Research Policy 52 (2023) 104705

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Firm exit from open multiparty alliances: The role of social influence, uncertainty, and interfirm imitation in collective technology development

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ARTICLE INFO

Keywords:
Emerging technologies
Innovation management
Interfirm collaboration
Open multiparty alliances
Networks

ABSTRACT

This study examines exit dynamics in open multiparty alliances, an important form of interfirm collaboration that includes committee-based standard-setting organizations, research and technology consortia, and other types of open meta-organizations. Open multiparty alliances differ markedly from more commonly studied dyadic alliances and closed multiparty alliances due to the open nature of membership and the broad diversity of firms that collaborate towards shaping the trajectory of emerging technologies in a sector. Drawing from literature on interfirm imitation, we posit that under conditions of elevated uncertainty about the technologies under development and the ability of diverse alliance members to work together effectively, firms are subject to social influence from their industry peers and thus tend to imitate them in exiting open multiparty alliances. However, we also argue that firms that are central in the wider network of alliances have access to superior information on sector developments as well as key resources that immunize them from such social influence effects. Analyses of the exit dynamics of the nine most influential open multiparty alliances that shaped the global mobile phone sector between 2000 and 2012 support our predictions. Our findings contribute to research on interfirm collaboration in technology-intensive contexts, in particular on open collaboration between multiple partners.

1. Introduction

> I founded this organization 15 years ago and I'm quite surprised that it's still going strong. An organization like that takes a life on its own […] We created a system […] that will foster innovation, that will achieve its goals, and sometimes it's our role to make companies feel that their contributions are valuable and it's in their best interest to participate. Companies need to sometimes be reminded of that but ultimately, it's up to them to decide; we cannot force companies to participate […] there is no contract. We don't really have control over [member] exit. It's purely a voluntary effort.
>
> (Founder of RapidIO)

Interfirm collaboration is a common means for firms to access complementary resources and overcome the uncertainty ubiquitous in innovation environments (Galaskiewicz, 1985; Oliver, 1990; Salancik and Pfeffer, 1978). Open multiparty alliances are open-membership collectives of three or more organizations from diverse industries that work collectively towards a common goal of shaping the trajectories of emerging technologies. Over recent years, they have played a key role in the evolution and growth of technology-intensive sectors such as that of mobile phones (Cohen et al., 2016; Lavie et al., 2007; Leiponen, 2008). These alliances are a key vehicle by which firms can manage an environment of technological uncertainty (Cohen et al., 2016; Lavie et al., 2007), as they offer opportunities for firms to learn about and adapt to wider technological developments in a sector, as well as to influence their direction (Ranganathan et al., 2018). A well-known example is Google's initiative to form the Open Handset Alliance (OHA), an open multiparty alliance comprising firms across the mobile phone ecosystem that enabled the launch of the widely successful Android platform[1] (Gulati et al., 2012; Kenney and Pon, 2011).

Recently, scholars have started to document open multiparty alliances[2] as an increasingly common form of collaborative innovation (Davis, 2016; Lavie et al., 2007; Ranganathan et al., 2018; Roelofsen

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[1] The Android operating system enabled by OHA rapidly captured 25 % of the smartphone market within 15 months of its launch (Kenney and Pon, 2011).

[2] Many of the multiparty alliances studied in prior research are open in nature but were not explicitly labeled as such. For simplification purposes, we refer to the collaboration initiatives in such studies as "open multiparty alliances".

https://doi.org/10.1016/j.respol.2022.104705
Received 16 February 2022; Received in revised form 25 November 2022; Accepted 3 December 2022
Available online 23 January 2023

et al., 2011) that differs fundamentally from the more commonly studied dyadic alliances (e.g., Hohberger et al., 2020; Kogut, 1989; Kok et al., 2020; Zhang et al., 2007). This emerging stream of research has primarily focused on the formation and growth of open multiparty alliances (Rosenkopf and Padula, 2008), the timing of firm entry and consequences on performance (Lavie et al., 2007), and the dissolution of such alliances (Heidl et al., 2014). However, the determinants of firms exiting open multiparty alliances have largely been ignored. Due to the unique, group-like membership dynamics that only surface after entry (Davis, 2016), firms in open large-scale alliances may influence one another in deciding to stay or leave.

In this study, we examine how social influence mechanisms among alliance members affect firms' decisions to exit them. Although imitation dynamics have been documented in other high-uncertainty contexts, such as exits from technological markets (Pontikes and Barnett, 2017) and investment syndicates (Gaba and Terlaak, 2013), it is important to understand whether, and under what circumstances, such mechanisms also manifest when it comes to exiting open multiparty alliances. As the opening quote illustrates, open multiparty alliances rely primarily on self-selected membership and do not impose barriers to exit (Gulati et al., 2012). These conditions could lead to firm exits in large numbers, which can have a profound impact on the direction of technological exploration within such alliances, and on the chances that the technologies under development will succeed (Yue, 2012). We posit that, in light of the elevated uncertainty surrounding the potential of emerging technologies (Cohen et al., 2016; Roca et al., 2017) and the difficulty of assessing the trustworthiness of other group members as collaboration partners (Fonti et al., 2017), firms imitate the alliance exits of their peers in the same industry. This is because firms interpret peer-firm exits as valuable signals about the technological direction being taken and the desirability of the alliance as a collaborative effort (Cohen et al., 2016; Fonti et al., 2017; Yue, 2012) and because firms desire to maintain the status quo in the industry-wide efforts to develop potentially competing technologies (Garcia-Pont and Nohria, 2002). We further posit that the imitation effect is weakened for firms that hold positions of high betweenness centrality in the wider network of alliances between firms within the relevant sector. Occupying such positions in the network gives firms superior access to information and resources, and thus renders them less dependent on signals sent by their industry peers (Lawrence, 2008).

To test our predictions, we collected a rich and unique longitudinal dataset of the membership of 1960 firms in the nine major open multiparty alliances that drove the emergence and growth of the mobile phone sector between 2000 and 2012,[3] primarily based on archival Internet data, and in combination with patent and dyadic/closed multiparty alliance data. We complemented our quantitative data with contextual information from 32 interviews with the presidents and firm members of these alliances. The period under study was marked by radical technological change as, thanks to advances in digital technology and wireless communication, mobile phone handsets transitioned from competing primarily on hardware, to competing on software (Fuentelsaz et al., 2015). Because of the elevated levels of technological uncertainty in this environment, the period witnessed a rapid increase in collaborative activities, and particularly of open multiparty alliances (Davis, 2016). These were aimed at coordinating technological progress, improving the mobile phone user experience, and resolving potential compatibility issues among technology components (Fuentelsaz et al., 2015). Firm representation within these alliances cut across industry boundaries, allowing us to explore the extent to which imitation behavior is contained within industry subgroups.

We found empirical support for our predictions: firms imitate the exit decisions of their industry peers, but firms with high betweenness centrality in the sector network are largely immune to these imitation effects. To probe our argument that it is social influence that underpins imitation, we conducted additional analyses to explore the mechanisms that we expect to drive social influence effects.

Our findings advance the understanding of interfirm collaboration dynamics in three main ways. First, we extend the growing literature on open collaboration between multiple partners in technology-intensive contexts such as open and committee-based standard-setting organizations (SSOs) (Ranganathan et al., 2018; Wiegmann et al., 2017), research and technology consortia (Fonti et al., 2017; Lavie et al., 2007; Roelofsen et al., 2011), and other forms of open meta-organizations (Gulati et al., 2012). In response to calls to attend to the unique dynamics in such collaborations (Davis, 2016), we show that open multiparty alliances display group-like dynamics in which firms infer the desirability of remaining a member from the actions of their industry peers. These dynamics set open multiparty alliances apart from dyadic alliances where such group dynamics are by definition absent (Davis, 2016) and from closed multiparty alliances such as industry constellations (e.g., Garcia-Pont and Nohria, 2002; Lazzarini, 2007), market-based SSOs and closed consortia (e.g., Rosenkopf et al., 2001; Schilling, 2002), in which contractual constraints impose limits on premature exit (Gulati et al., 2012). Second, and relatedly, our research shows how a combination of broad diversity in organizational membership across industry boundaries and ease of entry/exit in open multiparty alliances creates ideal conditions for social influence dynamics to manifest in firms' decisions to give up membership. This finding informs research into the conditions under which social influence impacts collective technology development activities (Garcia-Pont and Nohria, 2002). Due to similarities in the nature of the collaboration conditions (i.e., openness and diversity of membership), these findings may extend to other forms of open collaboration such as open-source software communities (Lakhani and Von Hippel, 2003) and digital platforms (Kenney and Zysman, 2016; Nambisan et al., 2018). Finally, in line with claims that imitation is often more complex and imperfect than assumed in existing theories (Posen et al., 2013; Sharapov and Ross, 2023), we reveal sources of variance in the tendency to imitate industry peers in interfirm collaboration, documenting an important contingency that explains why some firms are more prone to social influence than others while some are immunized from social influence altogether. Firms occupying a central position in the sector's wider web of interfirm relations have access to superior information and resources to their peripheral peers, thus serving as a protective shield from social influence effects.

2. Theory and hypotheses

2.1. Open multiparty alliances compared to other types of alliances

Innovation research has a long tradition of studying interfirm collaboration in technology development (Gulati, 2007; Hohberger et al., 2020). Although collaboration can take a wide variety of organizational forms, collaborative innovation has been most often explored in the context of dyadic alliances between pairs of firms (Kogut, 1989; Kok et al., 2020; Prashant and Harbir, 2009; Reuer and Zollo, 2005; Zhang et al., 2007). Only relatively recently have scholars started to shed light on an increasingly common open multiparty collaborative form (Lavie et al., 2007; Ranganathan et al., 2018) that plays a central role in shaping the trajectories of technologies and the growth of their associated sectors (Leiponen, 2008).

We define "open multiparty alliances" as open-membership collectives of three or more organizations from diverse industries working towards a common goal of shaping the trajectories of emerging technologies. Open multiparty alliances are typically large, diverse entities composed of a variety of for-profit and not-for-profit organizations, including firms from multiple industries, research centers, universities, and governmental agencies, that work collectively towards common technological goals despite differences in their individual organizational

[3] The nine open multiparty alliances in the chronological order of formation are: OSGi, Khronos, RapidIO, OMA, DLNA, MIPI, OHA, WPC, and WAC.

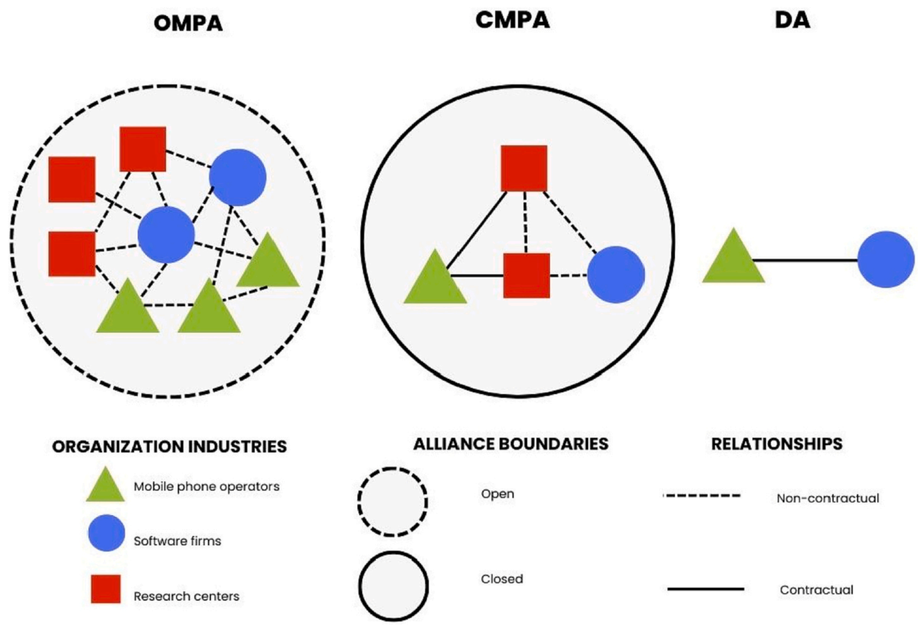

Fig. 1. Typology of commonly studied alliance types.

goals (Fonti et al., 2017; Lavie et al., 2007).[4] In recent years, literature on interfirm collaboration comprising more than two members – commonly referred to as "multiparty alliances" – has been growing. Yet, it often treats open and closed multiparty alliances under a single umbrella (e.g., Dorobantu et al., 2020; Fonti et al., 2017; Lavie et al., 2007; Li et al., 2012). This can be problematic when studying membership dynamics (Gulati et al., 2012), as the process by which firms enter open multiparty alliances is different from that in closed multiparty alliances. Closed multiparty alliances operate through a restricted, selective membership model. For example, some closed multiparty alliances such as loan syndications have a complex two-stage selection process whereby a selected lead firm drives the collaboration initiative and carefully selects partners based on resource and geographical location complementarities (Dorobantu et al., 2020). Instead, members voluntarily self-select into open multiparty alliances. Open multiparty alliances have open membership policies (Lavie et al., 2007; Ranganathan et al., 2018), stating explicitly in their terms of agreement that applicants are admitted automatically on payment of an annual membership fee.[5] Therefore, firms that wish to access the resources being developed in the alliance and to contribute towards the shared objective of technology advancement can enter freely. This allows firms to circumvent the complexities of judging resource compatibilities that are to the fore when choosing dyadic partners for technological collaboration (Kok et al., 2020) or assembling members in closed multiparty alliances (Dorobantu et al., 2020). Also, as each member voluntarily contributes their unique set of resources to the alliance (Browning et al., 1995; Fonti et al., 2017), orchestrators of open multiparty alliances cannot consider resource complementarity and redundancy among members in advance, as is the case in dyadic or closed multiparty alliances (Dorobantu et al., 2020; Harrison et al., 2001; Kok et al., 2020).

We thus argue that open multiparty forms of collaboration merit scholarly attention because they exhibit complex and unique membership dynamics (Lavie et al., 2007) that differ significantly from those in dyadic alliances and closed multiparty alliances (Gulati et al., 2012). Fig. 1 depicts the core differences between open multiparty alliances (OMPA), closed multiparty alliances (CMPA), and dyadic alliances (DA), whereas Table 1 provides a comprehensive comparison of core characteristics of these three most studied types of interfirm collaboration.

2.2. *Exit from open multiparty alliances*

Although the diversity of membership and ease of entry of open multiparty alliances offer clear benefits because they allow firms flexible entry to collaborative settings in which the returns may be uncertain, the flipside is that firms can also readily leave (Gulati et al., 2012). The openness of the membership policy, as well as the absence of exclusivity terms and penalties for leaving, implies that member firms can easily abandon an alliance if they no longer deem it worthwhile; indeed, firms do so automatically if they no longer pay the membership fee. Although the departure of a member firm does not automatically lead to the termination of the collaborative endeavor, as would be the case in a dyadic alliance (Hohberger et al., 2020; Kogut, 1989; Özdemir and van den Ende, 2021; Reuer and Zollo, 2005), exit in large numbers can have a detrimental effect on an alliance's technological success, and could ultimately lead to its failure. The departure of several firms from an open multiparty alliance can be interpreted by remaining members as indicative of a decline in support for the technological direction being pursued (Yue, 2012). In extreme cases, where firms exit in great numbers, this can result in the alliance's technologies being abandoned, regardless of their inherent potential (Abrahamson and Rosenkopf, 1993). Hence, the successful development and implementation of technologies depends strongly on collective support from stakeholders across the sector.

Recent research has started to examine the drivers of the formation, performance, and dissolution of open multiparty alliances (e.g., Heidl

[4] For instance, under the leadership of Google, the OHA has brought together several firms from diverse industries, including mobile phone operators, handset manufacturers, semiconductor firms, software firms, and commercialization firms. In this open multiparty alliance, several industries are represented, forming a diverse but coherent community of members cooperating to achieve common goals, which are then materialized in one or more technological projects.

[5] To illustrate, according to the OMA website membership policy, "We are fully open to membership […] We create a work environment that encourages inputs from companies of all sizes and shapes, provides equal opportunity to contribute, and prides itself on transparency." Our interview with the president of OMA further confirmed the website's statement on the openness of the application process: "Once you send in your application, it will be reviewed by the OMA board within a few days. But all companies get in honestly, I've been here for three years and I can attest that there have been no rejections."

Table 1
Comprehensive comparison of different types of alliances[a]
(source: authors' own summary of the literature).

	OMPA	CMPA	DA
Activator	Initiated by a self-selected small group of firms that take the role of alliance "architects". Architects are not necessarily market leaders and could come from various industries.	Steered by one "lead" firm (or less frequently, a small committee of lead firms). In some cases, a firm forms the alliance as its own initiative. In other cases, a firm is selected by the government, regulatory bodies, or syndicates to drive industry growth. Alliance lead firm is typically a market leader.	Initiated by either of the two firms or by both firms simultaneously when strategically beneficial for both parties to collaborate.
Member Entry	Self-selected entry of interested members in the alliance. Firms are required to fill out an application form and pay yearly membership fees to become members. No specific expectations of resource commitment. Firms are free to join other alliances in parallel to their membership. Rejection of a membership application is highly unlikely.	Lead firm selects members by considering a "group of partners" taking into account the combination of resources and/or countries, rather than multiple partners as separate entities. Once the alliance starts forming, introducing a new member requires approval from lead firm *and* existing members. Contractual binding terms are in place (i.e., expected resource contributions, time commitment, exclusivity, duration of membership).	Process begins with partner search driven by firm specific needs and considering resources that the partner can provide. Formation of alliance is based on negotiating contract terms (i.e., governance, resource expectations, goals, conflict management, duration of the alliance). Typically compared to a "marriage" between two independent partners.
Membership Criteria	Open and inclusive. Diverse members from various organizational forms (i.e., firms, research centers, government agencies), industries, sizes (i.e., market leaders and small players), and geographical locations.	Membership is controlled and criteria are intentionally set to serve goals of alliance and in some cases, those of the lead firm. Less diverse members than in OMPAs. In some alliances, only one industry is represented, while in others, lead firm diversifies membership scope depending on resource and technological needs.	Partners could be from same industry or from different industries depending on the purpose of the collaboration (i.e., expanding to new markets, growing an existing market, obtaining technological capabilities, entering a foreign market).
Interactions	Complex and dynamic coordination of exchange. Absence of formalized and contractual relationships between members. Relationships emerge organically as a result of interactions in subgroups (i.e., "working group" meetings, yearly conferences).	Multilateral interactions between alliance members. Alliance consists of formalized and contractual relationships between certain members (i.e., dyadic alliances), but other informal relationships could emerge organically between members.	Relationship is controlled through contractual binding terms.
Coordination Mechanisms	Flat organization and consensus-building efforts. Voting members (self-selected into roles) and working group members (selected by voting members) coordinate alliance activities. Informal power could stem from nature of interactions within alliance and is not necessarily linked to characteristics of powerful firm (i.e., market power, founding member). Firms could also achieve informal authority due to their status, reputation, expertise, and control of certain resources, technologies, and market information.	Hierarchical governance structure and active management by lead firm. Formal power is concentrated in the hands of lead firm. Lead firm pre-assigns member roles.	Contract is lengthy and elaborate delineating binding terms (i.e., resource contribution, duration of alliance, exclusivity conditions). Power asymmetries often emerge due to firm characteristics, such as market position and status.
Alliance Goals	Members pool in resources and collaborate to achieve common, system-level, technological goals. Knowledge is shared freely. End goals center around growing the market as a whole.	Lead firm decides on resources to pool while strategically controlling for potential redundancies. End goals center around growing the market as a whole but could also serve the private goals of lead firm.	Goals are pre-set by both partners. Resource expectations to achieve common goals is decided prior to forming alliance.
Alliance Size	Large due to lack of barriers to entry and architects promoting diverse membership.	Smaller than OMPAs as members are carefully hand-picked by lead firm.	Pair of firms.
Conflict	Large size of alliance, overrepresentation of certain industries, and lack of strategic control of redundancy from alliance architects could lead conflict driven by asymmetric power dynamics.	Faultlines could emerge between members. Partners in subgroups are sometimes at odds with each other. Lead firm aims to control and reduce conflict among members.	Conflict could result from incompatibilities between partners (e.g., resources, capabilities, working styles).
Member Exit	Members are free to exit at any time. They automatically exit the alliance once they stop paying yearly membership fees. Alliance does not halt its operations when technological goals are attained or when promoted technologies reach maturity. Alliance continuously suggests new technological goals to work on.	Duration of membership is delineated in contractual terms. Barriers to premature exit are pre-set (i.e., members cannot exit alliance until specific goals are achieved).	Termination date is pre-set conditional upon achieving the collaboration goals.
Empirical Examples	Committee-based SSOs (Wiegmann et al., 2017; Ranganathan et al., 2018); Technology/research/ R&D consortia (Browning et al., 1995; Fonti et al., 2017; Lavie et al., 2007; Olk and Young, 1997; Roelofsen et al., 2011); Organization-level open communities (O'Mahony and Lakhani, 2011).	Closed industry consortia (Gulati et al., 2012), Market-based SSOs (Schilling, 2002), Constellations (Garcia-Pont and Nohria, 2002; Lazzarini, 2007); Loan syndication (Dorobantu et al., 2020).	Technology strategic alliances (Hagedoorn, 1995); Research strategic alliances (Reuer and Zollo, 2005); Joint ventures (Kogut, 1989).

[a] Note: These are ideal types. Despite our effort to summarize the three most commonly discussed interfirm collaboration types in the literature, certain alliances do not fall neatly under one category. For instance, while the industry consortium SEMATECH was initially launched as a rather closed multiparty alliance, our reading of the case (e.g., Browning et al., 1995) indicates that it eventually evolved into a more open setup.

et al., 2014; Lavie et al., 2007). Although these studies have been important in shedding light on the unique dynamics of open multiparty alliances and their pivotal role in technological advancement, we still know little about the exit behaviors of individual firms in such collectives.

2.3. Technological and social uncertainty in open multiparty alliances

Firm decisions about whether to stay in or leave open multiparty alliances are typically taken under conditions of high technological (Cohen et al., 2016) and social (Fonti et al., 2017) uncertainty. In part, such uncertainty is at the alliance-level, i.e., shared among all alliance members, and in part it is specific to certain firms.

Alliance-level technological uncertainty arises from a broad range of novel technologies being under development in parallel (Cohen et al., 2016). While some of these technologies may prove mutually compatible, others directly compete; for example, for integration in technology platforms (Ozcan, 2018). Although participating in open multiparty alliances offers firms the opportunity to directly influence the direction of technology development in a sector (Leiponen, 2008), member firms still face substantial technological uncertainty, particularly in relation to the viability and market potential of the technologies supported by the alliance (Ozmel et al., 2017). Furthermore, the level of technological uncertainty can increase over time due to unexpected changes in the broader technological landscape around the alliance's promoted technologies (Anderson and Tushman, 2001). Yet, when evidence is increasing that a technology is headed towards becoming proven – or on the flipside is losing relevance – uncertainty about the promoted technology as experienced by members of the alliance decreases. The president of one alliance described this uncertainty as follows:

> Uncertainty is often caused by change, and the faster the change, the larger the uncertainty. Rapidly evolving technological fields such as machine learning can make it challenging [for us as an alliance] to gauge what technologies to work on, and when […] One day the technology is heading towards becoming an industry standard, the next it starts to lose relevance… That unpredictability creates stress and uncertainty for our members […] We try to minimize uncertainty by constantly evaluating what technologies are gaining or losing relevance in our domain.

Moreover, firms may experience technological uncertainty specific to them due to information asymmetries about a technology's potential, often because of (mis)alignment of their own technologies and those promoted by the alliance (Cohen et al., 2016). A firm's technological focus typically uses specific resources and underpinning knowledge bases (Kok et al., 2020; Makri et al., 2010). If these are distant from the alliance's focus, the firm has less information about the potential of the alliance's technologies than other members and thus may face elevated uncertainty (Ozmel et al., 2017), as described by one of the alliance presidents:

> Any organization needs to evolve to address changing market needs, and for us [the open multiparty alliance] the key is to be able to understand the evolving needs of our members and change to satisfy them. If [our alliance] pursued a technology direction that was not relevant to some of its members, then that would create hesitation and uncertainty [for these members] […] Although they could remain members, they become more uncertain [about us].

Besides technological uncertainty, firms could face substantial social uncertainty (Fonti et al., 2017; Zhang and Guler, 2020), which is particularly marked in open multiparty alliances (Gulati et al., 2012). Alliance-level social uncertainty, shared by all firms, is rooted in the difficulty to gauge the trustworthiness of other members as collaboration partners, such as their integrity, reliability, and commitment to common goals (McCarter et al., 2011). Under conditions of openness, large memberships, industry heterogeneity, geographical disparity, and a diverse range of corporate goals, the behavior of each specific alliance member is hard to evaluate (Fonti et al., 2017). While social uncertainty can occur in any collaboration agreement between firms, the drawbacks of large-scale open collaboration initiatives have been documented in previous research, linked primarily to freeriding, opportunistic behaviors, and cooperation failures (Fonti et al., 2017). Alliance partners in such large-scale initiatives might opt to underinvest in the collective goals, while still reaping the benefits of the created public good (Gulati et al., 2012; Fonti et al., 2017). In contrast to dyadic (Reuer and Zollo, 2005) and closed multiparty alliances (Dorobantu et al., 2020) in which partner selection tends to be diligent and lengthy, the membership inclusiveness of open multiparty alliances can attract a broad range of parties, including some without a track record of successful collaboration experience (Zhang et al., 2017).

Furthermore, firms may experience social uncertainty specific to them. Although the architects of open multiparty alliances seek to prevent specific firms from dominating them (Ranganathan et al., 2018), social uncertainty can arise in relation to the group dynamics among members as particular firms seek to shape the collective agenda and discourse (Lukes, 2005); for example, firms may attempt to favor their own vested interests by influencing what is discussed at meetings (Phillips et al., 2000). These challenges can heighten the social uncertainty experienced by other member firms, which may feel powerless, underrepresented, and/or uncertain about their own impact on the alliance's direction. One alliance president described the sources of firm-specific social uncertainty within their collective:

> Most companies that join [our alliance] will have an understanding of the technologies and the approaches, even if they are working on entirely new [uncertain] technologies. However, more so than technological uncertainty, there may be different uncertainties; for example, companies may have different approaches to achieving a common goal. There may be also uncertainty related to the different collaboration approaches of companies with different backgrounds, from different industries, all trying to achieve this common goal and you know it's not always easy.

2.4. Industry-peer imitation as a driver of firm exit from open multiparty alliances

Prior research on decision-making under uncertainty has shown that firms are inclined to imitate others when subject to uncertainty (Lieberman and Asaba, 2006; Sharapov and Ross, 2023). In a comprehensive study on imitation under elevated uncertainty, Lieberman and Asaba (2006) suggest that two theoretical explanations underpin imitation behaviors: information and rivalry. While imitation research has typically focused on only one of these explanations at a time, Lieberman and Asaba (2006) argue that both theories are not mutually exclusive and often lead to similar outcomes – that is, peer firms will homogenize their behaviors in response to elevated uncertainty and social influence pressures. Accordingly, we predict that firms are likely to imitate their industry peers when it comes to exiting an alliance for two main reasons.

First, firm-specific technological and social uncertainty may lead firms to imitate their industry peers for information-based reasons. Under the information-based imitation framework, uncertainty is rooted in a lack of access to accurate information (Beckman et al., 2004). Given such uncertainty, the behavior of firm peers becomes an important source of information (Semadeni and Anderson, 2010). For example, research has shown that firms evaluate the potential of technologies based on patterns of adoption by others (DiMaggio and Powell, 1983;

Tolbert and Zucker, 1983), interpreting the numbers that have embraced a technology as a signal of its legitimacy (Meyer and Rowan, 1977). Indeed, in extreme cases, a technology may become "infused with value beyond the technical requirements of the task at hand" (Selznick, 1957, p.17) while, conversely, negative feedback loops in adoption might trigger the abandonment of technologies (Abrahamson and Rosenkopf, 1993). In the context of technological and social uncertainty in open multiparty alliances, no single firm has full control over the direction of technology development. As a result, firm decisions on whether to leave an alliance are not taken in isolation but, rather, are affected by fellow members who – through their decisions on whether to stay or leave – provide information about their views of a technology's potential (Kitts, 2006).

We argue that, when interpreting the behavior of fellow members as informational cues, decision-makers are inclined to place more weight on signals that come from firms that resemble them, such as their industry peers (Abrahamson and Rosenkopf, 1993; Ozalp and Kretschmer, 2019). Typically, firms and other organizations that participate in open multiparty alliances belong to a broad range of industries and, therefore, differ significantly in the goals, agendas, and logics that drive their respective strategic actions (Fonti et al., 2017; Cohen et al., 2016). For example, while software firms may be interested in growing the overall market for the mobile phone sector, government agencies may be more concerned with policy implications or gaining access to corporate information on novel methods of manufacturing (Nakamura et al., 1997). As a result, firms tend to identify with the norms and expectations of the subgroups to which they belong rather than to those of the group as a whole (Thornton and Ocasio, 2008). We therefore anticipate that firms will interpret the exit decisions of their industry peers as cues to guide their decision-making on open multiparty alliance membership.

A second, complementary mechanism of social influence in exit decisions from open multiparty alliances is rivalry-based imitation; it can arise due to technological and social uncertainty that is shared among all members. In contrast to information-based imitation, which is rooted in the lack of access to accurate information, rivalry-based imitation is a potential defensive strategy (Sharapov and Ross, 2023). Under the rivalry-based theoretical framework, firms imitate their competitors to preserve the status quo in the industry (Chen and MacMillan, 1992), safeguard an advantageous market position (Gimeno et al., 2005), and inhibit certain market leaders from accruing strategic capabilities that could disrupt the status quo (Garcia-Pont and Nohria, 2002; Semadeni and Anderson, 2010). As a result, firms that imitate their competitors may become more effective in managing highly uncertain environments (Sharapov and Ross, 2023). In open multiparty alliances, we expect that rivalry-based mechanisms play an additional role in driving imitation decisions when it comes to leaving or remaining in the alliance. Firms that face fundamental uncertainty about an alliance and its technologies may have entered a given open multiparty alliance simply because their rivals did. But, for similar reasons, they may also leave that alliance again when rival firms exit. In contexts in which uncertainty is, at least in part, shared by all members of the alliance, for instance in dynamic environments where technological uncertainty increases unexpectedly, firms may be less prone to follow information-based imitation (Gaba and Terlaak, 2013; Sharapov and Ross, 2023). Instead, under such conditions where all alliance members have equally limited information about a technology's potential, firms may turn towards the rivalry-based logic of social influence and mimic decisions taken by their comparison industry groups, such as strategic groups (Garcia-Pont and Nohria, 2002), when it comes to exiting an alliance.

Thus, we argue that uncertainty about technological viability coupled with the behavioral unpredictability of other members in open multiparty alliances – whether common to all members or specific to certain firms – drive imitation in firm exit decisions, but this effect will manifest primarily among firms from the same industry. One president of an open multiparty alliance commented on peer imitation and exit as follows:

> We send a survey to understand why companies leave […] I would say they [companies] tend to imitate competitors because that is their only reliable source of information. And sometimes it's a problem for us as an organization because we can't have any influence on who stays and who leaves. We can't really control the cascading exits, even if, in some cases, it could be harmful for the alliance. For example, recently a significant amount of manufacturers started exiting for no particular reason and other manufacturers started bailing too because they assumed that was the right thing to do […] At the end of the day, it's just companies trying to figure out where the momentum is.

A representative of a phone company elaborated further on the firm's decision to leave an alliance in the past:

> I think there is a bandwagon effect in every walk of life; humans are wired to take notice of the actions of their community. […] I'll give you an example. We were a relatively satisfied member of [an alliance] […], I believe that was back in 2007. I recall that Alcatel from France, China Mobile, and a bunch of other smaller operators decided to leave the alliance. We did not have a direct conversation with them about the rationale behind this decision, but we immediately thought to ourselves, 'why are they leaving?', 'why are they abandoning the technology?', 'do they not believe in its relevance anymore'? That definitely made us question our membership and led us to leave the alliance eventually down the line […]

Taken together, we hypothesize:

Hypothesis 1. **(H1)**: Observed prior exits of industry peers from an open multiparty alliance will be positively related to the focal firm exiting the alliance.

2.5. Network position and industry-peer imitation

Whereas most studies on imitation in technology adoption and abandonment are centered on uniform imitation effects, researchers have become increasingly interested in the possibility that imitation may be driven by asymmetric effects (Yue, 2012). Despite the presence of general imitative tendencies and the homogenization of firm behaviors, some firms may be less likely than others to mimic the behaviors of their industry peers (Ethiraj et al., 2008), often as a result of superior access to alternative sources of information and resources that reduce their levels of uncertainty. Network scholars have long highlighted the role of advantageous network positions in the acquisition of alternative sources of information (Burt, 1992) and key resources (Astley and Sachdeva, 1984). Firms can gain superior access to information and resources through a variety of means, including their structural position in the wider network of collaborative ecosystem relations (Gilsing et al., 2008).

In the context of open multiparty alliances, one by-product of their policy of openness is the absence of barriers to joining several such alliances at the same time, enabling certain firms to occupy positions referred to as "boundary spanners" (Allen et al., 1979; Dahlander and Frederiksen, 2012). In addition, firms might be simultaneously involved in other forms of collaboration such as dyadic alliances (Ranganathan et al., 2018). Firms that enter a variety of multiparty (closed and open) and dyadic alliances gain greater betweenness centrality in the wider web of collaborative interfirm relationships within a sector, granting them greater access to information about technology developments and market dynamics (Lee, 2007). Furthermore, firms occupying advantageous network positions are better equipped to identify the resources, innovations, and skills, as well as the faults, of their close competitors (Lavie et al., 2007). Specifically, organizations that sit at the crossroads of multiple network environments have, in the words of Burt (2004), a "vision advantage". Having a foothold in multiple technology environments gives such firms the ability to detect overlaps, synergies, and conflicts between technologies that would be hidden from firms that belong only to a single alliance or are more peripheral to the ecosystem network. By spanning knowledge domains and technological boundaries, central firms can fuel the innovation process and provide greater value to the discussions and developments within an alliance (Yayavaram and Chen, 2015). In chaotic and uncertain environments, such "cross-pollination" may be particularly valuable (Fleming and Waguespack, 2007). One of the alliances presidents reaffirmed the benefits linked to cross-membership:

> Actually, we encourage our members to take part in several organizations [open multiparty alliances]. When you have your foot in several organizations in the sector, you can have critical information on the technologies before they are released and can then assist in their rectification […] non-members tend to be two years behind in time. So, these companies [involved in multiple organizations], have an edge – they get valuable information that others lack.

When evaluating the viability of a technology in a highly uncertain environment, central firms are more adept at benchmarking thanks to their exposure to more diverse realms of knowledge and social dynamics, enabling them, for example, to better forecast fluctuations in customer demand (Autio et al., 2013). Thus, the information and resource advantages that holding a more central network position provides tend to reduce the technological uncertainty experienced by such firms. For instance, in standard-setting contexts, firms in advantageous network positions have better access to market information about the newly emerging technologies in their sector and can leverage this information to play a more proactive role in shaping and influencing technology direction (Soh, 2010). According to one open multiparty alliance president:

> Familiarity or foresight in [relation] to disruptive business decisions by companies may well be affected by the business networks of these members outside [the alliance] and in the networks in the industry as a whole […] Any information communicated to our members is shared equally with all members but, of course, some members [thanks to their wider networks] may have better information on how technologies in the industry might evolve, information that is not shared within [the alliance] […] For example, a company that is a member of multiple alliances will have more benefits because they end up covering all bases […] They will have a complete picture of what is going on; they will have more valuable information.

Firms in central positions also experience less social uncertainty than their counterparts due to their exposure to broader sources of information (Wang et al., 2014) and access to key resources (Astley and Sachdeva, 1984). For instance, centrality promotes timely access to information before it may reach more peripheral peers at a later stage, if at all (Heidl et al., 2014). Furthermore, it is often argued that centrality may set in motion a self-reinforcing cycle whereby central firms gain greater status and power in the industry or ecosystem (Podolny, 1993), which in turn helps attract more partnership opportunities in the alliance network, which again helps them to gain greater access to resources as well as critical information on their close competitors and other sector players (Lavie et al., 2007; Powell et al., 1996; Whalen, 2018).

Because central firms are better informed about potential opportunities and have access to valuable resources, they may, therefore, be better able to assess the risks associated with particular technologies and to experience less uncertainty about players in the network (Wang et al., 2014). Whereas firms in more peripheral positions in the wider ecosystem network make decisions under conditions of elevated uncertainty, central players can base their decisions on extensive technological understanding and more detailed information about other firms' behaviors and intentions, rendering them less inclined to defer to signals from their firm peers that a technology may lack potential, or that an alliance may have unhelpful membership dynamics. Moreover, firms occupying central network positions may be less concerned about disrupting the industry status quo, as the access to superior resources bestows them with an advantageous competitive position. In a technological context where firms may compete for the dominance of their innovations, centrality is of strategic importance because central firms are able to influence the real value of their innovations and affect the expectations of other firms in the industry (Schilling, 2002). Therefore, we expect that such firms are more prone to set the industry rules themselves, are less likely to defer to defensive strategies, and are thus reluctant to follow the behavior of peer firms when deciding on membership in an alliance.

In sum, positions of high betweenness centrality act as a protective shield that immunizes firms from interfirm imitation effects, and we hypothesize:

Hypothesis 2. (H2): The positive relation between prior industry-peer exits and focal-firm exit from an open multiparty alliance will be weaker if the focal firm has higher betweenness centrality in the wider network of collaborative relations.

3. Data and methods

3.1. Sample

We tested our hypotheses by utilizing unique, hand-collected data on nine major open multiparty alliances in the global mobile phone industry between 2000 and 2012. As an initial step, we identified these alliances based on an extensive search for press releases on Factiva and from industry sources, such as the websites of GSMArena.com and Mobile World Congress (MWC) industry events. The observation period begins with the foundation of the industry's first major open multiparty alliance, in the year 2000. None of the nine open multiparty alliances had pre-set ending dates or final objectives that would lead to alliance termination, and none dissolved during our observation period. In line with the definition of open multiparty alliances, we included all alliances that fulfilled two criteria: first, we included alliances with firm representation across industry boundaries and along the entire mobile phone value chain, which allowed us to explore to what extent imitation effects are confined within industries; second, we only included those alliances with open membership that allowed firms to enter and exit freely, consulting the terms of reference of each alliance to verify their membership policies.[6] All the open multiparty alliances included in our dataset merely required members to sign the terms of agreement and to pay a yearly membership fee that varies according to their desired level of involvement. In line with the principle of openness, none of the alliances imposed restrictions on exclusivity. Table 2 provides details of the membership composition and goals of the alliances in our dataset.

3.2. Data sources

We made use of a broad range of data sources to compile our dataset. For data on the alliances, we relied on three main sources: first, we used the Internet Archive's "Way Back Machine" to extract detailed membership lists from each of the open multiparty alliance websites and then manually

[6] For example, OMA states on its website that "Joining OMA is a quick and simple process that requires the completion of a Membership Application, including acceptance of the bylaws, and the payment of applicable dues." According to the website, application approval takes a total of ten business days.

Table 2
Description of the nine OMPAs in our data*

OMPA**	Founded	Purpose	Founder Members	Total Technological Releases (Inception–2012)	# Members at Inception	# Members in 2012
OSGi	2000	Interoperability of applications and services over a broad variety of devices	IBM, Motorola, Deutsche Telekom, Sun Microsystems, National Semiconductor, Whirlpool, EDF, Oracle Corporation, Ericsson, Nokia, Echelon, GTE, Alcatel	10	51	154
Khronos	2000	Parallel computing, graphics, dynamic media, computer vision and sensor processing on a variety of platforms and devices	3Dlabs, ATI, Discreet, Evans & Sutherland, Intel, NVIDIA, SGI, Sun Microsystems	45	10	128
RapidIO	2002	Accelerate the needs of equipment designers in data centers, analytics, wireless infrastructure, edge networking, storage, scientific, military, and industrial markets	Motorola, Cisco Systems, Lucent Technologies, Nortel Networks	7	52	42
OMA	2003	Interoperability across international borders, networks and devices	IBM, Intel, HP, Nokia, Panasonic, Siemens, Sun Microsystems, and T-Mobile (including but not limited to)	85	177	129
DLNA	2003	Provide more convenience, choice, and enjoyment of digital content through a variety of devices	Fujitsu, HP, Huawei, IBM, Intel, Kenwood, Lenovo, Microsoft, Motorola. NEC, Nokia, Panasonic, Philips, Pioneer, Samsung, Sharp, Song, ST, Texas Instruments, Thomson, Toshiba	3	18	302
MIPI	2007	Standards for hardware and software interfaces in mobile devices	ARM, Texas Instruments, STMicroelectronics, Nokia	12	4	249
OHA	2008	Accelerate innovation in mobile and offer consumers a richer, less expensive, and better mobile experience	China Mobile Communications, KDDI, NTT DoCoMo, Sprint Nextel, T-Mobile, Telecom Italia, Telefonica, Audience, Broadcom, Intel, Marvell, NVIDIA, Qualcomm, SiRF, Synaptics, Texas Instruments	9	34	86
WPC	2010	Establish a global standard for wireless charging that makes all wireless chargers compatible with all phones and other battery-operated products	Convenient Power, Fulton Innovation, Logitech, National Semiconductor, Olympus, Philips, Sanyo, Sang Fei, Texas Instruments	3	8	150
WAC	2010	Increase the overall market for mobile applications and unlock the value of mobile network operators	China Mobile Communications, Softbank Mobile, Verizon Wireless, Vodafone	3	61	57

Data from 2012.
* Source: Internet Archive of OMPAs websites.
** It is recorded on the OMPAs' websites that, for legal reasons, the alliances are required to register their headquarters in a physical location but most meetings take place virtually to encourage all geographically dispersed members to contribute. For instance, one alliance president told us: "We are truly global… We have a diversity of membership: we have members from all over the world and from an array of industries."

tracked the entry and exit dates of all 1960 firms over our 13-year period.[7] We iterated through the lists multiple times to ensure that a firm's disappearance (i.e., presumed exit) was not due to a website failure in recording membership.[8] We also recorded voting and non-voting status of firms and working-group leadership positions. Second, we obtained archival data – again via the Internet Archive – on technologies released by the nine alliances during the period of our study. These data classify each of the technology releases according to the Cooperative Patent Classification (CPC) system, which allowed us to relate the technological focus of the alliances to those of their member organizations. Third, we used Factiva to collect data on press releases related to the alliances to obtain a proxy of an alliance's popularity over time.

To collect firm-level data, such as industry classification (SIC codes), nation of origin, age, size, subsidiary ownership, bankruptcy, and merger and acquisition activities, we relied on a variety of sources, specifically Compustat, Capital IQ, LinkedIn, and company websites. By combining these data sources, we were able to reduce the level of missing data to just 2.7 % of the entire dataset. For example, to obtain an indicator if a firm was a subsidiary of a larger firm, as a first step we matched our sample of firms with Compustat. Since that data source was not complete, we complemented it with data from CapitalIQ. In doing so, we ensured to capture ownership dynamically, considering whether firms were acquired by or merged with a parent firm during our sample period.

We followed a similar approach to gather patent data, combining data from the OECD Patent Database (covering EPO, USPTO, and PCT patents) with data from Google Patents. We used these data to construct firm-level patent portfolios as well as industry-level indicators of technological uncertainty. Specifically, we first identified our sample firms in the OECD Harmonized Applicant Names (HAN) database, and then retrieved the associated EPO, USPTO, and PCT patent families for the period from 1990 up to and including 2012. This exercise yielded the patent stock of approximately 1500 firms, representing around 75 % of our sample. For the remaining 500 firms, we manually searched Google Patents, which did not yield any further results, leading us to assume that these firms did not own any patents.[9]

To collect data about firms' wider networks, we complemented the

[7] The websites on Internet Archive are regularly updated (sometimes as frequently as once a week).

[8] For example, if Nokia was on the members' list of MIPI in April 2005, not on the list in May 2005, but then again listed as a member in June 2005, we assumed that this was due to an error in reporting rather than an actual exit. It is very unlikely that the firm would exit and then re-enter a month after, especially that membership fees are paid on a yearly basis. On the flipside, if we take IBM that was on the list of members in April 2005 and was no longer on the list consistently for several months in a row after each website update, we assumed exit.

[9] This is not unexpected because not all firms patent with the same intensity; although patenting is relatively common in the technology-intensive industries widely represented in our data, it is less common in some of the other, less technology-intensive industries also represented in our data (e.g., consulting firms).

Table 3
Main industries of OMPAs member firms in our sample
Industry categorization is based on Cohen et al. (2016).

Category*	Primary SIC	Percentage (%)
Equipment manufacturer	3571	2.9
Equipment manufacturer	3575	0.1
Equipment manufacturer	3577	2.2
Equipment manufacturer	3661	1.4
Equipment manufacturer	3663	4.2
Equipment manufacturer	3669	0.9
Equipment manufacturer	3674	16.4
Equipment manufacturer	3679	3.0
Phone company	4812	4.2
Phone company	4813	3.4
Maker of complementary products for end users	7372	11.1
Maker of complementary products for end users	3651	2.2
Maker of complementary products for end users	7375	0.1
Maker of complementary products for phone companies	3312	0.02
Maker of complementary products for phone companies	3714	0.3
Maker of complementary products for phone companies	3721	0.04
Maker of complementary products for phone companies	3812	0.4
Maker of complementary products for phone companies	3823	0.02
Maker of complementary products for phone companies	3825	0.8
Maker of complementary products for phone companies	4841	0.3
Maker of complementary products for phone companies	4899	1.5
Maker of complementary products for phone companies	5045	0.9
Maker of complementary products for phone companies	5065	0.5
Maker of complementary products for phone companies	7371	3.7
Maker of complementary products for phone companies	7373	9.6
		70.2
Other** (Mining; Construction; Transportation;	1000, 1741, 2741, 4810, 5063, 5731	29.8
Wholesale trade; Retail; Finance, Insurance,	6719, 7311	
Real estate; Services; Public administration)	8711, 9631***	
Total		100

* Category additional description:
"Equipment manufacturer" category includes manufacturers of electronic computers, telephone apparatus, and electronic components. "Phone company category" includes telecommunications and radio communications companies. "Maker of complementary products for end users" category includes pre-packaged software, audio and video equipment, and information retrieval services. "Maker of complementary products for phone companies" category includes computer integrated system designs and computer programming services.
** SIC codes representing "other" industries non-related to the mobile phone sector in our data.
*** Example SIC codes among 145 different SIC codes represented in the "other" category.

alliance affiliation data described above with data on dyadic and closed multiparty alliances from SDC Platinum. Using a combination of automated and manual searches, we identified 7445 other alliances in which our sample firms were involved during the 2000–2012 period. Because data on the termination dates of such alliances were unavailable, we assumed a five-year duration for each, following the approaches taken in previous networks literature (Hallen, 2008; Zhang et al., 2017). To test the sensitivity of our analyses, we reran our models using a three-year duration window (Cohen et al., 2016) and our results remained consistent to those reported.

Finally, to better understand our study context, we collected qualitative data from the following sources: publicly available data from alliance websites; business publications and industry journals; semi-structured interviews; material provided by interviewees. We conducted field interviews with open multiparty alliance presidents (10 in total) and innovation executives of member firms (32 in total). Each interview lasted about 90 min and was recorded and transcribed. The purpose of our interviews was to gain contextual understanding of the industry, insights into the strategies of the alliances, and accounts of the motivations of firms in entering and exiting these alliances.

3.3. Measures

3.3.1. Dependent variable

The dependent variable *Firm Exit* is a binary indicator, coded as 1 if focal firm *i* exited open multiparty alliance *j* in year *t*, and 0 otherwise. Firms that did not exit in a given year remained in the risk set for the subsequent year. The unit of analysis is the alliance-firm-year.

3.3.2. Independent and moderator variables[10]

To test H1, we calculated *Prior Industry-Peer Exits from Alliance* as the number of firms in the same industry as the focal firm that exited the focal open multiparty alliance. To build a fine-grained measure, we considered firms to be industry peers if they fulfilled one or both of the following two criteria: (1) they had at least one overlapping SIC code (out of up to four), the most commonly used proxy of industry similarity in imitation studies (e.g., Morck et al., 1990); (2) they belonged to the same industry category in the classification scheme used by Cohen et al. (2016).[11] Table 3 details the main industry categories represented by firms in our data and indicates the mapping of SIC codes onto industry categories.

Nearly 70 % of firms belong to one of the following four categories: equipment manufacturer, phone company, maker of complementary products for end users, and maker of complementary products for phone companies. We followed previous studies on imitation by counting prior exits with a one-year lag (Lanzolla and Suarez, 2012), which gives the focal firm enough time to process such exit information and decide on continuing its membership accordingly (Vedula and Matusik, 2017). We standardized the variable for ease of interpretation.

To test H2, we measured *Firm Betweenness Centrality* within the mobile phone sector network. We compiled the mobile phone sector network as the aggregate of two sets of relations. First, any two firms are connected if they are members of the same open multiparty alliance in the same year, consistent with studies on affiliation networks. Second, any two firms are connected if they are members of the same dyadic or closed multiparty alliance in our SDC Platinum data (assuming membership lasts five years from alliance foundation) (Ranganathan et al., 2018). We combined these two sets of relations in a single network for each observation year. We dichotomized the network, i.e., indicating the presence or absence of a network tie between firms, rather than the number of ties. We then calculated firms' betweenness centrality – defined as the number of times the shortest paths between all network members pass through the focal firm (Wasserman and Faust, 1994) – for each firm for each year, using UCINET 6. We standardized the variable for ease of interpretation.

3.3.3. Control variables

Our analyses include various control variables at different levels. First, we control for a range of firm-level characteristics that might affect

[10] All our independent variables and controls are lagged by one year unless specified otherwise.

[11] As this classification scheme is based on SIC codes, we used firms' primary SIC code to assign them to categories.

the probability of exit from an alliance. In accordance with the strategic management literature (Arend, 2006), we use a proxy dummy for *Firm Size* in which firms with 500 or more employees are coded 1 and the remainder 0. We also control for *Firm Age* because younger firms tend to be less experienced in managing collaborations and thus may be more likely to exit them early (Makino et al., 2007). Moreover, we control for whether the *Firm is a Subsidiary* to another firm, and for *Firm Bankruptcy* to account for firms exiting an alliance due to bankruptcy in the focal year. To characterize firms' technology focus, we control for a firm's *Diversification Entropy Index*, $\sum P_i * \ln(1/P_i)$, as proposed by Jacquemin and Berry (1979), where P_i is the percentage of sales in the firm's primary industry. Further, we measure *Firm Total Patent Stock* as the total number of patents in alliance-relevant classes[12] granted to the firm since 1990. Finally, we include fixed effects for *Firm Country of Origin* and for *Firm Main Industry* as designated by its primary SIC code.

For our second level of controls, we consider the firm-alliance level. Thus, we control for *Firm Voting Status* and *Firm Working-Group Leadership* over our 13-year period. Because voting status and working-group leadership confer various governance and control benefits, firms occupying these positions may have greater incentives to remain in an alliance. We also control for whether firms were *Founding Members* or whether firms that lost (or gave up) alliance voting status (*Firm Lost Voting Status*) in the focal year, because this may signal a reduction in their level of alliance involvement. To capture resource similarity and complementarity (e.g., Harrison et al., 2001; Lee et al., 2017) of the focal firm relative to other members, we adopted the approach suggested by Makri et al. (2010) and calculated *Firm Average Technology Similarity* and *Firm Average Technology Complementary* based on the portfolio of patents of exiting and focal firms in the three years before the focal year (i.e., the same as for all other patent-based variables). Similarity is measured in terms of similarity in patenting of the focal firm relative to other members in terms of overlapping four-digit CPC classes. Complementarity captures the extent to which a firm has patents in the higher-order (three digit) classes associated with the four-digit classes in which other members have patents.

Finally, we include alliance-level control variables. *Alliance Age* is the number of years since the open multiparty alliance's foundation; younger alliances might lack the legitimacy and experience to keep members involved. *Alliance Size* is the total number of members at any given point in time; alliance size may affect exit because members typically find it more challenging to collaborate in large-scale setups (Fonti et al., 2017; García-Canal and Sánchez-Lorda, 2007). As a proxy for alliance popularity, we control for *Alliance Press Releases* (divided by 1000), capturing media mentions of the alliance in a given year. Because press releases are a crucial medium by which alliances convey news about their technologies and create an industry presence to attract members, especially upon their foundation and when reaching key milestones (Pontikes and Barnett, 2017), a decline in media attention may render the alliance less attractive to its members. We control for annual *Alliance Technological Releases* as a measure of alliance productivity, and because completion of work on a technology may prompt firms to exit an alliance. We also include the *Alliance Share of Voting Members*, because we expect open multiparty alliances with a smaller share of voting members to exhibit different dynamics to those with a higher share (Ranganathan et al., 2018). Next, we measure the *Average Concentration of Ties in Alliance*, defined as the (average) extent to which member firms concentrate their membership ties on the focal open multiparty alliance (rather than elsewhere). Higher concentrations could result in an increase in imitative behaviors as firms monitor the actions of others within their social structure (Cohen et al., 2016). We measure the concentration of ties as the total number of alliances to which existing members of the focal alliance belong, divided by the total number of possible alliances of which firms can be a member, as per Everett and Borgatti (2005). Finally, we control for alliance entry dynamics. Because a rash of new entries can, for example, lead to crowdedness of competitors (Toh and Miller, 2017) or disruption of an alliance's existing collaboration dynamics (Zhang et al., 2017), we include a measure of total number of firms that entered in the preceding year (*Alliance Number of Entries*) as well as the number of industry peers that entered (*Alliance Number of Industry Peer Entries*). We also include a measure of *Alliance-Firm Redundancy in Membership*, calculated as the total number of alliance member firms who belong to the same industry category, same geographical region and same size class (above or below 500 employees) as the focal firm (García-Canal and Sánchez-Lorda, 2007; Garcia-Pont and Nohria, 2002). Redundancy could explain firm exit from the alliance as the resources brought by each individual firm become less unique in an increasingly crowded space (Toh and Miller, 2017).

3.4. Estimation

We estimated *Exit Likelihood* using Cox's semiparametric proportional hazard models. In these models, the dependent variable is the hazard rate, in our case the probability of focal firm *i* exiting the focal open multiparty alliance *j* at time *t*. Left censoring is not an issue because we track membership from entry into the focal alliance. We set our unit of analysis at the firm-alliance-year level, and include alliance, year, region, and industry category fixed effects in our models, unless specified otherwise. We cluster the standard errors at the firm level to account for non-interdependence of observations for firms that are members of multiple alliances.

4. Results

4.1. Main results

Over the observed period, the open multiparty alliances in our sample rapidly attracted membership, with growth rates of up to 200 % in the year following foundation. Over the full period, we were able to observe the behavior of 1960 firms that variously entered and exited the nine alliances (1439 exits overall). Figs. 2 and 3 summarize the changes in firm membership of the open multiparty alliances over 13 years.

Fig. 2 demonstrates that membership of all alliances fluctuated over time, with considerable variation in patterns of growth and decline between alliances. Whereas some alliances experienced ongoing growth throughout the 13-year period, others saw substantial reductions in membership numbers over the same timeframe. The figure also suggests that it is unlikely that decisions on membership were driven by any industry-wide external shocks, because membership among the alliances did not follow similar patterns of entries or exits, which might have signaled such shocks.[13] Instead, surges and declines in membership seem to be particular to each alliance. A comprehensive reading of alliance-specific press releases provided no pointers to any substantial alliance-specific events that might have triggered big membership changes. Fig. 3 shows more detailed membership data for two alliances, one relatively stable and the other with greater membership churn. The figure reveals how overall membership numbers can conceal continuous or fluctuating levels of firm exit, as well as showing quite dramatic changes in the type of firms represented in the alliances' leadership.

[12] We counted patents in classes relevant to the nine open multiparty alliances in our data, where relevance was determined by the CPC classes associated to alliance technology releases. For patents with multiple CPC codes, we only counted patents in terms of the proportion of CPC codes designated as relevant.

[13] For instance, one salient industry event during our study period was the 2007 introduction of the Apple iPhone. Yet, Apple was notably uninvolved in open multiparty alliances, and thus, despite the possible repercussions of this introduction, we can assume that it did not affect the behavior of other firms in our sample, at least in terms of membership of our nine alliances.

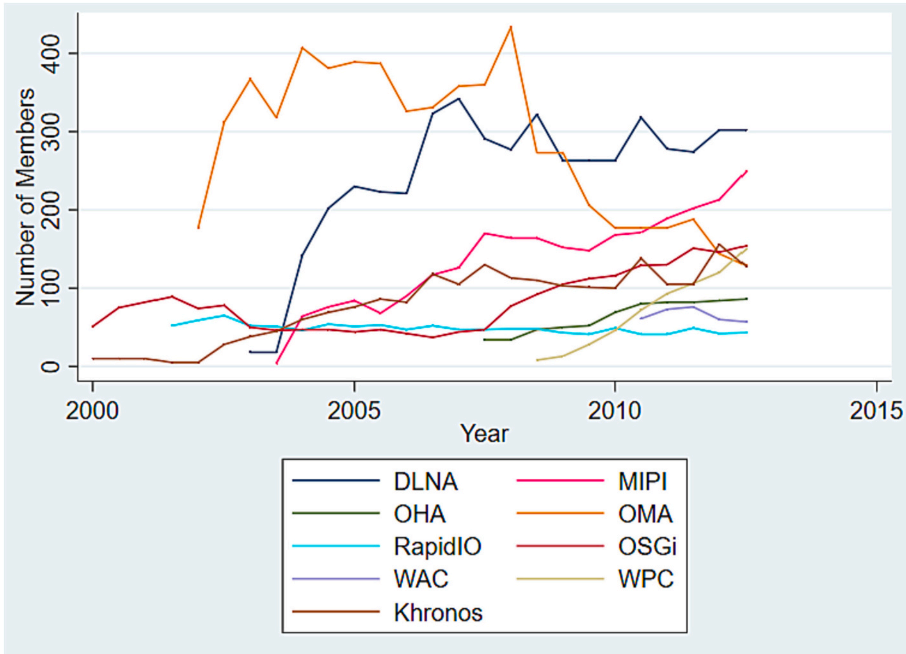

Fig. 2. Membership patterns in the nine OMPAs.

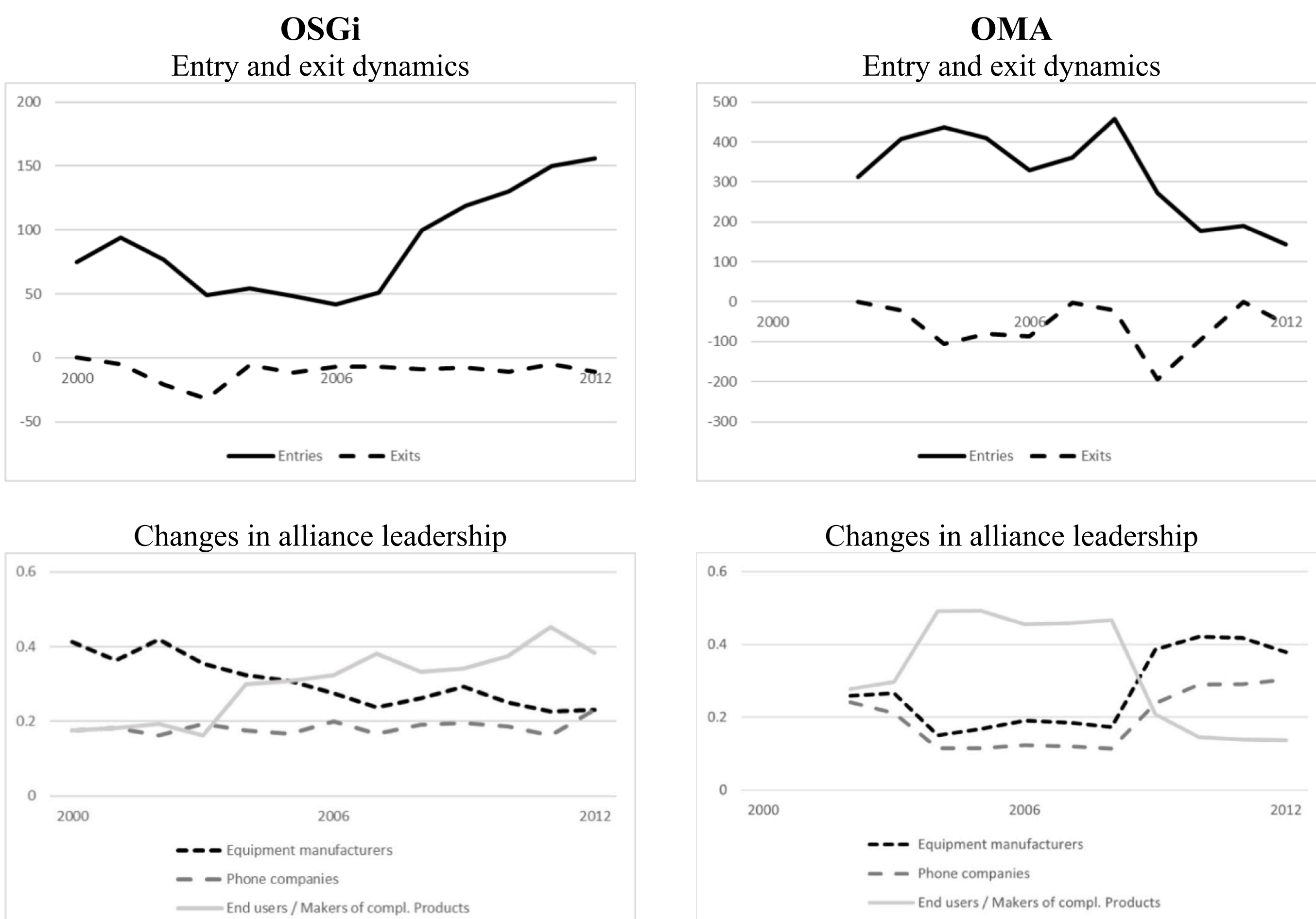

Fig. 3. Example membership dynamics in OSGi and OMA.

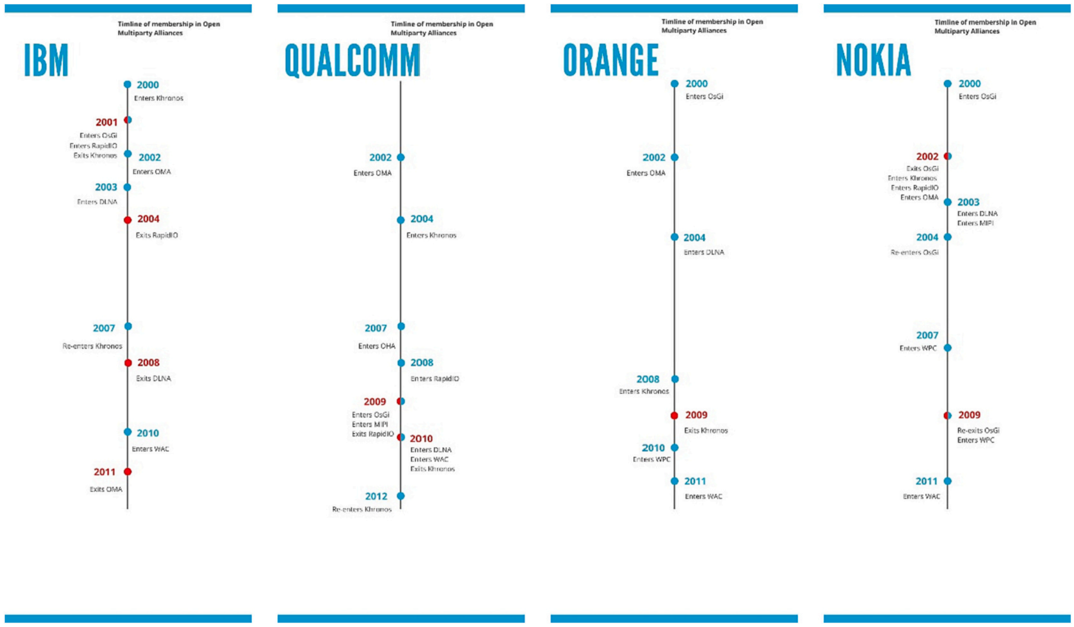

Fig. 4. Example timelines of firms entering and exiting multiple OMPAs.

Fig. 4 introduces illustrative cases depicting entry and exit dynamics of members from four core categories in our data – IBM (Maker of complementary products for end users), Qualcomm (Maker of complementary products for phone companies), Orange (Phone company), and Nokia (Equipment manufacturer). These cases showcase the volatility of membership in open multiparty alliances. Furthermore, the exit from one alliance is not necessarily followed by an immediate entry into another alliance. Despite the possible multiple alternative channels available to firms to obtain similar benefits (e.g., Olk and Young, 1997), the decisions in this context appear to be unrelated.

Table 4 provides descriptive statistics and correlations for all variables. As a first step in testing social influence in exits from open multiparty alliances, we compare the total imitation effect and the imitation effect separately for exiting industry peers and non-peers (cf. Garcia-Pont and Nohria, 2002) in Table 5. While the former assesses the presence of a general bandwagon effect, the separated-out effects test to what extent imitation effects are contained within industry groups. To gauge the raw effect of prior exits and avoid potential issues with "bad controls" (Carlson and Wu, 2012), we perform these analyses without further covariates and using alliance and year fixed effects only. Whereas we find no statistical association between the total number of prior exits and focal firm exit (Model 1) and no effect of exits by non-industry peers (Model 3), we find a positive and significant association (Model 2) between prior exits by a firm's industry peers and the focal firm probability to exit in the subsequent year ($\beta = 0.066$, $p = 0.012$; the corresponding odds ratio $= 1.068$). These findings provide initial support for Hypothesis 1.

In Table 6, we add our control variables. Model 1 is the baseline model with all the controls, but without the hypothesized effects. We find that larger firms, subsidiary firms, firms with voting membership, those leading working groups, and those with more similar technology compared to other members were less likely to exit any given open multiparty alliance, while firm diversification and the complementarity of their technology vis-à-vis other members increased the probability of exit. We also find that older alliances, alliances that issued more press releases, and alliances that released more technologies had lower incidences of firm exit, while larger alliances and those with higher joining rates in the preceding year tended to show higher odds of firm exit. Finally, we observe that greater levels of entry of industry peers increase the incidence of focal firm exit, while greater betweenness centrality (our moderator variable for H2) decreases the chances of exit.

In Model 2, we introduce industry-peer exits to test H1. In line with our prediction, we find that prior industry-peer exits are positively related to the exit of the focal firm from an open multiparty alliance ($\beta = 0.103$, $p = 0.001$; the corresponding odds ratio $= 1.109$).[14] In Model 3, we introduce the interaction between prior industry-peer exits from the alliance and the betweenness centrality of the focal firm within the industry network. In support of H2 and as shown in Fig. 5, we find that firms occupying positions of high betweenness centrality are less likely to imitate their industry peers in exiting an open multiparty alliance (interaction $\beta = -0.147$, $p = 0.041$). As plotted in Fig. 5, this suggests that firms with high centrality in the network tend to be more "immune" to social influence.

4.2. *Probing the mechanism of information-based social influence*

Thus far, we have found empirical evidence that a firm is more likely to exit a given open multiparty alliance in a given year if more of its industry peers exited that alliance in the previous year, and that these tendencies are attenuated for firms in more central positions in the wider network. To probe the credibility of our claim that these effects are rooted in large part in information-based social-influence mechanisms, we perform several post-hoc analyses, exploring a range of conditions in which one might expect information-based social influence to be stronger or weaker.

First, research has shown that information-based social influence tendencies tend to be weaker if levels of uncertainty are similar for all firms, but stronger if uncertainty is more specific to a firm (Gaba and Terlaak, 2013). This is because the information inferred from peer exits gains in salience if the focal firm faces uncertainties that other firms in the alliance do not. On this basis, we expect the tendency to imitate exiting industry peers to be dampened if technological or social

[14] We explore nonlinear effects of exits but find no evidence that these were manifest in our data.

Table 4
Descriptive statistics and correlation matrix.

Main variables	N	Mean	Std. dev.	Min	Max
1 Firm Exit from Open Multiparty Alliance	10,357	0.14	0.35	0	1
2 Firm Size	10,357	0.45	0.50	0	1
3 Firm Age	10,357	26.60	30.59	0	185
4 Firm is Subsidiary	10,357	0.02	0.15	0	1
5 Firm Bankruptcy	10,357	0.00	0.04	0	1
6 Firm Voting Member	10,357	0.30	0.46	0	1
7 Firm Working Group Leader	10,357	0.49	0.50	0	1
8 Firm Lost Voting Member Status	10,357	0.01	0.10	0	1
9 Firm Founding Member	10,357	0.05	0.22	0	1
10 Firm Diversification Entropy Index	10,357	0.06	0.03	0.03	0.17
11 Firm Total Patent Stock	10,357	5.73	12.98	0	110.14
12 Firm Average Tech Similarity (std)	10,357	0.02	1.01	-0.72	4.34
13 Firm Average Tech Complementarity (std)	10,357	0.00	1.00	-10.92	6.45
14 Alliance Age	10,357	5.42	3.08	0	12.50
15 Alliance Size	10,357	236.56	125.53	18	457
16 Alliance Press Releases	10,357	0.37	0.46	0	2.14
17 Alliance Technology Releases	10,357	1.44	2.17	0	12
18 Alliance Share of Voting Members	10,357	0.29	0.27	0	0.99
19 Average Concentration of Ties in Alliance	10,357	0.55	0.14	0.17	0.85
20 Alliance Number of Firm Entries *	10,357	55.02	60.85	0	312
21 Alliance Number of Industry Peer Entries	10,357	6.43	11.60	0	125
22 Alliance-Firm Redundancy in Membership	10,357	3.98	6.55	0	38
23 Prior Industry Peer Exits from Alliance *	10,357	11.99	18.80	0	144
24 Focal Firm Betweenness Centrality (std)	10,357	0.01	1.01	-0.43	8.35

Main variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 Firm Exit from Open Multiparty Alliance	1.00																						
2 Firm Size	-0.10	1.00																					
3 Firm Age	-0.07	0.38	1.00																				
4 Firm is Subsidiary	0.00	-0.06	-0.01	1.00																			
5 Firm Bankruptcy	0.11	-0.02	-0.02	0.29	1.00																		
6 Firm Voting Member	-0.07	0.24	0.20	-0.03	-0.02	1.00																	
7 Firm Working Group Leader	0.01	0.22	0.18	0.00	0.01	0.12	1.00																
8 Firm Lost Voting Member Status	0.00	0.03	0.01	-0.01	0.00	-0.06	0.01	1.00															
9 Firm Founding Member	-0.05	0.18	0.25	-0.01	-0.01	0.29	0.14	0.04	1.00														
10 Firm Diversification Entropy Index	-0.05	0.00	-0.02	-0.03	0.01	-0.13	-0.22	-0.03	-0.06	1.00													
11 Firm Total Patent Stock	-0.07	0.19	0.34	-0.02	-0.02	0.13	0.08	0.01	0.20	-0.02	1.00												
12 Firm Average Tech Similarity (std)	-0.03	0.03	-0.11	0.00	-0.01	0.10	0.08	0.00	0.05	-0.10	-0.03	1.00											
13 Firm Average Tech Complementarity (std)	0.04	-0.16	-0.12	0.02	0.00	-0.02	-0.01	-0.02	-0.04	-0.12	-0.07	0.51	1.00										
14 Alliance Age	-0.02	-0.02	0.03	-0.02	-0.02	0.07	-0.11	0.00	-0.08	-0.01	0.26	-0.03	0.02	1.00									
15 Alliance Size	0.11	-0.10	-0.10	0.04	0.03	-0.18	0.39	0.01	-0.10	-0.33	-0.13	0.07	0.10	-0.18	1.00								
16 Alliance Press Releases	0.00	0.03	0.03	0.02	-0.01	-0.14	0.07	0.03	0.01	-0.37	0.11	0.03	0.03	0.22	0.33	1.00							
17 Alliance Technology Releases	0.07	-0.06	-0.05	-0.03	0.00	0.19	0.10	-0.01	-0.07	-0.08	0.06	0.06	0.08	0.26	0.14	-0.18	1.00						
18 Alliance Share of Voting Members	0.02	-0.01	-0.01	-0.02	0.00	0.58	-0.04	-0.03	0.04	-0.21	-0.03	0.07	0.09	0.12	-0.32	-0.25	0.31	1.00					
19 Average Concentration of Ties in Alliance	0.02	-0.14	-0.10	0.07	0.01	-0.18	0.04	0.03	-0.11	-0.14	-0.17	0.02	0.09	-0.18	0.62	0.06	-0.09	-0.32	1.00				
20 Alliance Number of Firm Entries *	0.03	-0.05	-0.06	0.04	0.02	-0.07	0.03	0.00	-0.04	-0.11	-0.11	0.04	0.05	-0.44	0.49	0.01	-0.08	-0.13	0.51	1.00			
21 Alliance Number of Industry Peer Entries	0.07	-0.07	-0.14	0.02	0.05	-0.10	-0.08	-0.02	-0.04	0.12	-0.12	0.07	0.03	-0.26	0.25	-0.05	-0.07	-0.12	0.24	0.09	1.00		
22 Alliance-Firm Redundancy in Membership	0.05	-0.12	-0.16	0.02	0.04	-0.14	0.07	-0.02	-0.05	0.13	-0.07	0.09	0.05	-0.01	0.23	-0.01	0.05	-0.13	0.14	-0.02	0.47	1.00	
23 Prior Industry Peer Exits from Alliance *	0.07	-0.10	-0.10	0.00	0.00	-0.09	0.10	-0.01	-0.05	-0.09	-0.08	0.08	0.08	0.01	0.30	0.15	0.00	-0.06	0.16	-0.09	0.28	0.38	1.00
24 Focal Firm Betweenness Centrality (std)	-0.09	0.34	0.41	-0.02	-0.02	0.31	0.39	0.01	0.30	0.01	0.44	0.01	-0.10	0.04	-0.14	-0.02	0.01	0.07	-0.18	-0.10	-0.08	-0.06	-0.07

A table with descriptive statistics for variables included in our post-hoc analyses is available in Appendix A. Correlations larger than |0.026| are significant at the 0.01 level.

uncertainty are common to all firms in the alliance and amplified if they are more firm-specific. To measure *Alliance-Level Technological Uncertainty*, we measure the yearly number of patents released in technology classes relevant to the focal alliance, specifically in the CPC classes associated with the alliance's technology releases.[15] For emerging technologies, a lower patent count in the industry indicates higher uncertainty surrounding the viability of the alliance's technologies (Cohen et al., 2016) and, accordingly, we standardized and reversed the measure to obtain one in which higher values indicate greater uncertainty. We measure *Firm-Specific Technological Uncertainty* in terms of the change in alignment between the technology focus of the alliance and that of the focal firm, interpreting increased misalignment as an increase in firm-specific technological uncertainty (Browning et al., 1995).[16] The

Table 5
Total versus peer imitation effects.

	Model 1	Model 2	Model 3	Model 4
Prior Total Exits from Alliance	0.045			
	(0.03)			
Prior Industry Peer Exits from Alliance		0.066**		0.068**
		(0.03)		(0.03)
Prior Non-Industry Peers from Alliance			−0.0015	−0.015
			(0.03)	(0.03)
Alliance-level fixed effects	Yes	Yes	Yes	Yes
Year-level fixed effects	Yes	Yes	Yes	Yes
Wald chi2	361.5	366.1	372.5	370.1
N	10,357	10,357	10,357	10,357
Pseudo log likelihood	−10,087.9	−10,086.1	−10,088.7	−10,086.0

Standard errors in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[15] We assume that, in any given year, the alliance is working on its next technology release. Therefore, we consider all technology classes in the first technological release *after* a given year as "alliance-relevant" in that year.

[16] Increased misalignment can arise if a technology class in which a given firm has many patents is no longer used (deprecated) in an alliance's next technology release, or if a new technology class in which a firm has few patents is adopted for the alliance's next release. Building on Makri et al. (2010), we treat all firm patents in the same, broader, three-digit technology classes as being related to the four-digit classes associated with each alliance. We capped the measure at a minimum of −2 (i.e., a doubling of relevant patents) to avoid outliers caused by year-on-year increases in relevant patents from a very small base.

results for Model 1 in Table 7, together with Fig. 6A, support the argument that the tendency to imitate decreases when technological uncertainty at the alliance level is higher. Regarding firm-specific technology uncertainty, Model 2 in Table 7 shows a marginally significant ($p = 0.060$) interaction between firm-specific technological uncertainty and industry peer exits. Fig. 6B shows a stronger imitation effect when firm-specific technological uncertainty is high (an 86 % increase in probability of exit when industry peer exits increase from its minimum to the 90th percentile value) compared to when it is low (an equivalent 9 % increase).

When it comes to *social* uncertainty, one might expect the same asymmetric effects for alliance and firm-specific levels. Alliance-level social uncertainty arises if there is high information inconsistency because of many members simultaneously entering and exiting an alliance (Gaba and Terlaak, 2013; Zhang et al., 2017). Whereas growth in membership is typically interpreted as a positive signal of an alliance's stability, and a decline in membership sends an unambiguous signal in the opposite direction, inconsistency in such patterns can render the informational cues sent by exiting peers confusing and likely to dampen imitation tendencies as a consequence. Accordingly, we measure *Alliance-Level Social Uncertainty* as the information inconsistency that arises from churn in alliance entries and exits (Gaba and Terlaak, 2013).[17] In contrast, *Firm-Specific Social Uncertainty* increases under the influence of alliance leadership changes that may benefit some firms while disadvantaging others (Ranganathan et al., 2018). Thus, if the leadership representation of firms from the same category[18] as the focal firm decreases, we expect firm-specific social uncertainty to increase as firms become less confident that alliance collaboration dynamics will favor their own private interests. Therefore, we measure firm-level social uncertainty in terms of the relative decrease in the share of alliance leaders that belong to the same category as the focal firm. The results of Models 3 and 4 (see Table 7), together with Fig. 6C and D, support the argument that imitation tendencies are weaker when social uncertainty is common to all firms in the alliance, and stronger when such uncertainty is more firm-specific.

The second contingency concerns the leadership profile of the exiting firms, with other firms being more susceptible to social influence and imitation if their exiting peers occupy formal or informal leadership positions. In information-based social influence, firms attach more importance to the behaviors of firms with prominent traits, and will, therefore, be more likely to imitate their decisions (Haunschild and Miner, 1997). Because firms in formal leadership positions – voting members and working-group leaders – gain learning advantages because of having a better overview of the various technologies under development (Leiponen, 2008), they are perceived to have better information and are, therefore, more likely to be imitated. Likewise, firms in structurally advantageous network positions are likely to have access to information that is unavailable to other firms (Wang et al., 2014), and thus firms' tendency to imitate exiting peers will be stronger if exiting firms are boundary spanners. The results for Models 5 and 6 in Table 7, alongside Fig. 6E and F, support the arguments that imitative tendencies increase when a higher share of the exiting firms occupied formal leadership positions in the alliance or were members of several open multiparty alliances.

Table 6
Results of Cox hazard models predicting firm exit from OMPA.

	Model 1	Model 2	Model 3
Firm Size	−0.16***	−0.17***	−0.17***
	(0.06)	(0.06)	(0.06)
Firm Age	−0.0012	−0.0011	−0.0011
	(0.00)	(0.00)	(0.00)
Firm is Subsidiary	−0.60**	−0.61**	−0.62**
	(0.24)	(0.24)	(0.24)
Firm Bankruptcy	1.59***	1.63***	1.65***
	(0.27)	(0.26)	(0.26)
Firm Voting Member	−0.48***	−0.48***	−0.47***
	(0.08)	(0.08)	(0.08)
Firm Working Group Leader	−0.22**	−0.23**	−0.22**
	(0.09)	(0.09)	(0.09)
Firm Lost Voting Member Status	−0.042	−0.018	−0.012
	(0.25)	(0.25)	(0.25)
Firm Founding Member	−0.22	−0.22	−0.21
	(0.19)	(0.19)	(0.19)
Firm Diversification Entropy Index	11.5***	12.9***	12.6***
	(3.72)	(3.79)	(3.78)
Firm Total Patent Stock	0.0018	0.0016	0.0018
	(0.00)	(0.00)	(0.00)
Firm Average Technology Similarity to Other Members (std)	−0.11***	−0.11***	−0.11***
	(0.03)	(0.03)	(0.03)
Firm Average Technology Complementarity to Other Members (std)	0.074**	0.074**	0.073**
	(0.03)	(0.03)	(0.03)
Alliance Age	−1.71***	−1.71***	−1.71***
	(0.11)	(0.11)	(0.11)
Alliance Size	0.0069***	0.0072***	0.0071***
	(0.00)	(0.00)	(0.00)
Alliance Press Releases	−0.32***	−0.33***	−0.32***
	(0.10)	(0.10)	(0.10)
Alliance Technology Releases	−0.071***	−0.038	−0.038
	(0.02)	(0.02)	(0.03)
Alliance Share of Voting Members	−0.10	−0.20	−0.24
	(0.52)	(0.53)	(0.52)
Average Concentration of Ties in Alliance	−6.87***	−6.90***	−6.86***
	(0.52)	(0.52)	(0.52)
Alliance Number of Firm Entries	0.0021**	0.0030***	0.0029***
	(0.00)	(0.00)	(0.00)
Alliance Number of Industry Peer Entries	0.0048**	0.0036	0.0037
	(0.00)	(0.00)	(0.00)
Alliance Redundancy in Membership for Focal Firm	−0.0046	−0.0074*	−0.0080*
	(0.00)	(0.00)	(0.00)
Focal Firm Betweenness Centrality (std)	−0.16***	−0.15***	−0.18***
	(0.05)	(0.05)	(0.05)
Prior Industry Peer Exits from Alliance (std)		0.10***	0.051
		(0.03)	(0.04)
Prior Industry Peer Exits * Focal Firm Betweenness Centrality			−0.15**
			(0.07)
Alliance-level fixed effects	Yes	Yes	Yes
Year-level fixed effects	Yes	Yes	Yes
Region-level fixed effects	Yes	Yes	Yes
Industry-level fixed effects	Yes	Yes	Yes
Wald chi2	1729.1	1726.2	1725.7
N	10,357	10,357	10,357
Pseudo log likelihood	−9738.7	−9735.0	−9732.6
Log likelihood ratio test (comp M2 to M1; M3 to M2)		7.43***	4.75**

Standard errors in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3. Probing the mechanism of rivalry-based social influence

In our theorizing, we argued that rivalry-based social influence mechanisms are likely to complement information-based mechanisms. We argued that, whereas information-based social influence can be expected to drive imitation when uncertainty is firm-specific, rivalry-based factors come into play when uncertainty is at the alliance-level.

[17] Information inconsistency $= -\frac{|Exits_{t-1} - Entries_{t-1}|}{Exits_{t-1} + Entries_{t-1}}$

[18] For example, if equipment manufacturers start to dominate the leadership positions in an alliance, firms from other categories within the mobile phone industry (Cohen et al., 2016), such as phone companies or makers of complementary products for end users (e.g., software companies), might feel marginalized, underrepresented, and/or uncertain in relation to their own impact on the alliance's direction.

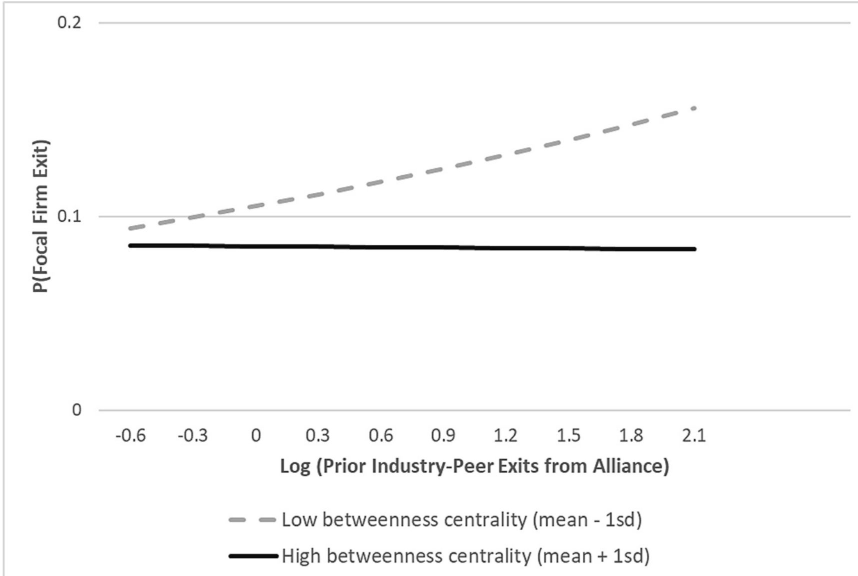

Fig. 5. Moderation effect of focal-firm betweenness centrality in sector network on the relation between prior industry-peer exits from OMPA and focal-firm exit.

Table 7
Probing the information-based social influence mechanism.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Prior Industry Peer Exits from Alliance (std)	0.11***	0.097***	−0.066	0.081**	−0.12**	−0.064
	(0.03)	(0.03)	(0.06)	(0.03)	(0.06)	(0.08)
Alliance-level technological uncertainty (std)	−0.25***					
(alliance-relevant patents)	(0.06)					
Prior Industry Peer Exits * Alliance-level technological uncertainty	−0.16***					
	(0.04)					
Firm-level technological uncertainty		0.26***				
(change in technological alignment)		(0.06)				
Prior Industry Peer Exits * Firm-level technological uncertainty		−0.063*				
		(0.03)				
Alliance-level social uncertainty			1.44***			
(information inconsistency)			(0.14)			
Prior Industry Peer Exits * Alliance-level social uncertainty			−0.30***			
			(0.09)			
Firm-level social uncertainty				−0.28***		
(change in alignment with firm category)				(0.08)		
Prior Industry Peer Exits * Firm-level social uncertainty				0.19***		
				(0.05)		
Alliance exits of firms in formal leadership positions					−0.55***	
					(0.13)	
Prior Industry Peer Exits * Alliance exits formal leaders					0.33***	
					(0.06)	
Alliance exits of firms in informal leadership positions						9.47***
						(3.08)
Prior Industry Peer Exits * Alliance exits informal leaders						8.38**
						(3.65)
Wald chi2	1797	1741.4	1723.9	1745.9	1747.6	1735.8
N	10,357	10,357	10,357	10,357	10,357	10,357
Pseudo log likelihood	−9717.6	−9725.2	−9690.6	−9727.3	−9717.8	−9731.7

The same control variables and fixed effects are included as in all other models (Table 6). Due to space constraints, the coefficients and standard errors are not shown here. Full tables are available on request.
Standard errors in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Although our analyses in Section 4.2 (Table 7) suggest tendencies to imitate are reduced at higher levels of alliance-level uncertainty – and thus support information-based over rivalry-based mechanisms – it is unlikely that rivalry-based social influence plays no role at all, given the fundamental uncertainties that surround technology development. That is, it may well be that firms imitate both alliance entry and alliance exit for oligopolistic reasons, in a bid to preserve the status quo in the industry-wide efforts to develop potentially competing technologies (Garcia-Pont and Nohria, 2002). If that is the case, one would expect firms to imitate the exits of peer firms that entered the alliance open multiparty alliance before them, but not necessarily those that entered at the same time or afterwards. Analyses with peer exits broken down by

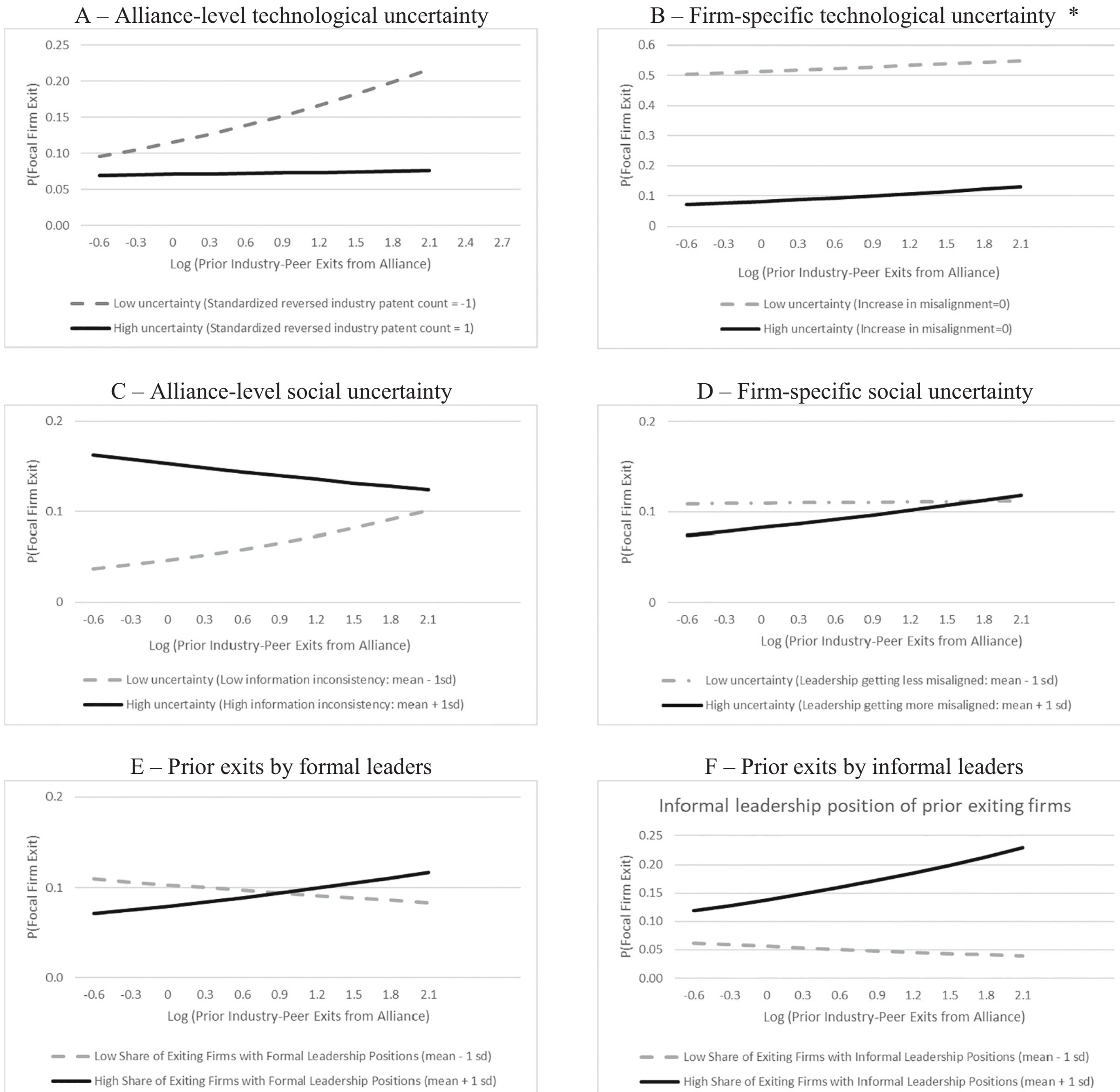

Fig. 6. Probing the information-based imitation mechanism: Contingencies of the effect of industry-peer imitation on focal-firm exit from OMPA.

relative time of entry (see Table 8 Model 1) support this prediction, suggesting the argument that firms might mimic both their peers' alliance entry and exit decisions. Such tendencies might emanate from firms' desire to preserve the status quo in the competitive landscape of technology development. As such, it is likely that rivalry-based imitation mechanisms are an additional driving force behind the peer imitation.

4.4. Further robustness checks

We conducted a series of robustness checks to assess the sensitivity of our results, particularly in terms of model specifications and covariate choices, and to address endogeneity concerns to the best extent possible. To start with the latter, it is conceivable that both the number of firms exiting an alliance in one year and the focal firm's decision to leave the following year are driven by the same unobserved factors. To test for this possibility, we ran an instrumental variable analysis, albeit using a probit framework rather than the hazard model of our main analysis and including only alliance, year, region, and industry category fixed effects

Table 8
– Probing the rivalry-based social influence mechanism.

	Model 1
Prior Exits of Industry Peers that Entered Earlier than Focal Firm	0.12***
	(0.02)
Prior Exits of Industry Peers that Entered in Same Year as Focal Firm	0.0074
	(0.03)
Prior Exits of Industry Peers that Entered Later than Focal Firm	0.00053
	(0.04)
Wald chi2	1736.2
N	10,357
Pseudo log likelihood	−9730.5

The same control variables and fixed effects are included as in all other models (Table 6). Due to space constraints, the coefficients and standard errors are not shown here. Full tables are available on request.
Standard errors in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9
Comparing industry, category, and regional imitation effects.

	Model 1	Model 2	Model 3	Model 4
Prior Industry Peer Exits from Alliance - same SIC only	0.10*** (0.03)			
Prior Industry Peer Exits from Alliance - same category only		0.10*** (0.03)		
Prior Industry Peer Exits from Alliance - same region			0.06 (0.04)	
Prior Industry Peer Exits from Alliance - same industry and same region				0.071** (0.03)
Wald chi2	1754.2	1743.6	1727.4	1735.3
N	10,357	10,357	10,357	10,357
Pseudo log likelihood	−9437	−9437.8	−9440.2	−9439

The same control variables and fixed effects are included as in all other models (Table 6). Due to space constraints, the coefficients and standard errors are not shown here. Full tables are available on request.
Standard errors in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10
Additional robustness checks.

	Model 1	Model 2	Model 3
Prior Industry Peer Exits from Alliance (std)	0.10*** (0.03)	0.10*** (0.03)	0.12*** (0.03)
Average Technological Similarity of Exiting Industry Peers	0.21** (0.09)		
Average Technological Complementarity of Exiting Industry Peers		−0.11* (0.06)	
Average Geographical Uniqueness of Exiting Industry Peers			−0.14*** (0.04)
Prior Exits of Industry Peers that Entered Earlier than Focal Firm			
Prior Exits of Industry Peers that Entered in Same Year as Focal Firm			
Prior Exits of Industry Peers that Entered Later than Focal Firm			
Wald chi2	1722.3	1724.6	1742.6
N	10,357	10,357	10,042
Pseudo log likelihood	−9733.5	−9734.1	−9569.1

The same control variables and fixed effects are included as in all other models (Table 6). Due to space constraints, the coefficients and standard errors are not shown here. Full tables are available on request.
Standard errors in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

and no further covariates.[19] For the instrumental variable, we exploit the high rate of corporate bankruptcy in the focal firm's industry (31 % of firm-alliance dyads experience one or more bankruptcies of industry peer firms). We expect this variable to be theoretically unrelated to the dependent variable – that is, an industry peer's bankruptcy should not directly affect a focal firm's desire to exit an alliance – but theoretically related to the main independent variable – that is, industry-peer bankruptcies increase industry-peer exits from an alliance. Incorporating the industry bankruptcies variable into our probit model regression supports the former ($\beta = 0.032$, $p = 0.135$), while a negative binomial regression at the alliance-year-industry level ($N = 860$) of industry bankruptcies on alliance exits supports the latter ($\beta = 0.209$, $p = 0.020$). As a final step, the instrumental variable regression (ivprobit) shows that the positive effect of prior industry-peer exits on focal-firm alliance exit persists when instrumenting the independent variable ($\beta = 0.016$, $p = 0.043$). A Wald test ($\chi^2 = 2.27, p = 0.13$) shows no strong evidence of endogeneity.

Second, we further gauge the nature of groups within which social influence and imitation effects occur. First, we break down our definition of industry peer groups into its two constituent components, namely peers with at least one overlapping SIC code and peers who belong to the same industry category as defined by Cohen et al. (2006). As shown in Models 1 and 2 of Table 9, we find that the industry peer imitation effects hold for both aspects of industry peer groups separately. We also explore to what extent imitation effects might occur within groups of firms that operate in the same region. As shown in Model 3, the prior number of exiting same-region firms has no statistically significant effect on focal firm exit, while a combined regional and industry peer effect as shown in Model 4 is positive and significant, albeit weaker (odds ratio is 1.051) than the pure industry peer imitation effect (odds ratio 1.109). These findings suggest regional effects play no major role in driving social influence effects in exits from open multiparty alliances.

Third, we explore to what extent firms might exit an open multiparty alliance, not merely because it is firms they consider peers who are leaving, but because of resource complementarities and redundancies of exiting firms (i.e., crowdedness), either in terms of technological focus (Toh and Miller, 2017) or geographical scope (García-Canal and Sánchez-Lorda, 2007). We relied on the formulas introduced by Makri et al. (2010) – and also used in focal firm control variables in all analyses – to calculate the average technological similarity and complementarity of a focal firm's exiting peers. We find that greater similarity of the patent portfolio of exiting peers increases the probability of focal firm exit from the open multiparty alliance (Table 10, Model 1), while greater technological complementarity of exiting peers decreases the odds that a focal firm will follow suit (Model 2). These findings suggest that in our setting, firms are less concerned about the crowdedness of the alliance with too many similar firms (cf. Toh and Miller, 2017), and more about potential productive overlaps due to technological similarity. In terms of the geographical scope effects (García-Canal and Sánchez-Lorda, 2007), we measure the extent to which exiting peers are unique representatives of their region within the alliance. Specifically, we calculate for each exiting firm at time t-1 the proportion of fellow members located in the same region. We then inverted this measure to create a measure of uniqueness as opposed to geographical overlap and averaged these uniqueness scores across all firms exiting the alliance at time *t-1*. We find that the average "geographical uniqueness" of exiting members decreases the probability that the focal firm exits an open multiparty alliance (Model 3). Thus, exits from firms with a unique geographical scope motivate the focal firm to remain a member of an alliance.

Finally, common industry shocks can drive alliance exit decisions. To account for this concern, we removed years 2003 (introduction of the 3G technology) and 2007 (introduction of the Apple iPhone) (Kenney and Pon, 2011) and reran our analyses (Giachetti and Marchi, 2017): the results remained consistent with those already reported.

5. Discussion

Our study sheds light on the complex membership dynamics of an increasingly important form of interfirm collaboration that we label "open multiparty alliances". Due to the open-membership policy and the lack of formal contracts governing these collectives, members can easily enter and exit. Furthermore, members collaborate under conditions of uncertainty stemming from the novelty of the alliance's technologies and the difficulty to gauge the trustworthiness of members from diverse industries. Thus, we examine how, under such conditions of uncertainty, social influence dynamics among members affect firm decisions to exit open multiparty alliances. We find that, in general, firms are sensitive to the actions of their industry peers and tend to mimic them in leaving open multiparty alliances. Information-based social influence

[19] The main effect of prior industry-peer exits on focal-firm exit in this revised setup: $\beta = 0.0038$, p-value $= 0.000$.

mechanisms are a primary driving force behind this imitation effect; firms seek to avoid or reduce social and technological uncertainties by interpreting the actions of their peers as critical sources of information about the desirability and viability of the collaborative effort and its promoted technologies. Rivalry-based mechanisms are an additional driver of social influence, in that open multiparty alliance members tend to imitate both the alliance entry and exit decisions of rivals in a bid to preserve the status quo in the industry's competitive landscape of technology development. Yet not all member firms experience uncertainty equally: we show that firms with a more central position in the wider network of alliances in the mobile phone sector have a lower tendency to imitate the exit decisions of their peers. This suggests that superior access to information about industry developments and to key resources *immunizes* firms from social influence.

5.1. Research and practical implications

The findings of this study carry theoretical implications for research on interfirm collaboration in technology and innovation management, as well as some practical implications.

First, our study contributes to the emerging stream of research on interfirm collaboration dynamics within multiparty setups, particularly in technology-intensive contexts (e.g., Heidl et al., 2014; Davis, 2016; Fonti et al., 2017; Gulati et al., 2012; Lavie et al., 2007; Ranganathan et al., 2018). We answer renewed calls to attend to the unique dynamics that emerge as a result of bringing multiple, often diverse partners together to collaborate on novel technologies, particularly in open-membership contexts (Davis, 2016; Gulati et al., 2012; Ranganathan et al., 2018). Previous literature on interfirm collaboration has commonly treated open multiparty alliances as a collection of independent dyads or pairwise collaborations (Ahuja, 2000; Gulati and Gargiulo, 1999). Yet this could be misleading because open multiparty alliances display group-like dynamics that have implications on firm membership decisions such as inferring the desirability of remaining a member from the actions of large numbers of peer firms, thus setting these alliances apart from dyadic alliances where such group dynamics are by definition absent (Davis, 2016). Moreover, while open multiparty alliances have been proliferating in practice and have gained substantial scholarly attention in recent years (e.g., Fonti et al., 2017; Lavie et al., 2007; Ranganathan et al., 2018), many studies have grouped these collaboration forms under the umbrella of multiparty alliances, i.e., without specifying their open or closed nature. Although some of the insights on closed multiparty alliances (e.g., Dorobantu et al., 2020; Lazzarini, 2007; Schilling, 2002) may be transferable to open multiparty alliances, treating both types of collaboration forms interchangeably could be problematic as unique dynamics emerge due to the nature of the highly inclusive and open setup (Gulati et al., 2012). Closed multiparty alliances such as market-based SSOs (Schilling, 2002), closed consortia and industry constellations (e.g., Garcia-Pont and Nohria, 2002; Lazzarini, 2007) impose contractual constraints to premature exit and are often associated with fewer, less diverse members (Gulati et al., 2012). Therefore, we posit that open multiparty alliances should be treated separately from closed collaboration forms, whether dyadic or multiparty in nature, and suggest that open multiparty alliances such as open committee-based standard-setting organizations (SSOs) (Wiegmann et al., 2017; Ranganathan et al., 2018), technology and research consortia (Lavie et al., 2007; Fonti et al., 2017), and other open, large-scale meta-organizations (Gulati et al., 2012) deserve scholarly attention in their own right.

Second, we integrate the interfirm collaboration literature with social influence studies to offer novel insights on the membership dynamics within and across open multiparty alliances. Our findings suggest that the combination of broad diversity of organizational membership and ease of entry and exit in open multiparty alliances creates ideal conditions for social influence dynamics to manifest in a firm's decision of whether to remain a member or abandon the collective (Gulati et al., 2012). In the absence of the common governance mechanisms that characterize dyadic alliances and closed multiparty alliances, such as formal contracts, clear hierarchical authority, and binding legal terms (e.g., Hohberger et al., 2020; Reuer and Zollo, 2005; Dorobantu et al., 2020), open multiparty alliances allow participating firms to freely enter and exit at any time. While the freedom of entry and exit create favorable conditions for collaboration such as resource diversity and a collective, broader innovation capacity that may better advance the technological goals of the alliance, on the flip side, these same conditions could give rise to elevated technological and social uncertainty experienced by certain members. Because firms in open multiparty alliances face uncertainty about the potential of the novel technologies under development (Ozmel et al., 2017) and the reliability of other members as collaboration partners (Fonti et al., 2017), they let themselves be guided to a significant degree by the signals that exiting industry peers send about their confidence in the alliance and the potential of the technologies being promoted, or simply imitate rivals' moves to preserve the status quo in the uncertain competitive landscape of technology development.

Our findings may also carry implications for other forms of open collaboration such as open-source software communities (Lakhani and Von Hippel, 2003) and digital platforms (Kenney and Zysman, 2016; Nambisan et al., 2018). Studies on open-source software communities have been increasingly interested in uncovering the complex membership dynamics that arise from collaborating under conditions of openness (e.g., Fleming and Waguespack, 2007). In such collaborations, similar mechanisms might operate as a result of open membership policies and may give rise to social influence and imitation tendencies in relation to membership decisions, as well as to advantageous network positions that shield certain members from those effects. Our findings could also be relevant to closely related research on digital platforms. In contrast to open multiparty alliances, digital platforms are typically shaped by one or several lead firms that orchestrate the ecosystem of complementors, yet both contexts share a set of characteristics that pose similar empirical puzzles. For instance, studies on digital platforms have been largely interested in exploring how complementors – who are often also industry peers – collaborate together to innovate (Kapoor and Agarwal, 2017). One might expect comparable dynamics to materialize in digital platforms due to elevated conditions of technological and social uncertainty (i.e., stemming from the novelty of emergent technologies and the large number of collaborators), a certain degree of openness,[20] and a diversity of firms pooling in resources (Gawer, 2014; Kapoor and Agarwal, 2017; Nambisan et al., 2018). It would be pertinent for future research to jointly investigate both phenomena in the same study. For instance, while we shed light on Open Handset Alliance (OHA) in this study, future research could examine the Android platform side of the story (Kenney and Pon, 2011) to offer a more comprehensive understanding of the empirical context, particularly that OHA and Android conjointly play a significant role in the emergence and growth of the mobile phone sector.

Third, in line with claims that imitation is often more complex and imperfect than assumed in existing theories (Posen et al., 2013; Sharapov and Ross, 2023), we contribute to the literature on the role of uncertainty in technology contexts (e.g., Cohen et al., 2016; Roca et al., 2017) by demonstrating that variation in structural positions within a wider network translates into variation in the extent to which firms are susceptible to peer-imitation pressures. While previous literature has extensively studied firms that are likely to be imitated due to their salient social cues (i.e., status, size, market leadership) (Sharapov and Ross, 2023; Vedula and Matusik, 2017), studies have yet to shed light on

[20] Similar to multiparty alliances (closed versus open), platforms could fall on either side of the openness spectrum (Kapoor and Agarwal, 2017). In the mobile phone sector, Android is an example of an open platform, while iOS is an example of a more closed platform.

a firm's decision to *not* imitate similar others in spite of social influence effects. We document an important contingency that explains why some firms are more prone to social influence than others while some are immunized from social influence altogether. Firms occupying a central position in the sector's wider web of interfirm relations have access to superior information to their peripheral peers and to valuable resources, thus serving as a protective shield from social influence effects.

Our findings carry practical implications for the management of open multiparty alliances and related forms of collaboration. Because a sudden rise in collective exits can lead to the abandonment of an alliance-supported technology (Heidl et al., 2014), regardless of its intrinsic potential (Abrahamson and Rosenkopf, 1993), the architects of alliances should monitor members' exit decisions carefully. Such architects should pay particular attention to firms in formal and informal leadership positions, which tend to be highly respected in technology-intensive communities (Fleming and Waguespack, 2007; Leiponen, 2008; Ranganathan et al., 2018) and that, as our post-hoc analyses have shown, carry greater weight in the dynamics of interfirm social influence. For example, the market dominance and innovation capabilities of Google largely depend on the commitment of firms across the value chain to the common technological projects under development in open multiparty alliances (Gulati et al., 2012). By implication, to maintain momentum, alliance architects need to closely monitor whether prominent members are considering abandonment of their alliance, because such actions could have significant repercussions for the value other firms then perceive in remaining members. Relatedly, because open multiparty alliances are inherently cooperative and thrive on collaboration and merit, alliance architects often seek to prevent specific members from becoming dominant within the arrangement (Ranganathan et al., 2018), regardless of their actual technological knowledge and market power. By understanding the membership dynamics, information asymmetries, and differences in levels of uncertainty experienced by members, organizing entities can take steps to better manage an open multiparty alliance; for example, by seeking to avoid the perception of certain firms that they are voiceless as a result of unfavorable network positions by encouraging them to get more involved in the alliance (Alexy et al., 2013). In this light, understanding the sources of superior information and resources that could lead to variation in the levels of uncertainty experienced by alliance members is paramount.

5.2. Limitations and future research

Despite these contributions, we acknowledge that our paper has limitations that offer future research opportunities. First, the collection of comprehensive interorganizational network data can be a challenging endeavor in network scholarship (Creswell and Creswell, 2017) and, despite our efforts to diligently track dyadic and closed multiparty alliances alongside the nine open multiparty alliances that were the main subject of our study, we were unable to observe the full gamut of formal and, in particular, informal interactions and relations among the firms in our sample, let alone the interpersonal channels of communication that embody them. Future research may more directly observe how multilevel interpersonal and interorganizational relations jointly orchestrate interfirm imitation dynamics in the context of open multiparty arrangements. In a related vein, while we relied on SDC Platinum, the most comprehensive dataset available to collect data on firm ties outside open multiparty alliances (i.e., dyadic and closed multiparty alliances), it has been noted that SDC Platinum alliance data can be sparse and incomplete in some instances (e.g., Ranganathan et al., 2018; Lavie et al., 2007). Future studies can build more complete datasets by manually tracking alliance termination and/or firm exit from (open and closed) multiparty alliances and, as a next step, rely on news platforms such as Factiva to complete missing data. A closely related avenue of future research, and building on such more complete sources of data, concerns the interplay between these various forms of collaboration in the context of open multiparty arrangements. Research on the multiplexity of ties, defined as the degree to which social ties embody several substantively different types of relationships, has started to gain momentum in recent years (e.g., Kim et al., 2016). Thus, future studies can empirically test the competition–cooperation dynamics (e.g., Browning et al., 1995) across membership in various types of collaborative forms – including open multiparty alliances – in technology-intensive industries (Cozzolino and Rothaermel, 2018).

Second, although we have suggested that our findings regarding social influence in exit decisions from open multiparty alliances may extend to other comparable contexts, we could not observe this directly. It would be worth directly examining whether and to what extent our findings apply to similar contexts, thereby furthering our understanding of the boundary conditions of interfirm imitation. Furthermore, despite our efforts to highlight the distinct characteristics of open multiparty alliances in relation to closed multiparty alliances and dyadic alliances, a comprehensive taxonomy is beyond the scope of this study. Future research can advance a taxonomy of different types of multiparty collaborative forms (Li et al., 2012), both open and closed (e.g., Ranganathan et al., 2018) – including market-based, government-based, and multi-mode SSOs, and newly emergent "hybrid" forms of multiparty arrangement (Wiegmann et al., 2017; Wiegmann et al., 2022) and compare them to the more commonly-studied dyadic alliances. Furthermore, it would be interesting to explore whether our research informs the growing literature on alliance portfolios (Hoehn-Weiss et al., 2017; Lavie and Miller, 2008; Lee et al., 2017; Martínez-Noya and García-Canal, 2021). This stream of research has shed light on the benefits resulting from the diversity of a firm's alliance portfolio of partners (e.g., Lee et al., 2017; Martínez-Noya and García-Canal, 2021) as well as the power positions stemming from its industry network position (e.g., Lavie et al., 2007). While our context differs substantially from that of alliance portfolios, particularly due to the unique, group-like membership dynamics that arise in open multiparty alliances, future research could build on our findings to investigate if social influence effects also operate in other comparable contexts such as alliance portfolios. For instance, partners from the portfolio particularly those from the same industry, could decide to abandon the focal firm under conditions of elevated uncertainty, thus hindering its efforts to build a successful alliance portfolio.

Third, in common with much work on imitation, our research is limited in its ability to infer causality between prior industry-peer actions and subsequent focal-firm decisions (Ozmel et al., 2017). Notwithstanding our efforts to rule out alternative explanations and the conduct of an instrumental variable analysis, future studies could embrace natural experiments and exogenous shocks to causally identify interfirm social influence and imitation effects. Moreover, while we do our utmost to disentangle the underlying mechanisms driving firm exit, as previous literature has pointed, it remains empirically difficult to distinguish between rivalry (oligopolistic)-based and information-based theories of imitation (e.g., Semadeni and Anderson, 2010). Future research can aim to explore the motivations behind individual firm exit decisions from open multiparty alliances and other comparable interfirm collaboration collectives. For instance, an in-depth qualitative study can unravel the information-based from the rivalry-based antecedents and empirically test whether firms are more inclined to follow the information-based logic under certain environmental conditions, such as high firm-specific uncertainty, consistent with the suggestions of previous research as well as our study.

Finally, we followed a novel approach to collect rich and unique data relying on the "Way Back Machine" by manually tracking the entry and exit dates of all firms over 13 years. Despite our efforts to reduce errors that could naturally result from the website failing to report membership, we cannot guarantee that our data are fully accurate. Future studies building on this method can aim to supplement the data with a qualitative approach, for example, specifically asking all member firms about their entry and exit into alliances or relying on press releases to further minimize errors in reporting. A closely related point is the interplay between entries and exits. Although we controlled for member entry, it was beyond the scope of the study to identify the possible interactions between firm entry and exit. Future research can study whether entry and exit impact each other – for instance, it would be relevant to explore where firms go after they exit the focal alliance, and if firms exiting a focal alliance enter another alliance shortly after, opt to join other types of interfirm alliances, or give up collaboration efforts altogether. This would further complete our understanding of the complex membership dynamics of open multiparty alliances as an important form of collective technology development.

CRediT authorship contribution statement

Both authors listed on the manuscript certify that they have contributed equally to the study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (Grant Agreement No. 715280). The authors thank Jaemin Lee and Anu Wadhwa for help in data access, and Jean-Luc Arregle, Paola Criscuolo, Michelle Rogan, Jan-Michael Ross, Dmitry Sharapov, and participants of seminars at Imperial College Business School, EMLYON Business School, and SCANCOR at Stanford University for comments on earlier versions of this paper.

Appendix A. Additional variables used in post-hoc analyses

		N	Mean	Std. dev.	Min	Max
1	Alliance-level technological uncertainty (alliance-relevant patents) (std)	10,357	0.00	1.00	−2.40	2.30
2	Firm-level technological uncertainty (change in technological alignment)	10,357	−0.48	0.94	−2	1
3	Alliance-level social uncertainty (information inconsistency)	10,357	−0.44	0.32	−1	0
4	Firm-level social uncertainty (change in alignment with firm category)	10,357	−0.02	0.27	−2.27	1
5	Alliance exits of firms in formal leadership positions	10,357	0.49	0.42	0	1
6	Alliance exits of firms in informal leadership positions	10,357	0.02	0.01	0	0.06
7	Number of bankruptcies in focal industry	10,357	0.57	0.98	0	3
8	Prior Industry Peer Exits from Alliance (same SIC only) *	10,357	10.43	17.44	0	140
9	Prior Industry Peer Exits from Alliance (same category only) *	10,357	6.62	9.04	0	55
10	Prior Same Region-Industry Exits from Alliance *	10,357	3.14	6.32	0	60
11	Average Technological Similarity of Exiting Industry Peers *	10,357	0.02	0.03	0	0.14
12	Average Technological Complementarity of Exiting Industry Peers *	10,357	0.00	0.02	−0.57	0.14
13	Average Geographical Uniqueness of Exiting Industry Peers *	10,357	8.71	4.36	0	18.86

* Non-standardized values are shown; standardized variables are entered into regression.

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