1.259
	(1.563)	(1.594)	(1.385)	(1.411)
	[0.380]	[0.368]	[0.419]	[0.372]
Denovo	1.833	1.978	1.473	1.550
	(1.636)	(1.659)	(1.473)	(1.480)
	[0.263]	[0.233]	[0.317]	[0.295]
Within-category complementors Nest	0.0312	0.0288	0.0313	0.0174
	(0.0340)	(0.0335)	(0.0339)	(0.0323)
	[0.358]	[0.390]	[0.356]	[0.591]
Within-category complementors Alexa	0.0242	0.0217	0.0243	0.0225
	(0.00703)	(0.00770)	(0.00700)	(0.00723)
	[0.001]	[0.005]	[0.001]	[0.002]
Within-category complementors SmartThings	0.00421	0.00685	0.00384	0.000420
	(0.0177)	(0.0177)	(0.0177)	(0.0177)
	[0.812]	[0.699]	[0.828]	[0.981]
Within-category complementors Wink	0.0427	0.0411	0.0426	0.0509
	(0.0268)	(0.0265)	(0.0267)	(0.0267)
	[0.110]	[0.120]	[0.110]	[0.056]
Constant	9.664	9.930	11.65	12.72
	(1.922)	(1.953)	(1.759)	(1.744)
	[0.000]	[0.000]	[0.000]	[0.000]
Observations	1,145	1,145	1,145	1,145
Number of compid1	41	41	41	41

Standard errors in parentheses, p-values in brackets

Table 8 Results of Margins Analysis (H4)

Delta-method	dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Average multihoming time						
_at						
0	0.002	0.008	0.240	0.811	-0.013	0.017
5	-0.012	0.008	-1.600	0.109	-0.027	0.003
10	-0.026	0.010	-2.600	0.009	-0.046	-0.006
15	-0.040	0.014	-2.880	0.004	-0.067	-0.013
20	-0.054	0.018	-2.960	0.003	-0.090	-0.018
25	-0.068	0.023	-2.980	0.003	-0.112	-0.023
30	-0.082	0.027	-2.980	0.003	-0.136	-0.028
35	-0.096	0.032	-2.970	0.003	-0.159	-0.033
40	-0.110	0.037	-2.970	0.003	-0.182	-0.037
45	-0.124	0.042	-2.960	0.003	-0.205	-0.042
50	-0.138	0.047	-2.950	0.003	-0.229	-0.046
55	-0.151	0.051	-2.950	0.003	-0.252	-0.051
60	-0.165	0.056	-2.940	0.003	-0.276	-0.055
65	-0.179	0.061	-2.940	0.003	-0.299	-0.060