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Coopetition: A vehicle for business model distinctiveness

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A R T I C L E I N F O

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A B S T R A C T

The increasing environmental turbulence of today calls for a new era of coopetition research, particularly in the context of evolving business models through alliances with other firms. Collaborating with competitors—firms operating in the same markets—can generate innovative approaches to business model change. Our empirical study, based on a multi-sector survey of 302 dyadic R&D alliances, combined with longitudinal data from 2010 to 2019, reveals that market overlap between partnering firms follows an inverted U-shaped relationship with business model change, which we interpret as new value configurations. Our finding implies that firms with moderate market overlap are best positioned to drive business model change. The success of this relationship depends heavily on whether the firms have collaborated before or plan to continue their partnership in the future. Furthermore, we find that, over time, the business models of these firms tend to diverge, leading to greater (relative) distinctiveness at the firm level. Our insights open up new directions for coopetition research, suggesting that by focusing on distinctiveness, firms may enhance their resilience and success in turbulent environments.

1. Introduction

Coopetition as the co-presence of collaboration and competition (Bengtsson & Kock, 2000) has attracted significant research interest over the past two decades (Crick, Friske, & Morgan, 2024). The phenomenon has been mainly analyzed by the resource based view, relational view, and transaction cost theory (Gernsheimer, Kanbach, & Gast, 2021). Given the Covid-19 pandemic and the new era of global disorder (Crick, Crick, & Chaudhry, 2023; Luo, 2024; Zheng, Wechtler, Heyden, & Bouncken, 2024), it seems that firms need to pay more attention to changing their business models to align with environmental turbulence and to develop new value configurations. To master these turbulent environments, firms need to be more than just market oriented (Crick & Crick, 2020; Crick, Karami, & Crick, 2022) and may involve competitors in their business model changes (Ritala & Sainio, 2014; Sanchita & Gupta, 2023), such as in the development of novel value creation and capture models (Bouncken, Fredrich, Ritala, & Kraus, 2020; Fredrich, Bouncken, & Tiberius, 2022). Such business model changes among coopetitors can occur as novel value configurations (NVCs) by skipping, adding, or replacing existing value stages (Stabell & Fjeldstad, 1998). These business model changes may increase the coopeting firms' distinctiveness defined as the degree to which firms are perceived by their audiences as different and unique (Täuscher & Laudien, 2017). Yet, the involvement of competitors in business model changes may entail risks for the firms connected in this type of arrangements (Crick & Crick, 2021).

Previous research has shown that if firms operate in overlapping markets, where some percentage of a firm's sales is generated in a market space also served by its partner, the appropriability risks increase in these coopetition arrangements (Kale, Singh, & Perlmutter, 2000; Ritala & Hurmelinna-Laukkanen, 2013). Still, previous research also indicated that market overlap between coopetitors can improve breakthrough innovation (Yan, Dong, & Faems, 2020). In general, product innovation may serve as a trigger for new business models that have become a major topic of today (Hock-Doepgen, Heaton, Clauss, & Block, 2024) and for coopetition arrangements (Yadav, Kumar, & Malik, 2022). At the same time, competitive dynamics were assumed to trigger business model change (Lanzolla & Markides, 2021; Snihur & Markman, 2023).

As such, there is a dilemma: On the one hand, market overlap increases risks in coopetition. On the other hand, it supports novel solutions in coopetition that may permit greater distinctiveness of the involved firms in the market (Täuscher, Bouncken, & Pesch, 2021). While the predominantly qualitative literature has made some

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interesting advancements regarding R&D alliances between coopetitors and their business model changes (Velu, 2016), it has not yet reached the point of understanding the role played by market overlap in shaping the underpinnings of this relationship and if firms' business models converge over time or become more distinctive. Accordingly, our research pursues the objective to provide a better understanding of how market overlap among firms influences the (1) *degree* of business model change (via NVCs) and the (2) *relative direction* of business model change (via converging or diverging business models).

Our study addresses this objective by following the attention-based view (ABV). There are several reasons for choosing this theoretical lens, which has been largely overlooked in coopetition studies but may stimulate a new era of coopetition research. Specifically, the ABV has gained relevance for the study of matters that demand decision-makers attention, such as risky decisions, strategic alliances, firm change, and business model changes (Ocasio, 1997; Ocasio & Joseph, 2005), especially under environmental turbulence (Crick et al., 2024). Following the ABV logic, alliances can increase and focus firms' attention, which is bounded (Maula, Keil, & Zahra, 2013; Ocasio, 1997). Hence, firms are restricted in their capacity to register and digest multifaceted information. Our core assumption is that greater attention may stimulate business model change.

We test our model using primary, secondary, and time-lagged data from $N = 302$ dyadic R&D alliances ($N = 604$ firms). Our findings indicate that market overlap exhibits an inverted *U*-shaped relationship with NVCs. NVCs become most likely when allying firms share a 40 % market overlap with their partner. Hence, we reveal that "balanced" market overlap stimulates the emergence of new business models. More precisely, NVCs will increase the distinctiveness of firms' relative business models. Furthermore, our findings specify that the maximum of the inverted *U*-shaped relationship shifts towards higher market overlap levels when firms have joint history as in repeated ties. Also, the expectation of the firms that the arrangement will proceed (as in anticipated future ties) will steepen the curve. Accordingly, it seems that attention to not proceeded coopetition arrangements helps to achieve NVCs and by that realize more distinctive relative business models.

The current study contributes to a new era of coopetition research concerning how to deal with environmental turbulence in different ways (Crick et al., 2023; Crick et al., 2024; Klimas, Czakon, & Fredrich, 2022; Yadav et al., 2022). First, we combine the ABV with organizational distinctiveness theory as a new theoretical lens for coopetition research (Zhao, Fisher, Lounsbury, & Miller, 2017). Our findings stress that greater attention to temporary and non-repeated collaborations might activate finding NVCs. Previously, non-repeated or new ties were mainly seen as adding risk to alliances and to coopetition in particular (Bouncken, Clauß, & Fredrich, 2016; Bouncken, Fredrich, Ritala, & Kraus, 2018; Gulati, 1995; Roijakkers, Hagedoorn, & van Kranenburg, 2005). Counter to that, we accentuate that those partners may add greater novelty for new value configurations. Furthermore, we bring more understanding to research on business model innovation and change (Hock-Doepgen et al., 2024; Spieth, Breitenmoser, & Röth, 2023). This research has been still only rudimentarily interested in alliances and coopetition and has concentrated on the firm level (Bouncken & Fredrich, 2016; Ritala & Sainio, 2014). The increasing environmental turbulence today calls for the development of distinctive business models between firms in global coopetition (Crick et al., 2023; Crick et al., 2024; Luo, 2024).

2. Theoretical background

The attention-based view (ABV) assumes that attention available for the "noticing, encoding, interpreting, and focusing of time and effort" (Ocasio, 2011, p. 1287) is limited (Ocasio, 1997). Some issues, tasks, or domains attract more attention than others (Cho & Hambrick, 2006; Tuggle, Sirmon, Reutzel, & Bierman, 2010). Insufficient attention might lead to rejecting otherwise relevant alternatives (Durand, 2003), whereas more attention can lead to higher-quality decisions and better performance (Vuori & Huy, 2015). The ABV argues that similarities in "homophilous relationships" (Maula et al., 2013, p. 927), hence of similar firms operating in same markets, can enhance understanding between firms, raise attention, and improve performance. For example, invention in R&D alliances depends on the level of market overlap (Runge, Schwens, & Schulz, 2022). However, such similarities also include high risks related to knowledge exchanges and appropriation at the partner's expense (Reagans, 2010). Accordingly, relationships between firms in same markets might increase their attention and better allow dealing with today's environmental turbulence.

The co-presence of collaboration and competition has been labeled "coopetition" (Bengtsson & Kock, 2000; Brandenburger & Nalebuff, 1996). In coopetition, value creation underlies strong dynamics of value inputs and value captures due to diverging interests, bargaining, conflicts, and relational instabilities (Das & Teng, 2000). Several studies have shown that knowledge exchange in coopetition has risks and benefits (Bouncken, Gast, Kraus, & Bogers, 2015), especially in R&D alliances between competitors (Runge et al., 2022). When facing competitive overlap, firms need to prevent knowledge leakage (Inkpen, 2000). Moreover, they can reach better innovation outcomes if they protect their core knowledge (Ritala & Hurmelinna-Laukkanen, 2013). Competitive overlap is higher when firms compete for the same customers, and their products are substitutes (Chen, 1996). The higher the coopetition intensity, the greater the opportunities for utilizing coopetition-specific common market understanding, scale advantages, and technological developments.

Especially the turbulences due to the Covid-19 pandemic and the war in Europe have demonstrated how important it is for firms to change their business models rapidly. A business model (BM) is "the rationale of how an organization creates, delivers, and captures value" (Osterwalder & Pigneur, 2010, p. 14). Change in business models may consist of new structures and processes that enable new ways of value creation, value delivery, and value capture (Chesbrough, 2007). Coopetition can complement changing firms' business models (Bouncken & Fredrich, 2016). Business model changes may be triggered by collaborative sensemaking, resourcing, interacting, learning-by-doing, formalizing, and adjusting (Nailer & Buttriss, 2020). We define collaborative business model changes inclusively as *any* relative changes to firms' business models over time. Specifically, we label these business model changes as (1) *novel value configurations* (Bouncken & Fredrich, 2016; Stabell & Fjeldstad, 1998) and theorize about their underlying dyadic business model similarity over time. Increased business model similarity implies *business model convergence,* while decreased similarity signals *business model divergence* (Fredrich et al., 2022). In coopetition, competitive dynamics may trigger business model change (Snihur & Markman, 2023).

With the growing importance of environmental turbulence that comes with changing value chains, disrupted supply chains, or new digital business models, managers need to pay close attention to business model change and how other firms react to these changes. Following the ABV, business model change can be triggered by collaboration among competitors in the same markets. Business model changes require managerial attention to effectively handle coordination tasks, manage expectations, and maintain consistent efforts (Ocasio & Joseph, 2018; Osiyevskyy & Dewald, 2015; Velu, 2016). Involving competitors in the business model change can help firms navigate uncertain environments (Ritala & Sainio, 2014). As such, the optimal level of market overlap between firms remains unclear for collaborative business model changes to emerge as NVCs (Bouncken & Fredrich, 2016; Stabell & Fjeldstad, 1998). Presumably, market overlap may support NVCs as defined by skipping, adding, or replacing existing value stages. Fig. 1 outlines our research model, which we will explain in detail.

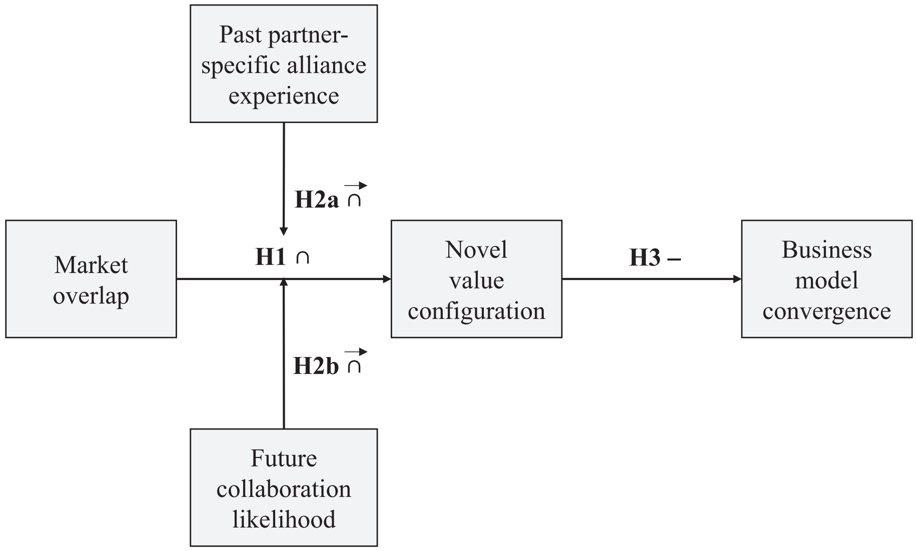

Fig. 1. Research model.

3. Hypotheses

3.1. Market overlap and novel value configurations

Initially, with more market overlap among allying firms (Gnyawali, He, & Madhavan, 2006; Gnyawali & Park, 2011; Rai, 2016), managers' mental models and attention patterns exhibit greater similarity (Hoffman & Ocasio, 2001; Surroca, Prior, & Tribó Giné, 2014). Similarities ease the transfer of information and shape common information bases, allowing more detailed information to be processed (Lubatkin, Florin, & Lane, 2001; Maula et al., 2013). Greater and more detailed information is crucial under environmental turbulence. Thus, greater market overlap facilitates managerial attention to and understanding of the alliance partner's actions and resources relevant to its operations in their common markets.

Yet, the risk of appropriating value at the other's expense also gradually increases (Ritala & Hurmelinna-Laukkanen, 2013) and sets risks that are particularly hard to control in turbulent times. While these risks are tremendous in product innovation alliances, their significance might differ for alliances that pursue NVCs. Greater access to knowledge increases the accuracy of assessments made by the focal firm of its alliance partner's relative competencies in executing different activity sets. The accuracy of such evaluations, in turn, increases the likelihood of the focal firm knowing where and how reliance on its alliance partner's resources and value processes might improve the value configuration at the alliance level. Moreover, greater market overlap increases the likelihood that partner firms possess complementary resources and configure them to create value (Yan et al., 2020).

The degree to which a firm's resources are similar to those of its alliance partner positively affects the ease with which they are potentially transferred between and assimilated by the partners for changing business models (Velu, 2016). The closely matching expertise of managers stemming from initial increases in market overlap fosters improved and more accurate information exchange to create value from novel configurations (Haas, Criscuolo, & George, 2015). Managers see more detail and devote more effort and time to in-depth problem solutions in this context. Similar attention patterns improve understanding of resource profiles and the creation of NVCs. Thus, when market overlap initially increases, mutual understanding of the partner's resources, ambitions, structures, and processes also increases, as does the potential for finding new activities, changing activities, and orchestrating new activity architectures (Möller & Halinen, 2017; Runge et al., 2022).

Nonetheless, while similar attention patterns facilitate the exchange of information and resources among allying firms (Joseph & Wilson, 2018), they entail risks of unintended knowledge leakage. The risks of rivalry, asymmetric value creation, and opportunistic behavior are severe when alliances involve uncertainty and innovation (Bouncken, Fredrich, Ritala, & Kraus, 2020; Joseph & Wilson, 2018). The higher perception of risk keeps decision-makers alert; however, market overlap might reach a threshold beyond which negative issues, such as cognitive framing, blindness, inertia, and myopic thinking, captivate the greater part of managerial attention (Raffaelli, Glynn, & Tushman, 2019; Withers, Ireland, Miller, Harrison, & Boss, 2018). For example, when market overlap is exceptionally high, managers might use the same intra-industry sources of information and knowledge that might restrict creativity to inspire NVCs as managers focus on routine business issues (Maula et al., 2013). The lack of innovative thought among firms serving the same or highly overlapping markets reinforces prior, more standard, or less novel value configurations at the alliance level. Moreover, complete or very high market overlap creates negative tensions between firms that impede innovative efforts (Bouncken, Fredrich, & Kraus, 2020; Tidström, 2014). In such cases, inter-partner rivalry and the risks of knowledge leakage can become excessive. Managers might be hesitant to contribute time and resources or focus on defensive strategies that might reduce future market potential. Thus, value configurations tend to be less novel in alliances of firms serving highly overlapping markets. Even if firms in the same or overlapping markets find it easier to communicate, opportunism and value capture uncertainty risks might be too high for NVCs to emerge.

In short, increasing levels of market overlap can facilitate NVCs up to a threshold level beyond which its effects decline. Very high market overlap entails less diverse knowledge bases between allying firms and affords fewer learning opportunities while introducing high opportunism risks. Medium levels of market overlap might best support NVCs.

Hypothesis H1. *Market overlap exhibits an inverted* U*-shaped relationship with novel value configurations in dyadic alliances. Low and high levels of market overlap are associated with lower levels of novelty, whereas moderate levels of market overlap are associated with higher levels of novel value configurations.*

3.2. Repeated or anticipated future ties among firms

Repeated and anticipated future ties influence alliance outcomes (Gulati, Lavie, & Singh, 2009; Weber, Bauke, & Raibulet, 2016). Such relations can promote social processes, partner-specific absorptive capacity, and learning (Dyer & Hatch, 2006; Dyer & Singh, 1998). Additionally, knowledge exchanges in repeated and anticipated future ties help firms improve paying attention to their partner-specific understanding and discover further complementarities (Weber et al., 2016). Still, studies have shown that such ties can reduce alliance performance (Goerzen, 2007; Sampson, 2007). Following the ABV, intense and long-term interactions can induce partner "blindness," escalating commitments, and ignorance of external information (Szulanski, Cappetta, & Jensen, 2004). Repeated relationships often become more redundant in their knowledge and activities over time (Goerzen, 2007) and are less apt to result in optimal or innovative solutions (Jeffries & Reed, 2000). Furthermore, relational inertia resulting from long-term interactions reduces an alliance's adaptability to change (Thorgren & Wincent, 2011). In addition, repeated and anticipated future ties are less likely to trigger questioning, scrutiny, validation, or research (Szulanski et al., 2004; Zahra, Yavuz, & Ucbasaran, 2006), as social bonds can discourage challenging shared beliefs that lead to underperforming alliances (Young-Ybarra & Wiersema, 1999). Moreover, decision-makers might try to disguise underperforming alliances so that change is less likely (Patzelt, Lechner, & Klaukien, 2011). In short, the effects of repeated and anticipated future ties on alliance outcomes are far from clear. The ABV offers important insights into the matter, especially when firms operate in turbulent environments.

As mentioned, attention is contextually and socially embedded (Ocasio, 1997). Attention theory assumes that personal exchanges can support managerial attention and induce new thoughts, changes, and novel outcomes (Barnett, 2008). High levels of attention can promote the discovery and exploitation of complementarities for NVCs (Amit & Han, 2017). When the attention of managers remains high, their similarities associated with higher market overlap might have a less limiting effect on the novelty of the value configuration and instead play out as a facilitator for finding complementarities. Repeated or anticipated ties might increase similarities and thus inertia but also reduce risks among firms. Specifically, attention that triggers novelty remains high when a specific risk is accorded to the partner's behavior, particularly in cases of higher market overlap. The risks of market overlap include reinforcement of existing understandings and inertia (Li & Rowley, 2002). In contrast, repeated or anticipated ties reduce perceived risk. Repeated ties generate more understanding, trust, and mutuality, which drives the search for innovative joint results. Thus, when ties are repeated and expected to continue, firms become more proficient at finding NVCs.

However, when market overlap increases, firms tend to monitor the alliance closely, and underperforming alliances are less likely to fly under the radar. Correspondingly, excessive trust becomes less of a threat. Alliances between firms with higher market overlap thus result in increased levels of attention as manifested through questioning, scrutiny, validation, and research. The combination of higher market overlap and repeated and anticipated future ties may foster complementarity (Hughes, Morgan, Ireland, & Hughes, 2014). Notably, repeated and anticipated future ties under high market overlap can encourage the ongoing search for complementarities, resulting in NVCs. Moreover, these ties can build commitment, which increases attention and can motivate firms to invest ideas and resources in the alliance (Bruyaka, Philippe, & Castañer, 2018) such that NVCs become more likely. Greater commitment may diminish the adverse effects of high risk when market overlap is high. Firms that intend to ally in the future might avoid engaging in opportunistic actions because they do not want to damage the relationship. Hence, repeated ties, or those with a high likelihood of being continued, focus on increasing complementarities (Chung, Singh, & Lee, 2000). However, under high market overlap, allying firms have highly similar knowledge bases and, as such, maximum opportunism and rivalry risk (Cui, Yang, & Vertinsky, 2018). Thus, there will be a turning point shift to the right of the optimum level of market overlap for allying firms that pay close attention to each other in the past or expect to do so in the future.

Summarizing, repeated ties and anticipated future ties better allow for the creation of NVCs under higher market overlap than newly established relationships, in which managers must learn how to use their overlap and dissimilarities best while dealing with relational uncertainty. There are likely declining returns for very high or complete market overlap because similarities will discourage further novelty. Repeated and anticipated future ties are more likely to inform efforts for co-specialization and NVCs. In turn, risk awareness reduces opportunistic behavior.

Hypothesis H2a. *A firm's prior partner-specific alliance experience moderates the inverted* U*-shaped relationship between market overlap and novel value configurations in dyadic alliances. Specifically, repeated ties with the focal partner will shift the optimal level to the right.*

Hypothesis H2b. *A firm's likelihood of future collaboration moderates the inverted* U*-shaped relationship between market overlap and novel value configurations in dyadic alliances. Specifically, future ties with the focal partner will shift the optimal level to the right.*

3.3. Divergence—relative distinctiveness of firms' business models in the dyad

Business models can change when firms form alliances, especially when they coopete. Yet, the direction of these business model changes is not clear. One set of arguments points towards the convergence of business models. Instead, from attention-based reasoning and seeking distinctiveness, firms might develop divergent business models.

Following the convergence arguments, firms become more familiar with each other and learn common practices throughout the alliance (Duysters, Lavie, Sabidussi, & Stettner, 2019). Firms' business models might converge by mimicking and imitating each other's practices and activities. Convergence entails the process and outcomes whereby boundaries diminish over time, such as those related to technology, knowledge, industry, and value propositions (Basole, Park, & Barnett, 2015). Similar knowledge bases, activities, and technical proximity facilitate convergence, which depends on firms' motivation and learning (Duysters et al., 2019) and improves the sharing and synthesis of information, resulting in similar interpretations (Maitlis & Christianson, 2014). Comparable environments and similar activities (i.e., higher market overlap and joint value configurations) may draw managerial attention to common problems and issues and, in turn, increase the convergence of the involved firms' business models. Convergence becomes more likely when firms do not follow deliberate and top-down change processes (Duysters et al., 2019).

In contrast, we assume that managers pay more attention to positioning their business models differently from their partner to reduce opportunism risks, imitation, and increase the firm's distinctiveness (Suddaby, Bitektine, & Haack, 2017). Business model change demands deliberate decisions. When establishing an alliance in overlapping markets, firms consider changing their business model to become more different from their partner. Firms might use NVCs to consciously, deliberately, and strategically develop a more distinctive firm-level business model for global competition (Tallman, Luo, & Buckley, 2018). Over time, firms understand partner-specific complementarities and distinctiveness better while becoming aware that their business models' convergence holds risks and might reduce complementarities in the long run. Firms may also concentrate on distinctiveness and departing from their partners by developing divergent business models, especially under environmental turbulence and global disorder (Luo, 2024). In light of the allying firms' respective value contributions, the partners might aim to establish more relatively distinct firm-level business models consisting of unique firm-specific configurations of value creation activities, value capture activities, and customer-focused value propositions (Duysters et al., 2019; Tallman et al., 2018). In short, we propose that the attention and strategic decision-making towards distinctive business models will bring about that NVCs at the alliance level facilitate the relative divergence of allying firms' business models.

Hypothesis H3. *Novel value configurations in dyadic alliances are negatively associated with the convergence of allying firms' business models.*

4. Methodology

4.1. Sample

The multi-sector population of this study consists of 35,553 firms from 94 countries that participated in any of six independent international trade fairs hosted in Germany during 2015–2017. Following a key-informant approach, we invited representatives from top and middle management to participate in a survey based on a paper-and-pencil questionnaire or tablet and collected 2348 questionnaires. Forty-seven percent of respondents did not disclose their alliance partner's firm name in the first data collection stage (2015–2017 = *t*). After researching missing secondary data, we personally (re)invited initial participants to fill out a short questionnaire on the same alliance in the following year (2016–2018 = $t + 1$). In this second data collection stage, we gathered a total of 768 matching questionnaires with lagged dependent information. After excluding invalid cases, multi-partner alliances, non-R&D alliances, cases in which the respondent was not sufficiently knowledgeable of the initial alliance, and cases with missing model variables, 450 dyadic R&D alliances remained. We screened their 900 web pages for information about their (dyadic) *business model convergence* during $t + 2$ (2017–2019). Dyads with incomplete history logs were excluded. Our final sample consists of 302 dyadic R&D alliances with three temporal measurement points ($t + 2$ = 13 % of raw cases during *t*). We modeled the selection process at two data collection stages to control for potential selection biases (Clougherty, Duso, & Muck, 2016). We further compared descriptive statistics of selected industry-, firm-, and alliance-level characteristics in the world's largest alliance database, Securities Data Company SDC Platinum (Schilling, 2009), with our primary data. The overall industry distribution is very similar ($Blau_N = 0.93$ for SDC vs. 0.92 for our data), with a greater tendency for coopetition (i.e., collaboration between competitors with identical 4-digit SIC codes: 19.9 % for SDC vs. 13.1 % for our data), primarily due to the greater representation of big firms in the SDC data (23 % SMEs vs. 90 % SMEs in our final sample).

On average, the responding firms in our final sample achieved a 19 % return on equity (median = 15 %), with annual sales of €113 M (median = €9 M). The focal alliances contributed 15 % (median = 10 %) to the responding firms' annual sales. Twenty-seven percent (median = 18 %) of the responding firms' overall annual sales originated from markets also served by their dyadic alliance partners.

4.2. Measures

The first stage-dependent measure of *novel value configurations* (NVCs) was measured during $t + 1$ at the dyadic alliance level. We modified Bouncken and Fredrich's (2016) Likert-type scale to assess "value configurations" by asking respondents how much the focal alliance contributed to (1) "innovative configurations" (std. loading during $t + 1$: $\lambda = 0.67, p < .001$), (2) "new configurations allowing us to *skip* one or more stages in the value chain" ($\lambda = 0.83, p < .001$), (3) "…to *replace* one or more stages in the value chain" ($\lambda = 0.87, p < .001$), and (4) "…to *add* one or more stages to the value chain" ($\lambda = 0.75, p < .001$), anchored at 1 = "no value at all" and 5 = "very significant value." Confirmatory factor analysis revealed a reliable and valid measure (Composite Reliability [CR] = 0.86, Average Variance Extracted [AVE] = 0.61, Fornell-Larcker [FL] criterion = 0.13, Root Mean Square Error of Approximation [RMSEA] = 0.058, Standardized Root Mean Square Residual [SRMR] = 0.027, Comparative Fit Index [CFI] = 0.991, Tucker–Lewis Index [TLI] = 0.973; cf. Hair, Black, Babin, Anderson, & Tatham, 2010).

For our newly developed second-stage dependent measure of dyadic business model similarity (BMS), we build on the prominent nine-dimensional *business model canvas* by Osterwalder and Pigneur (2010). We extend their firm-level BM categorization to the alliance level—-specifically, the dyad level—and apply the logic of BMs as linguistic devices or narratives that affect different stakeholder groups (Täuscher, 2018). Therefore, we used 48 binary indicators from their seminal book and screened 900 online presences (i.e., firm webpages of 450 identified dyadic alliances) for any information fitting these indicators. We added a 49th indicator to the subdimension of key partnerships if one (or both) firm(s) disclosed the focal alliance online. Webpages are updated irregularly; thus, it is difficult to know precisely when information became publicly available. Hence, we used an internet archive (Wayback Machine: https://archive.org/web/) in conjunction with Google Translate (if the English version was unavailable) and retrieved all information in 2020 that had already been publicly available during *t* and $t + 2$ to calculate *marginal* dyadic business model similarity, which we interpret as dyadic *business model convergence* for increasing similarity or *divergence* for decreasing similarity.

We randomly assigned 10 % of all dyads twice (overall $N = 495$ dyads) to a group of 10 instructed research assistants who independently coded the web pages according to multiple examples provided for all 49 indicators (see Table 1). An ANOVA revealed no significant inter-rater differences. We calculated a "substantial" inter-rater reliability (Cohen's kappa $\kappa > 0.60$; Landis & Koch, 1977) based on 4410 codes for 45 dyads ($\kappa = 0.61, p < .001$). Dyads with incomplete history logs were excluded. To avoid severe selection biases, we applied a second-stage inverse Mills ratio as a control variable (Certo, Busenbark, Woo, & Semadeni, 2016). Additionally, we captured the total *number of words* on all web pages to normalize for size-related dynamics. Table 1 summarizes all indicators and raw frequencies for our final sample of $N = 302$ dyads that allowed us to calculate Jaccard's similarity scores ($J = |A \cap B| / |A \cup B|$) for binary data (Choi, Cha, & Tappert, 2010)—about a quarter of the BMS-related content remained stable over the two years ($r = 0.48, p < .001$). On average, BMS dropped by 11 % ($BMS_t = 37$ %, $BMS_{t+2} = 26$ %), even though the proportion of maximum dissimilarity (i.e., $J = 0$ %) also dropped ($t = 14$ %, $t + 2 = 4$ %). Both distributions yielded desirable psychometric properties (during *t*: min = 0 %, median = 38 %, max = 100 %, skewness $S = 0.20$, kurtosis $K = -0.04$; during $t + 2$: min = 0 %, median = 26 %, max = 85 %, $S = 0.81$, $K = 2.06$, well below $S < |\pm 2|$ and $K < |\pm 7|$; West, Finch, & Curran, 1995).

For our predictor variable *market overlap* during *t*, we asked respondents to disclose the percentage of firm-level sales in markets also served by their dyadic alliance partner. This quantitative measure implies asymmetric competitive dynamics (firm A's overlap with firm B ≠ firm B's overlap with firm A; see Chen, 1996) and shows a reduced natural skew after log-standardization (min = −2.08, mean = 0.00, median = 0.17, max = 1.46, $S = -0.63$, $K = -0.39$). We established two interdependent temporal contingencies of repeated and anticipated future ties during *t*: (1) prior ties with this dyadic partner accumulating in *partner-specific alliance experience* (47 % of respondents indicated repeated ties, while 53 % had no previous alliances with this partner); and (2) future *collaboration likelihood*, which measures attribution of future attention to the dyadic alliance using an ordinal 5-point indicator for "*How likely is it that your firm will collaborate with this partner in the future?*" (11.9 % indicated "≤ 20 %," 10.6 % "21–40 %," 11.3 % "41–60 %," 21.5 % "61–80 %," and 44.7 % chose "> 80 %"). This forward-looking measure ("shadow of the future"; Poppo, Zhou, & Ryu, 2008) demonstrates external validity by predicting *alliance termination* before our second survey during $t + 1$ using logistic regression ($\beta = -0.47, p < .001$). We control for additional temporal relationship lifecycle characteristics (Jap & Ganesan, 2000), such as *early* and *late relationship stages* (the reference model represents middle stages) and overall *relationship duration* by the log-number of months since the firms started doing business with each other.

We included several firm- and alliance-level controls. The purposes and outcomes of R&D alliances are heterogeneous (e.g., for link or scale alliances; Dussauge, Garrette, & Mitchell, 2000), and NVCs might not be the primary goal of the focal R&D alliance. Thus, we control the number

Table 1
Measurement of the dyadic business model convergence.

Dimension	Indicator description	Frequencies in t			Frequencies in t + 2		
		A	B	A ⋂ B	A	B	A ⋂ B
	1. *Mass market*: High standardization, e.g., consumer goods.	10 %	12 %	1 %	13 %	14 %	2 %
Customer segments:	2. *Niche*: Small markets serving customer-tailored products.	41 %	39 %	23 %	42 %	41 %	25 %
For whom business creates value?	3. *Segmented*: Segmentation of customer groups, e.g., banks.	24 %	23 %	8 %	29 %	28 %	16 %
	4. *Diversified*: Mix of all above for B2B & B2C, e.g., Amazon.	18 %	19 %	8 %	30 %	29 %	16 %
	5. *Multi-platform*: Various inter-dependent platforms.	2 %	2 %	0 %	5 %	5 %	1 %
	6. *Cost reduction*: E.g., outsourcing of cost-intensive areas.	13 %	12 %	3 %	11 %	10 %	4 %
	7. *Risk reduction*: E.g., granting guarantees of repair services.	17 %	13 %	3 %	21 %	15 %	5 %
	8. *Price*: Same value at a lower price, e.g., airlines like EasyJet.	12 %	13 %	2 %	14 %	18 %	4 %
Value propositions:	9. *Convenience/usability*: Focus on comfort, e.g., iTunes.	21 %	19 %	5 %	21 %	22 %	8 %
How is value created for segmented customers?	10. *Performance*: High-end products, e.g., computers.	73 %	71 %	55 %	75 %	72 %	58 %
	11. *Accessibility*: Highly specialized services, e.g., private jets rent.	6 %	4 %	0 %	23 %	22 %	16 %
	12. *Design*: E.g., smartphones, sports cars, fashion clothes.	9 %	10 %	2 %	10 %	10 %	2 %
	13. *Customization*: E.g., customized products with various features.	50 %	41 %	24 %	46 %	43 %	25 %
	14. *Sales force*: Own sales employees, e.g., account managers.	56 %	59 %	40 %	54 %	50 %	39 %
Channels:	15. *Web sales*: E.g., automated online order or hotlines.	11 %	16 %	2 %	23 %	25 %	12 %
Which channels reach customer segments?	16. *Own physical retail stores*: E.g., Adidas stores.	4 %	5 %	0 %	5 %	6 %	0 %
	17. *Partner stores*: E.g., Aldi offering food by different suppliers.	22 %	18 %	6 %	21 %	18 %	6 %
	18. *Wholesaler*: No own production, only distribution of products.	4 %	5 %	1 %	9 %	9 %	2 %
	19. *Personal assistance*: Focus on human interaction.	86 %	84 %	74 %	83 %	81 %	72 %
Customer relationships:	20. *Self-service*: No direct contact, e.g., ATMs, vending machines.	11 %	9 %	2 %	23 %	18 %	12 %
What type of relationship customer segments expect?	21. *Automated services*: E.g., automatic purchase recommendation.	2 %	3 %	0 %	3 %	4 %	1 %
	22. *Communities*: E.g., forums and platforms for customers.	3 %	6 %	0 %	3 %	7 %	1 %
	23. *Co-creation*: E.g., beta software releases for customer feedback.	7 %	8 %	1 %	7 %	9 %	2 %
	24. *Asset sale*: E.g., physical items, hardware, consumer goods.	54 %	49 %	32 %	52 %	45 %	34 %
	25. *Usage fee*: E.g., mobile phone service providers per minute.	1 %	1 %	0 %	13 %	11 %	0 %
	26. *Subscription fee*: Fixed usage fee, e.g., monthly flat rates.	1 %	1 %	0 %	1 %	2 %	0 %
	27. *Lending/renting/leasing*: E.g., car leasing.	0 %	0 %	0 %	0 %	1 %	0 %
Revenue streams:	28. *Licensing*: Royalties, e.g., for usage of software solutions.	1 %	1 %	0 %	1 %	1 %	0 %
Which value capture mechanisms?	29. *Brokerage fee*: Transaction-based fees, e.g., cash withdrawal.	0 %	0 %	0 %	0 %	0 %	0 %
	30. *Advertising*: E.g., pop-up windows for third-party advertising.	0 %	0 %	0 %	0 %	0 %	0 %
	31. *Fixed price*: E.g., by list prices or additional features.	5 %	4 %	1 %	6 %	5 %	1 %
	32. *Dynamic price*: E.g., by negotiation, real-time, or auction.	9 %	11 %	5 %	13 %	12 %	6 %
	33. *Physical*: E.g., deposits, IT infrastructure, logistics, etc.	25 %	21 %	10 %	25 %	20 %	10 %
Key resources:	34. *Intellectual*: E.g., trademarks, patents, property rights.	73 %	69 %	55 %	79 %	71 %	62 %
What resources does value proposition require?	35. *Human*: E.g., employees in manufacturing industry.	48 %	47 %	26 %	53 %	50 %	34 %
	36. *Financial*: E.g., bank, stock markets, funds, etc.	4 %	6 %	1 %	12 %	12 %	6 %
Key activities:	37. *Production/distribution*: E.g., manufacturing industry.	76 %	62 %	49 %	79 %	66 %	57 %
What activities does value proposition require?	38. *Problem-solving*: E.g., consulting, individualized solutions.	27 %	31 %	11 %	42 %	41 %	26 %
	39. *Platform/network effects*: E.g., eBay, Visa credit cards.	3 %	4 %	0 %	10 %	11 %	3 %
	40. Focal alliance partner disclosed on webpage?	15 %	12 %	5 %	16 %	16 %	7 %
Key partnerships:	41. *Optimization & economies of scale*: E.g., merger & acquisitions.	9 %	10 %	2 %	8 %	9 %	3 %
Who is key partner?	42. *Acquisition of resources & activities*: E.g., in-house consulting.	4 %	3 %	0 %	6 %	5 %	1 %
	43. *Reduction of risk & uncertainty*: E.g., Blu-ray, Star Alliance.	2 %	2 %	0 %	3 %	3 %	0 %
	44. *Cost-driven*: Focus on cost leadership, e.g., EasyJet.	10 %	12 %	3 %	11 %	9 %	3 %
	45. *Value-driven*: Focus on quality, e.g., luxury hotels.	64 %	61 %	44 %	59 %	54 %	43 %
Cost structure:	46. *Fixed costs*: E.g., salaries, machinery, maintenance.	2 %	2 %	0 %	18 %	18 %	14 %
What type of costs?	47. *Variable costs*: High volume dependency, e.g., power generators.	10 %	15 %	6 %	7 %	10 %	4 %
	48. *Economies of scale*: E.g., learning decreases variable costs.	1 %	2 %	0 %	2 %	2 %	0 %
	49. *Economies of scope*: E.g., merging of redundant activities.	1 %	2 %	0 %	1 %	2 %	0 %

Notes: $N = 302$ dyadic alliances coded by screening $N = 604$ webpages for year t & t + 2 using the Wayback Machine in 2020 (https://archive.org/web/).

of dyadic linkages as potential sources of NVCs originating at various *innovation stages,* from concept development to market launch (Ahmed & Shepherd, 2010). The tendency to adjust a value configuration is likely to depend on firms' *general alliance experience*. Therefore, we also control for the responding firms' overall number of alliances in the past five years. We further control both firms' *sizes* in terms of the number of employees and *ages* in terms of years since the firms' founding.

As NVCs might result from collaborating firms' technology development (Chesbrough, 2007), we further control for firm-level *R&D intensity* (Hashai & Almor, 2008), *geographical distance* (Hagedoorn, Letterie, & Palm, 2011), and *technological distance* based on applied IPC4-patent classes in the five years before our first stage of data collection. We chose the *symmetric* min-*complement* technological distance, the only commonly used measure that satisfies the independence axiom (Bar & Leiponen, 2012). We control for both firms' inverse normalized Herfindahl index to account for asymmetric knowledge bases, which captures firm-level *technological diversity* (Duysters et al., 2019). Furthermore, we implement a binary control for *equity participation*, the dyad representing an *international alliance*, and an industry dummy for *medical devices* as the largest subsample.

4.3. Analysis

We test our hypotheses by applying covariance-based structural equation modeling (CB-SEM) with Mplus 8.8. Specifically, we rely on scaled log-likelihood ratio tests for global improvement of model fit under maximum likelihood robust (MLR) estimation of nested models adjusted for non-normality and non-independence (Muthén & Muthén, 1998–2022). CB-SEM (Kline, 2023) is our method of choice for rigorous theory testing (vs. prediction) because of its ability to (1) assess global fit for multiple endogenous constructs, (2) account for measurement error in observational data with latent constructs, (3) implement residual dependencies for endogeneity testing, and (4) rigorously test for complex mediation effects (such as ours: first-stage moderated instantaneous indirect-only effects).

5. Results

Table 2 shows all bivariate correlations in our final sample, including the squared market overlap and interactions with its moderators, as Haans, Pieters, and He (2016) recommend.

Table 3 presents four nested models, starting with Model A. The partner's firm size and the responding firm's equity participation increase the likelihood of NVC during $t+1$, whereas relationship duration and late stages reduce this likelihood. We find support for an inverted *U*-shaped relationship between market overlap during *t* and NVC during $t+1$, as postulated in our H1 (Model A: $\beta = -0.16$, SE = 0.071, $p = .022$, $f^2 = 0.032$; with $f^2 > 0.02$, $f^2 > 0.15$, and $f^2 > 0.35$, marking "small," "medium," and "large" effect sizes; see Cohen, 1988). The linear-only relationship between market overlap during *t* and NVC during $t + 1$ was highly significant ($\beta = 0.26$, SE = 0.070, $p < .001$, $f^2 = 0.048$); however, the decomposition yields a greater combined effect size ($f^2 = 0.082$) and suggests an optimum level of market overlap for maximum NVC. Fig. 2 illustrates the curvilinear relationship of H1, including 95 % confidence intervals and regions of significance. In short, market overlap below 1 % reduces average levels of NVC during $t + 1$ significantly, improves NVC for market overlaps greater than 15 %, reaches a maximum at 40 %, and becomes insignificant above 50 %.

Negatively significant influences on our second-stage dependent variable of marginal business model similarity may be interpreted as drivers of dyadic business model divergence. Progressing relationship duration, technological distance, and responding firms' technological diversity drive dyadic business model divergence. In H3, we proposed that NVC during $t+1$ would induce future business model divergence. We find a negative relationship supporting our H3 ($\beta = -0.18$, SE = 0.064, $p = .004$, $f^2 = 0.037$).

The next two nested models (B and C) introduce moderations of the first stage of the *indirect effect* via partner-specific alliance experience and collaboration likelihood separately and jointly in Model D. In Model B, we added two-way interactions of (binary) partner-specific alliance experience with market overlap and squared market overlap, yielding slightly significant global model improvement ($\Delta TRd = 5.52$, $\Delta df = 2$, $p = .063$). However, the variance explanation of NVC during $t + 1$ decreased from 28.9 % to 28.7 %, primarily due to the significance of linear market overlap shifting towards a positively significant *linear* two-way interaction with partner-specific alliance experience. We postulated a turning point shift to the right in the presence of partner-specific alliance experience, hence repeated ties in H2a. A significant two-way interaction between linear market overlap and partner-specific alliance experience ($\beta_{\text{lin}} = 0.18$, SE = 0.086, $p = .041$) is necessary but insufficient to show a significant turning point shift. We applied a formula developed by Haans et al. (2016, p. 1187) and calculated a slightly significant turning point shift to the right for partner-specific alliance experience ($p = .094$), supporting our H2a (see Fig. 3).

Fig. 3 demonstrates that the turning point of the inverted *U*-shaped relationship between market overlap and NVC_{t+1} moves from 10.3 % to 27.5 % when a firm has prior alliance experience with its partner. Notably, the previously significant *linear* parameter of market overlap is *fully* moderated by partner-specific alliance experience and becomes insignificant ($\beta_{\text{lin}} = 0.08$, $p = .466$). Consequently, both turning points are lower than the previous one at 40 % for the entire sample. Model C focuses on two-way interactions between market overlap and collaboration likelihood. Hypothesis 2b assumed moderation via a turning point shift to the right for continued ties. However, the moderation indicated does not support a turning point shift. Instead, we find a steepening effect (see Fig. 4) of the inverted *U*-shaped relationship for growing levels of collaboration likelihood ($\beta_{\text{quad}} = -0.17$, SE = 0.080, $p = .031$, $f^2 = 0.038$), partially rejecting our H2b.

After controlling for these two-way interactions, the previously insignificant direct effect of collaboration likelihood becomes significantly negative ($\beta = -0.17$, SE = 0.078, $p = .031$, $f^2 = 0.039$). Notably, the *conditionally* negative direct influence of collaboration likelihood pushes the steeper curve downward (= quasi-moderation). Nevertheless, the anticipation of future ties *fully* moderates the quadratic parameter of market overlap, which becomes insignificant ($\beta_{\text{quad}} = -0.09$, $p = .231$). We further calculated the moderator's values at which the inverted *U*-shape becomes linear and flips (Haans et al., 2016). The mathematical shape-flip point ($Z^* = -0.25$, which corresponds to the cross-over between the third and fourth categories ≙ 60 % of likelihood) lies within the empirical range of collaboration likelihood (min = −2.76, max = 1.25), demonstrating the high sensitivity of the inverted *U*-shape to linearly increasing collaboration likelihood, thereby stressing the importance of H2b.

In our final Model D, the linear and quadratic parameters of market overlap both become insignificant and thereby conditional on our moderators: (1) past partner-specific alliance experience fully explains the significance of the linear parameter, and (2) future collaboration likelihood fully explains the significance of the quadratic parameter of the inverted *U*-shaped relationship between market overlap and NVC_{t+1}. Our final Model D yields robust findings and explains about one-third of the variance in both dependent variables (NVC_{t+1}: $R^2 = 0.32$, SE = 0.061, $p < .001$; BMS_{t+2}: $R^2 = 0.35$, SE = 0.053, $p < .001$). Throughout all nested models, the second stage of the indirect effect, our H3, remains significantly negative ($p < .01$).

In summary, the *instantaneous* indirect effect (Hayes & Preacher, 2010) of quadratic market overlap X^2 during *t* through NVC during $t+1$ on dyadic business model convergence $\hat{Y}$ during $t+2$ is negative for raw market overlap up to 14 % ($p < .05$). Market overlap beyond 14 %, on average, yields no indirect effect. In addition, this negative indirect effect is most significant in the absence of future ties with the same alliance partner, suggesting strong attention-based relational dynamics. Although all postulated individual effects are "small" (Cohen, 1988), we did not expect more significant effects due to institutional pluralism driving the heterogeneity and multi-layered complexity of business model changes and related governance strategies (Ocasio & Radoynovska, 2016). For example, past failure experiences will drive managerial attention, coopetition, and business model innovation (Nyuur, Donbesuur, Owusu-Yirenkyi, Ampong, & Tantawy, 2023). Overall, our combined effect sizes assure meaningful variance explanations in our final Model D ($R^2 > 30$ %).

6. Discussion

The escalating environmental turbulence and recent global crises necessitate firms to develop greater resilience and adapt their business models (Zheng et al., 2024). Collaborating with competitors—referred to as coopetition—offers a potential solution to these challenges and opens the door to a new era of coopetition research. Our study builds on this premise by exploring how firms can change their business models while preserving or enhancing their distinctiveness. Through our empirical analysis, we examined how coopetition, particularly as market overlap within alliances, fosters novel value configurations (NVCs), which in turn facilitate business model changes. This process ultimately drives divergence at the firm level, reinforcing each company's unique position in the market.

In short, findings reveal that (1) market overlap among allying firms exhibits an inverted *U*-shaped relationship with NVCs, (2) repeated ties between the allying firms tend to shift the maximum of the curve towards higher market-overlap levels, (3) high expectations of future collaborations with one's alliance partner steepen the curvature of this relationship, and (4) NVCs trigger a divergence of allying firms' business models. In essence, balanced levels of market overlap facilitate business model change and more distinct business models of collaborating firms.

6.1. Theoretical implications

First, our study acknowledges environmental turbulence (Zheng et al., 2024) and suggests that coopetition, as a facilitator of change,

Table 2
Bivariate correlation matrix.

Measures	Mean	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. Business model similarity in t + 2	0.26	1.00	−0.21***	0.48***	−0.03	0.03	−0.02	0.00	0.01	0.12*	−0.04	−0.02	0.04	−0.05
2. Novel value configurations in t + 1	0.27	−0.21***	1.00	−0.06	0.31***	−0.30***	0.03	0.31***	−0.23***	−0.11*	0.17**	−0.21***	−0.09	0.12
3. Business model similarity in t	0.37	0.47***	−0.07	1.00	0.08	−0.02	−0.02	0.01	−0.02	0.04	0.07	−0.08	−0.09	−0.11
4. Log market overlap	2.71	−0.02	0.28***	0.06	1.00	−0.48***	0.10	0.62***	−0.22***	0.04	0.24***	−0.18**	0.04	0.08
5. Log market overlap^2	1.69	0.03	−0.21***	0.00	0.02	1.00	−0.14*	−0.22***	0.61***	0.18**	−0.16**	0.29***	0.03	−0.07
6. Partner-specific alliance experience (SAE)	0.47	−0.02	0.03	−0.03	0.08	−0.13*	1.00	0.10	−0.13*	0.01	0.04	0.02	0.01	−0.05
7. Log market overlap × SAE	1.34	0.05	0.27***	0.01	0.59***	0.03	0.21***	1.00	−0.35***	0.06	0.21***	−0.11	0.01	0.07
8. Log market overlap^2 × SAE	0.64	0.00	−0.12*	−0.03	0.04	0.61***	−0.42***	−0.05	1.00	0.15*	−0.08	0.23***	0.01	−0.10
9. Collaboration likelihood (CL)	3.76	0.09	−0.15**	0.04	0.10	0.17**	0.00	0.09	0.16**	1.00	−0.01	−0.14*	0.16**	−0.18*
10. Log market overlap × CL	10.29	−0.08	0.12*	0.08	0.30***	0.00	0.05	0.17**	0.06	0.10	1.00	−0.38***	−0.08	0.03
11. Log market overlap^2 × CL	6.89	−0.01	−0.14*	−0.10	−0.07	0.26***	0.02	−0.03	0.17**	−0.26***	−0.11	1.00	0.01	−0.01
12. Firm A’s general alliance experience	3.61	−0.01	−0.08	−0.10	0.05	0.06	0.02	0.03	0.02	0.13*	−0.07	−0.03	1.00	0.13
13. Log firm A’s R&D intensity	2.29	−0.03	0.10	−0.10	0.07	0.00	−0.04	0.04	−0.05	−0.21***	0.01	0.05	0.12	1.00
14. Log firm A’s size	4.17	0.11	0.01	0.12*	0.06	−0.09	0.12*	0.10	−0.06	0.06	0.02	−0.04	0.14*	−0.04
15. Log firm B’s size	5.17	0.00	0.14*	0.02	0.12*	−0.05	0.16**	0.13*	−0.05	−0.01	0.00	−0.04	0.06	0.02
16. Log firm A’s age	3.29	0.17**	−0.01	0.21***	0.04	−0.01	−0.04	0.04	0.02	0.03	0.09	−0.04	0.11	−0.14*
17. Log firm B’s age	3.31	0.01	−0.03	0.05	0.04	0.01	0.09	0.14*	−0.04	−0.02	0.09	0.04	0.05	−0.05
18. No. of mutual innovation stages	1.83	0.00	−0.01	−0.03	0.09	0.10	0.08	0.09	0.05	0.20***	−0.08	0.07	0.00	−0.01
19. Firm A’s technological diversity	0.28	0.00	−0.08	0.10	0.03	−0.03	0.04	0.03	−0.07	0.04	0.06	0.00	0.11	0.18**
20. Firm B’s technological diversity	0.33	0.03	−0.01	0.03	−0.05	0.04	0.04	0.07	−0.01	−0.04	−0.10	0.03	0.01	0.09
21. Technological distance	0.96	−0.10	0.07	−0.10	−0.01	−0.07	0.01	−0.01	−0.09	−0.07	−0.05	0.04	0.04	−0.13
22. Log geographical distance	5.75	−0.06	0.10	0.04	−0.02	−0.07	−0.11	−0.06	0.05	−0.08	0.06	−0.04	−0.01	0.06
23. Log relationship duration	4.12	−0.04	−0.17**	0.10	0.20***	−0.02	0.11	0.07	−0.07	0.20***	0.12*	−0.12*	0.11*	−0.15*
24. Mills ratio 1st stage	14.95	0.13*	0.02	0.15**	0.10	−0.01	0.00	−0.01	−0.03	0.11	−0.01	−0.09	0.16**	−0.01
25. Mills ratio 2nd stage	6.60	0.00	0.14*	0.01	0.18**	−0.12*	0.16**	0.18**	−0.10	−0.13*	0.09	0.02	−0.08	0.35***
26. Log words on webpage A in t	6.98	0.10	0.00	0.04	0.07	0.03	0.05	0.03	−0.01	0.06	0.06	0.01	0.13*	0.02
27. Log words on webpage B in t	7.00	0.01	0.08	−0.05	0.11	0.09	0.07	0.13*	0.07	0.03	−0.02	0.05	0.13*	0.07
28. International alliance (binary)	0.44	−0.03	0.10	0.07	0.01	−0.05	−0.09	−0.05	0.05	−0.07	0.06	−0.03	−0.09	0.12
29. Early alliance stage (binary)	0.13	0.01	0.02	−0.05	−0.16**	0.02	−0.16**	−0.08	0.08	−0.14*	−0.05	0.08	−0.02	0.08
30. Late alliance stage (binary)	0.07	0.08	−0.20***	0.14*	0.01	−0.03	−0.01	0.00	−0.02	−0.20***	−0.12*	0.01	−0.04	−0.05
31. Alliance termination (binary)	0.08	0.07	−0.14*	0.07	−0.04	0.02	0.01	0.00	0.00	−0.19**	0.00	−0.07	−0.12*	0.12
32. Equity participation (binary)	0.18	−0.09	0.20***	−0.01	0.06	−0.08	0.04	0.02	−0.09	−0.03	0.05	0.07	−0.11	−0.01
33. Medical devices industry (binary)	0.57	−0.05	−0.06	−0.13*	−0.04	0.06	−0.05	−0.05	0.07	−0.03	0.00	−0.02	0.01	0.23***

Measures	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.
1. Business model similarity in t + 2	0.13*	−0.03	0.14*	−0.03	−0.01	0.01	0.02	−0.17**	−0.05	−0.05	0.23***	0.01	0.08	−0.05
2. Novel value configurations in t + 1	−0.02	0.13*	−0.01	−0.08	0.02	−0.07	−0.03	0.05	0.07	−0.16**	0.03	0.20***	−0.01	0.04
3. Business model similarity in t	0.11	−0.01	0.19***	0.03	−0.05	0.09	0.03	−0.19**	0.03	0.12*	0.13*	0.07	0.05	−0.05
4. Log market overlap	0.05	0.13*	0.07	0.01	0.09	0.04	−0.06	−0.05	0.01	0.19***	0.02	0.16**	0.04	0.08
5. Log market overlap^2	−0.11	−0.07	−0.09	0.02	0.11	−0.07	0.04	0.03	−0.07	−0.06	−0.08	−0.17**	0.04	0.06
6. Partner-specific alliance experience (SAE)	0.10	0.18**	−0.05	0.07	0.10	0.04	0.04	0.03	−0.11*	0.14*	−0.06	0.12*	0.07	0.06
7. Log market overlap × SAE	0.10	0.10	0.10	0.04	0.11*	0.05	0.07	−0.03	−0.06	0.02	−0.01	0.16**	0.01	0.06
8. Log market overlap^2 × SAE	−0.07	−0.03	−0.09	−0.02	0.09	−0.09	−0.04	0.00	0.03	−0.03	−0.06	−0.09	0.01	0.05
9. Collaboration likelihood (CL)	0.06	0.05	0.01	−0.02	0.23***	0.03	−0.02	0.01	−0.03	0.19***	0.10	−0.10	0.10	0.07
10. Log market overlap × CL	−0.02	0.00	0.09	0.10	−0.06	0.04	−0.05	−0.04	0.04	0.10	0.01	0.04	0.03	−0.01
11. Log market overlap^2 × CL	−0.04	−0.06	−0.08	0.02	0.09	0.02	−0.04	0.04	−0.06	−0.08	−0.05	−0.01	−0.03	0.02
12. Firm A’s alliance experience	0.17**	0.08	0.10	0.03	0.00	0.08	0.00	0.04	0.01	0.08	0.08	−0.13*	0.14*	0.14*
13. Log firm A’s R&D intensity	−0.01	0.06	−0.13	−0.07	0.03	0.19**	0.08	−0.12	0.02	−0.14*	−0.02	0.30***	0.04	0.08
14. Log firm A’s size	1.00	0.24***	0.35***	0.12*	−0.01	0.28***	0.12*	−0.11	0.06	0.06	0.40***	0.24***	0.16**	0.03
15. Log firm B’s size	0.22***	1.00	0.07	0.50***	0.08	0.02	0.47***	0.01	0.06	0.15*	0.09	0.13*	0.14*	0.29***
16. Log firm A’s age	0.37***	0.10	1.00	0.18**	−0.07	0.16**	−0.01	−0.08	−0.01	0.19***	0.18**	−0.17**	0.15*	0.02
17. Log firm B’s age	0.11	0.45***	0.19***	1.00	0.09	0.03	0.33***	0.04	0.01	0.16**	0.07	−0.05	0.06	0.18**

(*continued on next page*)

Table 2 (*continued*)

Measures	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.
18. No. of mutual innovation stages	0.01	0.06	−0.03	0.08	1.00	0.01	0.07	0.07	−0.11	0.09	−0.10	−0.09	0.11	0.11
19. Firm A's technological diversity	0.28***	0.07	0.18**	0.04	0.00	1.00	0.19***	−0.26***	−0.04	0.01	0.06	0.00	0.09	0.00
20. Firm B's technological diversity	0.12*	0.48***	−0.03	0.33***	0.08	0.19***	1.00	−0.24***	−0.02	−0.01	0.04	0.02	0.11	0.16**
21. Technological distance	−0.17**	−0.16**	−0.08	−0.04	0.00	−0.44***	−0.43***	1.00	−0.03	0.01	−0.04	0.01	−0.05	−0.01
22. Log geographical distance	0.06	0.02	−0.05	0.03	−0.10	−0.05	−0.03	−0.03	1.00	0.08	0.07	0.07	−0.03	0.01
23. Log relationship duration	0.08	0.15*	0.19**	0.16**	0.10	0.02	−0.02	0.00	0.08	1.00	0.06	−0.22***	0.04	0.09
24. Mills ratio 1st stage	0.48***	0.15*	0.30***	0.04	−0.03	0.07	0.04	−0.05	0.03	0.06	1.00	0.18**	−0.06	−0.16**
25. Mills ratio 2nd stage	0.29***	0.15*	−0.16**	0.01	−0.06	0.12*	0.09	−0.05	0.04	−0.29***	0.31***	1.00	−0.07	−0.10
26. Log words on webpage A in t	0.13*	0.08	0.13*	0.06	0.09	0.07	0.09	−0.04	−0.05	0.05	0.01	0.00	1.00	0.36***
27. Log words on webpage B in t	0.00	0.23***	0.03	0.14*	0.07	0.02	0.17**	−0.04	−0.02	0.11	−0.08	−0.06	0.37***	1.00
28. International alliance (binary)	0.04	0.02	−0.01	−0.01	−0.07	−0.03	−0.01	−0.07	0.77***	0.03	0.06	0.02	−0.09	−0.07
29. Early alliance stage (binary)	−0.10	−0.13*	−0.10	−0.12*	−0.03	−0.04	−0.03	−0.02	−0.07	−0.36***	−0.13*	−0.05	−0.04	−0.09
30. Late alliance stage (binary)	0.03	0.01	−0.02	0.03	−0.05	0.00	−0.03	0.03	0.09	0.07	0.00	0.04	0.06	0.06
31. Alliance termination (binary)	−0.05	0.03	−0.04	0.03	−0.04	−0.07	−0.05	0.03	−0.02	−0.07	−0.04	0.02	0.06	0.07
32. Equity participation (binary)	0.02	−0.02	−0.09	−0.03	−0.07	−0.07	−0.06	0.01	−0.01	−0.06	0.06	0.14*	−0.05	−0.09
33. Medical devices industry (binary)	−0.15**	−0.03	−0.18**	−0.07	−0.08	0.00	−0.07	0.02	0.14*	0.03	0.07	−0.02	0.05	−0.04

Notes: N = 302, * $p < .05$, ** $p < .01$, *** $p < .001$, above diagonal are Pearson zero-order correlations, below non-parametric Spearman correlations.
Log market overlap was mean-centered before quadratic or interactive transformation.

supports NVCs and more distinctive business models (Tallman et al., 2018). Although there is consensus that external triggers, such as Covid-19, spur *reactive* and disruptive business model changes, literature about the competitive dynamics and *proactive* and incremental business model changes at the intermediate alliance level remains scarce (Snihur & Markman, 2023). Previous research has shown that coopetition permits new business models (McDonald & Eisenhardt, 2020; Yadav et al., 2022) and that competitive dynamics facilitate business model change (Lanzolla & Markides, 2021; Snihur & Markman, 2023). Our findings extend these insights by showing that moderate levels of market overlap push business model change which then leads to more distinctive business models of the involved coopetitors. We contribute to a deeper understanding of coopetition-induced business model changes by extending the internally focused ABV (Ocasio, 1997) to the dyadic alliance level (Chen & Miller, 2015) and considerations of firm-level distinctiveness (Täuscher et al., 2021). In times of success and stability, firms have a low incentive to change a "running system" by searching for NVCs. Yet, similar mindsets and competitive pressures of firms in coopetition facilitate finding NVCs that might be able to deal with environmental turbulence and inform about what a business model contains and what not. Hence, we propose coopetition as a vehicle to better carve out the content and boundaries of firms' business models.

Second, our study emphasizes that moderate levels of market overlap, hence the typical form of coopetition (Bengtsson & Kock, 2014), trigger business model change as NVCs and facilitate the development of distinctive business models (Zhao et al., 2017). Interestingly, these findings are fully contingent on repeated past ties and anticipated future ties. In considering these ties, our study extends previous studies in that repeated ties have potential downsides (Gulati et al., 2009). Repeated ties signal security and reduce attention and alert, which might be detrimental in turbulent times. A potential curse of repeated ties tends to reduce managerial attention to firm-level changes through cognitive biases, path dependency, and organizational inertia (O'Reilly III & Tushman, 2021). Despite these known barriers, the precise nature of cognition and attention that propels decision-makers to endorse novelties such as NVCs is poorly understood (Mount, Baer, & Lupoli, 2021). Our findings contribute to filling this research gap by suggesting that firms' attention bounded in their capacity to register and digest alliance-specific information, such as "too little" or "too much" market overlap, is fully contingent on their anticipation of alliance continuation (Bó, 2005) in search of NVCs (see Fig. 4)—and hence, their future relative positioning within overlapping markets (Chen & Miller, 2015).

Third, we elucidate how collaboration among firms targeting completely different markets can limit or preclude an understanding of how a partner's resources might be utilized in service to the focal firm's markets (Kapoor & Furr, 2015). If firms target distinct markets with different resource bases, alliance partners may not possess the resources relevant to exploiting complementarities for NVCs (Kapoor & Furr, 2015; Zott & Amit, 2010). Complementarities might be most important in turbulent times. Similarly, technological distance is a major barrier to business model change (Fredrich et al., 2022). Instead, a very high market overlap between collaborating firms can reduce the likelihood of NVCs (Dai, Zhang, Zhang, & Mao, 2024). The optimum level of market overlap corresponds to coopetition research in which firms collaborate and compete simultaneously in a balancing act (Bengtsson & Kock, 2014; Bouncken, Fredrich, Ritala, & Kraus, 2020; Gnyawali & Ryan Charleton, 2018; Park, Srivastava, & Gnyawali, 2014).

Fourth, we explicate how the business models of allying firms may diverge due to those firms serving overlapping markets in search of firm-level distinctiveness (Täuscher et al., 2021; Zhao et al., 2017). Traditionally, business models have been understood and depicted as valuable because they are tightly integrated and optimized for efficiency (Amit & Zott, 2012; Zott & Amit, 2008). Our findings support more open boundaries, even among firms in overlapping markets. In this, we nuance that contradictions between value-creation logics become salient and provide opportunities for business model change and the

Table 3
Regression results.

$N = 302$ dyadic R&D alliances	Model A		Model B		Model C		Model D	
	1st stage DV: NVC_{t+1}	2nd stage DV: BMS_{t+2}	1st stage DV: NVC_{t+1}	2nd stage DV: BMS_{t+2}	1st stage DV: NVC_{t+1}	2nd stage DV: BMS_{t+2}	1st stage DV: NVC_{t+1}	2nd stage: BMS_{t+2}
Mills ratio 1st stage	0.06 ($p = .264$)	0.19 ($p = .007$)	0.07 ($p = .167$)	0.19 ($p = .007$)	0.06 ($p = .217$)	0.19 ($p = .007$)	0.07 ($p = .126$)	0.19 ($p = .007$)
Mills ratio 2nd stage	0.04 ($p = .590$)	−0.06 ($p = .333$)	0.03 ($p = .668$)	−0.06 ($p = .331$)	0.06 ($p = .445$)	−0.06 ($p = .345$)	0.05 ($p = .515$)	−0.06 ($p = .342$)
Business model similarity BMS in t	−0.01 ($p = .831$)	0.46 ($p < .001$)	−0.01 ($p = .876$)	0.45 ($p < .001$)	−0.02 ($p = .733$)	0.45 ($p < .001$)	−0.02 ($p = .780$)	0.45 ($p < .001$)
Log words on web page A in t	0.02 ($p = .730$)	0.06 ($p = .246$)	0.04 ($p = .537$)	0.06 ($p = .239$)	0.02 ($p = .718$)	0.06 ($p = .241$)	0.04 ($p = .505$)	0.06 ($p = .234$)
Log words on web page B in t	0.07 ($p = .325$)	−0.02 ($p = .756$)	0.07 ($p = .284$)	−0.02 ($p = .763$)	0.07 ($p = .255$)	−0.02 ($p = .747$)	0.08 ($p = .220$)	−0.02 ($p = .753$)
Medical devices industry (binary)	−0.07 ($p = .265$)	−0.05 ($p = .291$)	−0.08 ($p = .238$)	−0.05 ($p = .289$)	−0.08 ($p = .207$)	−0.05 ($p = .298$)	−0.09 ($p = .177$)	−0.05 ($p = .296$)
Firm A's general alliance experience	−0.08 ($p = .284$)	0.03 ($p = .515$)	−0.08 ($p = .282$)	0.03 ($p = .517$)	−0.06 ($p = .379$)	0.04 ($p = .492$)	−0.06 ($p = .379$)	0.04 ($p = .491$)
Log firm A's R&D intensity	0.04 ($p = .560$)	0.06 ($p = .349$)	0.03 ($p = .646$)	0.06 ($p = .357$)	0.03 ($p = .627$)	0.06 ($p = .351$)	0.03 ($p = .714$)	0.06 ($p = .360$)
Log firm A's size	−0.09 ($p = .305$)	0.02 ($p = .808$)	−0.10 ($p = .251$)	0.02 ($p = .793$)	−0.09 ($p = .274$)	0.01 ($p = .813$)	−0.11 ($p = .210$)	0.02 ($p = .801$)
Log firm B's size	0.18 ($p = .046$)	−0.00 ($p = .978$)	0.19 ($p = .030$)	−0.01 ($p = .954$)	0.17 ($p = .054$)	−0.00 ($p = .963$)	0.18 ($p = .037$)	−0.01 ($p = .939$)
Log firm A's age	0.06 ($p = .408$)	0.03 ($p = .619$)	0.04 ($p = .567$)	0.03 ($p = .619$)	0.05 ($p = .444$)	0.03 ($p = .615$)	0.04 ($p = .605$)	0.03 ($p = .616$)
Log firm B's age	−0.13 ($p = .112$)	−0.05 ($p = .432$)	−0.14 ($p = .095$)	−0.05 ($p = .437$)	−0.12 ($p = .135$)	−0.05 ($p = .438$)	−0.12 ($p = .129$)	−0.04 ($p = .445$)
No. of mutual innovation stages	0.06 ($p = .365$)	0.02 ($p = .653$)	0.06 ($p = .408$)	0.02 ($p = .660$)	0.08 ($p = .263$)	0.02 ($p = .672$)	0.07 ($p = .302$)	0.02 ($p = .678$)
Firm A's technological diversity	−0.04 ($p = .597$)	−0.11 ($p = .039$)	−0.03 ($p = .694$)	−0.11 ($p = .041$)	−0.03 ($p = .687$)	−0.11 ($p = .038$)	−0.02 ($p = .806$)	−0.11 ($p = .040$)
Firm B's technological diversity	−0.06 ($p = .426$)	−0.01 ($p = .842$)	−0.09 ($p = .253$)	−0.01 ($p = .850$)	−0.06 ($p = .445$)	−0.01 ($p = .889$)	−0.08 ($p = .256$)	−0.01 ($p = .895$)
Technological distance	0.08 ($p = .339$)	−0.10 ($p = .073$)	0.07 ($p = .374$)	−0.10 ($p = .070$)	0.08 ($p = .337$)	−0.10 ($p = .069$)	0.07 ($p = .370$)	−0.10 ($p = .067$)
Log geographical distance	0.05 ($p = .596$)	−0.02 ($p = .762$)	0.04 ($p = .671$)	−0.02 ($p = .741$)	0.05 ($p = .605$)	−0.02 ($p = .774$)	0.04 ($p = .682$)	−0.02 ($p = .752$)
Log relationship duration	−0.16 ($p = .034$)	−0.17 ($p = .002$)	−0.15 ($p = .057$)	−0.17 ($p = .002$)	−0.17 ($p = .030$)	−0.17 ($p = .002$)	−0.15 ($p = .055$)	−0.17 ($p = .002$)
International alliance (binary)	0.06 ($p = .529$)	−0.03 ($p = .661$)	0.08 ($p = .404$)	−0.03 ($p = .671$)	0.05 ($p = .558$)	−0.03 ($p = .635$)	0.07 ($p = .429$)	−0.03 ($p = .643$)
Early alliance stage (binary)	−0.00 ($p = .981$)	−0.04 ($p = .484$)	−0.01 ($p = .846$)	−0.04 ($p = .481$)	−0.00 ($p = .972$)	−0.04 ($p = .482$)	−0.01 ($p = .849$)	−0.04 ($p = .481$)
Late alliance stage (binary)	−0.19 ($p = .005$)	−0.03 ($p = .515$)	−0.20 ($p = .004$)	−0.03 ($p = .528$)	−0.18 ($p = .005$)	−0.03 ($p = .517$)	−0.20 ($p = .003$)	−0.03 ($p = .532$)
Equity participation (binary)	0.13 ($p = .030$)	−0.07 ($p = .102$)	0.13 ($p = .033$)	−0.07 ($p = .097$)	0.14 ($p = .020$)	−0.07 ($p = .098$)	0.14 ($p = .020$)	−0.07 ($p = .093$)
Alliance termination (binary)	−0.12 ($p = .133$)	0.04 ($p = .518$)	−0.11 ($p = .145$)	0.04 ($p = .491$)	−0.15 ($p = .059$)	0.04 ($p = .511$)	−0.14 ($p = .062$)	0.04 ($p = .483$)
Log market overlap	0.20 ($p = .010$)	−0.02 ($p = .782$)	0.08 ($p = .466$)	−0.02 ($p = .746$)	0.19 ($p = .021$)	−0.02 ($p = .769$)	0.07 ($p = .505$)	−0.02 ($p = .733$)
H1: Log market overlap^2	−0.16 ($p = .022$)	−0.04 ($p = .450$)	−0.17 ($p = .059$)	−0.04 ($p = .482$)	−0.09 ($p = .231$)	−0.04 ($p = .495$)	−0.10 ($p = .296$)	−0.03 ($p = .527$)
Partner-specific alliance experience (SAE)	0.01 ($p = .894$)	0.04 ($p = .455$)	−0.01 ($p = .841$)	0.04 ($p = .479$)	0.01 ($p = .873$)	0.04 ($p = .468$)	−0.01 ($p = .864$)	0.03 ($p = .493$)
Collaboration likelihood (CL)	−0.11 ($p = .138$)	0.09 ($p = .098$)	−0.13 ($p = .093$)	0.09 ($p = .095$)	−0.17 ($p = .031$)	0.09 ($p = .106$)	−0.18 ($p = .014$)	0.09 ($p = .102$)
H2a: Log market overlap × SAE			0.18 ($p = .041$)				0.18 ($p = .039$)	
Log market overlap^2 × SAE			−0.00 ($p = .959$)				−0.00 ($p = .986$)	
H2b: Log market overlap × CL					0.01 ($p = .918$)		−0.01 ($p = .902$)	
Log market overlap^2 × CL					−0.17 ($p = .031$)		−0.18 ($p = .019$)	
H3: NVC in t + 1		−0.18 ($p = .004$)		−0.17 ($p = .007$)		−0.18 ($p = .005$)		−0.17 ($p = .009$)
Variance explanation R^2	0.29 ($p < .001$)	0.35 ($p < .001$)	0.29 ($p < .001$)	0.35 ($p < .001$)	0.31 ($p < .001$)	0.35 ($p < .001$)	0.32 ($p < .001$)	0.35 ($p < .001$)
AIC	12,092.59		12,092.16		12,092.44		12,091.87	
Sample-size adjusted BIC	12,137.87		12,138.51		12,138.79		12,139.30	
Log-likelihood (no. of free parameters)	−5962.30 (84)		−5960.08 (86)		−5960.22 (86)		−5957.93 (88)	
Scaling correction factor for MLR	1.100		1.093		1.097		1.089	

(*continued on next page*)

Table 3 (*continued*)

N = 302 dyadic R&D alliances	Model A		Model B		Model C		Model D	
	1st stage DV: NVC_{t+1}	2nd stage DV: BMS_{t+2}	1st stage DV: NVC_{t+1}	2nd stage DV: BMS_{t+2}	1st stage DV: NVC_{t+1}	2nd stage DV: BMS_{t+2}	1st stage DV: NVC_{t+1}	2nd stage: BMS_{t+2}
Scaled chi-square difference ΔTRd (Δdf):			χ^2 (2) = 5.52, p = .063		χ^2 (2) = 4.21, p = .122		χ^2 (4) = 10.10, p = .039	

Notes: DV = Dependent Variable, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, df = degrees of freedom, MLR = (two-tailed) Maximum Likelihood Robust *p*-values in brackets.

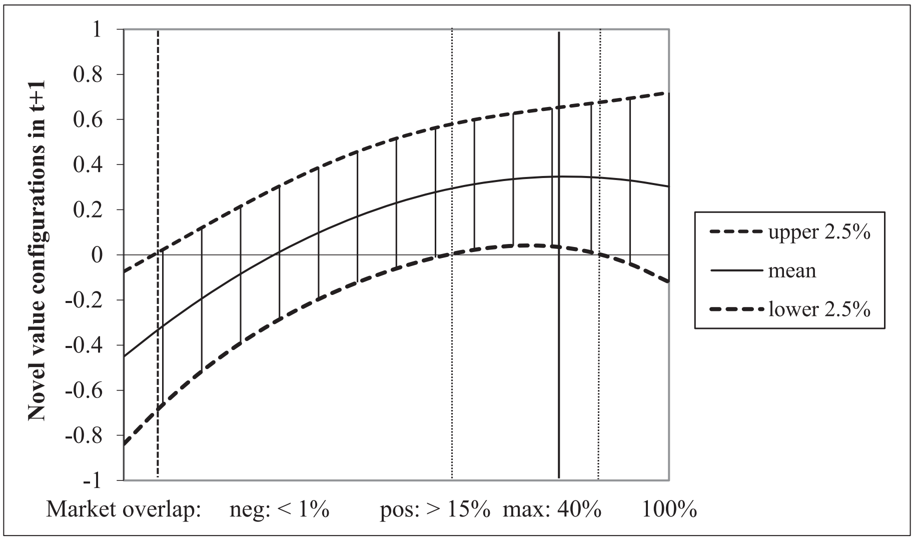

Fig. 2. Plot of H1 results.

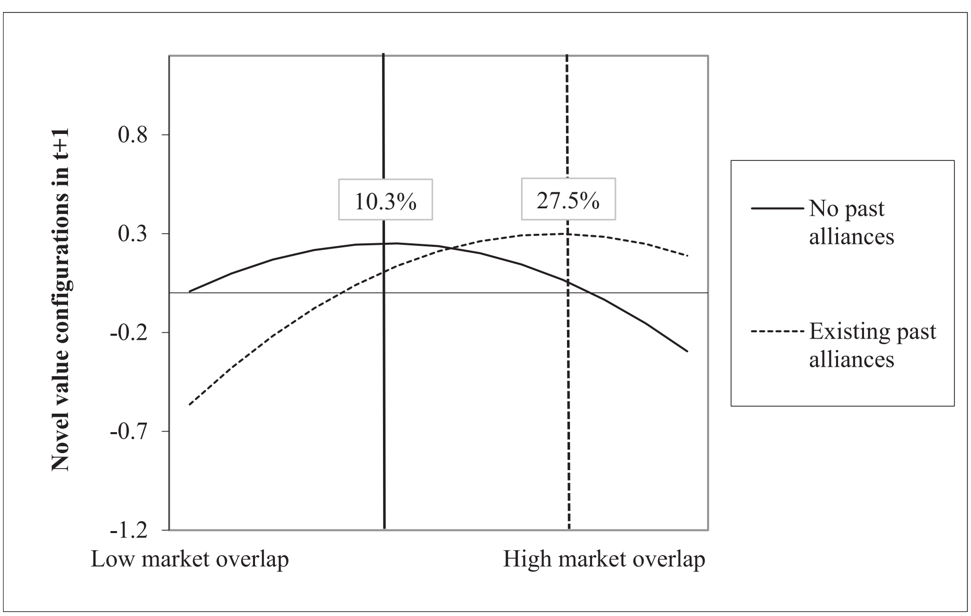

Fig. 3. Plot of H2a results.

achievement of firm-level distinctiveness (Ocasio & Radoynovska, 2016; Zhao et al., 2017). Distinctive features of competing business model designs can promote natural isolation mechanisms and prevent excessive inter-partner competition in the future (Fredrich et al., 2022; Martins, Rindova, & Greenbaum, 2015; McDonald & Eisenhardt, 2020). The orchestration challenge in complex value chains is particularly vivid when actively managing the generalist-specialist contribution tension (Geurts, Broekhuizen, Dolfsma, & Cepa, 2022).

6.2. *Practical implications*

Managers know that their business model defines their success and needs to be modified over time. Today, given the need to manage greater uncertainty, managers aim to increase their “robustness” and “agility”

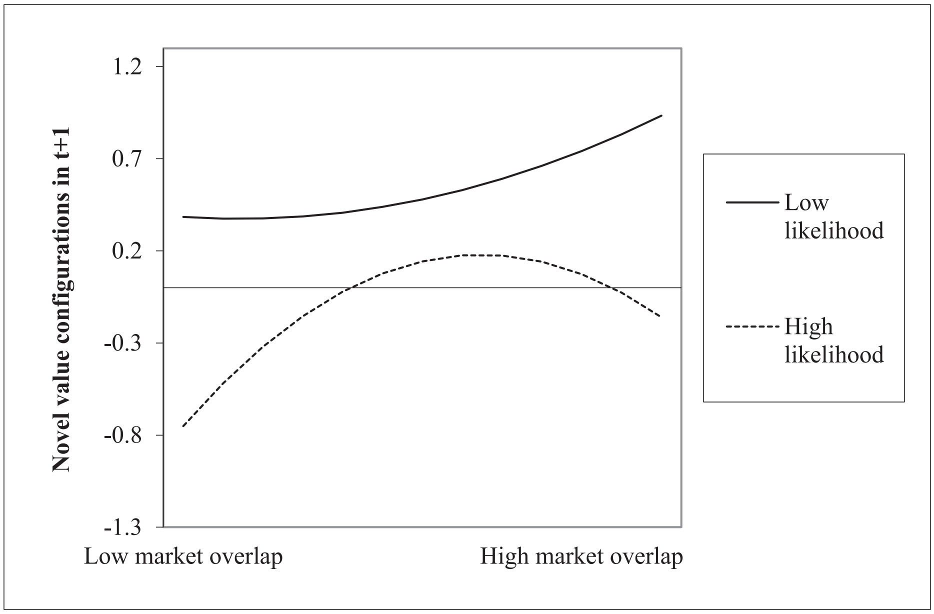

Fig. 4. Plot of H2b results.

and can do so by collaborating with competitors. Our study shows that to achieve business model change, managers should devote significant attention to understanding the market overlap of firms. Typically, managers should pursue partners they know (i.e., repeated ties) and prioritize partners with moderate levels of market overlap. Especially in today's increased environmental turbulence, managers must proactively design relationships to detect threats early and jointly create and implement novel solutions. Hence, managers should develop metrics and portfolio considerations regarding which previous partners with whom they share moderate market overlap might allow them to create alternative business models. However, there is also an option involving high market overlap. Even risky relationships with highly similar firms may increase the likelihood of change when they intend to play a single "game" that is well protected against future opportunism. Hence, managers should use formal protection and natural isolation mechanisms properly.

Our key and counterintuitive lesson is that firms should closely interact with their partners and learn how to differentiate themselves from them rather than mimic each other's "playbooks." Specifically, managers should consider how and what to learn from their partners to develop a different and unique—i.e., distinctive—business model. As coopetition always has inherent risks, it is essential for managers to be aware of the benefits of "learning to be different" and to exhibit an intention to learn while not copying the other firm. Hence, firms should openly discuss this and what they aim to learn from the other firm to utilize in modifying their business model, as well as how to best design business models that enable learning processes as a point of departure. This sharing and joint development of divergent business models will also support organizational resilience against future market shocks (Bocken & Geradts, 2020).

6.3. Limitations and future research directions

First, coopetition partners serving an overlapping market may not be direct competitors (Boyd & Spekman, 2008) or even be perceived as such (Chen & Miller, 2015). Second, what, specifically, a focal firm's alliance partner serving a common market brings to the collaborative effort as an enabler of NVCs was beyond our study's scope. As such, while we can conclude that market overlap affects NVCs, which subsequently affect business model divergence, we do not understand the specific combinations of partner-sourced resources and capabilities through which these changes occur. Third, the firm-level performance implications of NVCs and business model divergence are beyond the scope of our study. Typically, business model changes have ambivalent short- and long-term performance implications (Aversa, Furnari, & Haefliger, 2015). A meta-analysis by White, Markin, Marshall, and Gupta (2022) supports that the link between business model innovation and firm performance is context-specific and positive, on average. Fourth, our findings reflect the idiosyncratic characteristics of R&D alliances. These characteristics could be necessary triggers of NVCs and limit the transferability of our findings to other types of alliances. Fifth, our measure of business model similarity might suffer from selective non-disclosure of relevant business model elements or be subject to storytelling for differentiation purposes. We ran a series of validity checks and assessed this risk as low due to informational asymmetry between alliance partners, especially between competitors. However, we cannot rule out this risk entirely and highlight business models as linguistic devices or narratives (Täuscher, 2018). Lastly, since the full data-generation process behind our findings spans 2010–2019, their implications do not reflect exogenous global shocks, such as pandemics and wars post-2019. We expect even more pronounced coopetitive business model divergence in the current era of global disorder (Luo, 2024).

Our results invite future research in three areas. First, more research on the management practices in alliances that potentially increase and maintain managerial attention is necessary. For example, Ocasio and Joseph (2018) claim that a common strategic agenda helps achieve attentional coherence among allying firms, making them more likely to agree on tackling problems and allocating resources and effort. Second, future research on alliance management "best practices" of firms serving overlapping markets is warranted (Bouncken, Fredrich, & Kraus, 2020). The current results indicate that a particular form of business model changes—namely NVCs—can result when alliance partners serve a common market. However, our research did not explore how partners might individually and jointly manage their alliances to realize the most significant benefit from their collaborative NVC effort. Third, past research has focused on industry-level or firm-level drivers of business model change while neglecting the intermediate alliance level (Osiyevskyy & Dewald, 2015). Here, we propose investigating business model convergence vs. divergence as an additional dimension of business model changes. Furthermore, and on a different note, we encourage research about how artificial intelligence technology may help firms to develop new ideas and new value configurations in coopetition (Bouncken & Vogt, 2025).

7. Conclusion

Times have changed, bringing greater environmental turbulence and, with it, the need for firms to quickly adapt their business models. One vehicle to master these challenges is coopetition between firms. This study has demonstrated how competitive dynamics within dyadic alliances where firms may have market overlap—hence are in coopetition—can foster business model change. We find that NVCs can trigger (relative) business model divergence, which then can permit greater distinctiveness of firms in common markets. Specifically, moderate levels of market overlap drive NVCs the most. Yet, these effects are fully contingent on repeated and anticipated future ties. In repeated ties, firms require greater levels of market overlap to achieve equivalent NVCs compared to non-repeated ties. Surprisingly, firms can achieve highest levels of NVCs from market overlap if they do not anticipate future collaboration with the same partner. Our study adds to and complements an attention-based view of business models to coopetition research. Overall, we contribute to a better understanding of how firms can navigate coopetition in an era of global disorder characterized by unstable supply chains, hyper-competition, de-globalization, digital transformation, and global disasters. The key counterintuitive finding is that firms should use coopetition to learn how to differentiate themselves and develop distinctive business models.

CRediT authorship contribution statement

Ricarda B. Bouncken: Writing – original draft, Supervision, Conceptualization. **Viktor Fredrich:** Writing – review & editing, Validation, Software, Methodology.

Declaration of competing interest

None.

Data availability

The data that has been used is confidential.

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