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Compatibility promotion between platforms: The role of open technology standards and giant platforms

Sebastian Spaeth¹ · Sven Niederhöfer¹

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Abstract

Most platform literature focuses on single platforms and their governance, e.g. concerning app developers. Yet, platform competition and dynamics are increasingly important as they form connections with each other and build complex networks. More focus on platform-to-platform relationships and the role of standards is warranted. Therefore, the goal of this study is to investigate how platform sponsors select platforms to promote as compatible with their own products, taking open standards and “giant platforms” into account. To address these questions, we construct a unique data set covering 157 platforms in the smart home market. We conduct a network analysis based on an exponential random graph model (ERGM) to incorporate platform features, dyadic characteristics, and structural processes. We find that platform-to-platform compatibility promotion is determined by a careful selection of platforms with dissimilar industry sectors and ecosystem niches. We identify two strategic approaches to select and promote platforms as compatible, based on standard complementarity and the size of the installed base. We find that platforms more often promote other platforms with similar supported standards. The majority of endorsements are directed at giant platforms, allowing platforms to support a smaller number of standards and thus a reduced degree of openness at the technology level. Platforms often integrate several giant platforms at the same time. Our study makes two major contributions to the literature. First, we extend the concept of selective promotion (Rietveld et al. 2019) to include inter-platform compatibility and open technology standards. Second, we demonstrate how platform sponsors compensate for higher accessibility at the technology level with transparency at the marketplace level.

Keywords Platforms · Ecosystems · Standards · Openness · Competition · Internet of things

Jel classification M31

Introduction

Digital product platforms (Hilbolling et al., 2020; West, 2003), which comprise physical devices with embedded digital functions and are organized along a layered

modular architecture (Yoo et al., 2010), enable the building of vibrant ecosystems of interconnected products and services around a platform (Henfridsson et al., 2018). Platform ecosystems consist of a relatively stable core—the platform—and a set of complementary products and services in the periphery that are connected to the platform via standardized interfaces (Baldwin & Woodard, 2009). In the area of home automation within the Internet of Things (IoT), such complex product systems are installed in the homes of end-users, forming local infrastructures of “smart” devices from multiple vendors that are interconnected via communication standards (Rowland, 2015a, 2015b).

The platform business model has become the dominant model in some industries (Rietveld & Schilling, 2021), changing their structures and driving their convergence.

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In the smart home market, even manufacturers of conventional products try to launch digital product platforms to gain a foothold in the platform business (Shin et al., 2018). Examples include lighting manufacturers such as Signify and home appliance manufacturers such as LG Electronics. They are offering platform solutions to control a wide range of complementary smart home devices, including their own.

Smart home systems encompass many application areas (cf. Shin et al., 2018) that exceed a single company's product portfolio. At the same time, the value of the entire platform depends on the availability of various complementary products (Boudreau, 2010; Gawer, 2009), leading to interdependencies between the actors in the smart home market. These interdependencies are exacerbated by users' desire for cross-vendor compatibility (Shin et al., 2018).

Therefore, platform sponsors often need to open their platforms to third-party participation—including competitors—to provide a comprehensive offering to their customers. Access to a platform includes not only access to technical resources such as the code base but also access to a market of users of the platform through its distribution channels (Benlian et al., 2015). Platform openness generally refers to the extent to which external actors have access to a platform's resources and the constraints on their use (Boudreau, 2010; West, 2003) and comprises two broad dimensions: accessibility and transparency (Benlian et al., 2015).

An often-overlooked factor in previous research is the choice of open technology standards (West, 2003), which determine the subset of products and platforms that are compatible at the hardware level. In the case of smart home products, wireless communication protocols such as ZigBee, Z-Wave, or Bluetooth Low Energy are of particular importance because they are embedded in hardware and are certified and promoted to consumers through the alliances behind those standards.¹ By selecting a set of supported technology standards, a platform sponsor can specify in the design phase of the platform and products with which third-party products and platforms they can interoperate.

Platform openness implies a strategic dimension: while it is necessary to leverage the capabilities of external complementors to increase the variety of complements, it also requires some loss of control, which Boudreau (2010) calls the tradeoff between variety and control. While open systems may come with a loss of control (West, 2003), open technology standards that enable communication between smart devices may allow platform providers to make devices from

other platform providers compatible without collusion. As a result, digital product platforms are increasingly interconnected, forming complex platform constellations (Mosterd et al., 2021) or "ecologies of platforms" (Hilbolling et al., 2020). Platform providers on the smart home market thus simultaneously act in the role of complementary providers for other platforms, intentionally or unintentionally.

This dual role of platform providers as complementors to other platforms enables some tactics to signal openness to end-users while diverting their attention from direct competitors. This strategic tension can be addressed through endorsement (Rietveld et al., 2019). For example, it can be observed that platform providers, such as Samsung only promote third-party products as compatible, which are not in their own product portfolio.

At the same time, large platforms established in other markets, such as Apple, Google, or Amazon, have entered the smart home market and offer certification programs to establish interoperability between platforms. Previous literature has highlighted the importance of such giant platforms² in cross-platform compatibility considerations (e.g., Hilbolling et al., 2020).

Taken together, it becomes apparent that it is vital to understand the role of open technology standards in platform ecosystems and how platforms promote compatibility with one another in light of platform openness and platform competition. Against this backdrop, we address the following research question:

RQ: How do platform sponsors choose the platforms to promote with respect to technology standards and platform type (i.e., giant vs non-giant)?

To address this question, we perform two consecutive content analyses on data retrieved from several web-based sources, accompanied by a network analysis of relationships between platform sponsors. In doing so, we construct a unique data set covering 157 platforms in the smart home market.

This study is expected to contribute to the extant literature on several fronts. First, we extend the research on platform strategy by introducing the concept of compatibility promotion as a particular form of selective promotion (see Rietveld et al., 2019). In contrast to selective promotion, compatibility promotion is used by platform sponsors to sift through the *shared* stock of complementary devices that goes back to different platform ecosystems to make a considerate decision about which devices to promote, taking into account the characteristics of the platform in each of these ecosystems,

¹ This study refers to open wireless communication standards that are integrated into many smart home products. A table with the standards considered and their properties can be found in Appendix 1.

² See Table 5 in Appendix 1 for an overview of considered giant platforms.

to strike a balance between adoption and appropriability. We test two strategic approaches to promoting selected platforms as compatible, based on (1) standard complementarity and (2) the size of the installed base of the platform (giant platforms). We find strong support for the second approach, with giant platforms receiving most of the promotions, while the likelihood to promote giant platforms is conditioned by the number of standards and the number of giant platforms with which promoting platforms integrate. In particular, platforms promoting giant platforms support fewer open technology standards, reducing the degree of openness at the technology level and overall costs. At the same time, we observe a strong preference to integrate with multiple giant platforms simultaneously, which we believe serves to mitigate potential platform envelopment. As such, two strategic preferences arise contingent on the number of standards supported: (1) integrating with multiple giant platforms for fewer standards, and (2) promoting more non-giant platforms with similar sets of supported technology standards when supporting more standards. Overall, platforms in our sample can be divided into two groups, with one group integrating at most two standards and one group integrating more than two standards. We identify further factors driving compatibility promotion. Second, we extend platform research on platform openness, particularly focusing on the multidimensionality of openness. We find empirical evidence to promote compatible platforms based on dissimilarity in the primary industry sector and ecosystem niches, suggesting that platforms compensate for higher accessibility at the technology level (i.e., configuration of open technology standards) by adjusting transparency about compatibilities at the marketplace level (i.e., curation of compatible platforms).

The paper is organized into six sections. In the following section, we derive our research model for platform-to-platform compatibility promotion, drawing on the literature on platform openness and platform competition on compatibility. Next, we elaborate on our research setting, describing the content analyses and network analyses as well as our research context before passing on to the presentation of our results from the network analysis. The last section concludes the paper by discussing our contributions and the limitations of our study and pondering possible future research.

Theoretical background and hypotheses development

Platform-to-platform compatibility promotion

A platform's value is determined by the availability of various complements, their quality, and the end-users' perception of these (Boudreau, 2010; Gawer, 2009; Schilling, 1998). Previous literature has discussed various approaches

to platform openness to manage ecosystem value, including governance measures such as control mechanisms and information policies (Benlian et al., 2015), partner programs (Wareham et al., 2014), and boundary resources (Ghazawneh & Henfridsson, 2013), predominantly considering openness towards developers. Recent literature highlights the multifaceted nature of openness to different activities and actors (e.g., Benlian et al., 2015; Boudreau, 2010; Broekhuizen et al., 2021). As such, openness can be defined concerning different roles (Eisenmann et al., 2009), including competing platforms (e.g., Karhu et al., 2018), which determines how platforms connect and interact (Mosterd et al., 2021). Platform-to-platform openness offers the potential to extend the functionality of a (complementary) platform and its connected complements (Mosterd et al., 2021). Ondrus et al. (2015) also point out that interoperability between platforms can lead to higher market potential.

Openness is closely related to network externalities, particularly in the initial phase (Ondrus et al., 2015), requiring platform sponsors to achieve a certain degree of openness that fosters adoption by leveraging network effects, while maintaining enough control for value appropriation (Eisenmann et al., 2009; Landsman & Stremersch, 2011; West, 2003). West (2003) describes this tension as 'adoption vs appropriability'. Vast literature highlights the role of network externalities underlying competitive dynamics between platforms, which can lead to a tipping of the market and thus a winner-take-all outcome (e.g., Farrell & Saloner, 1992; Katz & Shapiro, 1985; Schilling, 2002). In markets with strong network externalities, platform companies may therefore be particularly inclined to rapidly build an installed base to gain a competitive advantage (Cennamo & Santalo, 2013; Parker & Van Alstyne, 2005). In this context, fostering network effects by offering sufficient complementary products is particularly important to overcome initial barriers to adoption (e.g., Armstrong, 2006; Caillaud & Jullien, 2003).

In an attempt to balance adoption and appropriability, Ondrus et al. (2015) derived a framework, distinguishing three levels of openness—provider, technology, and end-users – that reflect restrictions imposed on each of these groups. At the technology level, platforms may establish compatibility with other platforms through the adoption of common technology standards (Farrell & Saloner, 1992; Ondrus et al., 2015).³ Generally, platform sponsors face the decision of whether or not to make their platform compatible with that of competitors (Bessen & Farrell, 1994).

As such, even if *de facto* compatibility exists, platform sponsors have a stake in steering (prospective) end-users'

³ Compatibility denotes "the ability of machines, especially computers, or computer programs to work successfully with other machines or programs." (<https://dictionary.cambridge.org>).

attention away from rivals' offerings. We draw on Rietveld et al.'s (2019) concept of selective promotion to derive our theoretical concept of compatibility promotion. Selective promotion denotes a strategic approach of deliberately choosing a subset of *compatible* (software) complements to promote, intending to increase the perceived value of a focal platform ecosystem. In contrast, compatibility promotion involves screening a *shared* stock of complementary devices that goes back to different platform ecosystems and making a considerate choice as to which devices to promote in light of the platform's characteristics in each of these ecosystems to balance adoption and appropriability.⁴

While compatibility may be promoted to complements and platforms alike (Mosterd et al., 2021), we focus on *platform-to-platform compatibility promotion*, where platform sponsors deliberately choose platforms and their complements to promote. As such, platform-to-platform compatibility promotion reflects the cooperative nature of relationships in ecosystems (Bogers et al., 2019), appearing as *established and promoted* compatibility. This implies that platform sponsors combine openness at the technology level (adoption of open technology standards) with openness in their marketplaces (which categories and brands to curate) with transparency as the dominant dimension (Benlian et al., 2015; Broekhuizen et al., 2021).

Specifically, the consideration of compatibility between competing platforms is crucial, as it makes it easier for consumers to substitute platforms (David & Greenstein, 1990). Thereby, particularly open technology standards make it easier to build up a large and diverse set of complementary products and services across platforms but make it more difficult for an individual platform to reach the critical mass (Ruutu et al., 2017). By adopting open technology standards, a platform devolves some control to industry committees that decide on these standards (West, 2003).

While a lower level of compatibility makes it easier for platform sponsors to differentiate from competing platforms, weakening its competitive position, a higher degree of *visible* compatibility (cf. Besen & Farrell, 1994) increases the value perceived by users, making the platform more useful, which may facilitate adoption. Thus, platform sponsors may address this tension by decreasing the level of compatibility by adjusting openness of boundary resources (Eaton et al., 2015; Karhu et al., 2018) or by promoting certain complementary products and services in a favorable way (Rietveld et al., 2019). The level of compatibility between platforms and their respective ecosystems is hence influenced

by strategic tradeoffs concerning platform openness and competition.

Especially in the IoT area, platforms predominantly go back to manufacturers of conventional products who digitize them and often offer complementary cloud services for them. Despite the introduction of a platform, not all manufacturers necessarily then adopt a platform logic that provides access to manufacturers of complementary products by opening up the platform to stimulate overall growth (Pellizzoni et al., 2019; Sandberg et al., 2020). Instead, some may choose to follow a product manufacturer's logic and maintain the focus on selling their complementary products due to the market position of the firm (Eisenmann et al., 2009) or maturity of the firm or platform (Boudreau, 2010), resulting in a rather closed platform.

Both openness to complementors and platforms will often be correlated since companies do not necessarily distinguish between different forms of openness (Mosterd et al., 2021). Still, a higher degree of openness exposes a platform to threats from competitors (Eaton et al., 2015; Ghazawneh & Henfridsson, 2013; Karhu et al., 2018), making competition between platforms an essential factor influencing openness decisions (Mosterd et al., 2021). This is likely to be particularly evident in the IoT sector with product manufacturers subject to certain competitive structures within their industries. Accordingly, we expect to observe platform-to-platform compatibility promotion to be an approach to balance openness and competition, and hypothesize:

H1: Platform-to-platform compatibility promotion is positively related to the degree of marketplace openness of a platform, negatively moderated by the level of competition.

Compatibility promotion to platforms with complementary standards

There are at least two approaches to establishing and promoting compatibility, either in a direct fashion to certain platforms or indirectly by leveraging converters (Mantera & Sara, 2012; Ondrus et al., 2015). In a direct fashion, a platform can establish compatibility with another platform at two different levels: (1) software level and (2) hardware level. At the software level, interoperability can be established through direct cloud-to-cloud integrations, usually by opening application programming interfaces (APIs) to specific partners (Rowland, 2015b). APIs are typically based on more general standards such as the Internet Protocol and are based on flexible software frameworks that provide platform sponsors with greater design freedom. As such, platform sponsors can implement control mechanisms to regulate access to and use of platform resources (Ghazawneh & Henfridsson, 2013; Karhu et al., 2018).

⁴ This also comprises software complements, but is not within the focus of this study, as we are interested in the role of wireless communication protocols connecting complementary hardware devices.

At the hardware level, interoperability can be achieved through common interoperability standards that allow two platforms to understand each other semantically (Rowland, 2015a). In this context, platform sponsors can provide gateway devices that act as converters between more specialized standards used locally by devices and more general standards such as Wi-Fi or the Internet Protocol for connecting to the Internet (Rowland, 2015b). Overall, compatibility decisions at the hardware level can be described as adoption decisions related to open technology standards (West, 2003).

Generally, a technology standard can be understood as "a set of specifications to which all elements of products, processes, formats, or procedures under its jurisdiction must conform" (Tassey, 2000, p. 588). Standards can vary in the degree of openness, with proprietary and open source representing the extremes (West, 2003). West (2003) assumes that proprietary standards are developed by a platform sponsor for its own use, with an appropriation regime. In contrast, more *open technology standards* are subject to fewer constraints on their integration into products, their certification, and their commercialization (Boudreau, 2010; West, 2007).⁵

Adopting open technology standards eliminates the need to identify and grant access to complementors because interoperability is de facto established (Funk, 2003; West, 2003). Any firm that integrates the standard into a product inevitably becomes a complementor to that platform. As such, it contributes to the formation of "arm's length relationships" (Boudreau, 2010) where platform sponsors cannot exercise direct control over complementors.

At the same time, a platform ecosystem that supports certain open standards and thus practices openness at the hardware level also makes its complementary products available to other platforms, which affects platform competition (cf. Besen & Farrell, 1994; Farrell & Gallini, 1988). The more standards two platforms share, the greater the overlap in complementary products that both support, leading to multi-homing in offerings (Armstrong, 2006) and reducing differentiation between platforms (Hagiu & Lee, 2011), gradually driving consumers indifferent between competing platforms but increasing overall incentives for adoption (Landsman & Stremersch, 2011). While standard adoption choices usually go back to characteristics of the standard and the alliance developing the standard (Baron & Spulber, 2018; Leiponen, 2008) and drive openness at the technological level, transparency about the resulting cross-platform

compatibility at the marketplace level positions the platform within a network of platforms (Henfridsson et al., 2018). However, firms face resource constraints, affording efficient strategic choices.

As such, to differentiate their platforms from those of competitors by selecting how dissimilar the complements in two ecosystems should be (Cennamo & Santalo, 2013), while facing a fragmented market consisting of several competing, yet complementary standards, an efficient way to cover most of the technology standards and thus devices, can be achieved by promoting platforms with a complementary set of supported technology standards. Particularly, different technology standards usually serve different purposes and thus come with different technical specifications (Chaudhary et al., 2021), fitting different use cases unequally well (Rowland, 2015a),⁶ and thus drive technology standards complementary to some extent.

Taken together, this could lead platform sponsors to favor other platforms with a certain degree of difference in standard configuration, appearing as an inverted-U shape relation between standard overlap and platform-to-platform compatibility promotion:

H2: Platform-to-platform compatibility promotion exhibits an inverted U-shaped relationship to the standard overlap between two platforms.

Compatibility promotion to giant platforms

Alternative to directly promoting compatibility to certain platforms, platform sponsors can choose to promote giant platforms (Hilbolling et al., 2020). Particularly, for smaller platforms, one viable approach is to establish compatibility with a platform that has a larger installed base of users (Katz & Shapiro, 1985, 1992; Venkatraman & Lee, 2004). Empirical results show that this can lead to demand spillover effects (Li & Agarwal, 2017), or at least awareness spillover effects where a third party gains increased awareness by offering complementary goods on a well-known platform (Song et al., 2021). Compatibility with larger platforms is particularly critical in markets with "excess inertia," i.e., the market is biased toward existing products (see Katz & Shapiro, 1992). Some scholars, therefore, argue that compatibility with dominant players is preferable (Cusumano & Gawer, 2002; Xie & Sirbu, 1995). For example, Venkatraman and Lee (2004) demonstrate that game developers in the video game industry are more inclined to join a dominant platform.

⁵ Please note that a distinction between proprietary and open standards is not easy, as there are different perceptions with respect to criteria for openness West (2007). For our study, we consider open standards as communication standards that can be adopted by interested parties and are thus shared by many firms, leading to compatibility. We leave further criteria such as restrictions concerning participation in standards development and royalty fees out of scope.

⁶ For example, Wi-Fi achieves higher data rates than ZigBee and can transmit video data, but also has higher power consumption and is therefore unsuitable for battery-powered devices such as light switches.

Platforms seeking platform leadership within the market must fulfill a fundamental function for the industry (Cusumano & Gawer, 2002). Addressing fragmentation in standards by creating interoperability between platforms represents such a function, allowing a broader platform to concentrate many interconnections from more specialized platforms and improve its value appropriation capabilities (Henfridsson et al., 2018). Accordingly, they can influence the industry architecture in their favor and become a “bottleneck” (Jacobides et al., 2006). This is especially the case for digital technology markets, where platforms occupy different positions in the technology stack (Yoo et al., 2010) and can jointly create a market by offering different complementary functions (Kwak et al., 2018).

Hence, to overcome the adoption barrier of fragmentation, platform sponsors seeking compatibility with a larger set of devices may choose to certify their products with one or multiple giant platforms. This yields three predominant benefits: First, by certifying the interoperability of all devices and platforms that integrate with the giant platforms, they act as a de facto “converter” (Farrell & Saloner, 1992) within the network of connected platforms. This reduces the need to adopt multiple technology standards and the associated costs since integrations with giant platforms are typically implemented via cloud-to-cloud connections over the Internet Protocol (Hou et al., 2017; Rowland, 2015b). Second, platform sponsors do not need to promote compatibility with direct rivals, but can establish an indirect path via giant platforms. Third, as giant platforms offer co-branded certification programs (i.e., “works-with” logos)⁷ while having large installed bases of users, the potential for demand spill-overs opens up (Li & Agarwal, 2017). Accordingly, platform sponsors can signal users of giant platforms a quick and easy entry into using their platform, lowering perceived barriers to adoption.

Yet, integrations with giant platforms drive up coordination costs as they require technical changes to the devices and platforms and increase the platform’s dependence on the giant platform (Hilbolling et al., 2020). These costs are in addition to the cost of memberships and product certifications with standards development organizations. For some giant platforms, in addition to certifications with all standards development organizations, products must then go through the certification process with the giant platform before they can be launched into the market.⁸

Hence, we expect integrations with giant platforms to be particularly attractive for platforms not supporting many open technology standards natively. Therefore, we hypothesize as follows:

H3: Platform-to-platform compatibility promotion towards giant platforms negatively interacts with the number of open standards a promoting platform supports.

While integrations with giant platforms offer benefits, it harbors the danger of “platform envelopment” (Eisenmann et al., 2011) by the giant platforms. In particular, by integrating with giant platforms and obtaining demand spillovers, the user bases of the integrating and giant platforms become gradually more similar, which improves the conditions of platform envelopment by the giant platform. In addition, users can draw on applications of the giant platform, sidelining the initial offering of the integrated platform and further increasing the risk.

One way to mitigate the risk of platform envelopment by a giant platform is to integrate with several giant platforms (Hilbolling et al., 2020). This way, a platform sponsor can reduce dependency on one particular platform and increase the leeway to respond to hostile approaches by a giant platform. In addition, platform sponsors also increase the potential benefits of such integrations, as these may host installed bases of users that may complement one another (e.g., Android users versus iOS users), increasing potential spillover effects. Taken together, we thus posit that:

H4: Platform-to-platform compatibility promotion towards giant platforms is conditioned by multi-homing to multiple giant platforms.

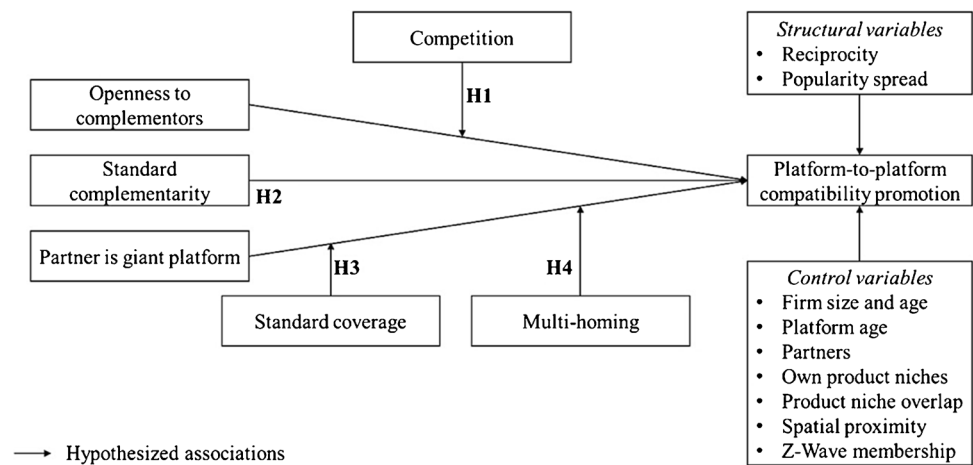
Research model

Based on our literature review, we have derived our research model as illustrated in Fig. 1. The premise of the model is that platform-to-platform compatibility promotion reflects transparency at the marketplace level about de facto established compatibility at the technology level, balancing adoption and appropriability (H1). The model, therefore, tests two efficient strategic approaches to cover most of the standards, compatibility promotion to platforms with different standards in a direct fashion (H2) and giant platforms reaching the market in an indirect fashion (H3, H4). As such, the model reflects some of the factors underlying openness decisions at the technology level as identified by Mosterd et al. (2021), providing the starting point for promoted compatibility in the marketplace. To this end, we focus first on the fundamental decision to open up (organizational factor) and second on competition between firms (market level factor).

⁷ <https://partnermarketinghub.withgoogle.com/brands/google-assistant/>, <https://developer.apple.com/homekit/>, <https://developer.amazon.com/en-US/alexa/devices/connected-devices/business-resources/works-with-alexa>

⁸ <https://developers.google.com/assistant/smarthome/concepts/fulfillment-authentication>, <https://smarthings.developer.samsung.com/docs/devices/hub/hub-connected-device.html>

Fig. 1 Research model. Note: Arrows denote associations. Competition, standard complementarity, product niche overlap spatial proximity are edge covariates, whereas all the other variables are nodal attributes



Research methodology

Data sources and content analyses

We chose the context of the Internet of Things because it offers a fragmented environment with several competing technology standards that have emerged in recent years and covers a variety of platforms. We focus on the smart home market as one of the most established (consumer-facing) application areas of IoT technology (Chaudhary et al., 2021). This environment provides an interesting context for exploring our research question, as there are network externalities that force companies to quickly establish connections to complementary products and services to gain a competitive advantage (Katz & Shapiro, 1985; Schilling, 2002). At the same time, they share a common stock of devices that support the same standards, making competition more difficult (Landsman & Stremersch, 2011). Although platform providers aspire to leadership within a market (Cusumano & Gawer, 2002), no single market leader has yet emerged (Ali & Yusuf, 2018), while at the same time giant platforms like Google and Amazon have entered the playing field (Shin et al., 2018).

The entire data collection process is guided by two successive web-based content analyses (Krippendorff, 2004; McMillan, 2000), as illustrated in Fig. 2 and described in more detail in the online appendix. Content analyses allow scholars to obtain a systematic, objective, and quantitative description of the content of (transcribed) conversations, articles, and other texts. In addition, it allows for the inclusion of more context in the analysis by considering graphical representations and the nature of the document (cf. Krippendorff, 2004).

As a starting point, we expanded a data sample we had previously created by crawling (Baron & Spulber, 2018; Leiponen, 2008) member companies of the Z-Wave Alliance, a consortium of more than 800 companies that manufacture

products based on the Z-Wave standard.⁹ The Z-Wave standard provides a relevant research context, as it is embedded in more than 3,000 smart home products, constituting a larger part of the overall market, with a tiered membership structure allowing an easy adoption and certification.¹⁰

Overall, we consider a firm to be a platform firm if it offers (1) a smart home app, (2) home automation software, and/or (3) a standalone device that can be used to connect and control a variety of smart home products. We exclude pure cloud service providers as we are interested in consumer-facing platforms where network effects are particularly relevant.

In total, 157 firms meet at least one of our criteria, of which 81 are Z-Wave firms and 76 are partner firms.

Network analysis

We conducted a network analysis to tackle our research questions. We could not simply use logistic regression with compatibility promotion as the dependent variable, since a platform company's decision to cooperate with other platforms depends partly on the structural characteristics of the network itself, e.g., on how many other actors promote compatibility with a given actor due to network effects (Albert & Barabási, 2002). Consequently, observations are not independent, violating a fundamental assumption of general linear models (Pattison & Wasserman, 1999; Robins, 2014).

To account for the structural features that underlie firms' decisions, we rely on network analysis as a method that allows us not only to estimate social processes and structural

⁹ The data sample comprises all member firms between 2005 and 2019, aggregated to one list. All data on products and apps as well as all documents for the content analyses and network analysis were collected in 2020.

¹⁰ <https://z-wavealliance.org/>

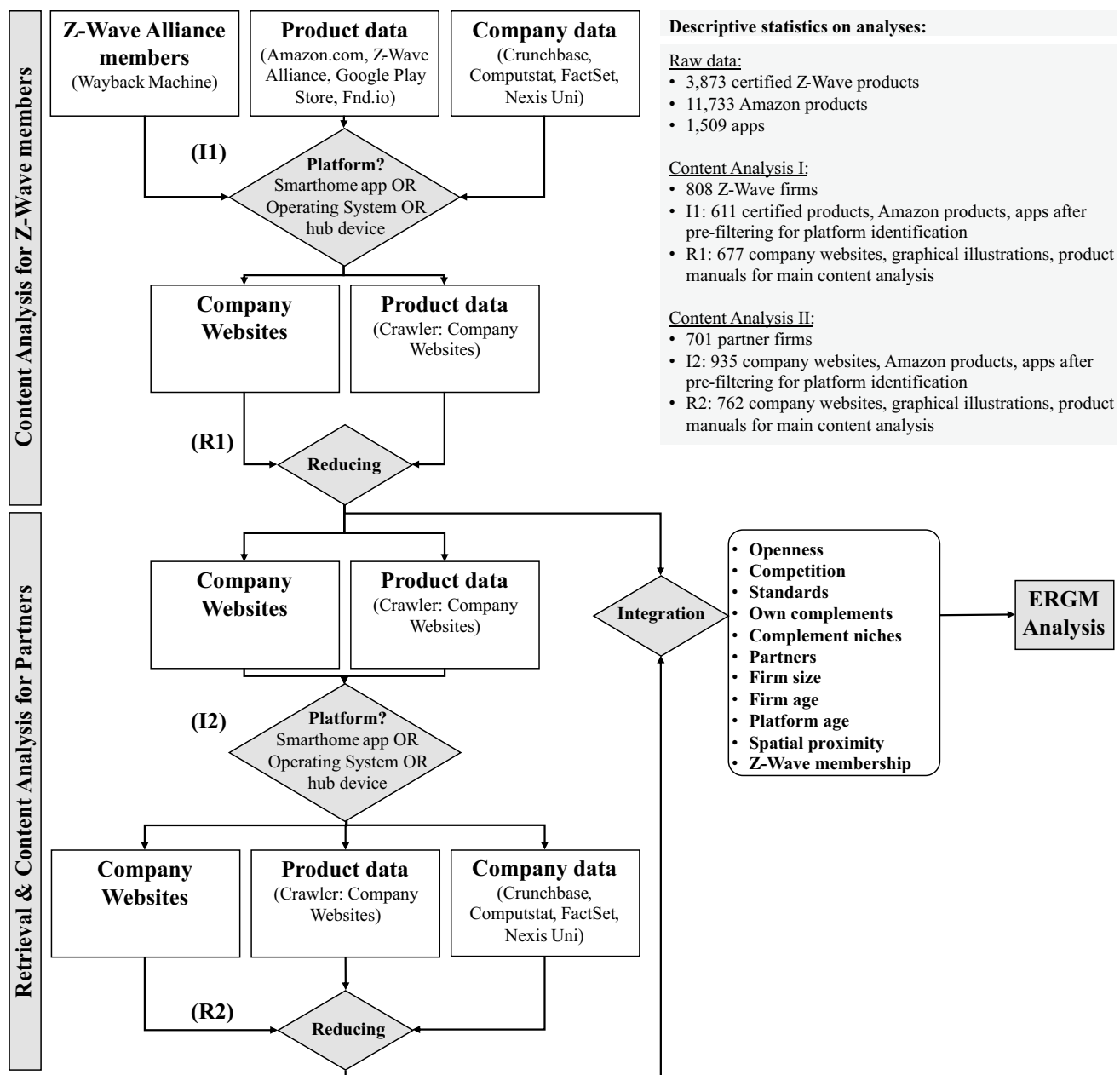


Fig. 2 Overview of data collection and analysis

features that govern network formation but also to visualize relationships and simulate networks (Borgatti & Halgin, 2011; Oinas-Kukkonen et al., 2010).

We use an exponential random graph model (Pattison & Wasserman, 1999; Wasserman & Pattison, 1996) to estimate the underlying processes. In recent algorithms (such as in the “statnet” R package we used), ERG models are usually estimated using Monte Carlo Markov chain maximum likelihood estimation (MCMC-MLE), taking starting values from a computationally less expensive maximum pseudo-likelihood estimation (Robins, 2014). Generally, an ERGM

is modeling an observed network by weighting hypothesized network statistics (parameters) using the following form

$$\Pr(X = x) = \left(\frac{1}{k}\right) \exp \left[\sum_A \eta_A g_A(x) \right]$$

where X and x are the adjacency matrices of the predicted and observed networks; A refers to different network configuration types (i.e., triangle, reciprocated tie, etc.) to be included in the estimation; η_A reflects the relative importance of each configuration type in A , $g_A(x)$ is the network statistic (i.e., edge count, triangle count, number of reciprocated

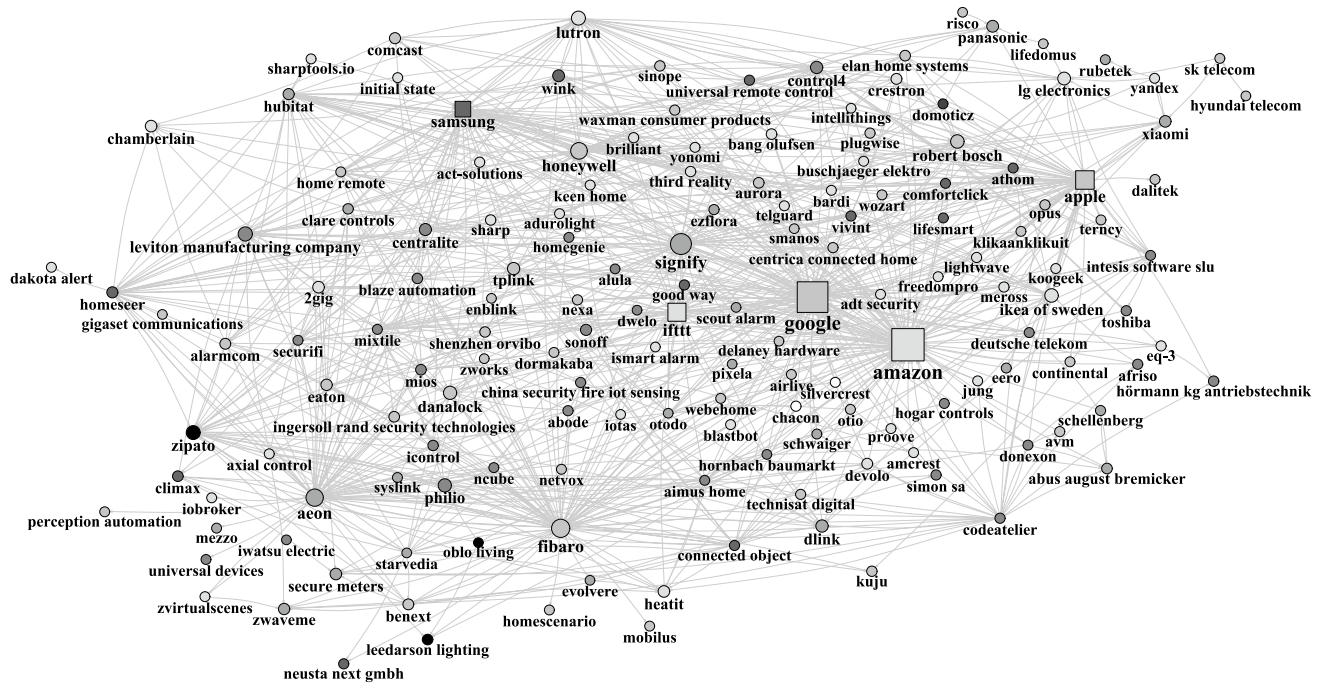


Fig. 3 Network graph of platform-to-platform compatibility promotion in the Z-Wave-based smart home market. Note: Network plot of all 157 platforms positioned using Multi-Gravity ForceAtlas2 algorithm. Node size reflects in-degree, node color corresponds to num-

ber of supported standards (white = 0, black = 7). Node shape reflects whether it is classified as a giant platform (square shape) or not (circle)

ties, etc.) for each type in A ; k normalizes the exponential function to fit a proper probability distribution (cf. Robins, 2014).

For our analysis, we construct a network graph consisting of platform firms as nodes connected by directed (unweighted) edges, indicating whether a platform sponsor (sender) promotes compatibility with another platform ecosystem (receiver). The edges here include listed partners, manufacturers of listed complementary hardware, and integrations to platforms (“works-with” logos, see Hilbolling et al., 2020). The network consists of 157 nodes and 879 directed edges, as shown in Fig. 3. For our analysis, we resorted to the statnet package for R (Handcock et al., 2008).

We include nodal attributes and edge covariates to capture platform-specific and relational effects. Nodal attributes (i.e., firm and platform attributes) capture differences in selection (out-degree) or attraction (in-degree) arising from differences in idiosyncratic characteristics of a sender or receiver, respectively. Dyadic parameters capture social selection processes such as homophily (heterophily), in which actors in a network form edges with actors who are similar (different) in certain characteristics (McPherson et al., 2001; Robins, 2014). Structural effects generally capture decisions based on an actor’s perception of topological features. We follow the general recommendation to incorporate at least one parameter for network density and parameters for degree

distributions and triad closure to account for the network structure at different levels (Robins et al., 2009; Snijders et al., 2006).










Variables and measures

In our model, we predict *Platform-to-platform compatibility promotion* (PCP), which is reflected by the formation of a directed edge in the network graph. We consider several parameters in our analysis. An overview of parameters and measures included in our model is presented in Table 1

Main parameters To measure the effect of a platform’s underlying tendency to be open, we introduce the network statistic *Sender(Openness)*, which reflects the number of platforms with a product marketplace or compatibility list published on their websites. We measure the effect of competition via the Standard Industrial Code (SIC), introducing a network statistic *Competition* that reflects the number of platform firms that are active in the same primary industry. We test Hypothesis 1 by the interaction of *Sender(Openness)* and *Competition*.

To account for selection preferences going back to heterophily in standards (H2), we construct a valued sociomatrix with edge weights corresponding to the overlap in the

Table 1 Overview of effects included in the ERGM estimation for P2P compatibility promotion

Parameter	Diagram	Hypotheses	statnet term
Main parameters			
<i>Sender(Openness)</i>			nodeofactor(Openness)
<i>Competition</i>			nodematch(SIC)
<i>Sender(Openness) x Competition</i>		H1	nodeofactor(Openness): nodematch(SIC)
<i>Standard overlap</i>		H2	edgecov(Standard overlap)
<i>Standard overlap^2</i>			edgecov(Standard overlap^2)
<i>Receiver(Giant platform)</i>			nodeifactor(Giant platform)
<i>Sender(Standards)</i>			nodeecov(Standards)
<i>Sender(Standards) x Receiver(Giant platform)</i>		H3	nodeecov(Standards): nodeifactor(Giant platform)
<i>Sender(Multi-homing)</i>			nodeofactor(Multi-homing)
<i>Receiver(Giant platform) x Sender(Multi-homing)</i>		H4	nodeifactor(Giant platform): nodeofactor(Multi-homing)
Control parameters			

standard sets S_i and S_j of two nodes i and j , defined as the Jaccard Index $S_i \cap S_j / S_i \cup S_j$. We then introduce a network statistic *Standard overlap* that computes the edge covariates to determine the relationship between standard overlap and compatibility promotion.¹¹ We also add a network statistic *Standard overlap^2* to test for the existence of a maximum in standard overlap, which is analogously incorporated and defined as $(S_i \cap S_j / S_i \cup S_j)^2$. We do this by using open technology standards rather than all standards (i.e., also proprietary standards), as they better reflect the baseline interoperability of a platform.¹²

¹¹ In easier terms, we can think of it as constructing an additional network for each variable, consisting of edges ($i \rightarrow j$) that – reflected by their edge weights – measure the degree of homophily between i and j for a given attribute (e.g., standards). Yet, we do not add these edges to our actual network, as this would drastically change network statistics, such as degrees. In contrast, we compare the network of actual relationships to the homophily networks by computing correlations for edges connecting the same nodes.





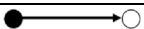



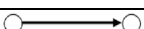
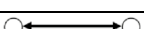
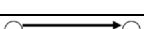
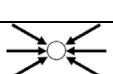
¹² See Appendix Table 4 for an overview of considered technology standards.

In addition, we incorporate the network statistic *Receiver(Giant platform)*, which counts the number of platforms that are classified as giant and receive compatibility promotion, to measure the basic propensity to promote compatibility with giant platforms. We classify a platform as giant if it provides a certification program to address the bottleneck of incompatibility and offers co-branding in the form of a “work-with” logo. Following these criteria, we classify Apple (HomeKit), Amazon (Alexa), Google (Google Assistant), Samsung (SmartThings), and IFTTT as giant.¹³

To capture the effect of the number of supported technology standards on the propensity to promote compatibility, we include a nodal covariate *Sender(Standards)*. We use the count of open standards to construct these measures. To

¹³ See Appendix Table 5 for an overview of considered giant platforms.

Table 1 (continued)

<i>Sender(Niches)</i>			nodecov(Niches)
<i>Receiver(Niches)</i>			nodeicov(Niches)
<i>Niche overlap</i>			edgecov(Niche overlap)
<i>Niche overlap^2</i>			edgecov(Niche overlap^2)
<i>Sender(Partners)</i>			nodecov(Partners)
<i>Platform age</i>			nodecov(Platform age)
<i>Sender(Firm size)</i>			nodecov(log emp)
<i>Sender(Firm age)</i>			nodecov(Firm age)
			nodecov(Integrations)
Structural parameters			
<i>Spatial proximity</i>			nodematch(Country)
<i>Sender(Z-Wave)</i>			nodeifactor(Z-Wave)
<i>Receiver(Z-Wave)</i>			nodeofactor(Z-Wave)
<i>Arc</i>			edges
<i>Reciprocity</i>			mutual
<i>Giant platform reciprocity</i>			edgecov(Giant platform reciprocity)
<i>Popularity spread</i>			gwidegree

measure the propensity for edge formation from a platform to a giant platform, which is conditional on the number of technology standards supported by the sending platform (H3), we add the *Sender(Standards) x Receiver(Giant platform)* interaction as a network statistic in our model.

Furthermore, we introduce a network statistic *Sender(Multi-homing)* that reflects the number of endorsing platforms with integrations to more than one giant platform. To test hypothesis 4, we include the interaction *Receiver(Giant platform) x Sender(Multi-homing)*.

Control parameters As prior literature has highlighted that platforms tend to carefully populate their niches (Boudreau, 2012; Inoue & Tsujimoto, 2018), we introduce three control parameters *Sender(Niches)*, *Receiver(Niches)*, *Niche*

overlap, and *Niche overlap^2*, analogously defined to our measures on standards.

Since the basic probability of endorsing compatibility to platforms is also likely to depend on the total number of partners (platforms and non-platforms) endorsed by platforms, we capture the effect due to differences in partner numbers with a variable *Sender(Partners)*.

Moreover, platforms that were launched earlier also had more time to build relationships with other companies (Parker et al., 2017). Hence, we introduce a parameter *Sender(Platform age)* calculated as the difference between 2020 and the year of introduction. Similarly, we introduce the two controls *Sender(Firm age)* and *Sender(Firm Size)* that measure the effect of age as well as $\log(\text{number of employees})$, as larger firms tend to have larger asset stocks (Sierzchula et al., 2015; Sørensen & Stuart, 2000). We also include a

Table 2 Descriptive statistics on network characteristics and key measures

Measure	Value	Parameter	Min	Max	Mean	Std. Dev
<i>Size (Nodes)</i>	157	<i>Openness</i>	0	1	0.401	0.492
<i>Connections (Edges)</i>	879	<i>Edge-wise competition</i>	0	1	0.137	0.344
<i>Integration Edges</i>	280					
<i>Density</i>	0.036	<i>Number of Standards</i>	0	7	2.573	1.464
<i>In-Degree Centralization</i>	0.577	<i>Edge-wise standard overlap</i>	0	1	0.359	0.253
<i>Out-Degree Centralization</i>	0.222	<i>Giant platform</i>	0	1	0.032	0.176
<i>Betweenness Centralization</i>	0.188	<i>Multi-homing</i>	0	1	0.541	0.500

Table. 2 (a) on the left reports graph-level measures; Table. 2 (b) presents descriptive statistics on key measures for statistical inference

variable that measures the spatial proximity of the headquarters of two platform firms on the formation of edges (*Spatial proximity*).

We further add two parameters to account for membership in the Z-Wave Alliance on both in-degree (*Receiver(Z-Wave)*) and out-degree (*Sender(Z-Wave)*). Partner firms may show lower in-degrees due to the nature of data collection and potential differences in compatibility choices among Z-Wave members.

In addition, platform firms may enter into formal partnership agreements, unfolding in mutual signaling of compatibility. Thus, we account for *Reciprocity*¹⁴ (Pattison & Wasserman, 1999). To control for the extent to which this effect is due to the excess connections to and from giant platforms, include the network statistic *Giant platform reciprocity*, capturing dyad-wise covariates.¹⁵

A commonly observed effect is preferential attachment (Venkatraman & Lee, 2004; Weiss & Gangadharan, 2010), reflecting the tendency of nodes with low degrees to form edges to nodes with high degrees and vice versa (Albert & Barabási, 2002). Following Snijders et al. (2006), such preferences can be incorporated into the model by using geometrically weighted degrees, where the measure reflects anti-preferential attachment (Hunter, 2007), i.e., the coefficient estimate is positive if the degrees tend to be similar for all nodes. The parameter *Popularity spread* is used to capture this effect.

Results

Descriptive statistics and network statistics

Before turning to our analysis, we want to present some network statistics together with descriptive statistics on

our main variables and measures to provide more insights (Table 2).

The network consists of 157 nodes (i.e., platforms) that are connected by 879 directed edges (i.e., compatibility signaling), resulting in a relatively low density of 3.6%. Of 879 directed edges, 280 (i.e., 31.9%) go back to integrations with large general smart home platforms (i.e., Apple, Amazon, Google, IFTTT, and Samsung).

Freeman's graph centralization measures¹⁶ provided in the table reflect the degree of inequality in degrees, i.e., how heterogeneous a population is in terms of structural positions (Freeman, 1978; Hanneman & Riddle, 2014, p. 365). The in-degree and out-degree centralities of 0.577 and 0.222, respectively, indicate a substantial concentration in the network, particularly for in-degrees. The betweenness centralization¹⁷ on average equals 0.188, which reflects relatively homogeneous betweenness centrality of the platforms.

Looking at the descriptive statistics of the main parameters, we observe that about 40.0% of the platforms are classified as open. 13.7% of the edges are between firms that are active in the same industry. Platforms on average support 2.57 standards, ranging from 0 to 7, while edge-wise there is a mean overlap in standards of 35.9%, ranging from 0 to 100%. About 3.2% of the platforms meet our definition of giant platforms, and 54.0% of platforms integrate with multiple giant platforms.

¹⁴ That is, the propensity to form an edge from a node *i* to a node *j*, which is higher when there is already an edge from *j* to *i*.

¹⁵ Therefore, we construct a binary sociomatrix corresponding to a subgraph containing only edges from incumbent platforms.

¹⁶ Degree centrality generally provides a measure for node connectivity, reflecting the importance of nodes based on many "one-hop"-edges they hold to all other nodes in a graph, and is closely related to the notion of "social capital" (Borgatti & Everett, 2006; Hanneman & Riddle, 2014, p. 24). A high in-degree centrality reflects popularity (i.e., frequently getting promoted as compatible), while a high out-degree centrality reflects broader compatibility (i.e., promoting compatibility with many platforms). It equals 1 if one node has a full degree (star graph) and 0 if all nodes have equal degrees (circle graph).

¹⁷ Betweenness centrality generally measures the number of times a node is on the shortest path (geodesics) between all other node pairs, and thus acts as a "bridge", while usually having access to a larger fraction of information flows (Borgatti & Everett, 2006).

Table 3 Propensity to promote compatibility to other platforms

Parameter	(1)	(2)	(3)	(4)	(5)
<i>Sender(Openness)</i>		0.85** (0.08)			1.10** (0.10)
<i>Competition</i>		0.00 (0.17)			0.15 (0.19)
<i>Sender(Openness) x Competition</i>		-0.38° (0.22)			-0.51* (0.24)
<i>Standard overlap</i>			0.68° (0.34)		1.04* (0.46)
<i>Standard overlap²</i>			-0.11 (0.35)		-0.39 (0.45)
<i>Receiver(Giant platform)</i>				1.26** (0.28)	0.74* (0.29)
<i>Sender(Standards)</i>				0.15** (0.03)	0.09* (0.03)
<i>Receiver(Giant platform) x Sender(Standards)</i>				-0.23** (0.07)	-0.27** (0.07)
<i>Receiver(Giant platform) x Sender(Multi-homing)</i>				2.47** (0.25)	2.66** (0.26)
<i>Sender(Multi-homing)</i>	0.81** (0.09)	0.81** (0.09)	0.84** (0.09)	0.35** (0.10)	0.32** (0.10)
<i>Sender(Niches)</i>	-0.03* (0.01)	-0.01 (0.01)	-0.02° (0.01)	-0.07** (0.01)	-0.05** (0.01)
<i>Receiver(Niches)</i>	0.02** (0.01)	0.02** (0.01)	0.02** (0.01)	0.01 (0.01)	0.01 (0.01)
<i>Niche overlap</i>	0.91* (0.34)	0.91* (0.35)	0.77* (0.35)	2.23** (0.46)	2.33** (0.47)
<i>Niche overlap²</i>	-1.95** (0.49)	-1.90** (0.49)	-1.84** (0.50)	-2.66** (0.58)	-2.80** (0.58)
<i>Sender(Partners)</i>	0.01** (0.00)	0.01** (0.00)	0.01** (0.00)	0.01** (0.00)	0.01** (0.00)
<i>Platform age</i>	0.01° (0.00)	0.01* (0.00)	0.01* (0.00)	0.00 (0.01)	0.00 (0.00)
<i>Sender(Firm age)</i>	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
<i>Sender(Firm size)</i>	-0.07** (0.02)	-0.07** (0.02)	-0.07** (0.02)	-0.09** (0.02)	-0.09** (0.02)
<i>Spatial proximity</i>	0.29** (0.06)	0.29** (0.06)	0.27** (0.06)	0.34** (0.07)	0.26** (0.07)
<i>Sender(Z-Wave)</i>	0.47** (0.08)	0.35** (0.08)	0.44** (0.08)	0.39** (0.10)	0.27* (0.10)
<i>Receiver(Z-Wave)</i>	-0.11** (0.03)	-0.10** (0.04)	-0.16** (0.04)	-0.08° (0.05)	-0.16** (0.04)
<i>Popularity Spread</i>	-4.10** (0.13)	-4.09** (0.13)	-4.05** (0.13)	-3.28** (0.14)	-3.44** (0.12)
<i>Reciprocity</i>	1.53** (0.13)	1.44** (0.12)	1.50** (0.13)	1.58** (0.15)	1.36** (0.14)
<i>Giant platform reciprocity</i>	1.33** (0.23)	1.17** (0.23)	1.34** (0.23)	0.81** (0.25)	0.74** (0.25)
<i>Arc</i>	-3.34** (0.12)	-3.76** (0.13)	-3.58** (0.14)	-3.67** (0.16)	-3.78** (0.19)
Nodes	157	157	157	157	157
Edges	879	879	879	879	879
AIC	5773.58	5664.59	5747.58	5111.53	4818.26
BIC	5903.28	5818.61	5893.49	5273.65	5020.91
MCMC Std. Err	0.7412	0.691	0.7888	0.6535	0.5806
DoF	24,476	24,473	24,474	24,472	24,467
LogLikelihood	-2870.79	-2813.30	-2855.79	-2535.76	-2384.13

ERGM estimations on the sample with 157 platform sponsors and 879 compatibility promotions among them. Standard errors in parentheses

Significance levels: ° $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. Mean variance inflation factor equals 7.11

Findings: Platform-to-platform compatibility promotion

As part of our analysis, we computed five models, including (1) only control variables (base model), (2), the impact of openness and competition (3) the effect of standards, (4) integration with giant platforms, and (5) a combination of all previous models (full model). We interpret the full model (5) presented in Table 3.

As the MCMC-ML algorithm of the *statnet* package computes log-odds, which are generally difficult to interpret and compare (Hoetker, 2007), we further computed average marginal effects (King et al., 2000) for the full model, which we describe together with coefficient estimates. Our results are reported in Tab. 5, together with the Akaike information

criterion (AIC), the Bayesian information criterion (BIC) to evaluate model fit, and MCMC standard errors (MCSE) as a measure for additional uncertainty induced by the MCMC estimation procedure.¹⁸ Overall, our full model provides the best fit with respect to AIC and BIC, where the MCMC standard error of 0.5806 is relatively low.

¹⁸ Given that AIC and BIC were generally developed to assess the fit of models meeting the criterion of independence of observations, scholars suggest that these measures are not most accurate for dyad-dependent ERGMs (Harris, 2014). We thus complement our analysis by running the MCMC diagnostics procedure and the goodness-of-fit procedure provided by the *statnet* package. We discuss the latter at the end of this section.

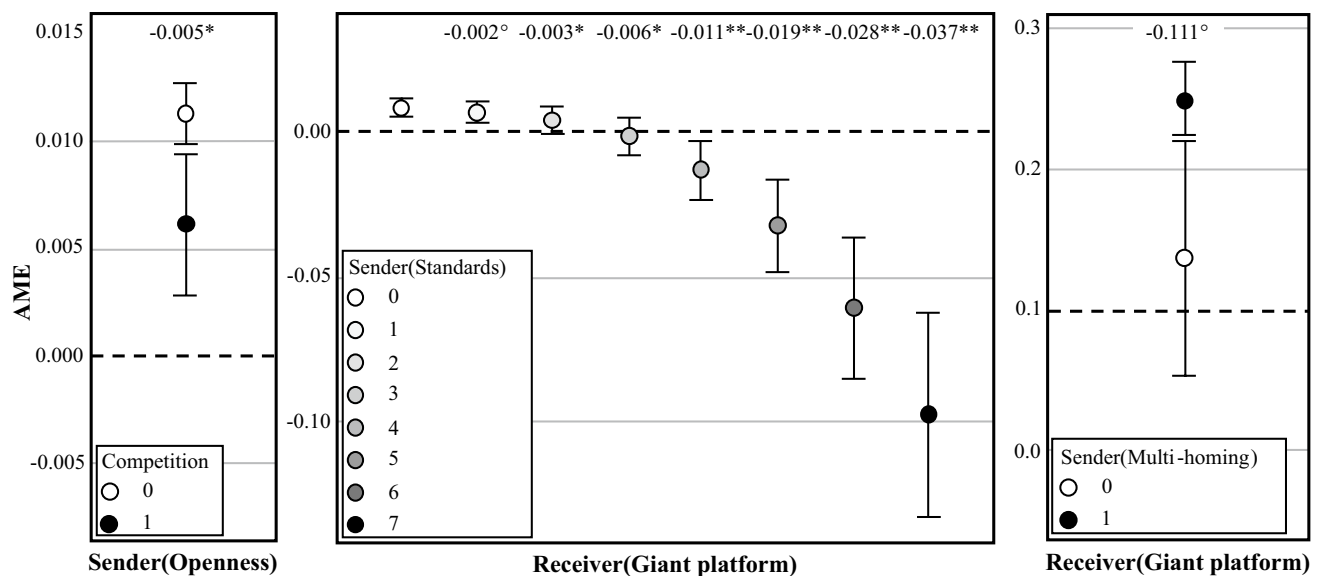


Fig. 4 Interaction plots for H1, H3, and H4. Note: Interaction plots for average marginal effects for *Sender(Openness) x Competition* on the left (a), *Receiver(Giant platform) x Sender(Standards)* in the middle (b), and *Receiver(Giant platform) x Sender(Multi-homing)* on

the right (c). 95%-confidence intervals are shown for (a) and (b), and 90%-confidence interval for (c). Second differences presented at the top of the graphs

Parameter estimates of the full model (5) show that platform-to-platform compatibility promotion (PCP) is significantly associated with the basic tendency of openness, where an open-appearing platform (*Sender(Openness)*) exhibits a significantly ($p < 0.01$) increased baseline probability of PCP, with average marginal effects of 1.2% for open platforms. No significant main effect emerges for competition. In fact, the statistically significant difference is due to the interaction effect with openness ($p < 0.05$), supporting H1. Accordingly, platforms do not necessarily exhibit a lower tendency to promote compatibility with platform firms in the same industry but do so in interaction with their decision to open their marketplaces to external complementors. The interaction plot in Fig. 4 (a) shows that the average marginal effects for PCP are 0.5% ($p < 0.05$) lower for open platforms that consider links to industry competitors, compared to open platforms that do not match primary industries.

Moreover, the probability of PCP increases with the similarity of the standard configurations (*Standard overlap*; $p < 0.05$), where platforms with a full overlap of the supported standards show a 1.1% ($p < 0.05$) higher probability of PCP. Nevertheless, we do not find a statistically significant estimator for the squared standard overlap (*Standard overlap²*), albeit the estimator is negatively pronounced. The AME is also not statistically significant. A deeper look into the dataset reveals that most platforms focus on the broader Wi-Fi standard, sometimes in combination with Z-Wave or ZigBee. It is therefore not surprising that it is more likely to achieve a greater similarity in the standard

configurations. We, therefore, find no support for hypothesis 2.

Turning to the number of open technology standards a platform supports (*Sender(Standards)*), the analysis shows a significant positive ($p < 0.05$) relationship with the likelihood of PCP (AME: 0.1%; $p < 0.05$). Looking at giant platforms (*Receiver(Giant platform)*), we observe a statistically significant ($p < 0.05$) and positive correlation between being a giant platform and being a target of PCP (AME: 0.8%; $p < 0.05$). The interaction of the number of supported open standards of the sender on one side and a receiving giant platform on the other side (*Receiver(Giant platform) x Sender(Standards)*) exhibits a significant negative ($p < 0.05$) relationship. The negative estimate reflects a decrease in the propensity to promote compatibility with giant platforms with an increasing number of standards the sending platform supports. The interaction plot in Fig. 4 (b) shows that the average marginal effect of *Receiver(Giant platform)* is significantly positive for sending platforms that support less than three open technology standards, while then gradually becoming more negative. Put differently, compatibility promotion towards giant platforms more frequently occurs for platforms supporting lower numbers in supported standards. The finding indicates that integrations with giant platforms are particularly interesting to platform sponsors that focus only on a few standards due to resource constraints or strategic considerations. The estimate conforms to hypothesis H3.

Also, compatibility promotion is associated with a significant ($p < 0.01$) tendency to multi-homing

(*Sender(Multi-homing)*), with the baseline probability being 0.3% ($p < 0.01$) higher. When looking at the interaction between being a receiving giant platform on one side and the multi-homing tendency concerning integrations by the sender on the other side (*Receiver(Giant platform) x Sender(Multi-homing)*), we observe a statistically significant ($p < 0.01$) and positive relation. Accordingly, H4 finds support. The interaction plot in Fig. 4 (c) shows that the average marginal effect of *Receiver(Giant platform)* is 11.1% ($p < 0.10$) higher for promoting platforms that simultaneously integrate with multiple giant platforms.

Next, we consider the control parameters. Looking at parameters related to product categories in the ecosystems, there is a significantly ($p < 0.01$) lower tendency of PCP with a higher number of market niches that can be served by the sending platform with its products. We further observe that platforms show heterophily in terms of categories of complementary products, where compatibility promotion increases with the number of common product categories (*Niche overlap*; $p < 0.01$) but where, however, the correlation shows diminishing returns (*Niche overlap*²; $p < 0.01$). The results suggest that platforms are more inclined to promote compatibility with platforms with a moderate level of category overlap (mean: 26.5%), leaving sufficient potential for complementarity.

Our further firm-level controls show that rather smaller firms (*Sender(Firm size)*; $p < 0.01$) show a higher activity to promote compatibility. Yet, we do not observe a significant difference between platform age (*Platform age*) and firm age (*Sender(Firm age)*). We believe this goes back to relatively similar platform and firm ages in our sample. Besides, a significant positive ($p < 0.01$) relationship between the number of partners (*Sender(Partners)*) of an endorsing platform and PCP is shown. In addition, we observe a significant correlation in *Spatial proximity* ($p < 0.01$). Considering Z-Wave memberships, we observe differences in activity for Z-Wave members (*Sender(Z-Wave)*) showing a higher propensity to promote compatibility ($p < 0.05$) and a lower propensity to be the target of compatibility promotion (*Receiver(Z-Wave)*; $p < 0.01$).

Turning to the basic structural features, the parameter estimate for *Popularity spread* is negative and significant ($p < 0.01$), indicating the presence of dispersion in the in-degree distribution. The negative estimate suggests that some platforms in our sample are listed as compatible disproportionately often. Indeed, in our sample, we observe that the highest in-degrees go back to giant platforms, underscoring their importance within the market and reflecting the network's in-degree centralization measure.

In addition, we observe a higher significant ($p < 0.01$) tendency toward *Reciprocity* in PCP, which is even higher in the case of giant platforms (*Giant platform reciprocity*; $p < 0.01$) and equals an average marginal effect of 0.8% ($p < 0.01$).

Accordingly, promoting compatibility with giant platforms leads to reciprocity, allowing sending platform sponsors to gain visibility of their installed bases.

Furthermore, the parameter estimation for *Arc* is strongly negative and statistically significant ($p < 0.01$), reflecting that the basic propensity to promote compatibility is overly low. In other words, platforms would not promote compatibility with other platforms if it were not for structural features, such as preferential attachment or the need for complementary devices, as discussed above.

Goodness-of-fit assessment

As ERGM parameter estimations occasionally do not produce simulated networks similar to the original one, it is necessary to visually inspect distributional fit on at least in-degrees, out-degrees, edge-wise shared partners, and geodesic distance (Hunter et al., 2008). The plots are generated by simulating 1,000 network graphs using the estimated parameters to then infer confidence intervals. The distributions are presented in Fig. 5.

The four plots compare the log-odds for each value in the distributions of in-degree, out-degree, edge-wise shared partners, and geodesic distance in the observed network to the range of log-odds in the simulated networks. Overall, the full model shows a fair similarity between the simulated networks and the observed network, increasing our confidence in the model.

Robustness

Next, we discuss alternative measures to inspect the robustness of our findings against different sets of standards and size variables. The robustness tests are reported in Table 6 in Appendix 2.

First, our parameter on the openness of a platform only covers the existence of a compatibility list or marketplace. To map a somewhat stricter definition of the term, we use an alternative measure that captures openness based on the relation of own complements to third-party complements (model (1)). Accordingly, a platform is assumed to be open if the platform curates more third-party complements than its own complements. The results do not differ significantly from those of our main model.

Second, the main model incorporated only open technology standards, as they can potentially be adopted by any platform, in contrast to proprietary standards. Yet, some platform sponsors offer proprietary standards, which may shield rivals from establishing compatibility. This may introduce a selection bias. Therefore, we construct an alternative model, incorporating all standards we initially coded (model (2)). The results are close to that of the main model.

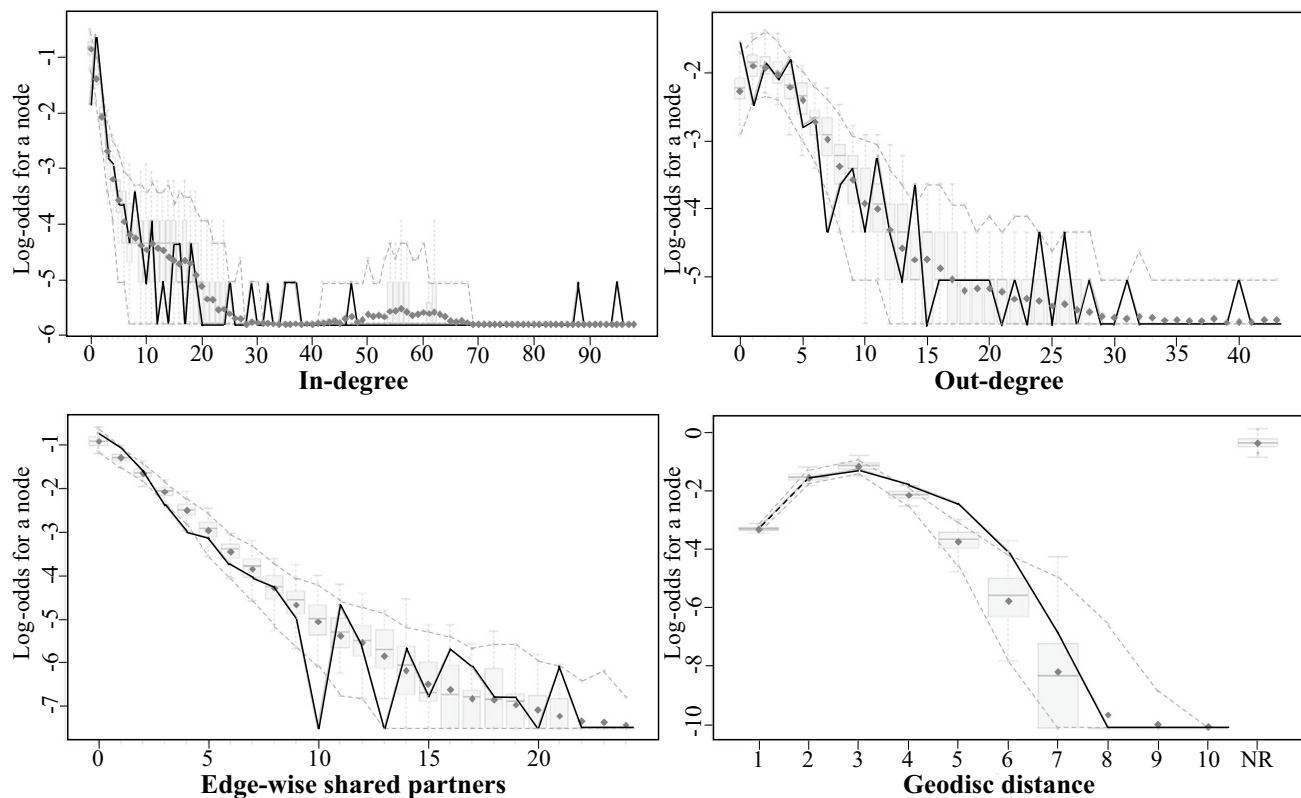


Fig. 5 Goodness-of-fit plots for the full model

Finally, an alternative explanation for the moderation of the number of standards may be differences in firm size. Accordingly, we replace standard measures in the interaction terms with a firm size parameter. The results are reported in models (3), (4), and (5). The estimates are consistent with our main model, suggesting that firm size differences do not explain the variances.

Discussion

Digital product platform providers such as those in the smart home market face a complex decision in terms of opening up to complementors that offer their own platforms. In contrast to platform ecosystems that rely on software complements, platform ecosystems in this context rely on hardware complements that incorporate open technology standards and are certified in industry consortia. Hence, platform sponsors need to navigate in a setting with a shared market of components and end-users, imposing a dual role of platform sponsor and complementor. One promising approach to balancing the tension between opening up to create adoption and safeguarding against the competition in this context is to endorse certain compatible offerings.

Theoretical implications

This study provides theoretical contributions to research on the management of ecosystem value (Benlian et al., 2015; Boudreau, 2010; Inoue & Tsujimoto, 2018; Rietveld et al., 2019). Most previous studies focused on software complements that are developed for particular platforms (e.g., Benlian et al., 2015; Rietveld et al., 2019), with deliberate choices by developers to port their complements to other platforms as well (Landsman & Stremersch, 2011). This study examines how platform sponsors manage their ecosystems in settings with hardware complements developed for a shared technology market, with industry consortia coordinating development efforts and providing the certification infrastructure. To this end, the study shows that platform sponsors address the devolution of control going back to the integration of open technology standards by selectively promoting complementary products and platforms, thus balancing the tension between openness and competition. As such, the study extends the concept of selective promotion. We observe that about 60% of the platforms in the sample promote compatibility with certain partners and even 70% integrate with giant platforms. The study examines two complementary approaches to balance openness and

competition: (1) complementarity in standards as a way to seek differentiation and cover a wider array of standards, and (2) integrations with giant platforms to seek indirect connections with fewer standards. Our study lends particular support to the second approach, with similarity in standards driving promoted links among platforms. We believe, that while it is an efficient strategy to cover most of the underlying standards with a few promoted links, complementarity in standards does not play a major role in this setting. We rather observe that platforms tend to focus on other platforms within the same standards, underscoring the relevance of alliances to identify (potential) partners (Leiponen, 2008), with the number of standards two platforms support considerably driving the likelihood to promote cross-platform compatibility.¹⁹ The study identifies a range of factors that are associated with compatibility promotion that are in line with previous findings, including spatial proximity (Sierzchula et al., 2015), preference for heterogeneity in ecosystem niches (Hagiu & Lee, 2011), and dissimilarity in the primary industry sector (Mantena & Saha, 2012). Compatibility promotion can be viewed as a strategic approach to managing an ecosystem's value through balancing value creation by end-users and value captured by the platform sponsor. In particular, the study shows one form of how platforms make use of what Henfridsson et al. (2018) call 'path channeling'. Following their framework, platform sponsors create value connections to the digital resources of other platform sponsors by integrating the same set of open technology standards or opening APIs (i.e., value creation through design recombination). While end-users create value through combining digital resources of various suppliers – even in undesired forms – (i.e., value creation through use recombination), compatibility promotion denotes a form of path channeling, aiming at capturing more value by steering value connections made by end-users. Particularly giant platforms attract much of the value connections defined by platform sponsors. In line with previous research (Weiss & Gangadharan, 2010), we observe a power-law distribution in promoted links between platforms. Together, the five giant platforms account for almost one-third of all promoted compatibility in our network graph of 157 platforms. As such, our study supports anecdotal evidence of how giant platforms make their digital resources more center-stage in the

smart home market, allowing them to capture more value (Henfridsson et al., 2018). Even more so, as tight integrations with their platforms give them access to larger portions of the data streams in the smart home market. Accordingly, giant platforms shape the industry architecture in such a way that they become "bottlenecks" (Jacobides et al., 2006), which increases their chance of becoming platform leaders in the emerging market (Cusumano & Gawer, 2002).

Second, the study contributes to the literature on platform openness by considering platform-to-platform openness (Mosterd et al., 2021). As such, the study addresses recent calls to advance understanding of openness (Broekhuizen et al., 2021; Mosterd et al., 2021; Ondrus et al., 2015), where it particularly considers platform sponsors as the target of openness decisions. Most of the previous literature focused on developers as the target of openness decisions by platform sponsors largely ignored the inclusion of customers and rarely specified sub-dimensions of openness (cf. Broekhuizen et al., 2021). Our study considers open technology standards as a source of platform openness at the technology level (Ondrus et al., 2015; West, 2003), with more standards corresponding to a higher degree of openness. Overall, the platforms in our sample can be divided into two groups of the almost same size, with one group integrating at most two standards and the other group integrating more than two standards in their platforms.²⁰ We find empirical evidence that with an increase in technological openness in terms of the number of open standards, the likelihood to promote compatibility to more platforms increases as well. Those platform sponsors that integrate with giant platforms, however, support fewer technology standards, which also reflect a higher degree of openness at the technology level. While open technology standards determine the degree of openness in technical terms by defining with which and to what extent platforms interoperate, compatibility promotion addresses the perception of platform openness, rather than changing the actual degree of interoperability. Similar to Benlian et al.'s (2015) framework of *developers'* perception of platform openness, the study shows how platform sponsors influence the *end-users'* perception of platform openness by varying the degree of transparency. However, in contrast to transparency about the market mechanisms of the distribution channels faced by developers, platform sponsors in our study vary the degree of transparency about the categories and brands that can be used in conjunction with their platforms. Hence, compatibility promotion corresponds to 'category openness' (Broekhuizen et al., 2021),

¹⁹ Note that in our sample, the combinations of standards the platforms are integrated with vary considerably. Hence, there is no single combination dominating adoption choices. However, Wi-Fi/IP denotes the most widely adopted standards. Overall, our sample is divided into two approaches, one where platforms adopt one standard (mostly Wi-Fi) or two (mostly Wi-Fi + X), and one where platforms support three or more standards. Overall, the standard domains in which a platform is located determine its links to other platforms. As such, platform competition and openness also to some extent depend on the alliances behind open technology standards.

²⁰ That is, 26% support one open standard only, 30% support two open standards, and 44% support three and more open standards. While configurations of adopted standards differ across platforms, 134 of 157 platforms support the more general Wi-Fi/IP standards, allowing to establish cloud-to-cloud connections.

which complements technological openness (i.e., accessibility in terms of interoperability). In this regard, the study adds to the body of literature on the multidimensionality of platform openness (Benlian et al., 2015; Broekhuizen et al., 2021; Ondrus et al., 2015) by showing how platform sponsors compensate for undesirable effects of accessibility at the technology level with transparency at the marketplace level. More specifically, while most of the platforms in our sample support Wi-Fi/IP standards and many support Z-Wave, only a fraction of interoperability between these platforms is promoted, particularly between platform sponsors with dissimilar sectors and high niche complementarity.

Previous studies created a profound understanding of the mechanisms underlying platform competition, stressing differences in pricing schemes and technology core (Katz & Shapiro, 1985; Mantena & Saha, 2012). Yet, as studies on compatibility between platforms usually apply mathematical models, conceptualizing platforms as two-sided markets, they are limited to dyadic relationships (two platforms). As our approach is based on an exponential random graph model estimation, it helps us capture structural features that go beyond dyads that otherwise would have imposed a bias on our estimation (Pattison & Wasserman, 1999; Robins, 2014).

Managerial implications

Our study also yields practical contributions by offering a strategic perspective on platform openness, informing design considerations, and, more broadly, by helping to better understand the underlying mechanisms driving interconnections between platforms. Our study offers concrete recommendations.

First, our study shows that platforms can draw end-users' attention to specific compatible platforms, particularly those in other sectors that are complementary in terms of device niches, regardless of the *de facto* prevailing compatibility. We generally observe considerable differences in form (i.e., partner curation, product curation, promotion of system/platform integration) and magnitude (i.e., number of platforms promoted as compatible) in which platform sponsors promote other platforms as compatible. It is further shown that compatibility promotion is characterized by reciprocity. Accordingly, promotion by many complementary platforms can also lead to promotion by many platforms. An example in our dataset represents Fibaro, which promotes relatively many platforms and receives relatively much promotion back. Overall, promoting compatibility can lead to three relevant outcomes. First, a user adopts the focal platform and uses compatible complementary devices of another platform. Second, a user adopts the other platform and uses complementary devices of the focal platform. Third, the user adopts both platforms and uses both together with their

complements. The first case depicts the ideal case, which allows a platform sponsor to offer superior services, such as smartphone applications or cloud services, making the focal platform the “daily driver” of a user. The second case depicts a scenario in which the competing platform is superior and degrades the focal platform to a mere complement provider and possible converter. In the last case, different platforms symbiotically coexist in the consumers' homes, as access to APIs fosters demand-side multi-homing, making it more important to offer different services and/or device niches (Boudreau, 2012; Inoue & Tsujimoto, 2018). By promoting certain platforms and their complements, platform sponsors influence the position within the network of interconnected platforms and as such the value paths to and from other digital resources of which they become part (Henfridsson et al., 2018).

Second, integrations with giant platforms can be an attractive target for cloud-to-cloud integrations. While some platforms are surrounded by larger existing installed bases from adjacent markets and offer proprietary standards based on widely adopted Internet-based standards, integrations with these platforms offer a fruitful avenue to overcome constraints imposed by incompatible standards, while avoiding advertising rival platforms and drawing on the potential to receive demand spillovers (Li & Agarwal, 2017) or awareness spillovers (Song et al., 2021). Our results demonstrate that some fraction of reciprocity in promotion goes back to giant platforms, as they curate products, allowing users of these platforms to easily identify integrated platforms. Moreover, especially giant platform sponsors show high betweenness centralities, reflecting their central role in bridging between (incompatible) platforms. Nonetheless, such integrations increase dependence, as they require a tight coupling, and bear the potential to sideline the initial offering of the platform, which harbors the danger of platform envelopment by the giant platform (Eisenmann et al., 2011; Hilbolling et al., 2020). Therefore, simultaneous integration with multiple giant platforms proves to be a way to reduce the risk of platform envelopment. As such, multi-homing in terms of integrations with multiple giant platforms can be a third viable strategy to defend against platform envelopment, in addition to opening to find many allies and making the own bundle similar to that of the attacker (Eisenmann et al., 2011). In addition, combining the integration with multiple giant platforms with fewer open technology standards integrated with the focal platform appears as the preferred approach by many platforms. We believe this goes back to a reduction in costs.

Limitations and directions for future research

All research designs imply tradeoffs. A usually mentioned issue in network analysis considers the selection of nodes

(Laumann et al., 2017). An “incorrect” node selection, possibly includes “irrelevant” nodes, while excluding potentially important nodes. This is especially crucial as networks generally do not possess well-defined boundaries (in contrast to formal groups), which makes it difficult, if not impossible, to determine the complete set of actors (Borgatti & Halgin, 2011). With our extensive triangulation of platform stakeholders through web searches, standards memberships, and Amazon product pages we believe we included the most important actors relevant to the study. As standardization plays a dominant role in our study, we started with a relatively well-defined group of firms, i.e., Z-Wave Alliance members, and captured promoted compatibilities directly with other actors inside and outside this group, getting a fair picture of relations from and to Z-Wave platforms. Yet, we did not include software extensions (“apps”) in our network, as we are interested in communication protocols that are embedded in devices. Future research may extend this study and analyze differences in relations going back to promoting compatible devices and third-party software extensions. Specifically, the different approaches of giant platforms provide an interesting starting point to study strategic implications with respect to compatibility promotion in platform ecosystems spanning a larger fraction of the layered modular architecture. In addition, future studies may verify the findings of this study for platforms outside the Z-Wave Alliance. Similar settings can be found for service firms providing APIs where complements are mashups for Android or iOS, such as banks or insurances (Kazan et al., 2018; Weiss & Gangadharan, 2010).

A related concern focuses on the definition of “platform” in our study. We, on purpose, defined platforms in a rather narrow way to study similar platforms (i.e., offering stand-alone solutions for the consumer mass market). Consequently, this study covers smart home platforms, which are perceived by end-users and deemed most relevant in the industry. Platform firms offering back-end solutions in a business-to-business manner usually have a different view on network effects with respect to consumers. As such, B2B platforms show different behaviors, as they are either pure cloud platforms running in the background without visible connections or merely provide white label solutions with a general tendency towards creating as many edges as possible. Both cases create upward or downward biases. However, future research may also consider the behaviors of back-end solution providers to determine their role in standardization and compatibility choices (Papert & Pflaum, 2017).

Another concern, considering network analysis, is the argument that one cannot accurately predict the observable network structure without considering the network’s full trajectory, as it is the result of a longer evolutionary process (Borgatti & Halgin, 2011). Robins (2014) serves as a

defense for analyzing snapshot data: “because of the relative constancy of network organizing principles, a single network observation captures the accumulation of social processes, like an archaeological trace. Stable organizing principles will result in patterns of network ties that can be observed in the data, even when data are from a single instance in time. These patterns of network ties are indeed the structural signature of the network and provide evidence from which we may infer something of the social processes that build the network.” (p. 484). Yet, a longitudinal study on the evolution of compatibility structures over time provides an interesting space for further research. Especially cascading effects within networks (Borgatti & Halgin, 2011) can be studied, such as how platform competition unfolds and propagates through the network.

Particularly web repositories such as The Wayback Machine prove a good source to construct unique datasets covering several years in the past. Also, directories such as the ProgrammableWeb can provide good starting points, as demonstrated in Weiss and Gangadharan’s (2010) study.

Conclusion

Embedded in digital infrastructures, platforms increasingly form interconnections between each other, driven by the employment of boundary resources such as application programming interfaces. As platform sponsors seek to balance adoption and appropriability in an attempt to defend platforms against the competition, this study introduces the concept of platform-to-platform compatibility promotion. We constructed a unique dataset covering 157 platforms and conducted a network analysis based on an exponential random graph model (ERGM) to incorporate platform features, dyadic characteristics, and structural processes. Our results suggest that platforms’ compatibility promotion choices concerning other platforms reflect a trade-off between openness and competition, compensating access at the technology level with transparency at the marketplace level. We find a strong tendency to integrate with giant platforms (about 70%), allowing to support lower numbers of standards (i.e., openness at the technology level) but multi-homing to several giant platforms to address the threat of platform envelopment. We do not find evidence for a pronounced preference toward platforms with dissimilar sets of supported standards. Platform sponsors rather prefer to promote platforms with higher similarity in supported standards. Overall, platforms tend to focus on a smaller number of standards, most often including the broader Wi-Fi/IP standards allowing to establish direct cloud-to-cloud connections.

Appendix 1

Considered open technology standards and giant platforms

Table 4 Overview of open standards covered by this article (as of December 2020)

Standard	Radio	Sponsor	Product categories	Adopters ^a	Certified products ^b	URL
Bacnet	No	ASHRAE	Interfaces, controllers, routers	208	1,100+	http://www.bacnet.org/
Bluetooth	Yes	Bluetooth Special Interest Group	Mainly file transfer, audio/headsets, HID, device synchronization, access control	36,560+	250,000+	https://www.bluetooth.com/
DECT ULE	Yes	ULE Alliance	Security, energy, cordless telephones	130+	50+	https://www.ulealliance.org/
DMX	No	ESTA	Lighting	100+	N/A	https://my.esta.org/directory
EnOcean	Yes	EnOcean Alliance Inc	Lighting, temperature, air quality, security, smart metering	400+	1,400+	https://www.enocean-alliance.org/
GSM (3G, 4G, 5G)	Yes	GSM Association	Mobile connectivity	400+ ^c	N/A	https://www.gsma.com
KNX	Yes	KNX Association	Security, energy, light	500+	5,000+	https://www.knx.org/
Modbus	No	Modbus Organization Inc	Controllers	40+	80+	https://modbus.org/
Thread	Yes	Thread Group	Gateways, semiconductors	300+	35+	https://www.threadgroup.org/
Wi-Fi	Yes	IEEE, Wi-Fi Alliance	Local networks, mainly phones, routers, and TVs certified	750+	61,900+	https://www.wi-fi.org/
X10	Yes	X10 (USA) Inc	Controllers	N/A	N/A	https://www.x10.com/
Zigbee	Yes	Zigbee Alliance	Light, security, energy	300+	2,600+	https://zigbeealliance.org/
Z-Wave	Yes	Z-Wave Alliance	Security, light, energy	160+	3,300+	https://z-wavealliance.org/

^aOnly provided for formal members of, e.g., an alliance

^bOnly if certification program available

^cOnly counting device manufacturers, excluding telecommunication network operators

Appendix 2

Robustness tests

Table 5 Overview of giant platforms and their adoption

Platform sponsor ^a	In-degree	Listed complements / partners / apps	User base	Primary industry
Amazon	95	121 / 83 / 828	<ul style="list-style-type: none"> • 46 mil. Amazon echo users • 100,000 Alexa skills • 60,000 supported devices • Alexa voice assistant 	E-Commerce
Google	88	0 / 0 / 230	<ul style="list-style-type: none"> • 27.1 mil. Google Home users • 2.8 bn. Android users • Google assistant 	Mobile phones
Apple	37	563 / 190 / 127	<ul style="list-style-type: none"> • 2.5 mil. Home Pod users • 1 bn. iPhone users • Siri voice assistant 	Mobile phones
IFTTT	35	0 / 0 / 666	<ul style="list-style-type: none"> • 18 mil. users • 650 partner services 	Web service
Samsung	25	1109 / 89 / 0	<ul style="list-style-type: none"> • 37.1% Android market share • Bixby voice assistant 	Mobile phones, appliances

^aSources: Amazon (<https://www.statista.com/statistics/794480/us-amazon-echo-google-home-installed-base/>, <https://www.statista.com/statistics/912856/amazon-alexa-skills-growth/>), Google (<https://www.statista.com/statistics/794480/us-amazon-echo-google-home-installed-base/>, <https://www.businessofapps.com/data/android-statistics/>), Apple (<https://www.statista.com/statistics/794480/us-amazon-echo-google-home-installed-base/>, <https://backlinko.com/iphone-users#iphone-users>), IFTTT (<https://www.computerworld.com/article/3239304/what-is-ifttt-how-to-use-if-this-then-that-services.html>), Samsung (<https://www.businessofapps.com/data/android-statistics/>)

Table 6 Robustness tests on the propensity to promote compatibility to third-party platforms

Parameter	1	2	3	4	5
<i>Sender(Openness)</i>		1.11** (0.10)	1.22** (0.18)	1.09** (0.10)	1.09** (0.10)
<i>Sender(Openness to complementors)</i>	0.88** (0.10)				
<i>Competition</i>	-0.04 (0.17)	0.16 (0.19)	0.16 (0.19)	0.21 (0.18)	0.16 (0.19)
<i>Sender(Openness to complementors) x Competition</i>	-0.23 (0.23)				
<i>Sender(Openness) x Competition</i>		-0.50* (0.24)	-0.53* (0.24)	-0.49* (0.23)	-0.52* (0.24)
<i>Sender(Openness) x Sender(Firm size)</i>			-0.02 (0.03)		
<i>Standard overlap</i>	0.90* (0.44)		1.07* (0.46)	1.05* (0.47)	1.06* (0.46)
<i>Standard overlap^2</i>	-0.29 (0.44)		-0.41 (0.46)	-0.38 (0.46)	-0.40 (0.45)
<i>All standard overlap</i>		1.28* (0.47)			
<i>All standard overlap^2</i>		-0.59 (0.46)			
<i>Abs. firm size diff</i>				0.05** (0.01)	
<i>Receiver(Giant platform)</i>	0.65* (0.29)	0.75* (0.29)	0.73* (0.29)	0.68* (0.29)	0.65° (0.35)
<i>Receiver(Giant platform) x Sender(Multi-homing)</i>	2.66** (0.26)	2.65** (0.26)	2.67** (0.26)	2.67** (0.26)	2.66** (0.26)
<i>Sender(Standards)</i>	0.11** (0.03)		0.09* (0.03)	0.10** (0.03)	0.09* (0.03)
<i>Receiver(Giant platform) x Sender(Standards)</i>	-0.25** (0.07)		-0.27** (0.07)	-0.28** (0.07)	-0.27** (0.07)
<i>Receiver(Giant platform) x Sender(Firm size)</i>					0.02 (0.03)
<i>Sender(Multi-homing)</i>	0.40** (0.10)	0.32** (0.10)	0.31** (0.10)	0.34** (0.10)	0.32** (0.10)
<i>Giant platform reciprocity</i>	0.67* (0.25)	0.71* (0.26)	0.76** (0.25)	0.61* (0.26)	0.75** (0.25)
<i>Sender(Niches)</i>	-0.03* (0.01)	-0.05** (0.01)	-0.05** (0.01)	-0.05** (0.01)	-0.05** (0.01)
<i>Receiver(Niches)</i>	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
<i>Niche overlap</i>	2.25** (0.48)	2.29** (0.48)	2.34** (0.48)	2.38** (0.48)	2.33** (0.48)
<i>Niche overlap^2</i>	-2.72** (0.60)	-2.78** (0.59)	-2.80** (0.59)	-2.86** (0.59)	-2.81** (0.58)
<i>Sender(Partners)</i>	0.01** (0.00)	0.01** (0.00)	0.01** (0.00)	0.01** (0.00)	0.01** (0.00)
<i>Platform age</i>	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
<i>Sender(Firm age)</i>	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
<i>Sender(Firm size)</i>	-0.07** (0.02)	-0.09** (0.02)	-0.07** (0.02)	-0.09** (0.02)	-0.09** (0.02)
<i>Spatial proximity</i>	0.25** (0.07)	0.26** (0.07)	0.27** (0.07)	0.27** (0.07)	0.26** (0.07)
<i>Sender(Z-Wave)</i>	0.31** (0.10)	0.27* (0.10)	0.27* (0.10)	0.28* (0.10)	0.27* (0.10)
<i>Receiver(Z-Wave)</i>	-0.15** (0.04)	-0.17** (0.04)	-0.17** (0.04)	-0.19** (0.04)	-0.16** (0.04)
<i>Popularity Spread</i>	-3.45** (0.12)	-3.43** (0.12)	-3.44** (0.12)	-3.40** (0.12)	-3.44** (0.12)
<i>Reciprocity</i>	1.33** (0.14)	1.38** (0.14)	1.36** (0.14)	1.39** (0.14)	1.36** (0.14)
<i>Arc</i>	-3.79** (0.19)	-3.81** (0.19)	-3.85** (0.21)	-4.01** (0.20)	-3.77** (0.19)
<i>Nodes</i>	157	157	157	157	157
<i>Edges</i>	879	879	879	879	879
<i>AIC</i>	4870.82	4814.66	4820.60	4798.20	4820.66
<i>BIC</i>	5073.47	5017.31	5031.36	5008.96	5031.42
<i>MCMC Std. Err</i>	0.5307	0.7499	0.7338	0.7119	0.3329
<i>DoF</i>	24,467	24,467	24,466	24,466	24,466
<i>LogLikelihood</i>	-2410.41	-2382.33	-2384.30	-2373.10	-2384.33

ERGM estimations on the sample with 157 platform sponsors and 879 compatibility promotions among them. Standard errors in parentheses

Significance levels: ° $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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