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Keystone effect on entry into two-sided markets: An analysis of the market entry of WiMAX

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ABSTRACT

We investigate a market entry scenario where a technologically-superior new platform may overcome its installed base disadvantage with the backing of a strong keystone species advantage within the business ecosystem, called keystone effect in this study, over an incumbent in a market that exhibits indirect network effects. The strength of the keystone species impacts the availability of complementary goods, which is a key factor for a platform to increase its installed base. This study proposes a dynamic economic model to map a market landscape that shows the internal condition (entrant's keystone effect) and external conditions (incumbent's keystone effect and indirect network effects) under which a new platform can successfully enter (i.e., maintain oligopoly or monopoly share) or fail to enter a two-sided market in a winner-take-all scenario. We then illustrate the model's applicability by examining the entry of Worldwide Interoperability for Microwave Access (WiMAX) into the global mobile telecommunications market, employing recent market data from 2009 to 2012 as well as forecast scenario data from 2010 to 2014. In both the historical data and hypothetical forecast scenario we find that WiMAX's keystone effect disadvantage and the market's indirect network effects were cumulatively strong enough to prevent the new technology standard from successfully competing with the incumbent (cellular 3G and Long Term Evolution) for oligopoly or monopoly share in the long run.

1. Introduction

One type of market which has been the subject of extensive study because of its contextual factors, namely the presence of network externalities, is the two-sided, or platform-based, market. Increasingly many industries are organizing around such platforms (Boudreau, 2010; Eisenmann et al., 2006; Iansiti and Levien, 2004a,b), which heightens the need for firms to tailor their business models to take advantage of the benefits and plan for the substantial impact of network effects (Rochet and Tirole, 2003). In a market that exhibits network externalities, a technology's installed base and the availability of complementary goods, called direct and indirect network effects respectively, both play major roles in user adoption (Brynjolfsson and Kemerer, 1996; Choi, 1994; Katz and Shapiro, 1986; Khazam and Mowery, 1996; Kristiansen, 1998; Schilling, 1999, 2003; Wade, 1995). While much of the extant literature regards technology adoption as an evolutionary process determined by consumers, this study discerns an invisible force driving suppliers' business networks, especially when two rival technologies are sponsored by a group of suppliers with shared interests (i.e. market monopolization) and consumers have little power or interest in the technology adoption process.

For this purpose, we employ an ecological perspective to explore the dynamic, interconnected forces of the business network impacting the standards battle. Adapting Moore's popular definition, a *business ecosystem* refers to an "intentional community of economic actors whose individual business activities share in some large measure the fate of the whole community" (Moore, 2006). As a corollary of this notion, the health of the ecosystem directly impacts its members' chances for survival. Therefore the keystone organizations, those crucial

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hubs within the business ecosystem that provide a stable and predictable set of common assets (e.g. Microsoft's Windows operating system and tools) that other organizations use to build their own offerings, are of paramount importance for the ecosystem's health and survival (Iansiti and Levien, 2004b). Specifically, in modern standards battles, business ecosystems are often formed to ensure de facto standardization, and victory predominantly goes to the ecosystem with stronger keystones, a process termed the *keystone effect* in this study.

Two noteworthy anecdotal examples of the impact of the keystone effect in standards competitions were, first, the battle for the videocassette recorder (VCR) standard between Sony's Betamax and Matsushita's (Panasonic) video home system (VHS), and second, the battle for the high-definition video format standard between Sony's Blu-ray and Toshiba's high definition digital versatile disk (HD-DVD). In the former case from 1975 through the late 1980s, the VHS format eventually dominated not from technological advantage but due to Matsushita's superior collaborative strategy of licensing and OEM arrangements that made the VHS ecosystem superior to that of Betamax (Wonglimpiyarat, 2005). In the latter case during 2003–2008, the two technologies were again both sponsored as Sony squared off against Toshiba. A substantial technological advantage was not the deciding factor since each format was similar in terms of performance, components, and availability of complementary goods, which could be either hardware or software depending upon the platform (Church and Gandal, 1992). HD-DVD had a legacy advantage because it, unlike Blu-ray, was compatible with the previous generation's standard, DVD, and it even entered the market at a lower price point than Blu-ray. Yet despite these disadvantages, Sony secured Blu-ray's eventual dominance by courting more significant content providers, in particular Warner Bros, one of the largest Hollywood studios which made an impactful switch to Blu-ray from HD-DVD. Sony leveraged its experience from the previous format war to focus on collaborative advantage attracting strong keystones of the home video industry, namely the major movie studios. Contrary to the traditional notion of pricing decisions and entry timing as the deciding factors for standardization among sponsored technologies (Katz and Shapiro, 1986), these examples of technology standards determined by the ecosystem's stronger keystone species demonstrate scenarios in which neither cost advantage nor technological superiority was sufficient to determine the outcome.

A more recent example can be found in the battle for the 4th generation (4G) mobile communication technology standard between Worldwide Interoperability for Microwave Access (WiMAX) and the third generation (3G) mobile technology standards, along with the mobile 4G standard, Long Term Evolution (LTE), which entered the market over two years later than WiMAX. As the first commercially available 4G option, WiMAX had a technologically superior position for the start of the data-led era of mobile computing that allowed it to capture some of the worldwide mobile broadband user base from the incumbent 3G standards group (hereafter referred to as "3G/LTE" to signify the consortium of manufacturers and network operators supporting the previous and subsequent generations of the incumbent technology standards). This quality advantage and user base momentum, with backing from some large names (e.g., Intel and Google) (Anon, 2008), seemingly should have given WiMAX a fighting chance at contending with the 3G/LTE. Nevertheless, the ecosystem of WiMAX built around weak keystones, namely relatively smaller or startup mobile network operators (MNOs), could not overcome the significant barriers to entry of a mobile telecom market that was nearly monopolized by the 3G/LTE ecosystem with dominant MNOs (Kang et al., 2011). Although, this "ecosystem war" viewpoint has been the subject of ongoing industry and media discussion (Anon, 2004, 2007, 2010b; Conti, 2010), it has received only limited attention from academic researchers regarding its implications for technology strategy and market entry decisions (Kang et al., 2011; Shin et al., 2011).

The research on business ecosystem theory as a strategy formulation tool is still in its early phase of development (Zhang and Liang, 2011). Most studies are qualitative analyses (Kang et al., 2011; Zhang and Liang, 2011) with little empirical support. More attention is paid to particular industries such as IT and biological technologies (Iansiti and Levien, 2004b; Gunasekaran and Harmantzis, 2008), Iansiti and Richards, 2006). The quantitative studies that have attempted modeling technology adoption with network externalities have generally neglected considering an ecosystem, which is crucial for accurately modeling modern standards battles (e.g., Church and Gandal, 1992; Farrell and Klemperer, 2007; Gandal et al., 2000; Park, 2004; Zhu and Iansiti, 2012).

Motivated by this gap, we aim to explore the importance of the keystone effect for platform competition in the presence of indirect network effects. Furthermore, this study intends to contribute to the ongoing discussion of market entry in the literature, and extend the discussion of platform competition by examining the conditions under which a new platform can successfully enter a two-sided market. For empirical analysis, we examine the failed entry attempt (i.e. failure in terms of market dominance) by WiMAX against 3G/LTE and evaluate it according to a dynamic model that incorporates indirect network effects, relative quality advantage, and a third factor that we introduce here, the keystone effect.

The paper proceeds as follows: The next section presents a brief review of the literature on keystone species in business ecosystems and telecommunications market externalities. Section 3 then formulates theoretical foundations into a dynamic market entry model, which we adapt from Zhu and Iansiti (2012) to fit this market context and allow for quantification of the keystone effect. We explain the equilibrium outcome conditions for the entrant platform, WiMAX, vis-à-vis 3G/LTE within the mobile telecom ecosystem. Section 4 presents the empirical analysis of WiMAX's entry into the global market by adapting regression equations from the theoretical model. Section 5 presents the method and results of the regression analysis. Finally, Section 6 offers the conclusions drawn from these results and their implications for management.

2. Literature review and industry overview

2.1. Keystone effect and the mobile telecommunications ecosystem

The concept of a keystone species that disproportionately impacts its ecosystems was borrowed from its biological origins and, like the ecosystem concept before it (Moore, 1993), applied to the realm of business. In a business ecosystem, the keystone species are the organizations which play a crucial role despite occupying disproportionately few nodes within the network (Iansiti and Levien, 2004b). The term "keystone species" signifies a classification for certain firms within their business ecosystem that are both integrally connected and strategically inclined to focus on shared value throughout the network, the result of which can be an impact that is disproportionately greater than their size. Keystone species may be identified by their position as "hubs," centrally connected and occupying positions of structural importance for the transfer of value through the network (Moore, 1996; Basole, 2009). These critically positioned firms may choose to pursue strategies of either value absorption, growing in size to control more of the network functions, or value transmission, enhancing the ability of other network members to perform value-creating functions. Differentiating between the keystone species of ecology and business should start from identifying the difference between the ecosystems. Moore (1996) posits that actors in the business ecosystem make conscious choices by understanding the situation and contemplating outcomes unlike the instinctively driven actions in biological ecosystems. Business ecosystem actors are thus intelligent agents capable of planning and seeing the future, and business ecosystems compete over members (Iansiti and Levien, 2004b). Lastly, an obvious yet important distinction worth repeating is that while business ecosystems aim to deliver innovations, natural ecosystems are dictated by the drive for survival (Basole, 2009).

In mobile telecommunications numerous scholars have adopted MNOs as the mobile telecom keystone species by analyzing their strategies, business model implementations, and ecosystem interconnectedness (Zhang and Liang, 2011; Basole, 2009; Tobbin, 2011; Stanoevska-Slabeva and Wozniak, 2010). However, their role is by no means fixed. The mobile computing era initiated a trend of convergence that has resulted in broadening the mobile telecom ecosystem's scope while rapidly increasing its complexity (Basole, 2009; Makinenl and Dedehayirl, 2012). It is yet uncertain whether this convergence of products and services may result in the weakening or displacement of the focal ecosystem's current keystone species; however, despite the convergence of the established mobile telecom ecosystem with the burgeoning mobile computing ecosystem, network analysis supports the still vital role of MNOs in the converged mobile ecosystem (Basole, 2009; Basole et al., 2012). From a graph-theoretic perspective, the importance of certain hubs in a network can be quantified with several centrality measures, and Basole et al. (2012) find that the normalized degree centrality of MNOs in the converged mobile telecom ecosystem is still highest among all functional segments, which demonstrates their highly central, value-transferring position. Thus, this study follows the literature and regards MNOs as the keystone species of mobile telecommunications.

Accounting for network externalities is essential in designing an adoption model of mobile telecommunications technologies since the installed based advantage of the incumbent technology standard is especially pronounced within the mobile telecom ecosystem. This is due in large part to numerous MNO-related factors, including in-network discounts, subscriber lock-in and other perceived switching costs that negatively affect subscribers' switching intentions (Chuang, 2011; Sobolewski and Czajkowski, 2012; Shin and Kim, 2008). While most subscribers would be willing to use a new technology standard if their MNO adopted it, a devastating problem for the entrant platform, WiMAX, was the comparatively miniscule installed bases of the MNOs that actually committed to it as their future 4G standard. Contrarily, a large installed base of loyal subscribers offered the incumbent platform, 3G/LTE, essentially guaranteed demand. This in turn ensured that third party network equipment providers (NEPs) as well as content providers were committed to producing 3G- and later LTE-compatible devices since the stable and high-volume demand allows for cost reduction through economies of scale. Simultaneously, the extensive selection of equipment produced by the 3G/LTE NEPs keeps their user base satisfied.

For the purpose of measuring the keystone effect of the MNOs in this study, we consider ecological precedents for the construct that may be transferrable from their original domain to business ecosystems. Numerous ecological studies have addressed the quantifiable effect of keystone species, particularly focusing on keystone predators (e.g. Fletcher, 1987; Navarrete and Menge, 1996; Owen-smith, 1987; Paine, 1966, 1969; Terborgh, 1986). However, a disadvantage of such attempts is that they are conducted through experimental removal of the keystone species for observation (Power et al., 1996), and thus their method is not transferable to business ecosystems. However, the conclusions we can infer from the ecological studies can still be useful to inform the modeling of keystone effects in business ecosystems. Davic (2003) proposed a power–law relationship in terms of biomass dominance of keystone species within their functional groups. Andriani and McKelvey (2007) chronicled this power–law relation in not only natural sciences but also social sciences, finding firm-related examples, including firm size, growth rates, supply chains, bankruptcies, and alliance networks, among numerous others. Furthermore, it has been suggested that such power–law relationships may allow for a priori identification of keystone species, until such time as empirical testing might discount them (Marquet et al., 2005).

This study proposes (in Section 3.3) and tests (in Section 5) a novel way of quantifying the effect of keystone species within their ecosystem based upon that power–law concept. However, the keystone effect cannot be measured in isolation from other market forces since business ecosystems, like ecological ecosystems, are complex, dynamical systems within which various interconnected factors impact firms' decision making and moderate the outcome of their actions. In particular, the thread of literature on market entry and platform competition most relevant to mobile telecom technologies generally focuses on platform quality, size of installed base, and network effects as the primary factors affecting a platform's chances for success (Zhu and Iansiti, 2012; Sobolewski and Czajkowski, 2012; Birke and Swann, 2006; Chou and Shy, 1990; Fu, 2004; Gerstheimer and Lupp, 2004; Grajek, 2010; Kim and Kwon, 2003; Maicas et al., 2009). Thus an appropriate model must account for these most pertinent decision criteria while simultaneously allowing for interaction between market effects.

2.2. Entry of the WiMAX technology standard

The data in Table 1 chronicle WiMAX's entry into the global mobile telecommunications market from 2009 through 2012. The first WiMAX phone was released in the fourth quarter of

Table 1
WiMAX market entry summary statistics.

WiMAX worldwide market share statistics	Year			
	2009	2010	2011	2012
Share of total installed base	1.02%	1.64%	1.94%	1.59%
Share of new subscriptions	1.71%	3.92%	2.56%	0.55%
Share of new handsets released	2.86%	3.74%	10.00%	1.25%
Share of mobile device production volume	1.58%	2.36%	1.87%	0.50%

2009. Although fixed WiMAX 802.16d and some customer premises equipment of mobile WiMAX 802.16e were available prior to 2009, we limit this study to the periods in which WiMAX produced mobile internet devices comparable to those of the 3G standards for direct comparison. The nascent technology standard made some headway during its first few years. WiMAX's share of global subscribers grew from 2009 to 2011 by 38% CAGR, with the share of new subscribers peaking in 2010. This spurred WiMAX manufacturers to develop more compatible products, and WiMAX's share of new smartphone models peaked in 2011. Despite absolute growth in WiMAX production volume to meet increasing demand through 2011, relative growth increased only in 2010, after which WiMAX lost ground as 3G/LTE customers consumed an increasing share of global mobile internet devices. Then 2012 witnessed the decline of WiMAX by all measures. Demand from both new and total subscribers decreased and supply of new handset models and quarterly production plummeted.

Barely five years after WiMAX entered the world market and only two years after the availability of WiMAX-capable smartphones, the wireless telecom technology standards “battle” for the future of 4G (Hamblen, 2008) was all but decided. WiMAX failed to garner support from the undecided operators and equipment developers who migrated en masse to the 3G/LTE group. Key WiMAX flagship companies scaled back operations or defected entirely, notably Intel discontinuing the WiMAX Rosedale chip and closing its WiMAX operation in Taiwan (Weissberger, 2009; Tofel, 2010). By the end of 2011, even the formerly staunch backers of WiMAX – namely Sprint in the U.S. who had partnered with Clearwire to gain early 4G data service differentiation (Woyke, 2008) – were jumping ship, announcing that they would begin to pursue LTE either jointly with WiMAX or instead of it in the future (Bensinger, 2011). The global tide shifted toward LTE as major developing markets, including China, Russia, even India, which were regarded as more suitable for WiMAX than developed markets with existing infrastructure, began investing in LTE networks (Bensinger, 2011; Gabriel, 2011a, b; Anon, 2011). Although WiMAX would still serve a limited function in bringing last mile broadband internet to lesser developed countries, particularly in rural areas, such a niche role was hardly what WiMAX backers were hoping to see half a decade earlier when they invested in WiMAX eager to take a central role in the future of mobile computing (Anon, 2007).

Entering the pre-4G standards race over two years ahead of LTE, it is reasonable to argue that WiMAX enjoyed an optimistic outlook prior to 2009. It had a mobile data quality advantage for subscribers and commercial readiness for MNOs and suppliers. It offered WiMAX operators a network cost advantage with its Orthogonal Frequency Division Multiple Access (OFDMA) approach to wireless data transmission over 3G's Code Division Multiple Access (CDMA)-based technologies (Rysavy, 2011). Given these considerations, the WiMAX camp might have expected to make a dent in 3G's user base opening the door for successful entry into the global market. Instead, however, WiMAX failed in its key markets, the U.S., Korea, Japan, and Taiwan, and it has since been relegated to a transitional technology in countries with still developing broadband telecommunications infrastructures.

3. Platform adoption model

3.1. Model formulation

In this study's model of the mobile telecom technology standards adoption process (see Fig. 1), we portray the representative consumer's and supplier's preferences for superior quality and lower cost as well as the market's indirect network effects. Unlike other familiar two-sided markets in the literature, such as software (Church and Gandal, 1992; Kotliar, 2008), video games (Zhu and Iansiti, 2012; Dube et al., 2010; Strube et al., 2007; Corts and Lederman, 2009; Prieger and Hu, 2010), VCRs (Park, 2004; Ohashi, 2003), compact disks (Gandal et al., 2000; Basu et al., 2003) or PDAs (Nair et al., 2004), complementary goods of mobile communication standards are primarily the hardware produced by NEPs, such as mobile handsets and tablets, different from video games or other software applications. The NEPs make their platform adoption decision first, followed by content providers producing software for mobile devices on one or both transmission standards. Therefore, in the hardware supplier adoption decision, the software content is yet undetermined and does not figure directly into this model on the supply side. The expectation of software variety and availability on a mobile platform's hardware, however, does impact the adoption decision of subscribers indirectly. Thus our empirical analysis in Section 4 considers software-weighted hardware volume as a proxy for suppliers.

For suppliers, we incorporate the potential for increasing or decreasing returns to scale of the installed base of subscribers, wherein the keystone effect represents this impact of the MNOs' user base size and loyalty and captures a supplier's motivation to adopt the platform with the greatest long-term demand. It is a product of the MNOs' central, interconnected role as hubs that promote value transfer within the mobile telecom ecosystem. The stronger MNOs attract and retain more subscribers and thus entice more supplier adoption relative to the weaker MNOs of the competing technology standard. In accordance with the literature on market entry and two-sided markets, we also include both quality and indirect network effects in this study's representative consumer utility function to model the market dynamics.

We adapt a dynamic model from Zhu and Iansiti (2012), chosen for its ability to address both quality and indirect network effects simultaneously, to examine the conditions under which a new platform can successfully enter a market dominated by an incumbent platform. We limit the following explanation to present only the equations necessary for understanding the model's main concepts and, primarily, to highlight the changes we make to the original version in

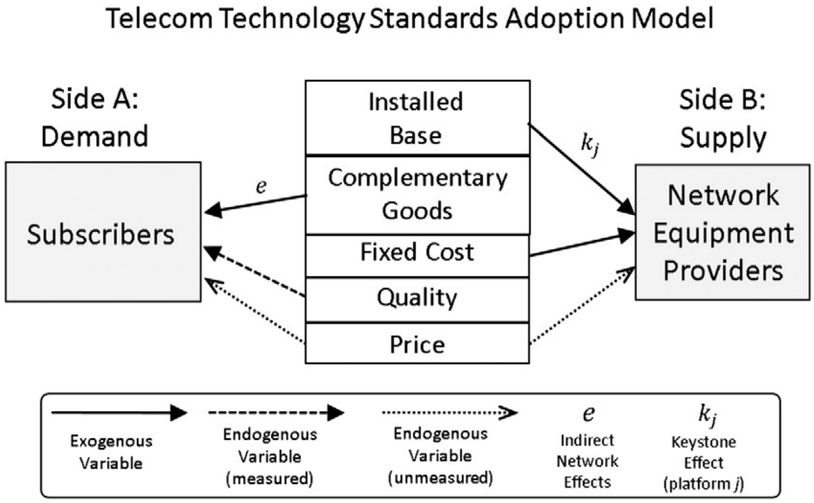

Fig. 1. Model of utility (subscribers) and profit (suppliers) components for platform competition.

applying it to the mobile telecom market with mobile devices as complementary goods. Definitions of variables are summarized in Table 2. For a full discussion of the concepts, we refer the reader to Zhu and Iansiti (2012).

The model captures head-to-head competition between two incompatible platforms, competing for subscribers from the same consumer population and manufacturers of mobile devices, also referred to herein as suppliers. For simplicity, each representative consumer adopts one platform, and each supplier produces for one platform. In each period of the dynamic model, two actions occur: (1) a certain number of new consumers subscribe to MNOs on one of the two technology standards and purchase hardware that is currently available for that standard, and (2) a group of new suppliers each select a standard, incur fixed costs and produce devices for the installed base of subscribers. The process then repeats until the two technology standards reach equilibrium levels of subscribers and suppliers. Since the interaction of the keystone effect and indirect network effects are this investigation's primary focus, we assume that each platform's complementary goods are priced similarly per period, as is common for this form of model (Zhu and Iansiti, 2012; Nair et al., 2004). Price is not the determining factor in subscriber adoption due to the large number of complements available as well as the common practice of price matching by manufacturers of comparable devices and the bundling of handsets with contracts by MNOs. Finally, assuming perfect competition with zero economic profit for each manufacturer facilitates our intention to isolate the combined impact of the market effects upon supplier and subscriber adoption decisions.

3.2. Consumer adoption

We use h_j and b_j to represent the new manufacturers and the new subscribers, respectively, joining platform $j \in \{E, I\}$ during period t. Each platform's life expectancy is necessarily greater than zero. Consumers are not forward-looking in their utility gained from mobile devices, but suppliers *are* forward-looking in their expectation of subscribers over the platform's

Table 2
Definition of variables.

Indices	
j	Platform $j \in \{E, I\}$ where E is the entrant and I is the incumbent platform
t	Time period
Variables	
B_{jt}	Total installed subscriber base of platform j at period t
$\tilde{B}_{jt}$	Discounted present sum of future installed subscriber base of platform j from period t until time horizon T_j, subject to discount factor φ_j
b_{jt}	New subscribers on platform j in period t
e	Strength of indirect network effects, $e > 0$
F_{jt}	Fixed cost of operating on platform j in period t
F	Ratio of fixed cost of operations for the two platforms, $F = F_{It}/F_{Et}$
H_{jt}	Total manufacturers producing for platform j in period t
h_{jt}	New manufacturers producing for platform j in period t
k_{jt}	Strength of keystone effect for platform j during period t
KR_j	Keystone effect ratio for platform j over competitor j', $KR_j = k_j/k_{j'}$, $j, j' \in \{E, I\}$, $j \neq j'$
M_t	Total number of subscribers that join a technology standard in period t
Q_j	Price-adjusted quality ratio of platform j vs. the competing platform j' for $j, j' \in \{E, I\}$, $j \neq j'$
Q	Quality advantage of the entrant platform, $Q = Q_E/Q_I$
S_{jt}	Proportion of new subscribers choosing platform j in period t, $S_{jt} \in [0, 1]$
T_j	Time horizon for manufacturer consideration of future installed base on platform j
U_{jt}	Representative consumer's utility from platform j in period t
x_{jt}	New subscriber's demand for each mobile device on platform j in period t
x^*_{jt}	New subscriber's optimal demand for each mobile device on platform j in period t
y	Consumer's budget constraint
Greek symbols	
α_t	Time specific constant of manufacturer adoption
β_j	Technology standard-specific constant
π_{jt}	Profit (myopic) of a manufacturer on platform j in period t
$\tilde{\pi}_{jt}$	Forward-looking profit of a manufacturer considering future subscribers on platform j as of period t
ρ_{jt-i}	Autocorrelation parameter of lag length i in supplier regression equation for platform j in each observation t
φ_j	Discount factor for manufacturer's future consideration of installed base of platform j, $\varphi_j \in [0, 1]$

lifespan. Subscribers typically sign one- to two-year contracts with MNOs and usually buy handsets at the time of subscription. This relatively long timeframe coupled with each consumer's limited quantity of hardware purchases essentially negates the impact of consumers' future considerations. However, suppliers do consider not only the current installed base but also the MNOs' subscriber loyalty and future expectations of demand for their products.

Our model follows a well-established representative consumer approach in demonstrating subscriber preferences (Church and Gandal, 1992; Zhu and Iansiti, 2012; Nair et al., 2004). It provides an aggregate description of the entire subscriber population. The preceding sections' review of the literature on consumer preferences for telecommunications products as well as the factors that affect entry into two-sided markets together form the basis for the indirect utility of each customer on platform j in period t:

$$V_{jt} = \ln y + \ln Q_j + e \ln H_{jt} \tag{1}$$

where y represents the consumer's budget constraint, Q_j is the price-adjusted quality ratio of platform j to the competitor platform, e is the indirect network effects, $e > 0$, and H_{jt} is the number of device suppliers on platform j in period t. This indirect utility function describes the average mobile telecom subscriber as valuing technology standard quality and complimentary goods variety and availability while accounting for network externalities related to complimentary goods.

In order to determine the customer's adoption decision, we proceed with a standard logit model[1] to capture heterogeneity of customer preferences (Nair et al., 2004; Clements and Ohashi, 2005). The proportion of new subscribers that choose platform j in period t, denoted as S_{jt} is represented by McFadden (1974):

$$S_{jt} = \frac{\exp\left(v_{jt}\right)}{\exp\left(v_{Et}\right) + \exp\left(v_{It}\right)}. \tag{2}$$

Substituting in Eq. (1) produces:

$$S_{jt} = \frac{QH_{jt}^{e}}{QH_{Et}^{e} + H_{It}^{e}} \tag{3}$$

where $Q = Q_E/Q_I$, and represents the quality ratio advantage of the entrant.

3.3. Supplier entry

We first express the myopic (i.e., not forward-looking) profit function of a representative manufacturer on platform j:

$$\pi_{jt} = B_{jt} x_{jt}^{*} \left(p_{jt} - c_{jt}\right) - F_{jt}, \tag{4}$$

where B_{jt} is the current installed base of platform j, x_{jt}^{*} is the new subscriber's optimal demand for each available mobile device, p_{jt} is the price and c_{jt} the marginal cost of products on platform j at time t, and F_{jt} is the fixed cost of operating on platform j in period t. We then allow the representative manufacturer to consider the potential for revenues from future customers, which is a change from Zhu and Iansiti (2012) model necessary to represent both consumers who are locked in by term-limited subscriptions (as opposed to one-time console purchases) and adoption considerations of device manufacturers (instead of software developers). This yields the supplier's hyperopic (i.e., forward-looking) profit function on platform j in period t:

$$\widetilde{\pi}_{jt} = \widetilde{B}_{jt} x_{jt}^{*} \left(\rho_{jt} - c_{jt}\right) - F_{jt}, \tag{5}$$

where $\widetilde{B}_{jt}$ is the discounted present sum of the current and future installed base of subscribers that are considered by the manufacturer on platform j in time t. It is limited within the manufacturer's time horizon, which could be related to numerous considerations involving the expected platform lifespan, the firm's cost of capital, the number of competitors at the time of market entry, etc. This covers the intuitive notion that the number of manufacturers joining a platform, and in turn the production volume and hardware variety of that platform, are determined not only by the current installed base at the time of adoption, but also, in large part due to each MNO's subscriber loyalty, by the expected number of customers that offer the highest potential for guaranteed demand and cost reduction through economies of scale in the future.

Denote $\widetilde{B}_{jt} = B_{jt} + \sum_{l=1}^{T_j} \frac{\left(B_{j,t+l} - B_{j,t+l-1}\right)}{\left(1+\varphi_j\right)^{l}}$, or the current installed base plus the discounted present sum of the future base of platform j from future period l until the investment decision time horizon, T_j, subject to the discount factor for the future subscriber base of platform j, $\varphi_j \in [0, 1]$. Now we introduce the platform keystone effect variable, k_{jt}, and let $k_{jt} = \log_{B_{jt}} \left[B_{jt} + \sum_{l=1}^{T_j} \frac{\left(B_{j,t+l} - B_{j,t+l-1}\right)}{\left(1+\varphi_j\right)^{l}}\right]$, $k_{jt} > 0$. This expression can be rewritten as $k_{jt} = \log_{B_{jt}} \widetilde{B}_{jt}$ or, equivalently, as $\widetilde{B}_{jt} = {B_{jt}}^{k_{jt}}$.

We proceed from the assumption that manufacturers of devices in two-sided markets choose a platform that will maximize their profits, and then apply the free entry condition that each manufacturer is a price-taker in a competitive market. Following Zhu and Iansiti (2007) we obtain h_{jt},[2] the number of new manufacturers joining the platform j in period t:

$$h_{jt} = \alpha_t \frac{{B_{jt}}^{k_{jt}}}{F_{jt}}, \tag{6}$$

[1] To address the concerns associated with the logit model's potential violation of the independence of irrelevant alternatives (IIA) assumption, we direct the reader to Zhu and Iansiti (2012) explanation. Essentially, since the focus of our study is head-to-head competition, wherein the second of two parties (WiMAX) is entering the market to compete with the first party (the group of 3G technology standards) without the market shares of additional parties to consider, there is no inherent danger of violating the IIA assumption.

[2] The new subscriber's optimal demand for each hardware product, x_{jt}^{*}, is used to determine the demand for each hardware product, which is substituted into the original CES utility function, to yield the subscriber's indirect utility function, Eq. (1) in this model.

where α_t is a platform-specific time constant,[3] F_{jt} is the fixed cost of manufacturing for platform j in period t, and ${B_{jt}}^{k_{jt}}$ is the keystone effect-adjusted subscriber base of platform j in period t. If the representative manufacturer were only to consider the current user base when making its adoption decision (i.e., consider zero future periods, $T_j = 0$), then $\widetilde{B}_{jt} = B_{jt}$ and, consequently, $\widetilde{\pi}_{jt} = \pi_{jt}$. However, we do not expect that this is true for the overwhelming majority of manufacturers making technology standards adoption decisions. From this equation we can see that a decrease in the fixed cost of platform j, an increase in the base of platform j, or, most substantially, an increase in the keystone effect of platform j, causes the number of manufacturers adopting the platform to increase as well.

3.4. Dynamic model and market structure over time

We now extend the single-period decision scenario into a multi-period market simulation. In order to allow subscribers and manufacturers to leave their platform or switch platforms, we introduce a platform decay proportion, δ_b, $\delta_h \in (0, 1)$ (Zhu and Iansiti, 2012). M_t is defined to be the total number of subscribers that join a technology standard in period t. Then, incorporating expression (4), the change in the subscriber base of platform E in period t – both the increase from adopters and the decay from those leaving the platform – is:

$$b_{Et} = M_t\left(\frac{QH_{Et}^{e}}{QH_{Et}^{e}+H_{It}^{e}}\right)-\delta_b B_{Et}. \tag{7}$$

Applying the same method for the entrant and incumbent subscribers and manufacturers yields the market evolution system of equations:

$$b_{Et} = M_t\left(\frac{QH_{Et}^{e}}{QH_{Et}^{e}+H_{It}^{e}}\right)-\delta_b B_{Et}, \tag{7.1}$$

$$b_{It} = M_t\left(\frac{QH_{It}^{e}}{QH_{Et}^{e}+H_{It}^{e}}\right)-\delta_b B_{It}, \tag{7.2}$$

$$h_{Et} = \alpha_t\frac{{B_{jt}}^{k_{Et}}}{F_{jt}}-\delta_h H_{Et}, \tag{7.3}$$

$$h_{It} = \alpha_t\frac{{B_{jt}}^{k_{It}}}{F_{jt}}-\delta_h H_{It}. \tag{7.4}$$

Fig. 2 maps the market landscape for the entrant platform as dictated by the supply side (keystone effect) and demand side (indirect network effect) externalities. We arrive at the market shares of entrant and incumbent for different values of keystone effect ratio ($KR_E = k_E/k_I$) and indirect network effects between 0 and 2.0 by running simulations of the system of Eqs. (7.1)–(7.4) until equilibrium[4]. The figure is essentially a map of the potential that a market offers for a given entrant platform to prevail against an incumbent. Several factors affect the landscape's composition, including the quality advantage of the new platform, the absolute values of the competing platforms' keystone species strengths, and the ratio of indirect network effects to each platform's keystone effect strength. The specific location of the entrant platform on the landscape is then determined by the ratio of the entrant's keystone effect strength to that of the incumbent (horizontal axis) along with the magnitude of the market's indirect network effects (vertical axis).

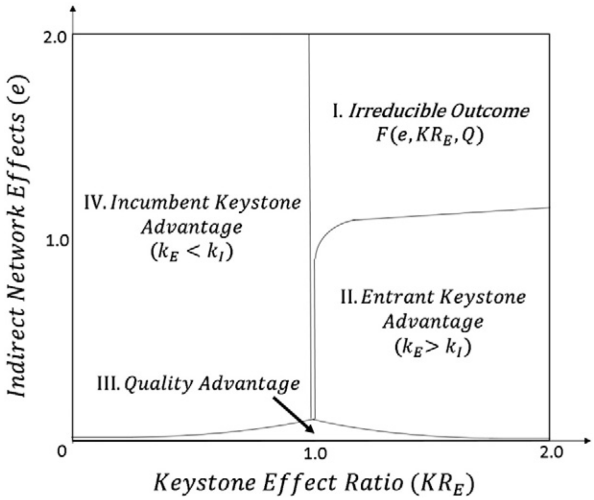

Fig. 2. Regions of determinants for successful platform entry (boundaries approximated for interpretation).

After conducting sensitivity tests of the model parameters[5], there emerge four regions discernable by the different factors that determine an entrant's equilibrium market share. These are summarized in Fig. 2. Starting from the top-right corner and proceeding clockwise, Region I is the usual focus of platform competition literature since, within it, a new platform's successful market entry is determined by a combination of indirect network effects and relative quality advantage along with the addition of this study, the relative strengths of the keystone species on each platform. Second, in Region II, the entrant platform's keystone effect ratio is a critical determinant given indirect network effects are below their threshold level (Zhu and Iansiti, 2012) and the entrant has a keystone effect advantage ($k_E > k_I$). Next, the region capturing quality advantage as the primary determinant of successful entry, Region III, only reaches where indirect network effects are negligible or non-existent. Thus this region is not relevant for most two-sided markets and certainly not applicable for this study's focus on competing platforms within a business ecosystem. Lastly, in Region IV, where the entrant has a keystone effect disadvantage ($k_E < k_I$), the platform competition outcome is entirely determined by the entrant's keystone effect ratio regardless of the market's indirect network effects

[3] The time constant, $a_t = \frac{(1-\varphi_h)\cdot y\cdot(\beta-1)}{\beta(1-\varphi_h\gamma_t)}$, is a simplified expression of numerous variables involved in the supplier equation derivation, including the budget constraint, y; discount factor for future software considered by subscribers, φ_h; the decay rate of fixed cost over time, γ_t; and the exponential parameters of the CES demand function, β and $(\beta - 1)$, that determine the indirect network effect variable (Zhu and Iansiti, 2007).

[4] Simulation results available upon request. Please contact the corresponding author.

[5] Please contact corresponding author for sensitivity test results.

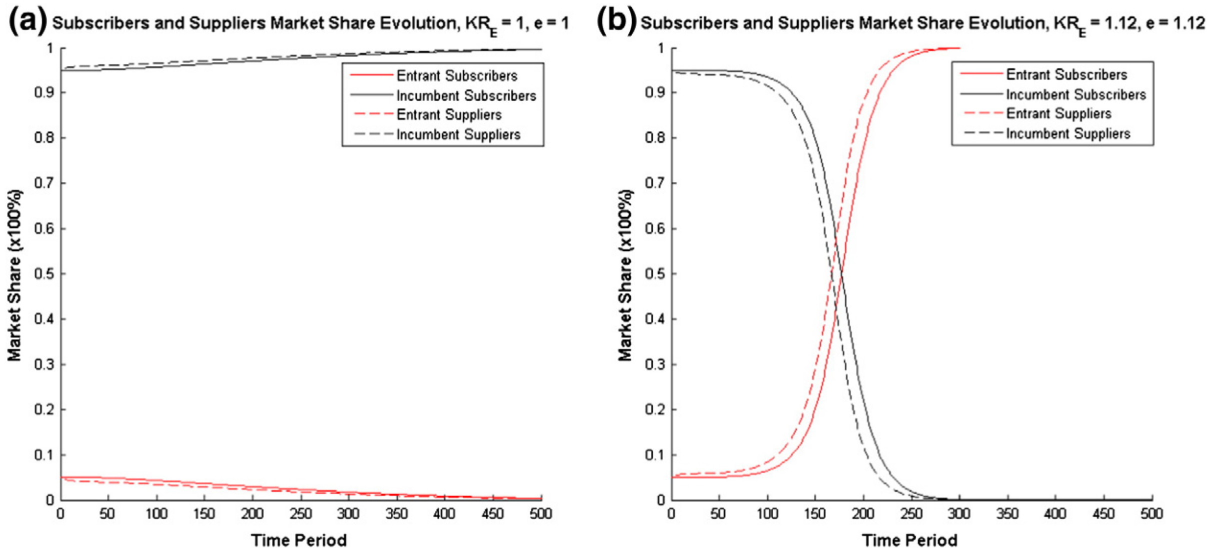

Fig. 3. Sensitivity of market share to changes in magnitude of externalities.

strength, which means almost certain defeat for the weaker entrant.

A major contribution of this study is its ability to demonstrate the full landscape of subscriber potential for a new platform, which is determined by the interaction of market effects on both the supply and the demand sides. Much of the literature on platform competition accounting for demand-based externalities essentially focuses on one quarter of the landscape shown in Fig. 2 (Region I) and thus misses the bigger picture. A fundamental implication of the simulation results summarized in Fig. 2 is that an entrant platform has little chance of achieving successful market entry without forming a camp that includes strong keystone species. However, such an assessment must be put into context, and in order to appreciate the often narrow margins between the equilibrium states discussed above, it is important to see the evolution of market shares for the competing platforms over time.

The relationship of subscribers and suppliers on each platform is shown in Fig. 3 at two different magnitudes of keystone effect ratio and indirect network effects. The change in each platform's share of suppliers (dashed lines) can be seen to precede (i.e., located to the left) the change in share of subscribers (solid lines). Fig. 3 presents the influence of the keystone and indirect network effects on market share, with (a) representing the scenario where both keystone and indirect network effects are 1.0, and (b) showing both effects slightly increased to 1.12. The gap between the dashed and solid lines is wider in (b) where both keystone and indirect network effect are larger than in (a). Additional simulations[6] show that increasing the difference in magnitudes of the interacting effects further widens the gap. These results demonstrate that even slight changes in the magnitudes of the effects (from 1.0 to 1.12) could precipitate a critical convolution of externalities whereby the entrant's keystone species advantage (i.e., $k_E > k_I \Rightarrow KR_E > 1$) on the supply side creates the possibility for the new platform to overcome the inertia of indirect network effects influencing the demand side (i.e., the incumbent platform's established portfolio of complementary goods) and begin gaining market share momentum. Fig. 3(b) shows that this combination of market circumstances may lead to the entrant platform's successful market entry when other factors are held constant. This simulation underscores the impact of externalities in platform-based markets by showing that advantageous combinations of market effects can facilitate an entrant platform's successful entry, while disadvantageous combinations can present nearly immediate barriers to entry.

4. Empirical analysis

4.1. Data

Table 3 describes secondary data used in the empirical analysis of WiMAX's market entry versus 3G/LTE. The regression data were collected quarterly from the introduction of the first WiMAX phone, 2009Q4, to the period of the most recent available data for all variables, 2012Q4. We obtained WiMAX subscriber data from the Market Intelligence and Consulting Institute (MIC, 2010, 2011a,b, 2012) with supplementary information about subscribership trends from TeleGeography (Anon, 2012). The incumbent platform's subscriber base was obtained from International Telecommunications Union (ITU) global subscribership data (Anon, 2013). Depreciation expense data sourced from Compustat was included as a proxy for the fixed cost variable in the supplier equation since depreciation represents the quarterly portion of fixed cost used, or expensed, by manufacturers operating on each platform. The WiMAX data includes the average quarterly depreciation of publically traded manufacturers of WiMAX equipment, and 3G/LTE depreciation data includes companies with North American Industry Classification System (NAICS) codes related to mobile devices and communications equipment manufacturing.

[6] Available upon request to the corresponding author.

Table 3
Regression data summary.

Variable	Obs	Mean	Std Dev	Min	Max
WiMAX (units)[a]					
New handset models	9	1.78	1.09	1	4
Cumulative handset models	9	8.33	5.61	1	16
WiMAX (millions)					
Subscriber base[b]	13	16.14	6.52	6.34	24.20
Fixed cost (US$)[c]	13	222.40	19.22	196.82	263.11
Software-weighted Avg of hardware volume	13	1.37	0.96	0.00	3.04
Cumulative SW-weighted Avg of HW volume	13	9.48	6.68	0.00	17.80
3G/LTE (units)[a]					
New handset models	9	24.56	6.31	18	38
Cumulative handset models	9	159.22	74.65	40	272
3G/LTE (millions)					
3G/LTE subscriber base[d]	13	907.66	237.53	615.00	1340.67
Fixed cost (US$)[c]	13	1178.23	175.15	879.63	1415.05
SW-weighted Avg of HW volume	13	111.44	40.98	53.91	169.18
Cumulative SW-weighted Avg of HW volume	13	753.18	461.69	172.38	1567.20

[a] The list of all WiMAX phones is available at <http://en.wikipedia.org/wiki/List_of_devices_with_WiMAX>. The lists of smartphones with 3G air interfaces are available at Wikipedia by operating system: Android <http://en.wikipedia.org/wiki/Android_devices>, Windows <http://en.wikipedia.org/wiki/List_of_Windows_Phone_7_devices> and <http://en.wikipedia.org/wiki/List_of_Windows_Phone_8_devices>, and Symbian <http://en.wikipedia.org/wiki/List_of_Symbian_devices>. The authors used data from www.gsmarena.com and www.phonearena.com to code the smartphone models by release quarter.

[b] Market Intelligence and Consulting Institute (MIC, 2010, 2011a,b, 2012).

[c] Compustat; list of WiMAX companies (Anon, 2009) and 3G/LTE from the NAICS codes 334220, Radio and Television Broadcasting and Wireless Communications Equipment Manufacturing, 334310, Audio and Video Equipment Manufacturing, and 334413 Semiconductor and Related Device Manufacturing.

[d] International Telecommunications Union (ITU) global subscribership data (Anon, 2013). ITU active mobile broadband subscriptions include both mobile handset- and computer-based subscriptions.

Two different data sources were used to represent new suppliers. The number of smartphone models released per period on each platform is the most direct proxy for supplier adoption, similar to Zhu and Iansiti (2012) using software titles as a proxy for software developer adoption of a platform. This data was compiled by the authors into time series suitable for analysis using numerous lists of WiMAX- and 3G-compatible phones publically available on Wikipedia. The variety of mobile devices offered on a platform not only represents greater supplier commitment to that platform but is also an important factor in a customer's adoption decision. The U.S. Federal Communications Commission (FCC) noted the importance of a manufacturer's handset portfolio as a non-price factor drawing consumer demand:

> Mobile handsets and devices are the end points of mobile wireless networks that connect consumers to the networks. They directly affect the quality of a consumer's mobile wireless experience and can factor into a consumer's choice of a wireless provider. Depending on the market strategy of the entrant, its portfolio of handsets and devices may be a significant non-price factor affecting its ability to compete for customers.
>
> [FCC, 2013]

Thus the increasing variety of handsets on each platform over time captures both supplier adoption and subscriber utility stemming from complementary goods. The limitation of this data, however, is the scarcity of WiMAX phone models released during its relatively brief lifespan. Using the count of new smartphones per period to proxy supplier adoption includes four periods with zero new WiMAX handsets, which must be omitted in a log-transform regression equation (see Section 4.2). To allow usable data for all periods in the regression timeframe and as a robustness check for the significance of the indirect network effects and keystone effects regression parameters, we include a second data source as proxy for supplier adoption, quarterly mobile device production volume weighted by software variety. WiMAX production volume data was provided by MIC (2012), and 3G/LTE smartphone production was obtained from Gartner (Gartner Pressroom quarterly release from 2009 to 2012).

Fig. 4 shows the quarterly and cumulative production volume of (a) 3G/LTE and (b) mobile WiMAX 802.16e devices plotted against the new and total number of handsets on each platform per period. Both data sources display a similar pattern of supply growth for the entrant and incumbent platforms. While the two sources of proxy data differ in absolute quantities by orders of magnitude, this is not prohibitive to the inclusion of the second since the conclusions drawn from the regression results compare the keystone effect parameters of the two platforms relative to each other, not in absolute terms. To ensure that the second proxy (production volume) adequately captures the consumer's preference for complementary goods variety, which is itself inherent in the first proxy (handset models), we use a software-weighted average of production volume for each platform in the consumer adoption equation—that is, the production volume totals are weighted by the proportion of mobile applications available on devices that are compatible with the entrant or incumbent platform per period.

4.2. Empirical specifications

Our empirical analysis involves two steps. First, we measure the strength of the indirect network effects, e, and keystone effects for the entrant, k_{Et}, and the incumbent, k_{It}, through regression analysis of the mobile telecom market data. Then we use these market effect strengths to locate WiMAX on the market landscape introduced in Section 3.4.

We develop the regression framework according to (Berry, 1994; Zhu and Iansiti, 2012), by transforming the equations for consumer indirect utility (1) and platform adoption proportion (2) to yield the following regression equation:

$$\ln S_{Et} - \ln S_{It} = \beta_Q + e[\ln(H_{Et}) - \ln(H_{It})] + Dummy_{WP} + \varepsilon_t, \tag{8}$$

where S_{jt} is the proportion of new subscribers who choose platform j in period t, β_Q is a coefficient roughly representing the quality advantage of the entrant, since the quality ratio is

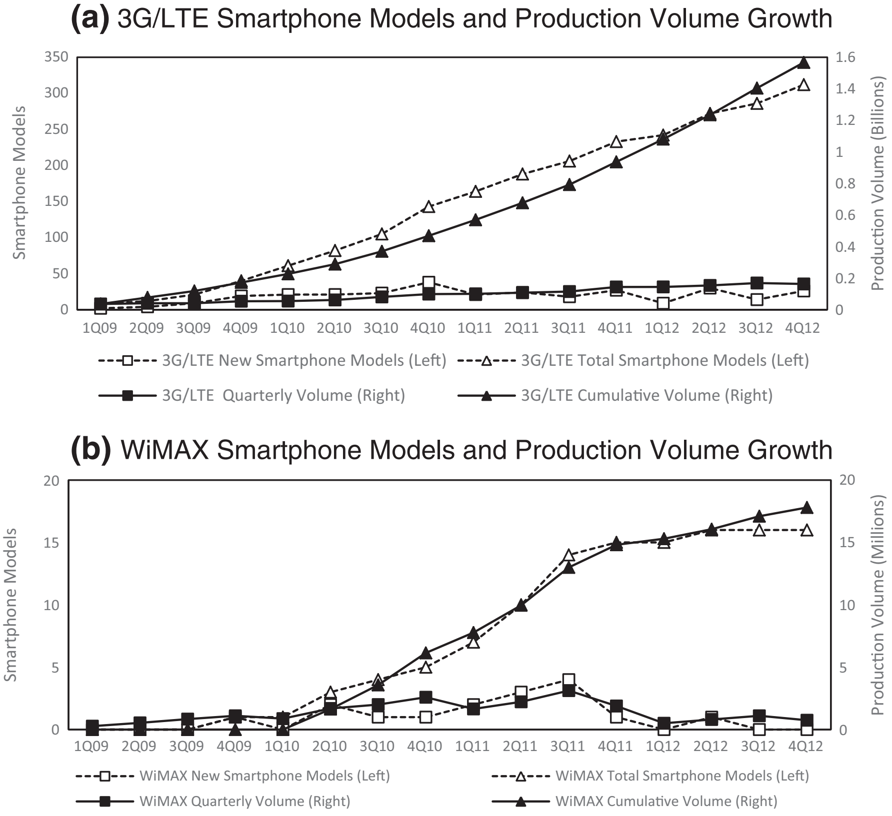

Fig. 4. Supply growth of (a) 3G/LTE and (b) WiMAX smartphone models versus production volume.
Sources: Gartner and Wikipedia.

$Q = \exp(\beta_Q)$. The indirect network effects are represented by e, and H_{jt} is the total number of suppliers on each platform (refer to Section 4.1 for the explanation of two different proxy data sources for this variable). Since the first WiMAX phone was introduced in the fourth quarter 2009 to a limited market but not until the second quarter of 2010 in the United States, where Clearwire and Sprint would account for 47% of global WiMAX demand (Anon, 2012), we introduce a dummy variable to control for the disparity in WiMAX subscriptions before and after WiMAX phones became widely available to subscribers.

On the supplier side, we take the natural logarithm of the supplier adoption expression (6) and use the following regression equation:

$$\ln h_{jt} = \beta_0 + k_j \ln b_{jt} - \beta_2 \ln F_{jt} + \varepsilon_{jt} \quad (9)$$

where k_j represents the keystone effect measured on platform j during the regression time frame, $t = \{1, 2, \ldots, T\}$, β_0 is a constant equivalent to a_t in Eq. (6), and β_2 is the effect of platform fixed cost on supplier adoption per period. Since production volume data, the second proxy for supplier adoption, are often serially correlated we also employ an autoregressive specification including lagged dependent variables (Table 4, column 4.3):

$$\ln h_{jt} = \beta_{jO} + k_j \ln b_{jt} - \beta_{j2} \ln F_{jt} + \sum_{i=1}^{T_j^*} \rho_{ji} \ln h_{j,t-i} + \varepsilon_{jt} \quad (10)$$

where ρ_{ji} is the autocorrelation parameter of lag length i on platform j for period $t - i$. The use of data for separate equations drawn from the same sample of observations can be expected to have correlated residuals between equations, also known as system equation bias, for subscriber and supplier adoption. Seemingly unrelated regression (SUR) (Zellner, 1962) with the autoregressive parameters allows us to account for potential violations of ordinary least squares (OLS) regression assumptions resulting from either system correlated or serially correlated error terms. All statistical analyses were performed used using SAS version 9.3.

5. Results

5.1. Historical data: 2009Q4–2012Q4

Table 4 shows the regression results for the empirical analysis of WiMAX's market entry. Three models are presented, the first using smartphone models as the proxy for supplier adoption (column 4.1) and the other two using production volume as the supplier proxy (columns 4.2 & 4.3). Panel A reports the results of the subscriber adoption regression equation, Panels B and C report the supplier adoption regression equation results for WiMAX and 3G/LTE respectively. A Hausman specification test (Wu, 1973; Hausman, 1978; Hausman and Taylor, 1981) for the comparative performance of SUR versus OLS yields m-statistic 1.06 for the model in column (4.1), and 0.62 and 0.11 for the

Table 4
Regression results for WiMAX vs. 3G/LTE supply and demand.

Data	Handset models	Production volume (3G/LTE smartphones; WiMAX 802.16e devices)	
	SUR (4.1)	SUR (4.2)	SUR-AR(p)(4.3) preferred
Panel A: subscriber adoption[a]			
Quality beta	−2.74*** (0.66)	0.41 (0.65)	0.50 (0.66)
Indirect network effects	0.50** (0.18)	0.45*** (0.06)	0.45*** (0.06)
Dummy WiMAX USA Phone	0.24 (0.17)	−2.49*** (0.40)	−2.54*** (0.40)
Observation	9	13	13
Adj R-Sq	0.72	0.93	0.93
Panel B: entrant (WiMAX) mobile devices supply[b]			
Constant	41.01 (31.27)	63.80*** (15.53)	88.16*** (4.32)
WiMAX keystone effect	0.39 (0.36)	0.17 (0.27)	0.25*** (0.04)
WiMAX fixed cost	2.44 (1.56)	2.72** (0.87)	4.05*** (0.24)
WiMAX supply AR 1 lag			−0.89*** (0.24)
WiMAX supply AR 2 lag			−1.41*** (0.32)
WiMAX supply AR 3 lag			−1.19** (0.37)
Observation	9	13	13
Adj R-Sq	0.14	0.39	0.79
Panel C: incumbent (3G/LTE) mobile devices supply[c]			
Constant	14.44 (7.83)	−5.44 (4.22)	−5.29 (3.65)
3G/LTE keystone effect	0.49 (0.30)	1.27*** (0.13)	1.22*** (0.15)
3G/LTE fixed cost	1.02** (0.34)	0.12 (0.24)	0.07 (0.10)
3G/LTE supply AR 1 lag			0.91** (0.34)
3G/LTE supply AR 2 lag			−0.53 (0.36)
Observation	9	13	13
Adj R-Sq	0.23	0.91	0.94

Note: results are (*) significant at 10%, (**) significant at 5%, and (***) significant at 1%, with standard errors in parentheses.
[a] Panel A reports regression results for worldwide technology standard adoption by subscribers.
[b] Panel B reports regression results for worldwide WiMAX devices supply (both handset models and 802.16e production volume).
[c] Panel C reports regression results for worldwide 3G/LTE devices supply (both smartphone models and smartphone production volume data).

models in columns (4.2) and (4.3), respectively, none of which reject the null hypothesis that SUR is efficient versus OLS. Thus, Table 4 reports only SUR parameter estimates (OLS results are available upon request).

In column (4.1), the results show that indirect network effects are significant with a slightly smaller magnitude than what has been found with software titles as complementary goods (Zhu and Iansiti, 2012), which is reasonable since mobile device purchases per period would be a fraction of the number of mobile application purchases for the average consumer. The keystone effect strength of the incumbent platform is greater than that of the entrant, though still not significant.

To allow suitable data for all periods of the regression timeframe, we employ mobile device production volume as the proxy for supplier adoption in columns (4.2) and (4.3). Indirect network effects of 0.45 in Panel A are significant (p-value <0.01) and remain similar to the result in column (4.1). The dummy variable for WiMAX phones in the USA not surprisingly shows that production volume was significantly less (p-value <0.01) in the periods before WiMAX phones were available in the USA and related markets. The results of Panels B and C show that the keystone effect is significant both for the entrant and incumbent while the strength of the keystone effect for WiMAX (Panel B) is much weaker than for 3G/LTE (Panel C).

Since the incumbent supply equation exhibits serial correlation (first-order Godfrey Lagrange Multiplier test value of 4.18, p-value 0.04 (Godfrey, 1978a,b)), we ran SUR-AR(p) (column 4.3) to avoid underestimating standard errors. The autoregression coefficients for lags 1, 2, and 3 of the entrant supply equation are significant (p-values <0.01, <0.01, and 0.03, respectively). The autoregressive parameter of lag 1 is significant in the incumbent's supply equation (p-value 0.03). The inclusion of these parameters fully corrects the auto-correlation present in column (4.1) (first-order Godfrey test LM value of 0.10, p-value of 0.75). In addition, a marked improvement is seen the adjusted R-squared value of the WiMAX supply equation (Panel B) from 0.39 to 0.79 without lowering the adjusted R-squared values of Panels A or C. This suggests that the model in column (4.3) is best suited to account for the variance in the dependent variables of all three equations. A distinct change is seen in the entrant's supply equation since the autoregressive parameters are able to account for not only the serially correlated errors of quarterly production volume but also the drop in WiMAX production in response to decreased demand after the 2011Q3. Therefore in model (4.3), we found significant positive indirect network effect of 0.45, significant WiMAX keystone effect of 0.25, and significant 3G/LTE keystone effect of 1.22. Given that this model is efficient versus OLS, best fitting for all three equations, and not in violation of any assumptions placed upon its error terms, we use these results in the final step of the empirical analysis.

Conducting the platform entry simulation with the regression results from model (4.3) yields the landscape of market effects shown in Fig. 5(a) into which WiMAX entered. From the relative keystone effect strengths of the two platforms it is

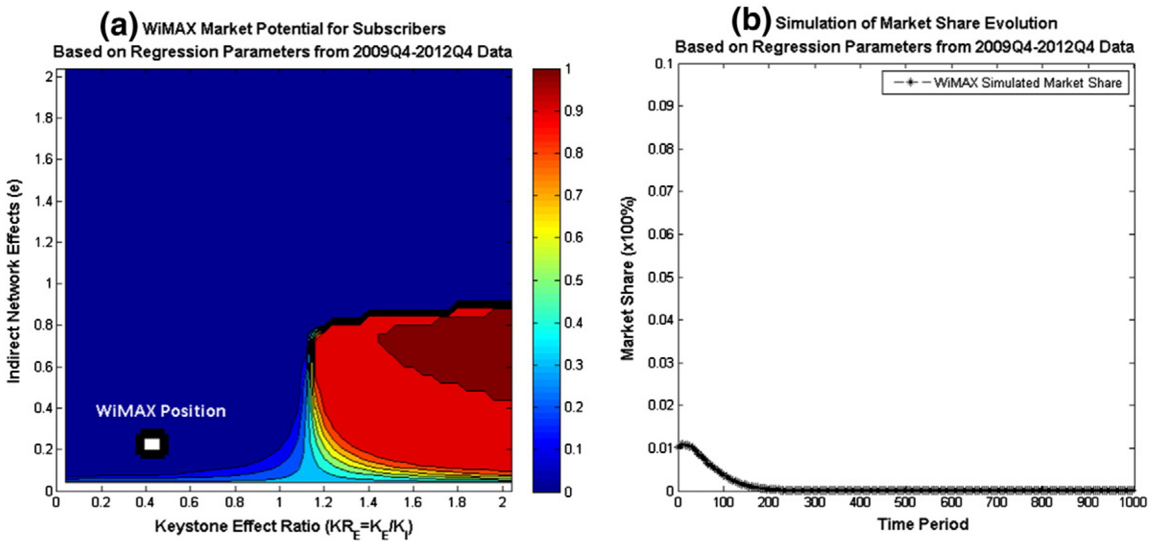

Fig. 5. Historical failed market entry of WiMAX.

evident that WiMAX was at a considerable disadvantage to 3G/LTE with $KR_E = k_E/k_I = 0.20$. This means that the 3G/LTE MNOs attracted more suppliers and maintained their support in providing a superior portfolio of compatible devices than the MNOs supporting WiMAX were able to manage. It is clear from the simulation result in Fig. 5(a) that WiMAX's market entry position was unwinnable given the disadvantageous combination of market effects, and the simulated change in market share of WiMAX subscribers over time, Fig. 5(b), demonstrates the dynamic effect of the entrant platform's keystone species' weakness. The simulation outcome is consistent with empirical evidence with an equilibrium position showing that WiMAX is prevented from securing substantial market share. Thus this study's model is well-suited to account for the externalities of the global mobile telecom market in explaining the result of WiMAX's market entry. The simulation and regression results support the argument that WiMAX's keystone effect disadvantage combined with the magnitude of the indirect network effects were cumulatively strong enough to prevent new platform from being able to enter the telecom market successfully.

5.2. Counterfactual analysis of forecast data: 2010Q1–2014Q1

It could be argued, however, that the circumstances surrounding WiMAX's market entry were disproportionately influenced by a few anomalies causing a market share trajectory in a short lifespan that is abnormal or unsuitable for conclusions to be drawn about the impact of keystone species upon platform competition in other markets. In theory we assert the contrary – that few but influential keystone species of a platform determine its fate by the nature of their interconnected role, not by exception or coincidence – yet it is instructive to examine whether WiMAX might have been able to enter the market successfully if it had met the optimistic expectations set for it prior to 2010. That is, as of 2010, if WiMAX were guaranteed to live up to the forecasted expectations of industry experts in terms of production volume and subscribership until 2014, even in that most optimistic scenario, would it have stood a chance versus 3G/LTE to gain the critical mass of installed base and complementary goods necessary to propel its market share trajectory upward toward oligopoly or monopoly? Such insight, had it been available prior to 2010, would certainly have been valuable information to suppliers choosing their future 4G technology standard. Given WiMAX's comparatively small or entirely new keystones, those MNOs supporting it as their 4G technology standard, we expect that WiMAX would have faced an insurmountable keystone species disadvantage even despite meeting optimistic short-term forecast expectations.

To investigate this counterfactual we use market forecast reports of 3G/LTE and WiMAX subscribers and production volume data released between mid-2009 and mid-2010 from Infonetics (Anon, 2010a,c), Senza Fili Consulting (Paolini, 2010), and 3G Americas (Rysavy, 2009). We assume fixed costs remain unchanged from the historical data. In 2009, WiMAX was expected to reach over 82 million subscribers by 2013 (Rysavy, 2011), which turned out to be over three times more than the actual subscriber count in 2012. In 2009, WiMAX was forecast to sell 46 million units quarterly by 2014 (Anon, 2010c), which was over 40 times more than the highest quarter of WiMAX production volume in 2012, and 15 times above WiMAX's overall peak period of production, 2011Q3. Hypothetical time series of quarterly production volume and subscribers generated from these forecast data should present a much fairer portrayal of the entrant platform's inherent market potential. Additionally, they allow a longer regression timeframe spanning 17 quarters.

Table 5 displays the regression results for the WiMAX vs. 3G/LTE forecast data. A Hausman specification test yields m-statistic 4.20 with p-value of 0.84, confirming the null hypothesis that SUR is the preferable model. Relevant coefficients are significant, and the model is very well fitting in terms of the adjusted R-squared values; however, the model exhibits pervasive autocorrelation (Godfrey serial correlation test significant for three lags in the subscriber equation (p-values <0.01, <0.01,

Table 5
Regression results for forecasted WiMAX vs. 3G/LTE supply and demand.

Panel A: subscriber adoption forecast[a]		
Data	Forecasted production volume (3G/LTE smartphones; WiMAX 802.16e devices) and subscribers	
	SUR (5.1)	SUR-AR(p)(5.2)
Quality beta	4.18*** (0.37)	5.65 (4.80)
Indirect network effects	1.85*** (0.08)	2.21** (1.00)
Subscriber difference AR 1 lag		1.96*** (0.42)
Subscriber difference AR 2 lag		−1.01* (0.49)
Observation	17	17
Adj R-Sq	0.96	1.00[b]
Panel B: entrant (WiMAX) mobile devices supply forecast[c]		
Data	Forecasted production volume (3G/LTE smartphones; WiMAX 802.16e devices) and subscribers	
	SUR (5.1)	SUR-AR(p)(5.2)
Constant	1.43*** (0.18)	1.82** (0.62)
WiMAX keystone effect	0.91*** (0.02)	0.84*** (0.04)
WiMAX fixed cost	−0.03 (0.03)	0.01 (0.03)
WiMAX supply AR 1 lag		1.81*** (0.41)
WiMAX supply AR 2 lag		−0.87* (0.40)
Observation	17	17
Adj R-Sq	1.00[b]	1.00[b]
Panel C: incumbent (3G/LTE) mobile devices supply forecast[d]		
Data	Forecasted production volume (3G/LTE smartphones; WiMAX 802.16e devices) and subscribers	
	SUR (5.3)	SUR-AR(p)(5.3)
Constant	2.29*** (0.67)	0.39 (5.50)
3G/LTE keystone effect	0.85*** (0.04)	0.95*** (0.27)
3G/LTE fixed cost	0.01 (0.02)	0.00 (0.00)
3G/LTE supply AR 1 lag		1.88*** (0.37)
3G/LTE supply AR 2 lag		−0.94* (0.49)
Observation	17	17
Adj R-Sq	0.98	1.00[b]

Note: Results are (*) significant at 10%, (**) significant at 5%, and (***) significant at 1%, with standard errors in parentheses.
[a] Panel A reports regression results for worldwide technology standard adoption by subscribers.
[b] Adjusted R-squared values approach 1.0 due to their generation from forecasted growth rates instead of random observations.
[c] Panel B reports regression results for worldwide WiMAX devices supply (both handset models and 802.16e production volume).
[d] Panel C reports regression results for worldwide 3G/LTE devices supply (both smartphone models and smartphone production volume data.

and 0.01), three lags in the entrant supply equation (p-values 0.01, 0.02, 0.04), and three lags in the incumbent supply equation (p-values all <0.01)), as well as heteroskedasticity in the subscriber adoption and entrant supplier adoption equations (White test p-values 0.03 and 0.04, respectively).

We correct these irregularities by including autoregressive parameters in all three equations of the SUR and using a heteroskedasticity-corrected covariance matrix estimator (HCCME) to produce regression parameter estimates (MacKinnon and White, 1985). The result is a generally well-behaving system of simultaneous equations.[7] The most noticeable result is the marked increase in the magnitude of network effects (still significant, p-value <0.05) from 0.45 in the historical data to 2.21 in the forecast data. The inflated value of the indirect network effects may be attributable to the optimistic nature of some of the market forecasts that focused on the absolute potential for volume growth of one technology standard without fully considering the effect that increased competition would have on its relative growth. As in the historical data regression results, WiMAX is again found to be at a keystone effect disadvantage to 3G/LTE, with a keystone effect ratio of $KR_E = k_E/k_I = 0.88$.

We use these coefficients from forecast regression model (5.2) to simulate (a) WiMAX's landscape of subscriber potential and (b) market share trajectory over time, shown in Fig. 6. The outcome is the same as the regression from historical data. WiMAX's entry position is untenable. Its keystone effect disadvantage and the strength of the market's indirect network effects present insurmountable barriers to entry in the form of installed base and complementary goods portfolio disadvantages. Even with the market effects regression parameters of the relatively favorable growth forecast for WiMAX, the market share of the entrant diminishes rapidly relative to that of the incumbent resulting in the incumbent's long-run control of the market.

6. Discussion and conclusion

This study contributes to the literature on two-sided markets, market entry, indirect network effects, and keystone effects by presenting an adaptation of a dynamic model (Zhu and Iansiti, 2012), which combines quality, indirect network effects, and relative keystone strengths. The unique contribution of this model is its ability to capture accurate levels of influence exerted by highly interconnected platform participants, keystone species, and the suppliers for whom they facilitate a competitive and robust business ecosystem. This is crucial for accurately modeling a technology standard entry scenario like other versions of platform competition, yet it is something that has been lacking in previous, primarily customer-focused, market entry studies (e.g. Church and Gandal, 1992; Farrell and Klemperer, 2007; Gandal et al., 2000; Park, 2004; Zhu and Iansiti, 2012). This research thus extends the scope of the existing literature on two-sided markets and market entry both empirically and theoretically by underscoring the importance of evaluating not only the internal factors (i.e., the resources and dynamic capabilities of the firm and the keystone strength of its platform) but also the external factors (i.e., network effects and the opponent platform's keystone effect strength) when firms make investment decisions such as platform adoption. Our results show

[7] The model in column (5.2) corrects for heteroskedasticity in all equations (all p-values of the White test >0.05), and serial correlations (all p-values for all lag lengths of the Godfrey test >0.05). There is still system skewness (Mardia skewness probability <0.01, Henze–Zirkler T <0.01) and non-normality (Shapiro–Wilk W test probability <0.05 for all three equations), but not all violated assumptions can be corrected while also correcting for serial correlation and heteroskedasticity. Although some non-normality or autocorrelation is unavoidable, since the forecast data are generated from growth rates and are thus inherently autocorrelated, these results nevertheless serve their purpose for strictly hypothetical comparison of the counterfactual scenario test.

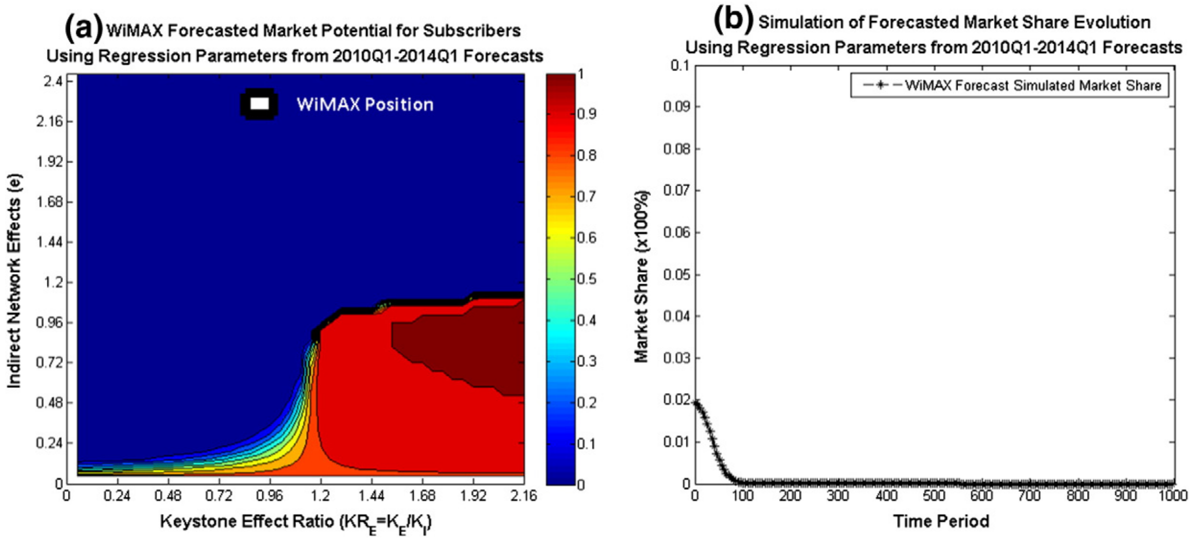

Fig. 6. Forecasted failed market entry of WiMAX.

that WiMAX's keystone effect weakness versus 3G/LTE and the mobile telecom market's indirect network effects were cumulatively strong enough to prevent the new technology standard from securing a monopoly or oligopoly share of the subscriber base in the long run.

6.1. Managerial implications

The substantial impact of the relative keystone effect strengths suggests that ecosystem dynamics may explain another means of successfully entering a market late and stealing market share from its incumbent. Besides offering revolutionary products or services, and in addition to platform envelopment (Eisenmann et al., 2011), this study's model proposes that keystone strength advantage increases the likelihood of successful entry for a new platform despite installed user base disadvantage. On the other hand, it demonstrates that an entrant with weaker keystones stands little chance of beating the entrenched incumbent. We also need to point out that, while keystone species are one type of firm that exists in almost any ecosystem, the keystone effect introduced in this study's model is not critical for every market entry. The conditions that characterize platform competition in which the keystone effect is a determining factor are (i) the existence of network externalities, (ii) approximately comparable performance between the competing platforms, (iii) separate sponsorship of each platform, and (iv) the preference of both users and suppliers for early standardization of a platform, regardless of which one wins. These conditions have been seen in such platform competitions as alternating current (AC) vs. direct current (DC), VHS vs. Betamax, Blu-ray vs. HD-DVD, and most recently WiMAX vs. 3G/LTE.

The importance of strong keystone species has codified in the 21st-century as the specialization of functions in the value chain evolved into the arranging of partners within a value web, each with blurred lines of cooperation and competition. The change in the speed and nature of competition is so vast that the 20th-century examples of platform competition above are scarcely comparable to those from the 21st-century. Much of this change is explained by two of the aforementioned conditions for keystone-influenced platform competition: (i) the impact of network externalities has increased sharply with the speed of business in the information age, and (iii) the sponsors of the competing technologies, upon recognizing the intensification of market forces, began compensating with a previously unseen strategic focus on the addition of valuable platform members. The organization of a new platform to compete with an established market presence requires strong collaboration, from the technology sponsors to the noteworthy companies bringing name recognition, from the niche suppliers of complementary goods to the few but vital keystone species positioned to link these other members together and contribute to a robust ecosystem. Building strategic ties within the ecosystem is crucial since the outcome of each new platform competition might be expected to reverberate beyond a single product life cycle and into successive technological generations if the platform remains dominant.

Of course, the impact that keystone species have on their ecosystems still depends on each ecosystem's particular composition. Markets that are highly susceptible to the keystone effect's impact likely have a high degree of interconnectivity, which often includes central hubs that link different sides or sections of the markets with others through paths of least distance. Two-sided markets are therefore a prime example of a keystone-dominated market type. The keystone species (e.g., MNOs in mobile telecommunications) link the two sides of the market by keeping the loyal user base and managing business relationships with equipment suppliers and digital content providers. Since two-sided networks have been shown to exhibit network effects, both direct and indirect, then studying this interaction between keystone effects and network effects on both sides of the two-sided market is necessary for accurately modeling the market dynamics and advising investment decisions within the market. This study offers a starting point for achieving these ends. It presents a novel way of quantifying the keystone effect from historical market data or even gauging expectations via forecast data. Both of these could prove valuable in informing firm adoption decisions for new platform-based technologies and even incorporated in cost–benefit analysis for evaluating investment in successive technology generations (Sohn and Ahn, 2003).

6.2. Limitations and future research

Every attempt was made to minimize the effects of irregularities in the data used for this empirical analysis; however, the use of sparse market data is an unavoidable limitation that may affect the model's ability to measure market effects as regression parameters. Particularly the use of new handset models as a proxy for supplier adoption was sensitive to this limitation. It is for this reason that we include a second proxy data source for supplier adoption, the volume of mobile device production weighted by the availability of software on each platform. This second data source allows more suitable observations and produces significant regression results for each of the focal parameters. The timeframe for this empirical analysis was limited by WiMAX's brief tenure as a competitive alternative to 3G/LTE. Although this is a condition of the available market data used for this analysis, the model presented herein could certainly be applied to other platform competition scenarios with data available in greater frequency or duration. This would prove an apt subject for further research.

The existing literature on business ecosystems would certainly benefit from future research that attempts to quantify the keystone effect in different markets and using different theoretical models. Recent utilization of visual analytics software tools has focused attention on the mapping of business ecosystems (Basole et al., 2012; Suh et al., 2013) for network analysis, analogous to the mapping of biological interaction networks and food webs. However, the effect that keystone species have on their fellow ecosystem members and on the ecosystem as a whole still needs to be quantified for use as a decision making tool. Since studies of business ecosystems cannot, for obvious reasons, measure keystone effects the same way that biological researchers do – through the experimental removal of the keystone species – then scholars of business ecosystems will have to continue to look for innovative ways to quantify the keystone effect in practice. Only then can business ecosystem researchers hope to move beyond merely classifying and describing keystone species to offering predictive tools for informing operational and investment decisions in business ecosystems.

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