Vardit Landsman & Stefan Stremersch

Multihoming in Two-Sided Markets: An Empirical Inquiry in the Video Game Console Industry

Two-sided markets are composed of platform owners and two distinct user networks that either buy or sell applications for the platform. The authors focus on multihoming—the choice of an agent in a user network to use more than one platform. In the context of the video game console industry, they examine the conditions affecting seller-level multihoming decisions on a given platform. Furthermore, they investigate how platform-level multihoming of applications affects the sales of the platform. The authors show that increased platform-level multihoming of applications hurts platform sales, a finding consistent with literature on brand differentiation, but they also show that this effect vanishes as platforms mature or gain market share. The authors find that platform-level multihoming of applications affects platform sales more strongly than the number of applications. Furthermore, among mature platforms, an increasing market share leads to more seller-level multihoming, while among nascent platforms, seller-level multihoming decreases as platform market share increases. These findings prompt scholars to look beyond network size in analyzing two-sided markets and provide guidance to both (application) sellers and platform owners.

Keywords: two-sided markets, multihoming, entertainment markets, indirect network effects, video game industry

A two-sided market is composed of two distinct user networks that provide each other with network benefits through a platform by either buying or selling applications for the platform (Rochet and Tirole 2006). We refer to these distinct user networks—the two sides of the market—as buyers and sellers, respectively. Two-sided markets are pervasive in today's economy. For example, consumers will prefer a credit card that many merchants accept, while merchants will prefer a credit card that many consumers carry. Similarly, buyers will prefer auction sites with a large number of sellers, while sellers will prefer auction sites on which many buyers bid. Other examples of two-sided markets are entertainment platforms (consumers and content publishers), shopping malls (consumers and retail outlets), and computer networks (computer users and software providers).

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Both economists and marketing scholars have investigated two-sided markets (for a review, see Stremersch et al. 2007), studying new product growth or competition between platforms. Prior literature examining two-sided markets has focused almost exclusively on quantity (i.e., the size of the two user networks) as the network benefit that the two sides of the market contribute to each other (e.g., Basu, Mazumdar, and Raj 2003; Church and Gandal 1992, 1993; Dranove and Gandal 2003; Frels, Shervani, and Srivastava 2003; Gandal, Kende, and Rob 2000; Katz and Shapiro 1985; LeNagard-Assayag and Manceau 2001; Nair, Chintagunta, and Dubé 2004; Stremersch et al. 2007). However, user networks may contribute to each other in dimensions other than their mere size—for example, in quality (Binken and Stremersch 2009) or in the extent of multihoming (the current study).

Multihoming refers to the choice of an agent in a user network to use more than one platform. Single-homing refers to the choice of an agent in a user network to use only one platform. Single-homing and multihoming are logical opposites, and we conceptualize and operationalize both concepts as such in the rest of the article. This article focuses in particular on multihoming decisions of sellers rather than of buyers.[1]

We differentiate seller-level multihoming on a given platform (i.e., the extent to which the applications of a particular seller on the platform are also available for buyers

[1]Multihoming among buyers (e.g., consumers owning multiple video game console platforms) is beyond the scope of the current study.

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of competing platforms) from platform-level multihoming (i.e., the extent to which applications on a particular platform are also available for buyers of a competing platform). Thus, platform-level multihoming represents the aggregation of seller-level multihoming over all sellers providing applications for a particular platform. A seller can multihome many (few) of its applications for a given platform, which in our terminology reflects a high (low) degree of seller-level multihoming. At the platform level, many (few) of the applications available for a platform across all sellers may be multihomed, which in our terminology reflects a high (low) degree of platform-level multihoming.

Theoretical models have suggested that the extent to which applications on a particular platform are multihomed (platform-level multihoming) constitutes an important driver of the outcome of platform competition (Armstrong 2006; Armstrong and Wright 2007; Caillaud and Jullien 2003; Hermalin and Katz 2006; Rochet and Tirole 2006). The special relevance of multihoming to platform owners (Shapiro 1999) stems from the fact that the differentiation of a platform partially lies with the differentiation of the characteristics of its user network(s) from the characteristics of the user network(s) of competing platforms, beyond the differentiation between the other characteristics (e.g., hardware) of the platforms.

Seller-level multihoming decisions are important decisions for sellers in two-sided markets. On the one hand, a seller that single-homes on a given platform forgoes potential revenues from the buyers of competing platforms. On the other hand, single-homing sellers may have lower costs (e.g., they avoid the cost of adapting their applications to multiple platforms) or be paid exclusivity fees by owners of platforms on which they single-home.

Multihoming decisions are of great importance to firms in many contexts. For example, researchers credit the single-homing decision by several movie studios (e.g., Warner Brothers) as an important factor in the platform battle between Toshiba's HD DVD and Sony's Blu-ray (Barnes 2007; Edwards and Grover 2008). Sony is also reported to have paid a substantial amount to movie studios to prevent attractive movies on Blu-ray from being multihomed to HD DVD.

The video game console market—the context of the current study—is another market in which sellers' multihoming decisions may significantly affect their profits. For example, Take-Two's Rockstar Games unit was reported to have received an estimated $50 million from Microsoft to create two episodes of *Grand Theft Auto IV: The Lost and Damned* and single-home them for Microsoft Xbox 360. However, by single-homing, Take-Two's Rockstar Games unit missed the revenues that these games might have generated, especially from Sony PlayStation3 users.

Despite the high relevance of multihoming in many industries and a stream of recent analytical research (mostly in economics), little empirical research on multihoming exists (for exceptions, which we in turn extend, see Binken and Stremersch 2009; Corts and Lederman 2009; Rysman 2004). More precisely, we study two research questions, which have remained largely unaddressed by prior (empirical) literature. First, we investigate what conditions affect seller-level multihoming decisions on a given platform (in our case, multihoming decisions of game publishers). Second, we study whether and under what conditions platform-level multihoming affects the sales of the platform (in our case, sales of video game consoles), explicitly controlling for the number of applications sold for the platform.

We focus on the age and market share of the platform as conditions that may influence the extent of seller-level multihoming on the platform and the effect of platform-level multihoming on platform sales. Both age and market share of a platform significantly affect the uncertainty that consumers face in their platform adoption decision. Uncertainty plays a dominant role in any new technology adoption, but does so especially in two-sided markets because the future adoption by the seller network affects the future utility of a platform for consumers. The uncertainty regarding a platform decreases with age and market share, which in turn affects the extent to which the platform needs a clearly differentiated positioning to be successful. Thus, in short, nascent and low-market-share platforms may have a greater need for a differentiated network of sellers than mature and high-market-share platforms.

Our empirical findings are as follows: We find that the (negative) effect of platform-level multihoming on platform sales is larger than the (positive) effect of the number of applications on platform sales. We also find that this negative effect of multihoming is prominent for nascent platforms and for platforms with a small market share but it fades as platforms mature and gain market share. These findings have implications for sellers and platform owners. They may provide sellers with a better understanding of the conditions under which the platform owner may be willing to pay more or less for single-homed applications. Platform owners can also gain understanding of the conditions in which it benefits them to encourage or discourage single-homed applications for their platforms. These findings may also affect the future behavior of industry observers (e.g., in the reports they publish) and academic scholars (e.g., in the models they develop) because they force both observers and academics to move away from the logic of network size to the logic of multihoming.

We also find that a platform's age and market share, among other factors, drive the extent of seller-level multihoming on that platform. On the one hand, the larger the market share of a mature platform among buyers, the more of its applications will be multihomed. On the other hand, the larger the market share of a nascent platform, the fewer of its applications will be multihomed.

We organize the remainder of this article as follows: In the next section, we review the literature on multihoming. Then, we develop hypotheses for the effects of multihoming on platform sales and for the determinants of multihoming. The fourth section presents the data we use to test the developed theory. We develop our model in the fifth section and present the estimation procedure in the sixth section. We present the estimation results in the seventh section. We conclude with a discussion of the implications and limitations of our research.

Prior Literature on Multihoming

We can distinguish two types of prior analytical models on multihoming in two-sided markets. The first type examines what the equilibrium outcome is if a multihoming option exists for a user group, without the (potential) existence of exclusive contracts (Armstrong 2006; Caillaud and Jullien 2003; Choi 2007; Doganoglu and Wright 2006; Rochet and Tirole 2003, 2006). Most relevant to our own inquiry is the theoretical model Choi (2007) proposes, which considers the level of suitability of a seller's applications for a specific platform as a determinant of that seller's decision to single-home its applications on that platform. In our theoretical framework, we also adopt this notion of seller–platform fit as one of the factors influencing multihoming decisions. We theorize that the fit between a seller and a given platform is conveyed through the sales success of the sellers' applications among the buyers of the platform.[2]

A second set of models examines the equilibrium outcome if a platform owner offers an option of an exclusive contract—a contract under which agents in a user network commit to single-home on a given platform—in a context in which the multihoming option exists, or in specific settings of platforms' competitive strength and life-cycle stages (Armstrong and Wright 2007; Balto 1999; Carrillo and Tan 2006; Doganoglu and Wright 2010; Mantena, Sankaranarayanan, and Viswanathan 2007; Shapiro 1999). Such exclusive contracts are relevant to market outcomes only when sellers would otherwise opt to multihome or to single-home on a competing platform. Scholars in this area debate the conditions under which the employment of such exclusive contracts has negative welfare consequences. Armstrong and Wright (2007) find that exclusive deals may actually promote a superior market outcome for both buyers and sellers under certain market conditions. Doganoglu and Wright (2010) find that exclusive deals are inefficient when offered by incumbent firms as a tool to dominate a market in the face of entry, and the seller network is the primary beneficiary of such deals.

Note that in our theoretical framework, as presented in the next section, we do not specifically distinguish different motivations for inducing single-homing through exclusive contracts, nor do we determine the beneficiaries of such actions. However, we consider the age and the market share of the platform as determinants of multihoming decisions and, in doing so, aim to generalize the conditions under which we can expect higher levels of multihoming. In this respect, a study of special relevance to our present inquiry is that of Mantena, Sankaranarayanan, and Viswanathan (2007). Their analytical model examines the conditions under which single-homing can be observed and the impact of single-homing on industry outcomes, taking into account the typical high level of uncertainty buyers in two-sided markets face. Mantena, Sankaranarayanan, and Viswanathan's work applies to the context of high technology and media markets, which share many features with our empirical context.

Empirical studies relevant to our context are few in number and different in nature from our current inquiry. Rysman (2004) documents network benefits between buyers (consumers) and sellers (advertisers) of a platform (yellow pages). For simplicity reasons, he assumes that buyers single-home and sellers choose platforms only on the basis of the number of buyers of the platform. Corts and Lederman (2009) study the influence of platforms' installed base of buyers on the number of single-homed and multihomed applications published. They also study the influence of the number of applications on own and competing platform sales, which allows them to be the first to provide evidence of network benefits gained not only for a given platform but also across competing platforms. Binken and Stremersch (2009) are the first to show that superstar applications—applications of very high quality (i.e., a quality rating $\geq 90/100$) that command a disproportionately large payoff in application sales—affect platform sales beyond the effect of the total number of applications. They find that the effects of single-homed and multihomed superstar applications on platform sales are similar.

Using new metrics for seller-level and platform-level multihoming, we extend this empirical literature by (1) quantifying the effect of platform-level multihoming on platform sales across the entire collection of applications and over all competing platforms in a direct manner, (2) theorizing and empirically documenting the moderating role of market share and age of the platform on the relationship between platform-level multihoming and platform sales, and (3) theorizing and empirically documenting contrary effects of platform market share on seller-level multihoming, depending on the age of the platform.

Theory Development

In this section, we first derive our theoretical expectations on the effect of platform-level multihoming on sales of the platform and the conditions that may influence this effect. In terms of conditions, we focus on the age and market share of the platform, because an increase in either may significantly lower the uncertainty that consumers face in their platform adoption decision. We expect that the greater this uncertainty, the more a platform needs a clearly differentiated positioning to be commercially successful. Then, we explore the effect of such conditions on seller-level multihoming on a given platform. Figure 1 provides a graphic overview of our conceptual framework and the hypotheses we posit. For the derivation of our hypotheses, we build on theories on differentiation and uncertainty in two-sided markets.

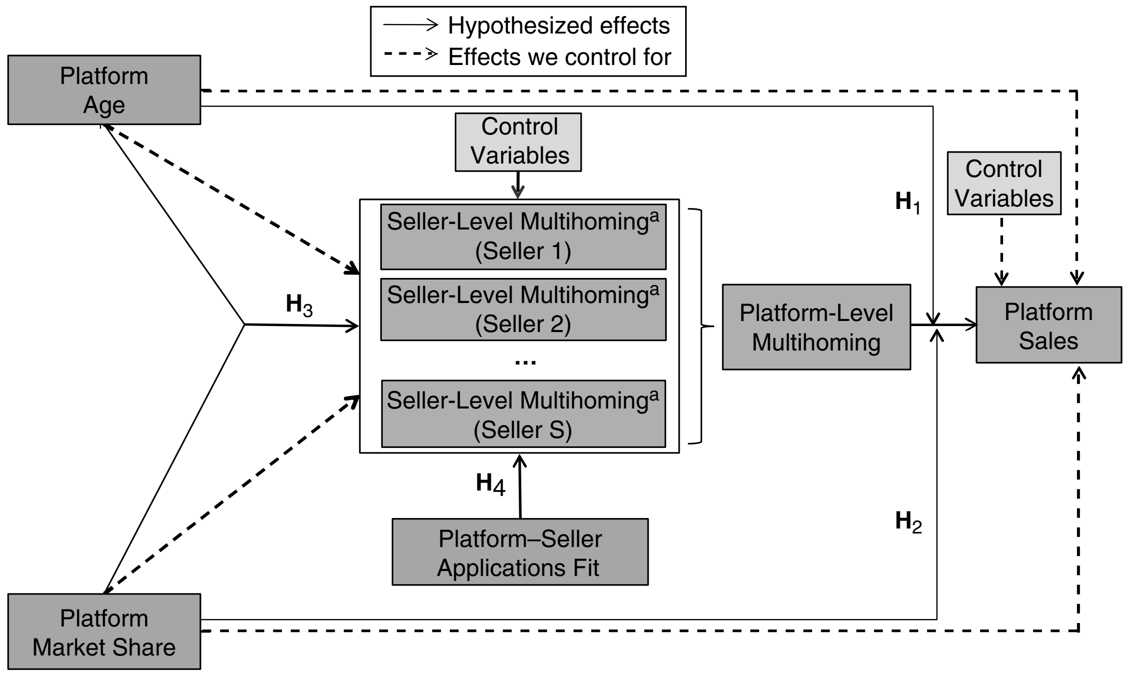
The Influence of Platform-Level Multihoming on Platform Sales

When a platform's applications are multihomed on other platforms, the platform may not be able to differentiate itself through the applications of its network of sellers. Differentiation provides brands with greater resistance to competitive attacks (e.g., Aaker 1991; Carpenter, Glazer, and Nakamoto 1994). Thus, in two-sided markets, in which buyers and sellers endow each other with network benefits, a platform for which few applications are multihomed can achieve greater differentiation than a platform for which many applications are multihomed (Mantena, Sankaranarayanan, and Viswanathan 2007). For example, the video game *Tetris*, which was single-homed on Game Boy, is credited for much of the Game Boy's success (Allen 2003; Rowe 1999).

Platforms might not all be equally affected by a lack of differentiation from multihoming. We expect that nascent

[2]In the section on robustness, we also consider an alternative measure of seller-platform fit that is based on application quality rather than application sales.

FIGURE 1
Conceptual Framework



[a]Multihoming across all the seller's applications for the platform.

platforms (i.e., platforms that have been introduced only recently) are more vulnerable to multihoming of their applications than mature platforms. The level of buyers' uncertainty on a nascent platform is high initially, after which uncertainty fades as the platform matures. Under the high uncertainty characterizing nascent platforms, buyers' preferences for a platform can more easily tip in favor of a platform for which few of its applications are multihomed than a platform for which many of its applications are multihomed, keeping the number of applications constant (Mantena, Sankaranarayanan, and Viswanathan 2007). As platforms mature, buyers' expectations about the ultimate success of the platform become more certain (Schilling 2002), and the need for differentiation through a platform's applications decreases. We hypothesize the following:

H_1: There is a negative relationship between platform-level multihoming of applications and platform sales for nascent platforms, which fades as platforms mature.

Two-sided markets are known to "tip" in favor of the largest-share platform (Arthur 1989). As a platform increasingly beats other platforms in terms of market share, other platform attributes (e.g., the extent of platform-level multihoming) become less important in buyers' platform choice. A large market share of a platform provides a clearer signal of the superior value the platform offers for buyers than attributes that are more difficult for a consumer to measure (Schilling 1999), such as the number of applications for the platform that are multihomed.

The important role of platform market share as a signal for superior value also fits prior findings in differentiation theory. Carpenter and Nakamoto (1989) argue that greater similarity between brands hurts only the nondominant brand and not the dominant brand. In the context of pioneering advantages, they attribute an overall perceptual distinctiveness to dominant brands that allows them to overshadow similar, but smaller, competitors. Feinberg, Kahn, and McAlister (1992), who study variety seeking, also find that when consumer preferences remain constant, sharing more features with competing brands hurts small brands but does not hurt dominant brands. As we argued previously, platform-level multihoming may lead to a lack of differentiation, which, according to this logic, would hurt dominant brands less than nondominant brands. Therefore, we hypothesize the following:

H_2: There is a negative relationship between platform-level multihoming of applications and platform sales for platforms with a small market share, which fades as platforms gain market share.

In our empirical tests of the preceding hypotheses, we control for several other variables that may affect platform sales in addition to platform age and market share.[3] First, we control for the number of applications that are available for the platform, which we expect to positively affect platform sales (Church and Gandal 1993; Katz and Shapiro 1994). Second, we control for the number of platforms that compete with one another. Competition may increase platform sales because it may benefit the growth of the industry (Agarwal and Bayus 2002), or it may decrease

[3]Note that in the application context of this study, the correlation between market share and platform sales is low (.33) because of the high category sales growth over time.

platform sales through platform switching (Carpenter and Lehmann 1985). Third, we control for the price of the platform, which we expect to negatively affect platform sales. Fourth, we include the number of superstar releases for the platform (Binken and Stremersch 2009). In addition, we control for seasonality in sales by including a December dummy, for inertia in sales by including the platform's sales in the previous period, and for other time-invariant platform features by including platform dummies. In our case, such platform features can be technical attributes such as data width, clock speed, memory, the type of controller, the media device (e.g., CD-ROM, DVD, Blu-ray), or the possibility to access the Internet, as well as other aspects such as the brand name and credibility of the platform owner.

Determinants of Seller-Level Multihoming

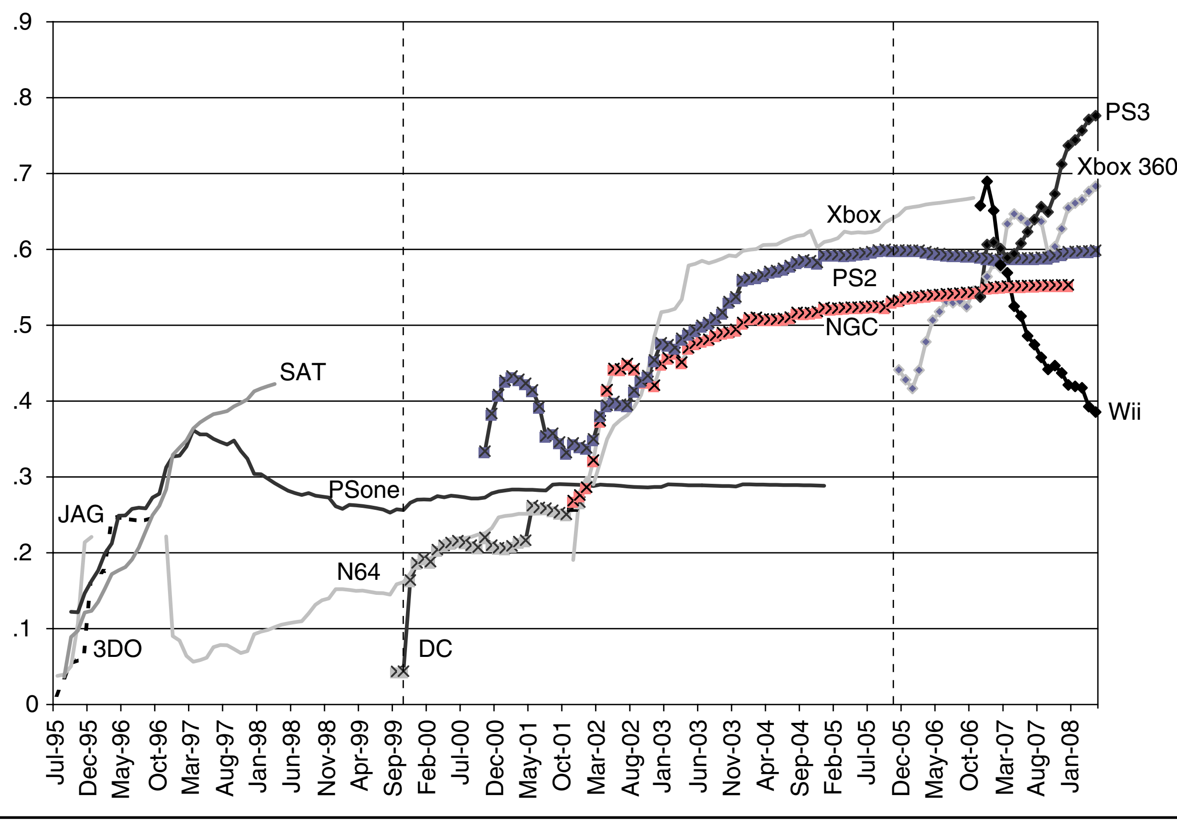
Seller-level multihoming is the outcome of the decision of platform owners to provide incentives to lower the level of seller-level multihoming and the decision of sellers on the level of seller-level multihoming, given such incentives. We theorize on the effects of age and market share of the platform and the seller–platform fit on the platform owner and seller decisions, and, in turn, on the level of seller-level multihoming.

As H_1 predicts, when a platform is mature, the platform owner has little need to offer sellers incentives to discourage them from multihoming. Owners of nascent platforms may have a greater need to offer sellers such incentives. These arguments may explain the increase in multihoming over the life cycle of a platform (as illustrated in Figure 2).

Beyond this direct effect, platform age may also interact with the market share of the platform. The owner of a mature platform with a large market share will have an even lower need to offer incentives to discourage sellers from multihoming than the owner of a mature platform with a small market share, because high-share platforms are hurt less by seller-level multihoming than low-share platforms. Therefore, as the market share of a mature platform increases, we expect the platform owner to offer sellers fewer incentives that discourage them from multihoming. At the same time, if a small-share, mature platform offers such incentives, sellers may still accept them, despite the low market share of the platform because such platforms may still represent sizeable buyer networks in absolute numbers (Mantena, Sankaranarayanan, and Viswanathan 2007). In summary, the incidence of seller-level multihoming among mature platforms likely increases with market share.

For nascent platforms, the opposite is true. In the early stage of the life cycle of a new platform in a two-sided market, buyers are still largely undecided, and the user base is still small (see Mantena, Sankaranarayanan, and Viswanathan 2007; Schilling 2002; Stremersch et al. 2007). Nascent platforms are therefore likely to offer sellers incentives to discourage them from multihoming because the lack of differentiation caused by multihoming may substantially hurt such platforms. Sellers will more easily accept such incentives from owners of platforms with a greater market share because their higher market share serves as a signal of superior value to sellers. Therefore, we expect to find a lower incidence of seller-level multihoming for

FIGURE 2
Multihoming for All Platforms (July 1995–April 2008)



nascent platforms with greater market shares (compared with nascent platforms with lower market shares). We hypothesize the following:

> H_3: The relationship between the market share of a platform among buyers and the extent of seller-level multihoming of applications for that platform is (a) negative for nascent platforms and (b) positive for mature platforms.

Next, we theorize that a better fit between a seller's applications and the characteristics of the platform or of the platform's buyers' network (Choi 2007) increases the platform owner's inclination to make high payments to the seller to reduce the degree to which its applications are multihomed. At the same time, the seller is more likely to accept such payments from the owner of a platform with which it shows a better fit than from the owner of a platform with which it shows a worse fit. We use the prior sales success of the seller's applications among the buyers of the platform as an indicator of seller–platform fit. We hypothesize the following:

> H_4: Seller-level multihoming increases as seller–platform fit decreases.

Note that a potential counterargument may lie in a cooperation dilemma known in the economics literature as the "holdup problem." This problem emerges in situations in which cooperation between two market players (in our case, the platform owner and the seller) is the most efficient strategy, and yet the players refrain from cooperation because they do not want to give the other party increased bargaining power (Edlin and Reichelstein 1996; Schwarz and Takhteyev 2010). However, in our context, this holdup problem is unlikely to occur, because the exclusivity agreements between sellers and platform owners are made for each application separately, often before the application is developed. In our empirical tests of the H_3 and H_4, we again control for the number of applications that already exist for the platform, inertia in multihoming decisions, and the characteristics of the platforms that are time-invariant (see previous discussion) using platform dummies.

Data

We test our hypotheses using data from the video game console industry. This section first describes this research context and our data collection procedures, after which it turns to the operationalization and description of the measures we employ.

Research Context: The Video Game Console Industry

The video game console industry dates back to the early 1970s. In 1972, the television maker Magnavox introduced Odyssey, the first home video game console. The system came with 12 games, including versions of tennis and Ping-Pong, and more than 100,000 game consoles were sold by the end of 1972. Since then, seven sequential generations of game consoles have been introduced, one every five to six years. Each generation is typically characterized by a superior technology, often with new and superior console accessories, and consists of a small number of competing, incompatible video game consoles and a collection of game titles. In the first generations of home video game consoles, the games were typically developed and published by the console owners. Over time, platforms (i.e., consoles) and applications (i.e., games) in the video game industry became increasingly separated, with large publishers specializing in games, without a footprint in console manufacturing (e.g., Electronic Arts).

The popularity of video game consoles has grown rapidly in the past two decades, with more than 55 million seventh-generation game consoles sold in the United States as of March 2010 (*Digital Digest* 2010). Recently, playing video games was rated the top fun entertainment activity by American households, outpacing watching television, surfing the Internet, reading books, and going to or renting movies (Interactive Digital Software Association 2001). ACNielsen's 2005 study "Benchmarking the Active Gamer" shows that the demographic of gamers widened between 2000 and 2005, with more women playing and an emerging market of males in the 25- to 34-year age range. This study also found that gamers spent more time (25% of their leisure time) playing games (*BusinessWeek* 2005).

The video game console market is well suited for testing the implications of multihoming in two-sided markets. First, this market is often cited as the canonical example of a two-sided market (Clements and Ohashi 2005; Shankar and Bayus 2003). Second, there is sufficient variation in this market, both over time and across consoles, in multihoming, the number of applications, and platform sales. Third, the business of publishing video games today is similar to the publishing of DVDs and other entertainment products.

Our data cover the sales of 12 home video game consoles from three consecutive generations (i.e., generations 5, 6, and 7), including unit sales and quality ratings for all games sold for the analyzed systems (4230 titles) in the United States over 154 consecutive months starting from July 1995. The consoles include Sega Saturn, Sony PlayStation, Nintendo 64, 3DO Multiplayer, Atari Jaguar, Sega Dreamcast, Sony PlayStation2, Nintendo GameCube, Microsoft Xbox, Microsoft Xbox 360, Sony PlayStation3, and Nintendo Wii.

The fifth video game console generation is known as the 32-/64-bit generation. This generation lasted approximately from 1993 to 2002. The three dominating consoles of the fifth generation are Sega Saturn (introduced in May 1995), Sony PlayStation (introduced in September 1995), and Nintendo 64 (introduced in September 1996). Other consoles that were part of this generation and are covered in our data are the 3DO Multiplayer and Atari Jaguar, but they had a much lower sales level and no significant impact on the structure of the market.

The sixth video game console generation, also known as the 128-bit generation, refers to video game consoles that were introduced between 1999 and 2001. Platforms of the sixth generation include Sega's Dreamcast (introduced in September 1999), Sony's PlayStation2 (introduced in October 2000), and the Nintendo GameCube and Microsoft's Xbox (both introduced in November 2001). The consoles of the sixth generation showed great similarity in terms of their technological characteristics.

The seventh video game console generation (the current generation) includes game consoles that have been released since 2005. This generation began on November 2005 with the release of Microsoft's Xbox 360. One year later, Sony's PlayStation3 and Nintendo's Wii were also introduced to the market. PlayStation3 was introduced with great delay and manufacturing cost concerns, given the inclusion of the Blu-ray reader format Sony had pioneered. Nintendo's Wii brought unique motion controllers to the market, which set it apart from Sony and Microsoft and enabled unique applications (e.g., motion-controlled sports).

Although our data on the fifth-generation consoles cover all months starting from their introduction, we chose July 1995 as the starting point of our analysis to avoid a potential bias in our multihoming measure caused by the sharing of titles with consoles of the fourth generation, on which we do not have data. We also exclude months that show very low platform sales figures (<5000 units) at the end of a platform's life cycle, because they represent nonactive periods in which the system is already abandoned.

We sourced data on console and game release time, sales, and prices from the NPD Group, a well-known market research firm that covers the game industry. NPD's data have been used previously in academic marketing research (Binken and Stremersch 2009; Stremersch et al. 2007). To evaluate the number of superstars released for each platform, we used NPD quality ratings and inferred whether a game was a superstar according to a metric developed by Binken and Stremersch (2009).

Measures

Our central construct is the platform-level multihoming, $\text{Platform\_Multi\_Homing}_{pt}$, which is the extent of platform-level multihoming for the applications of platform p at time t. We operationalize $\text{Platform\_Multi\_Homing}_{pt}$ as follows: We begin by developing an indicator variable, denoted as Home_{at}, which indicates for each application a, available for sale at time t, whether it is multihomed across platforms at time t:[4]

$$(1)\quad \text{Home}_{at} = \begin{cases} 0 & \text{if application a is single-homed at t} \\ 1 & \text{otherwise.} \end{cases}$$

Next, we calculate the extent of platform-level multihoming for each platform p at time t by weighing Home_{at} according to the relative share of application a in the overall application sales for platform p by time t (Share^{A}_{apt}), as follows:

$$(2)\quad \text{Platform\_Multi\_Homing}_{pt} = \sum_{a=1}^{A} (\text{Home}_{at} \times \text{Share}^{A}_{apt}),$$

where A is the overall number of applications in the market. In cases in which a platform offers only applications that are single-homed, $\text{Platform\_Multi\_Homing}_{pt}$ equals 0. As a platform's applications are increasingly multihomed, $\text{Platform\_Multi\_Homing}_{pt}$ approaches 1.

The seller-level multihoming on a given platform, $\text{Seller\_Multi\_Homing}_{pst}$, is the extent to which the applications of seller s for platform p are multihomed at time t. We calculate the extent of seller-level multihoming for each platform p at time t by weighing Home_{at} over all applications of seller s, A^{S}, according to the relative share of application a in the overall application sales for platform p by time t (Share^{A}_{apt}), as follows:

$$(3)\quad \text{Seller\_Multi\_Homing}_{pst} = \sum_{a=1}^{A^{S}} (\text{Home}_{at} \times \text{Share}^{A}_{apt}).$$

As Equations 2 and 3 show, the platform-level multihoming is an aggregation of seller-level multihoming across all sellers offering applications for the platform.

As theorized previously, we use the following variables to explain seller-level multihoming on a given platform, in addition to platform dummies and lagged seller-level multihoming: Platform_Age_{pt} is the number of months that elapsed between the introduction of platform p and time t; $\text{Platform\_Mar\_Share}_{pt}$, the market share of platform p at time t, is equal to the sales of the platform p at time t divided by the sum of sales for all platforms available at time t; $\text{nr\_Applications}_{pt}$ is the cumulative number of applications released for platform p by time t; and $\text{Seller\_Platform\_Fit}_{pst}$ is the average penetration rate, among the buyers of platform p, across all applications released by seller s for platform p by t.

$\text{Platform\_Sales}_{pt}$ is the number of units of platform p that are sold during month t. In addition to the aforementioned measures (e.g., $\text{Platform\_Multi\_Homing}_{pt}$, $\text{Platform\_Mar\_Share}_{pt}$, Platform_Age_{pt}, $\text{nr\_Applications}_{pt}$), we include the following measures for the other variables in the platform sales equation: $\text{Platform\_Comp\_Nr}_{pt}$ is the number of other active platforms in the market at time t; $\text{Platform\_Price}_{pt}$ is the retail price of platform p at time t, which we instrument for, as explained subsequently; $\text{Superstar\_Release}_{pt}$ is the number of applications for platform p released at time t with a quality rating of 90 and greater (following Binken and Stremersch 2009); and I^{Dec}_{t} is a December dummy that takes the value of 1 if t is the month of December and 0 if it is not. To control for inertia and contagion, we also include lagged platform sales. Finally, we include platform dummies to account for intrinsic, non-time-varying, differences between consoles.

To address the endogeneity of $\text{nr\_Applications}_{pt}$, we also specify an auxiliary regression for the number of applications of a given seller for the platform, $\text{nr\_Applications}_{pst}$. Beyond platform dummies, $\text{Platform\_Mar\_Share}_{pt-1}$, Platform_Age_{pt}, I^{Dec}_{t}, and $\text{nr\_Applications}_{pst-1}$, we also include the competition among sellers for platform p, denoted as $\text{Seller\_Comp\_Nr}_{pt}$, which we calculate as the number of sellers that have released applications for platform p by t.

Descriptives

Table 1 shows the descriptive statistics of the variables that enter our three equations. (The details on the specification of the three equations appear in the "Model" section.) Figure 2 shows the extent of platform-level multihoming for each platform in our data over time. It shows that platforms in Generation 6—Xbox, PlayStation2, and Nintendo GameCube—are similar in terms of platform-level multihoming of applications, while among platforms in Generations 5 and 7, there are larger differences in platform-level multihoming of applications across platforms. Figure 2 also reveals an increasing extent of platform-level multihoming in the video game industry over the analyzed time frame.

[4]In the robustness analysis, we also implement other measures for $\text{Platform\_Multi\_Homing}_{pt}$ and $\text{Seller\_Multi\_Homing}_{pst}$ grounded in alternative Home_{at} measures.

TABLE 1
Descriptive Statistics

A: Platform Sales Equation

	Platform Sales	Platform Multihoming	Platform Age	Platform Market Share	Number of Applications[a]	Number of Platform Competitors	Platform Price	Superstar Release	December Dummy
Platform multihoming	.14								
Platform age	–.06	.19							
Platform market share	.33	–.19	–.25						
Number of applications	.06	.33	.91	–.09					
Number of platform competitors	.11	.56	.14	–.38	.20				
Platform price	.02	.02	–.68	.23	–.56	.10			
Superstar release	.18	.18	–.02	.16	.06	.11	.01		
December dummy	.57	.01	–.02	–.03	–.01	.10	.02	–.04	
M	252,329	.37	34.91	.29	420.79	2.70	177.66	.24	.09
SD	322,275	.19	26.22	.20	423.82	.84	94.13	.55	.29

B: Multihoming Equation

	Seller-Level Multihoming	Platform Age	Platform Market Share	Number of Applications[a]	Seller–Platform Fit
Platform age	–.10				
Platform market share	–.06	–.33			
Number of applications	–.07	.90	–.12		
Seller-platform fit	.05	–.07	.01	–.04	
M	.27	48.43	.28	654.90	64.48
SD	.36	27.65	.19	468.71	14.51

C: Number of Applications Equation

	Number of Applications (Seller Platform)[b]	Platform Market Share	Number of Seller Competitors	Platform Age	December Dummy
Platform market share	–.03				
Number of seller competitors	.22	–.11			
Platform age	.20	–.33	.90		
December dummy	–1.98e-04	–.01	7.07e-04	8.72e-06	
M	9.72	.28	57.48	48.43	.09
SD	17.87	.19	24.20	27.65	.28

[a]The number of applications on a given platform.
[b]The number of a seller's applications on a given platform.

Model

To test our hypotheses, we specify a system of equations as follows. The dependent variable of the first equation ($Platform\_Sales_{pt}$) is the sales of platform p at time t. The dependent variable of the second equation ($Seller\_Multi\_Homing_{pst}$) is the extent to which applications of seller s for platform p are multihomed at time t. We implement a log-transform functional form for these two dependent variables, which enables us to pool data across platforms with different platform-level multihoming and platform sales levels (Binken and Stremersch 2009; Dranove and Gandal 2003; Gandal, Kende, and Rob 2000; Stremersch et al. 2007).

We specify the independent variables according to the theory we derived previously, using the symbols as introduced in the "Measures" section. We do not enter the number of superstar title releases, $Superstar\_Release_{pt}$, with a log-transform form, to allow for increasing returns to platform sales, consistent with superstar theory (Binken and Stremersch 2009; Jones and Walsh 1988). Finally, we include platform dummies (α_{0p}, β_{0p}) in the two equations to account for unobserved platform characteristics.

Because multihoming is a strategic decision between application sellers and platform owners (Choi 2007; Doganoglu and Wright 2010), we use Garen's (1984) approach (which has also been advocated in Hamilton and Nickerson [2003] and applied in Ghosh, Dutta, and Stremersch [2006]). In this approach, we include the residuals from estimating the equation of the strategic selection variable (in our case, seller-level multihoming) in the equation of the response variable (in our case, platform sales), as well as the interaction between each residual and the strategic selection variable.

Because the number of applications for a platform might also be endogenous, we include an equation with $nr\_Applications_{pst}$ as the dependent variable, in which we implement the same residual inclusion approach developed by Garen (1984). In addition, for this equation, we implement a log-transform functional form and take the specification for the independent variables most commonly used in the literature (Stremersch et al. 2007).

The system of equations we specify is as follows:

$$
\begin{aligned}
(4)\quad & \ln \text{Platform\_Sales}_{pt} \\
& = \alpha_{0p} + \alpha_1 \ln \text{Platform\_Multi\_Homing}_{pt} \\
& + \alpha_2 \ln \text{Platform\_Age}_{pt} + \alpha_3 (\ln \text{Platform\_Multi\_Homing}_{pt} \\
& \times \text{Platform\_Age}_{pt}) \\
& + \alpha_4 \ln \text{Platform\_Mar\_Share}_{pt-1} \\
& + \alpha_5 (\ln \text{Platform\_Multi\_Homing}_{pt} \\
& \times \ln \text{Platform\_Mar\_Share}_{pt-1}) \\
& + \alpha_6 \ln \text{nr\_Applications}_{pt} + \alpha_7 \ln \text{Platform\_Comp\_Nr}_{pt} \\
& + \alpha_8 \ln \text{Platform\_Price}_{pt} + \alpha_9 \text{Superstar\_Release}_{pt} \\
& + \alpha_{10} I_t^{Dec} + \alpha_{11} \ln \text{Platform\_Sales}_{pt-1} \\
& + \theta_1 \eta_{pt}^{\text{Multi\_Homing}} + \theta_2 (\eta_{pt}^{\text{Multi\_Homing}} \times \ln \text{Multi\_Homing}_{pt}) \\
& + \theta_3 \eta_{pt}^{\text{nr\_Applications}} + \theta_4 (\eta_{pt}^{\text{nr\_Applications}} \times \ln \text{nr\_Applications}_{pt}) \\
& + \varepsilon_{pt}^{\text{Platform\_Sales}},
\end{aligned}
$$

$$
\begin{aligned}
(5)\quad & \ln \text{Seller\_Multi\_Homing}_{pst} \\
& = \beta_{0p} + \beta_1 \ln \text{Platform\_Age}_{pt} + \beta_2 \ln \text{Platform\_Mar\_Share}_{pt-1} \\
& + \beta_3 (\ln \text{Platform\_Mar\_Share}_{pt-1} \times \ln \text{Platform\_Age}_{pt}) \\
& + \beta_4 \ln \text{nr\_Applications}_{pt-1} \\
& + \beta_5 \ln \text{Seller\_Platform\_Fit}_{pst} \\
& + \beta_6 \ln \text{Seller\_Multi\_Homing}_{pst-1} + \eta_{pt}^{\text{Multi\_Homing}} + \varepsilon_{pst}^{\text{Multi\_Homing}},
\end{aligned}
$$

and

$$
\begin{aligned}
(6)\quad & \ln \text{nr\_Applications}_{pst} \\
& = \gamma_{0p} + \gamma_1 \ln \text{Platform\_Mar\_Share}_{pt-1} \\
& + \gamma_2 \ln \text{Sellers\_Comp\_Nr}_{pt} + \gamma_3 \ln \text{Platform\_Age}_{pt} \\
& + \gamma_4 I_t^{Dec} + \gamma_5 \ln \text{nr\_Applications}_{pst-1} \\
& + \eta_{pt}^{\text{nr\_Applications}} + \varepsilon_{pst}^{\text{nr\_Applications}}.
\end{aligned}
$$

Because the platform sales equation is at the platform level while the two other equations are at the platform–seller level, there is no direct way to account for common unobserved shocks affecting the system. Therefore, we decompose the periodic error terms of these two platform–seller-level equations into a platform-level element ($\eta_{pt}^{\text{Multi\_Homing}}$ and $\eta_{pt}^{\text{nr\_Applications}}$) and a platform–seller-level element ($\varepsilon_{pst}^{\text{Multi\_Homing}}$ and $\varepsilon_{pst}^{\text{nr\_Applications}}$). We assume $\eta_{pt}^{\text{Multi\_Homing}}$ and $\eta_{pt}^{\text{nr\_Applications}}$ each have a multivariate normal distribution:

$$
(7)\qquad \begin{pmatrix} \eta_{pt}^{\text{Multi\_Homing}} \\ \eta_{pt}^{\text{nr\_Applications}} \end{pmatrix} \sim N(0, \Sigma_\eta).
$$

We then introduce $\eta_{pt}^{\text{Multi\_Homing}}$ and $\eta_{pt}^{\text{nr\_Applications}}$ concurrently in the sales equation, both as fixed effects and through interaction terms with the values of their corresponding independent variables. In addition, θ_1, θ_2, θ_3, and θ_4 in Equation 4 correct for possible endogeneity in the effect of multihoming and number of applications on platform sales due to strategic behavior in setting these variables. The terms θ_1 and θ_3 represent the effect of strategic deviations in the endogenous variables on the sales of the platform. The strategic deviations are represented by the differences between the actual value of the variables and their expected values as they are captured by the respective equations. The terms θ_2 and θ_4 in Equation 4 represent the effect of the interaction between these differences and the absolute values of the endogenous variables on platform sales.

Model Estimation

Following the estimation approach of Garen (1988), we compute the residuals $\hat{\eta}_{pt}^{\text{Multi\_Homing}}$ and $\hat{\eta}_{pt}^{\text{nr\_Applications}}$ from the equations for multihoming and for the number of applications (Equations 5 and 6, respectively) by calculating for each platform and time period the average of $\hat{\varepsilon}_{pst}^{\text{Multi\_Homing}}$ and $\hat{\varepsilon}_{pst}^{\text{nr\_Applications}}$ over all sellers in that time period. Then, we include these residuals as regressors in Equation 4, along with their interactions with the corresponding endogenous independent variables.

As Garen (1988) notes, the error term in Equation 4, $\varepsilon_{pt}^{\text{Platform\_Sales}}$, is likely to depend on the endogenous variables (in our case, $\text{Platform\_Multi\_Homing}_{pt}$ and $\text{nr\_Applications}_{pt}$) and thus may be heteroskedastic. Therefore, we estimate heteroskedasticity-consistent standard errors as proposed by White (1980).

A final endogeneity concern arises with the estimation of α_8, the effect of platform price on platform sales. Platform owners may set prices strategically to achieve superior sales. Consequently, these decisions may not be random but rather may be rooted in the expectations managers have regarding their effect on future outcomes. To address the potential endogeneity of price, we employ an instrumental variables (IV) procedure. We use a combination of two IVs in our analysis that have also been used in other studies analyzing platform sales in the video game industry (Clements and Ohashi 2005; Corts and Lederman 2009). The first IV is the price of the platform in Japan. This is a valid IV under the assumption that there are no common demand shocks in the U.S. and Japanese markets, which seems reasonable. Second, we use the exchange rate between the U.S. dollar and the currency in the country in which the platform was manufactured. As the U.S. dollar becomes stronger relative to the currency in the manufacturing country, the cost of the platform, and in turn its price in the U.S. market, is expected to decrease. This variable is a valid IV if the exchange rates are not correlated with unobserved demand shocks for the platform in the U.S. market, which seems to be a reasonable assumption.

Empirically, the two IVs adhere to the two requirements for instrumental variables. First, they correlate with the endogenous explanatory variable, conditional on the other covariates. In a regression explaining own platform price using the other model covariates and our set of IVs, the significance levels are .03 and .06 for the price in Japan and the exchange rate, respectively. Second, they are not highly correlated with the error term in our investigated model.

Results

Estimation Results

First, our model shows a good fit to the data, which is not surprising, given that we include all key variables and the lagged dependent variable ($R^2_{(\text{platform sales equation})}$ = .76, $R^2_{(\text{seller-level multihoming equation})}$ = .96, $R^2_{(\text{number of applications equation})}$ = .98). Table 2 reports the estimation results for Equations 4–6. The estimation results of the first equation are in Columns 1–3 (variable name, symbol, and coefficient with standard error in parentheses), followed by the estimation results of the second (Columns 4–6) and third (Columns 7–9) equations.

Columns 1–3 in Table 2 show that the coefficient for the main effect of platform-level multihoming is negative, indicating that higher levels of platform-level multihoming lead to lower own-brand sales ($\alpha_1 = -4.98$, $p \leq .01$). Confirming H_1 and H_2, we also find that this negative effect is mitigated by the age of the platform ($\alpha_3 = .05$, $p \leq .01$) and by its market share ($\alpha_5 = 2.84$, $p \leq .01$). Given the significant interactions of platform-level multihoming with platform age and market share, we need to account for the latter factors when testing the overall effect of multihoming, which we can do by calculating the elasticity of multihoming at the mean levels of age, market share, and the estimated error of the multihoming equation.[5] This elasticity is –2.71, confirming that, on average, platform-level multihoming negatively affects platform sales.

The number of applications for the platform has a positive effect on platform sales ($\alpha_6 = .22$, $p \leq .01$). The elasticity of the number of applications is only .22. That is, an increase of 1% in the number of applications for a platform will lead to an increase of .22% in platform sales. A comparison of elasticities allows us to conclude that the (negative) elasticity of multihoming on platform sales (–2.71) is much larger than the (positive) elasticity of the number of applications on platform sales (.22).

Furthermore, the number of competing platforms does not have a statistically significant effect on platform sales ($\alpha_7 = -.01$, $p = .90$). We find that platform price has a significantly negative effect on platform sales ($\alpha_8 = -1.70$, $p \leq .05$), while the number of new superstar releases ($\alpha_9 = .11$, $p \leq .01$), the December dummy ($\alpha_{10} = .95$, $p \leq .01$), and lagged platform sales ($\alpha_{11} = .17$, $p \leq .01$) each have a significantly positive effect on platform sales.

Among the four parameters that correct for sample selection with respect to the extent of multihoming and number of applications (θ_1, θ_2, θ_3, and θ_4), we find that only θ_2 is significantly different from zero ($\theta_2 = 6.74$, $p \leq .05$). This significant coefficient implies strategic behavior in setting multihoming levels. However, we do not find evidence of such strategic behavior with respect to the number of applications, probably because developing new applications in this market takes 12–18 months on average.

The estimation results for the seller-level multihoming model (Columns 4–6) show that, in line with our theoretical expectation, the extent to which sellers multihome their applications for a given platform is likely to increase as the platform ages ($\beta_1 = 1.71\text{e-}04$, $p \leq .01$). The market share of a given platform has a negative main effect on the extent of seller-level multihoming on that platform ($\beta_2 = -.05$, $p \leq .01$). Given the signs of the main effect of platform market share and its significant interaction with platform age ($\beta_3 = 1.23\text{e-}03$, $p \leq .01$), we calculate the elasticity of platform market share across the range of Platform_Age_{pt} to test H_3. We find that until the 44th time period (3.5 years), the elasticity of platform market share on seller-level multihoming is negative, after which it turns positive, confirming H_3. We also find that the fit between a seller and a platform has a significant, negative effect on the extent to which that seller multihomes for that platform ($\beta_5 = -.01$, $p \leq .01$), confirming H_4. The number of applications for the platform does not have a significant effect on the extent of seller-level multihoming for the platform ($\beta_4 = -.02$, $p = .09$). Finally, we find that seller-level multihoming shows a high level of inertia, given the significant lagged term ($\beta_6 = .98$, $p \leq .01$).

The estimation results for the model of the number of applications (Columns 7–9) show that the lagged market share of the platform ($\gamma_1 = .10$, $p \leq .01$), the age of the platform ($\gamma_3 = 1.85\text{e-}04$, $p = .07$), the December dummy ($\gamma_4 = .01$, $p \leq .01$), and the lagged number of applications ($\gamma_5 = .98$, $p \leq .01$) each have a positive effect on the number of applications that are released for the platform by a given seller. The level of competition among sellers on a platform has a negative effect on the number of applications released for the platform by a given seller ($\gamma_2 = -.05$, $p \leq .01$).

Robustness

We assessed the robustness of our results in many ways (for a summary of all robustness checks, see Table 3). First, we constructed alternative multihoming measures from alternative specifications of Home_{at} (Equation 1) based on various concentration measures (for more details, see the Web Appendix at http://www.marketingpower.com/jmnov11), such as the Herfindahl index, the Rosenbluth index, and the comprehensive concentration index. We also used the number of titles that are multihomed as an alternative measure. Our main estimation results remained the same across all these alternative measures. Second, we estimated a nonlinear effect of platform-level multihoming on platform sales by introducing a squared multihoming term to our full model. We find that the squared multihoming effect is positive and significant, and yet the marginal effect of multihoming remains negative.

Third, in addition to estimating the effects of platform-level multihoming across all platforms (as reported in Table 2), we estimated its effects for each platform separately by evaluating interactions between platform-level multihoming and platform dummies. We find that the effect of platform-level multihoming on platform sales is negative and significant in the case of six consoles (i.e., 3DO Multiplayer,[6] Sega Saturn, Nintendo 64, Sega Dreamcast, Nintendo GameCube, and Microsoft Xbox) and insignificant in the case of six consoles (i.e., Atari Jaguar, Sony PlayStation, Sony PlayStation 2, Microsoft Xbox 360, Sony PlayStation 3, and Nintendo Wii). Consistent with our theoretical expectations and model findings in Table 2, sales

[5]Given the log-log specification of our model, we calculate the elasticity as follows:

$$\begin{aligned}E_{\text{Platform\_Multi\_Homing}_{pt}} &= \alpha_1 + \alpha_3 \times \overline{\ln \text{Platform\_Age}_{pt}}\\ &+ \alpha_5 \times \overline{\ln \text{Platform\_Mar\_Share}_{pt-1}}\\ &+ \theta_2 \times \overline{\eta^{\text{Multi\_Homing}}_{pt}}.\end{aligned}$$

[6]The significance level for 3DO Multiplayer is slightly lower ($p = .94$).

TABLE 2
Estimation Results

Platform Sales Equation			Seller Multihoming Equation			Number of Applications Equation		
Variable	Symbol	Coefficient (SE)	Variable	Symbol	Coefficient (SE)	Variable	Symbol	Coefficient (SE)
Platform_Multi_Homing$_{pt}$	α_1	−4.98** (1.57)	Platform_Age$_{pt}$	β_1	1.71e-04** (.00)	Platform_Mar_Share$_{pt-1}$	γ_1	.10** (.01)
Platform_Age$_{pt}$	α_2	−.05* (.02)	Platform_Mar_Share$_{pt-1}$	β_2	−.05** (.0068)	Seller_Comp_Nr$_{pt}$	γ_2	−.05** (.01)
Platform_Multi_Homing$_{pt}$ × Platform_Age$_{pt}$	α_3	.05** (.02)	Platform_Mar_Share$_{pt-1}$ × Platform_Age$_{pt}$	β_3	1.23e-03** (.00)	Platform_Age$_{pt}$	γ_3	1.85e-04 (.00)
Platform_Mar_Share$_{pt-1}$	α_4	−.23 (.37)	nr_Applications$_{pt}$	β_4	−.02 (.01)	December dummy	γ_4	.01** (.00)
Platform_Multi_Homing$_{pt}$ × Platform_Mar_Share$_{pt-1}$	α_5	2.84** (1.08)	Seller_Platform_Fit$_{pst}$	β_5	−.01** (.00)	nr_Applications$_{pst-1}$	γ_5	.98** (.00)
nr_Applications$_{pt}$	α_6	.22** (.06)	Seller_Multi_ Homing$_{pst-1}$	β_6	.98** (.00)			
Platform_Comp_Nr$_{pt}$	α_7	−.01 (.11)						
Platform_Price$_{pt}$	α_8	−1.70* (.88)						
Superstar_Release$_{pt}$	α_9	.11** (.03)						
December dummy	α_{10}	.95** (.08)						
Platform_Sales$_{pt-1}$	α_{11}	.17** (.05)						
Atari Jaguar	α_{01}	9.13 (4.80)	Atari Jaguar	β_{01}	.08** (.01)	Atari Jaguar	γ_{01}	.17** (.02)
Sega Saturn	α_{02}	9.97* (5.08)	Sega Saturn	β_{02}	.12** (.01)	Sega Saturn	γ_{02}	.23** (.02)
3DO Multiplayer	α_{03}	9.95 (5.21)	3DO Multiplayer	β_{03}	.10** (.01)	3DO Multiplayer	γ_{03}	.20** (.02)
Sony PlayStation	α_{04}	1.34* (4.98)	Sony PlayStation	β_{04}	.12** (.01)	Sony PlayStation	γ_{04}	.21** (.02)
Nintendo 64	α_{05}	9.97* (4.74)	Nintendo 64	β_{05}	.10** (.01)	Nintendo 64	γ_{05}	.19** (.02)
Sega Dreamcast	α_{06}	9.28* (4.63)	Sega Dreamcast	β_{06}	.11** (.01)	Sega Dreamcast	γ_{06}	.22** (.02)
Nintendo GameCube	α_{07}	1.17* (4.88)	Nintendo GameCube	β_{07}	.12** (.01)	Nintendo GameCube	γ_{07}	.21** (.02)
Sony PlayStation2	α_{08}	11.40* (5.34)	Sony PlayStation2	β_{08}	.13** (.01)	Sony PlayStation2	γ_{08}	.21** (.02)
Microsoft Xbox	α_{09}	1.96* (5.25)	Microsoft Xbox	β_{09}	.13** (.01)	Microsoft Xbox	γ_{09}	.22** (.02)
Microsoft Xbox 360	α_{010}	11.93* (5.60)	Microsoft Xbox 360	β_{10}	.12** (.01)	Microsoft Xbox 360	γ_{10}	.22** (.02)
Sony PlayStation3	α_{011}	12.95* (6.08)	Sony PlayStation3	β_{11}	.14** (.01)	Sony PlayStation3	γ_{11}	.25** (.02)
Nintendo Wii	α_{012}	11.71* (5.40)	Nintendo Wii	β_{12}	.13** (.01)	Nintendo Wii	γ_{12}	.26** (.02)
$\eta_{pt}^{Multi\_Homing}$	θ_1	.50 (.63)						
$\eta_{pt}^{Multi\_Homing}$ × Multi_Homing$_{pt}$	θ_2	6.74* (2.86)						
$\eta^{nr\_Applications}$	θ_3	−2.42 (1.71)						
$\eta^{nr\_Applications}$ × nr_Applications$_{pt}$	θ_4	.64 (.46)						
R^2		.76			.96			.98

*$p < .05$.
**$p < .01$.
Notes: The "pst" subscript represents the periodic platform–seller level. That is, a variable with this subscript is defined over all applications of seller s for platform p at time t. For example, nr_Applications$_{pst}$ is the number of applications of seller s available for platform p at time t. The "pt" subscript represents the periodic platform level. That is, a variable with this subscript is defined for platform p at time t. For example, nr_Applications$_{pt}$ is the number of applications available for platform p at time t.

TABLE 3
Robustness Analysis: Summary

Variable	Alternative Measure Construction	Alternative Effect Specification	Additional Effects
Multihoming	Multihoming measure based on the Herfindahl index Multihoming measure based on the Rosenbluth index Multihoming measure based on the comprehensive concentration index Multihoming measure based on the number of titles that are multihomed	Including interactions between platform dummies and platform multihoming on platform sales	Nonlinear effect of platform-level multihoming
Seller–platform fit	Quality-based seller–platform fit measure, instead of sales-based measure		
Platform price	Platform-applications package price Average competitive price Average price of competitors as an instrument for price	Price not instrumented	
Platform age			Including a moderating effect of the number of platforms on the impact of platform age on platform sales
Endogeneity			Estimation of a simpler model of platform sales that does not control for the potential endogeneity of multihoming and number of applications.

of the smaller platforms are negatively affected by multihoming, while sales of the larger platforms are not. Fourth, we explored whether the number of competitors moderates the impact of age of the platform on platform sales. It does not, and all other results are robust to the inclusion of such an interaction effect.

Fifth, we tried estimating our model using a quality-based measure rather than a sales-based measure to represent seller–platform fit, which we evaluate as a potential factor affecting the extent of multihoming of that seller's applications for that platform. The alternative measure takes into account the quality ratings of the seller's applications for a given platform compared with their quality ratings on competing platforms. We find that the effect of the quality-based fit measure is insignificant. Therefore, on the basis of our estimation using a sales-based measure for seller–platform fit, we conclude that sellers and platform owners do seem to make single-homing decisions that are based on fit, and yet it appears that their assessment regarding fit is established through application sales rather than application quality ratings.

Sixth, we tested alternative specifications for price, such as a model that includes platform price not-instrumented and a model that includes a platform-applications package price not-instrumented. Note that the latter price is not entirely under the control of platform owners and thus not endogenous per se, because it also includes the average price of applications for the platform and the number of applications an average platform buyer purchases during the three months after buying the platform. In addition, we estimated the model using the average price of competitors as an instrument for price.[7] The estimation results of these three other models are similar to the results reported in Table 2.

Seventh, we also estimated a simpler model of platform sales that does not control for the potential endogeneity of multihoming and number of applications. This simpler model provides similar results to those reported in Table 2. Finally, the correlation tables presented in Table 1 indicate that some bivariate correlations are high. More specifically, there is evidence for a high correlation between the age of the platform and the number of applications (.91). This correlation is expected, given that the number of applications is measured as the periodic cumulative number of titles released for the platform.[8] Table 1, Panel A, also shows a negative correlation between price and age of the platform (–.68), because prices drop as the platform ages. It is well known that collinearity between regressors does not generate bias in coefficients, but it may inflate the standard errors around coefficient estimates. Thus, although we can make an unbiased inference on the theoretical expectations developed here, this inference is conservative in the sense that insignificant coefficients may be caused by collinearity between regressors. However, the results we report show

[7]We also estimated a model with average competitive price as an independent variable to investigate the exclusion restriction criteria for this variable and found it to have an insignificant effect on platform sales ($p = .94$). The other estimation results remain stable.

[8]Note that in our model, we implement a log–log transformation that slightly lowers the level of collinearity between these two variables to .835.

many significant effects, easing potential concerns about multicollinearity. We also performed a simulation exercise in which we estimated our model's parameters 100 times. In each step of the simulation, we used a random subset of our data (roughly 90%) to estimate the model. We found our parameter estimates to be stable at similar significance levels as reported in Table 2, further easing potential multicollinearity concerns.

Discussion

Despite the high relevance of multihoming decisions in many two-sided markets, the determinants of the multihoming decision and its effect on platform sales have received little empirical attention from academics. In the current study, we address this gap theoretically and empirically. We are the first to separately model and estimate the effects of the number of applications and of platform-level multihoming on platform sales, including platform age and market share as moderators. We are also the first to explicitly model sellers' decisions to multihome their applications for a given platform. Thus, we are able to provide novel insights for marketing managers, industry observers, and academic scholars. In this section, we first summarize our main findings and then discuss their implications. We conclude with a discussion of the limitations of the current study and directions for further research.

Summary of Findings

We find that the (negative) effect of platform-level multihoming on platform sales is larger than the (positive) effect of the number of applications on platform sales. However, thus far, prior research on network benefits in two-sided markets has focused almost exclusively on the effect of the number of applications on platform sales, utility, or demand. We also find that the negative effect of platform-level multihoming on platform sales is prominent for nascent platforms and platforms with a small market share but fades as platforms mature and gain market share.

Moreover, we find that a platform's age and market share, among other factors, drive the extent of seller-level multihoming. On the one hand, the larger the market share of a mature platform among buyers, the more applications for it will be multihomed. On the other hand, the larger the market share of a nascent platform, the fewer applications for it will be multihomed.

Implications

In view of our empirical findings regarding the effect of multihoming on platform sales and how it compares with the effect of number of applications on platform sales, the owners of nascent platforms and platforms with a small market share should attach greater importance to the extent to which applications for their platform are multihomed and move away from mere network size considerations. Academic scholars should also move away from the logic of network size in their study of two-sided markets, which has dominated the marketing and economics literatures for decades. These findings are also relevant for industry analysts, who commonly track the total number of sellers for a platform but underreport on the extent of multihoming across platforms.

For mature platforms and platforms with a large market share, the preceding conclusions do not apply. This may explain why applications are increasingly multihomed in the video game console market (see Figure 2), a phenomenon seemingly at odds with differentiation literature. With the maturation of consoles of large players (Microsoft, Sony, and Nintendo), the negative consequences of multihoming may fade, and from a sales perspective, it makes little sense for such firms to invest in reducing the level of multihoming for their applications at a later stage in the consoles' life cycle.

Our research findings also have substantial implications for sellers. For example, a seller's decision to design content that fits better with the tastes of buyers of a larger market share platform and less well with others is less risky when that platform is "young," because sellers are more likely to obtain single-homing offers early on, whereas as a large-market-share platform matures, owners' willingness to pay for single-homing will fade.

Although the industry practice seems on track, these findings also allow observers of two-sided markets to better understand and assess company decision making. For example, Nintendo's market share deteriorated substantially in the sixth generation with the GameCube. Moreover, game publishers invested relatively little in increasing the fit of their applications with this platform, given the limited user base. Therefore, Nintendo needed single-homed applications for the Wii, despite application publishers' lack of success for GameCube, to establish a lead in the seventh generation. Now that Nintendo has established the dominance of the Wii, our findings would imply that Nintendo can once again increase the extent to which its applications are multihomed.

The findings in this study may also help to explain, for example, the disappointing performance of Sony PlayStation3 in overall sales compared with other seventh-generation consoles (Brightman 2008). This console reached a multihoming level of almost .6 within one month after its introduction for a relatively small number of applications (17 games). The level of multihoming for the PlayStation3 has steadily increased over time to more than .75 in April 2008, which is the highest level of multihoming reached by any console in our data. The high level of multihoming for PlayStation3, and especially that with the incumbent Xbox 360, probably led to a lack of differentiation for the console on applications that consequently hurt its initial sales.[9] (Nascent platforms are hurt more by multihoming than maturing platforms are.)

Other markets for which researchers could build on our insights include the following: 3-D television (e.g., the importance of exclusivity deals between platform companies, such as Samsung, and movie studios), application stores (e.g., the competition between the "open" application world Google is promoting and the "closed" application world Apple has developed), and smart payment (e.g., the competition between new payment platforms through

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[9]Of the 14 games available for PlayStation3 at introduction, 8 were also available for the Xbox 360, including the popular games *Madden NFL 07*, which had already been available for the Xbox 360 since August 2006, and *Call of Duty 3*. Of the 17 games available for PlayStation3 within one month after its introduction, 10 were also available for the Xbox 360.

mobile devices and the multihoming decisions retailers will make across competing platforms and existing platforms, such as cash, debit cards, and credit cards).

Limitations and Directions for Further Research

The current study also has limitations that may direct further research. First, although the data we employ are rich, spanning different generations over 13 years on a monthly periodicity, the empirical analysis focuses on only one industry. Further research could examine the extent to which these market dynamics also exist outside the video game console market.

Second, our model includes fixed effects for the 12 platforms in our data set. These fixed effects control for all variation across the platforms that is time invariant and not explicitly modeled, such as variation in brand name, data width, clock speed, memory, the type of controller, the media device (e.g., CD-ROM, DVD, Blu-ray), and Internet access. While our model yields unbiased estimates given the (indirect) inclusion of such technology features in the fixed effects, it does not illuminate the effect of console enhancements on platform sales. Research that examines this issue would be most valuable. However, such research would need a richer collection of devices (e.g., studying the video game industry from its inception, or even better, a different market with a greater variety of devices) and a strong taxonomy to classify types of technological advancements.

Third, our model presents a first exploration of multihoming across the platform life cycle, and it shows that platform age is an important consideration for managers involved in or affected by multihoming decisions. However, the dynamics present in the market are, likely, much richer than age can proxy for. Further research that disentangles the many correlates of age may lead to interesting insights that are actionable for managers (e.g., the competitive growth of applications across multiple platforms). The main challenges for such a research endeavor are endogeneity and multicollinearity.

Fourth, in this study, we do not distinguish between multihomed applications for a platform that were previously single-homed on that platform (i.e., losing a single-homed application) and multihomed applications for a platform that were previously single-homed on a competing platform (i.e., gaining a multihomed application). Further research that makes such distinction—for example, by studying superstar applications that switch between being single-homed and multihomed—could lead to useful findings (e.g., by modeling the effect of such switches [i.e., as events] on platform sales).

Fifth, our model examines one main aspect that is relevant to marketers—namely, the effect of multihoming on platform sales. More work remains to be done to fully inform marketing managers in two-sided markets such that they will be able to make optimal decisions. Consider advertising decisions (Tucker and Zhang 2010). Should sellers or platform owners in two-sided markets advertise the extent to which they promote single-homing? While the iPhone was exclusively available to AT&T users, Apple and AT&T have communicated with one voice about Apple's commitment to single-home its iPhone on AT&T. Verizon attempted to counteract this partnership between AT&T as a platform and Apple as a seller, consequently leading to an advertising war (MacMillan and Satariano 2010; Raice and Kane 2011).

Sixth, in this article, we examine only seller-level multihoming. A possible path for further research would be to examine buyer-level multihoming. For example, what are the consequences of buyer-level multihoming for application buying behavior? Do buyers have a fixed budget? What drives budget allocation decisions in application purchasing across the multiple platforms that buyers use?

Further research endeavors may include the pricing of single-homing contracts between sellers and platform owners, the implications of multihoming or single-homing for the competitive strategies of both platform owners and sellers, and the channel decisions application sellers can make beyond choosing to supply applications to a certain platform (i.e., a seller's decision to single-home on a given platform does not necessarily imply that the only channel to the market available to the seller is that platform owner).

Further research—probably of an analytic nature because of a lack of data on costs and fees—could investigate profitability implications of multihoming. Such a study must take into account the costs required for the development of new applications and for application migration, because both types of costs have implications for side payments between sellers and platform owners. While development costs can be viewed as exogenous to platform owners, the owners do have some level of control over application migration costs.

Other avenues for further research are the role of vertical integration between sellers and platform owners and the role of multihoming in the incentives for both platform owners and sellers to innovate. Most importantly, further empirical and theoretical research should move beyond the influence of mere network size in the analysis of two-sided markets, which has dominated this literature for far too long.

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