ALLIANCE FORMATION ACROSS CLUSTERS: FIRM RESPONSES TO ASPIRATION GAPS UNDER MARKET AND TECHNOLOGICAL UNCERTAINTY

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ABSTRACT

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Keywords: Between-Cluster Alliances, Performance Feedback, External Uncertainties

Forming alliances beyond local clusters allows firms to access non-redundant knowledge unavailable within their local network. Although prior research has explored the antecedents of between-cluster ties (BCTs), it has largely overlooked the role of external uncertainty. This study addresses this gap, motivated by the rising prominence of market and technological uncertainty and the growing call to integrate these conditions into theories of strategic management. Under uncertainty, conventional risk analysis becomes less effective, and managers rely on heuristics that weigh both internal performance and external conditions. Under market uncertainty—where demand is volatile and attribution is ambiguous—managers heuristically give some weight to external, uncontrollable, and transient factors when interpreting underperformance, which reduces the urgency to engage in exploratory search. When performance exceeds aspirations, market uncertainty is seen as an opportunity, prompting the formation of BCTs to leverage success and buffer against potential downturns. Under technological uncertainty—where the direction of change is unpredictable and emerging technologies are difficult to evaluate—managers heuristically attribute underperformance partly to external technological shifts, which suggests a misalignment between current capabilities and future needs. This drives firms to form more BCTs in search of novel knowledge to adapt. When performance exceeds aspirations, firms still pursue more BCTs to reinforce their position and influence the direction of technological change, though with less urgency. Using panel data from North American public firms in 12 high-tech manufacturing industries (1990–2022), the study finds partial support for these hypotheses. The results show that market uncertainty amplifies the formation of BCTs when firms exceed their social aspirations. These findings contribute to the interorganizational network literature by clarifying how external uncertainty influences alliance behavior and network dynamics, and extend the firm's behavioral theory to uncertain environments.

ÖZET

KÜMELER ARASI İTTİFAK OLUŞUMU: FİRMALARIN PİYASA VE TEKNOLOJİK BELİRSİZLİK KOŞULLARINDA BEKLENTİ AÇIKLARINA VERDİĞİ TEPKİLER

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Yerel kümelerin ötesinde ittifaklar kurmak, firmaların kendi ağları içerisinde erişilemeyen, farklı ve tamamlayıcı bilgiye ulaşmalarını sağlar. Önceki araştırmalar, küme arası ittifakların (KAI) oluşum nedenlerini incelemiş olsa da, dışsal belirsizliklerin bu süreçteki rolü büyük ölçüde göz ardı edilmiştir. Bu çalışma, piyasa ve teknolojik belirsizliklerin artan etkisinden ve bu belirsizliklerin strateji kuramlarına entegre edilmesine yönelik giderek güçlenen çağrılardan hareketle bu boşluğu ele almayı amaçlamaktadır. Belirsizlik altında, geleneksel risk analizleri daha az etkili hale gelir ve yöneticiler hem içsel performansı hem de dışsal koşulları tartan sezgisel yöntemlere başvurur. Piyasa belirsizliği altında – talebin dalgalı olduğu ve neden-sonuç ilişkisinin belirsiz olduğu durumlarda – yöneticiler düşük performansı yorumlarken kontrol edilemeyen ve geçici dışsal etkenlere sezgisel olarak bir miktar ağırlık verir, bu da keşif amaçlı arayışa girme aciliyetini azaltır. Performans beklentileri aştığında, piyasa belirsizliği bir fırsat olarak görülür ve bu durum, başarıdan yararlanmak ve olası düşüşlere karşı tampon oluşturmak için KAI kurulmasını teşvik eder. Teknolojik belirsizlik altında – değişimin yönü öngörülemez olduğunda ve yeni teknolojilerin değerlendirilmesi zorlaştığında – yöneticiler düşük performansı sezgisel olarak kısmen dışsal teknolojik değişimlere atfeder, bu da mevcut yetkinliklerle gelecekteki ihtiyaçlar arasında bir uyumsuzluk olduğunu gösterir. Bu durum, firmaları uyum sağlamak için yeni bilgi arayışıyla daha fazla

KAI kurmaya yönlendirir. Performans beklentileri aştığında firmalar mevcut konumlarını güçlendirmek ve teknolojik değişimin yönünü etkilemek amacıyla, daha az aciliyetle de olsa, yine KAI kurmaya devam eder. 1990–2022 yılları arasında, 12 yüksek teknoloji imalat sektöründe faaliyet gösteren Kuzey Amerikalı halka açık firmaların panel verileri kullanılarak gerçekleştirilen analiz, bu hipotezlere kısmi destek sunmaktadır. Bulgular, piyasa belirsizliğinin firmalar sosyal beklenti düzeylerinin üzerinde performans gösterdiğinde KAI oluşumunu artırdığını göstermektedir. Bu bulgular, dışsal belirsizliklerin ittifak davranışlarını ve ağ dinamiklerini nasıl etkilediğini açıklığa kavuşturarak örgütler arası ağ literatürüne katkı sağlamakta ve davranışsal firma teorisini belirsiz çevresel koşullara uyarlayarak geliştirmektedir.

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To my dear wife, Aida,
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1. INTRODUCTION

Strategic alliances are formal interfirm agreements that have become a key element of competitive strategy, allowing firms to access resources, knowledge, and markets (Doz, 1996; Doz & Hamel, 1998; Eisenhardt & Schoonhoven, 1996; Hagedoorn et al., 2011; Hamel, 1991; Y. Wang & Rajagopalan, 2015). Limited information about potential partners' capabilities, trustworthiness, and intentions introduces significant risk and uncertainty into strategic alliances and increase search costs of finding appropriate partners (Gulati, 1995a). To economize on these search costs firms often ally with previous partners or the partners of their partners (Gulati, 1999). This pattern leads to the formation of organizational clusters, where firms become tightly interconnected through repeated alliances (Gulati et al., 2012; Owen-Smith & Powell, 2004; Powell et al., 2005; Schilling & Phelps, 2020).

Network research suggests that, although relatively rare, firms form alliances by creating bridging ties that extend beyond their dense local clusters (Baum et al., 2005, 2003; Gulati et al., 2012; Rosenkopf & Padula, 2008; Sytch et al., 2012). These between-cluster ties (BCTs) connect structurally cohesive network communities and shape the structural evolution of networks (Uzzi, 2008). BCTs also improve the reachability of each firm within a connected network component by linking isolated or weakly connected clusters, thereby enhancing information flow (Chang et al., 2023). While alliances within clusters offer reliable access to resources and trust-based collaboration, they can lead to redundant information due to tight local connections (Gulati et al., 2012; Uzzi, 1996). In contrast, firms embedded in clusters linked through BCTs tend to outperform those in more isolated clusters lacking such ties (Schilling, 2015; Schilling & Phelps, 2020). It is worth noting that BCTs differ from ties that span structural holes—gaps between unconnected actors that may exist even within a single cluster—as BCTs specifically connect separate clusters (Sytch et al., 2012).

Despite the importance of BCTs for firm performance and their role in shaping network structure, research on the factors driving their formation remains limited (Franco & Esteves, 2020; Sytch et al., 2012). Baum et al. (2003) showed that both central and peripheral firms can form BCTs. Later, Baum et al. (2005) viewed BCT formation as a form of risk-taking, finding that investment banks were more likely to form BCTs when their performance diverged from aspiration levels. Beyond this behavioral view, network-based research suggests that firms with prior BCT experience are more likely to form new cross-cluster alliances (Sytch et al., 2012). Additionally, status homophily (Rosenkopf & Padula, 2008) and knowledge redundancy within clusters (Gulati et al., 2012) have also been linked to BCT formation.

Although some studies have explored the antecedents of BCT formation (Baum et al., 2005, 2003; Gulati et al., 2012; Rosenkopf & Padula, 2008; Schilling, 2015; Sytch et al., 2012), the influence of external uncertainties on between-cluster alliances remains underexplored. This represents a significant and relevant gap in our understanding of alliance network evolution and the decisions behind forming such ties. Empirical evidence shows that the number of BCTs varies considerably over time and across industries, suggesting that external factors play a key role in their formation (Gulati et al., 2012; Rosenkopf & Padula, 2008; Schilling, 2015). Prior research has recognized that market and technological uncertainties can affect alliance decisions (Ahuja et al., 2012; Beckman et al., 2004; Howard et al., 2016). Furthermore, managers are likely to adjust their search strategies and BCT formation in response to external stimuli (Greve, 2018). However, our understanding of how external uncertainties influence the formation of BCTs remains limited. This gap is particularly important given the rising prevalence of uncertainty in today's business landscape and growing calls to incorporate it into theoretical frameworks (Alvarez et al., 2018; Schoemaker et al., 2018). This raises the key research question: how do external uncertainties influence BCT formation in interfirm alliance networks?

To answer this question, I draw on the resurgent literature on decision making under uncertainty (Artinger et al., 2015; Gigerenzer & Gaissmaier, 2011; Gigerenzer et al., 2022; Gigerenzer & Todd, 1999; Mousavi & Gigerenzer, 2017). Under uncertain conditions traditional decision-making tools and risk analysis break down (Bloom, 2014). This leads to application of heuristics – simple rules of thumb – to guide decisions (Gigerenzer & Todd, 1999). In business contexts, uncertainty increases the likelihood that managers will rely on compensatory heuristics—decision rules that integrate multiple causal attributions (Gigerenzer et al., 2022), both internal and external—when deciding to search through BCTs. This heuristic logic aligns with a behavioral view of organizational decision-making. I adopt a behavioral perspective on BCT formation, grounded in the behavioral theory of the firm (Cyert & March, 1963; Greve, 2003a). Specifically, I extend Baum et al. (2005) argument that firms respond to performance feedback relative to aspiration levels by engaging in strategic search behaviors. This perspective implies that firms' interpretations of performance feedback under uncertainty depend on the specific characteristics of the external environment they face.

Since the sources of uncertainties can generate different conditions that firm would experience (Wernerfelt & Karnani, 1987), I differentiate two most significant uncertainties in the strategy research as market and technological uncertainties (Jalonen, 2012). Under market uncertainty—where demand is volatile and attribution is ambiguous—compensatory heuristics lead managers to attribute performance below aspiration partly to uncontrollable, transient external factors, reducing the urgency to engage in exploratory search. When performance exceeds aspiration, they interpret market uncertainty as an opportunity, prompting the formation of BCTs to leverage current success and buffer against potential volatility.

Under technological uncertainty, managers cannot predict the direction of technological change and are unsure which emerging technologies will become dominant and gain acceptance from industry stakeholders, customers, or regulators (Oriani & Sobrero, 2008; Utterback, 1996). I argue that as technological uncertainty increases, compensatory heuristics lead managers in underperforming firms to attribute performance shortfalls not only to internal shortcomings but also to external technological shifts. When underperformance is attributed solely to internal shortcomings, managers respond by adjusting or refining existing routines and capabilities within the current strategic frame. However, when underperformance is attributed in part to external technological changes, the diagnosis implies that existing capabilities are not only insufficient but also potentially misaligned with the direction of technological progress. This recognition drives a more urgent and extensive search effort, as adapting to external technological shifts requires not just internal improvements but also the development of entirely new capabilities. Such development cannot be accomplished through incremental change alone; it demands access to diverse and novel knowledge. BCTs, by connecting the firm to non-redundant partners and unfamiliar domains, become critical vehicles for acquiring the exploratory knowledge needed to realign the firm's competencies with emerging technologies. Thus, the presence of technological uncertainty amplifies the search efforts compared to situations in which the problem is perceived as purely internal. Technological uncertainty also encourages BCT formation by firms performing above their aspirations, though with less urgency, as they seek to strengthen their position and steer technological change in ways that align with their existing capabilities.

These arguments were tested using panel data on North American public firms in 12 industries and over the period 1990 to 2022. The results provided partial but nuanced support for the proposed hypotheses. The most robust and consistent finding was that firms performing above their social aspiration levels are more likely to form BCTs, particularly under high market uncertainty, suggesting that these firms leverage favorable conditions and available slack to explore new knowledge domains. This interaction supports the notion that performance feedback and environmental cues jointly shape firm responses in distant alliance formation. In contrast, the hypothesized effects of underperformance were largely unsupported: performance below aspirations did not reliably predict BCT formation, and interaction effects were mostly weak or contrary to expectations. Notably, technological uncertainty moderated these relationships in unexpected ways. Instead of amplifying the positive influence of overperformance, it weakened it—implying that firms performing above their aspirations become more risk-averse under technological turbulence. Meanwhile, underperforming firms showed limited responsiveness under uncertainty, possibly constrained by resource scarcity or legitimacy concerns. These results indicate that the behavioral response to performance feedback is asymmetric and highly contingent on the type of uncertainty in clustered alliance contexts, challenging generalized assumptions of problemistic search and highlighting the role of slack-enabled logic in networked exploration.

This thesis makes five distinct contributions. First, it extends social network theory by showing how firms form BCTs under different types of external uncertainty. While prior studies have emphasized endogenous network features such as prior ties and structural position (e.g., Gulati et al., 2012; Sytch et al., 2012), this study highlights the behavioral microfoundations of network change. Specifically, it shows firms interpret performance feedback differently under market and technological uncertainty and these interpretations guide the formation of structurally ambitious, nonlocal alliances.

Second, the thesis contributes to the BTOF by examining where firms search, not just whether they search. While BTOF has been widely applied to domains like R&D, innovation, or acquisitions, few studies have linked performance feedback to alliance formation across network boundaries. This study shows that BCTs are not triggered by underperformance, but more reliably emerge when firms exceed their aspiration levels, particularly in volatile market and technologically stable environments. These findings potentially refine the assumptions of problemistic search and highlight the enabling role of external stimuli (Greve, 2018).

Third, the study clarifies the role of aspiration reference points in shaping search behavior. It shows that in the interfirm alliance context social aspirations become more influential under uncertainty compared to historical benchmarks when the decision is to form BCT formation. It explains outperforming peers—rather than improving on past performance—better predicts BCT formation under market volatility. The findings suggest that aspiration formation is context-sensitive, shaped by both external signals and competitive comparisons.

Fourth, this research integrates uncertainty into BTOF in a theoretically grounded way. Rather than treating uncertainty as background noise, it shows market and technological uncertainty differentially affect attribution of causes to performance outcomes, which in turn alters firm responsiveness. Market uncertainty increases the salience of peer comparisons and encourages confident overperformers to pursue cross-cluster alliances. Technological uncertainty, by contrast, introduces hesitation among successful firms in using risky and costly search through BCT formation.

Finally, this thesis draws on insights from decision-making under uncertainty in attribution theory, proposing that managers use compensatory heuristics to interpret ambiguous performance signals. These heuristics, which combine internal and external attributions, provide a cognitive mechanism to explain why similar performance signals can lead to different behaviors under different types of uncertainty. By linking attribution, aspiration, and performance interpretation, the thesis offers a novel approach to integrating cognitive and behavioral theories in the study of strategic decision-making.

2. LITERATURE REVIEW

2.1 Interfirm Alliances

2.1.1 Definition of an Alliance

An strategic alliance represents a crucial form of interfirm relationship defined as "a voluntary arrangement between independent firms to exchange or share resources and engage in the co-development or provision of products, services, or technologies" (see Adegbesan & Higgins, 2011, p. 188). Formation of an alliance is an acknowledgement that the alliance partners have useful resources to share (Inkpen, 1998). These relationships facilitate co-development or the provision of products, services, or technologies by partners (Gulati, 1998). For example, in 2001, Palm and Intel partnered to integrate Palm's operating system into Intel chips (Sytch et al., 2012). More recently, OpenAI and Microsoft have collaborated to advance artificial general intelligence (AGI) with broad economic benefits. As part of this partnership, Microsoft invested $1 billion in OpenAI, and both companies jointly develop a scalable hardware and software platform within Microsoft Azure to support AGI research and deployment (Microsoft, 2023).

Historically, alliances were considered ad hoc arrangements for specific needs, but their prevalence dramatically increased in the 1990s (Lavie, 2007). For instance, in the U.S. software industry, alliance engagement among publicly traded firms rose from 32% to 95%, with the average number of alliances per firm increasing from four to over 30 during the 1990s (Lavie, 2007). Today, alliances are not limited to peripheral activities but are integrated into various stages of the value chain, playing a crucial role in firms' competitive strategies (Powell et al., 1996). My analysis of alliance formation trends using SDC Platinum data reveals a similar pattern of growth in different industries. The number of new alliances formed each year increased from 3,332 deals in 1990 to a peak of 10,463 in 2021. However, following the COVID-19 pandemic, alliance formation declined to 8,507 deals, reflecting broader economic disruptions.

From a strategic perspective, alliances are often classified based on their purpose (Lavie, 2006; Rothaermel & Deeds, 2004). One common classification distinguishes between exploration and exploitation strategies (March, 1991). Exploration alliances focus on developing new resources, capabilities, and knowledge, fostering innovation in uncertain environments (Phelps, 2003). A notable example of an exploration alliance is the collaboration between the biotechnology company Biogen and the University of Zurich, which resulted in the discovery of Intron A—the first product to advance to clinical trials for treating certain types of leukemia and hepatitis C. In contrast, exploitation alliances emphasize leveraging existing competencies and commercializing established technologies or products (Rothaermel & Deeds, 2004).

Structurally, alliances can be horizontal, formed between competitors in the same industry to enhance market power and knowledge exchange (Garrette et al., 2009), or vertical, connecting firms at different stages of the supply chain to improve efficiency, coordination, and resource access (Bouncken et al., 2016; Gulati, 1998). Moreover, alliances can be structurally categorized based on the level of equity involvement and the formality of the agreement, with different governance structures influencing their stability and effectiveness (Gulati, 1998; Oxley, 1997). Equity-based alliances, such as joint ventures, involve the formation of a jointly owned legal entity by partner firms, providing enhanced commitment and governance structures (Hennart, 1988; Kogut, 1988). Non-equity alliances, such as contractual agreements, involve collaboration through licensing, R&D partnerships, or supplier-buyer relationships without forming a joint entity (Oxley, 1997). Looser arrangements include trade associations, which involve multiple firms collaborating on learning, data collection, and lobbying without formalized contracts (Oliver, 1990).

Alliances are inherently complex due to the multifaceted nature of their formation, management, and the exchange of knowledge and learning they facilitate (Barringer & Harrison, 2000). Forming an alliance involves more than simply identifying a suitable partner; firms must assess prospective collaborators for complementary strengths, strategic alignment, and perceived reliability (Hitt et al., 2000). The lack of complete and accurate information about a partner's capabilities, intentions, and trustworthiness adds a layer of complexity and risk to alliance decisions, making the formation process inherently uncertain (Gulati, 1995b; J. J. Li et al., 2008).

Managing alliances brings additional challenges, such as navigating cultural differences, ensuring effective coordination between partners, and safeguarding against unintended knowledge spillovers (Barringer & Harrison, 2000). Interorganizational relationships require continuous collaboration, and differences in corporate culture and strategic priorities can lead to friction between partners, making implementation difficult (S. H. Park & Ungson, 2001).

In this study, I consider all types of exploration and exploitation alliances, and equity-based and non-equity-based forms, as long as they involve formal interfirm agreements aimed at joint resource use or knowledge exchange. The key criterion is that these alliances allow firms to access knowledge, opportunities, and capabilities beyond their immediate network. This inclusive definition reflects the diverse strategic purposes and governance structures that characterize real-world alliance activity in multiple manufacturing and high-tech service industries.

2.1.2 Significance of Alliances

Strategic management scholars have long emphasized the critical role of alliances in enabling firms to access resources, share knowledge, accelerate market entry, and manage costs (Barringer & Harrison, 2000; Eisenhardt & Schoonhoven, 1996; Gulati, 1998; Inkpen, 1998). For instance, research have shown that alliances enhance innovation output (Ahuja, 2000; Stuart et al., 1999), facilitate new product development (Rothaermel & Deeds, 2004), and accelerate internationalization and foreign market entry (J. W. Lu & Beamish, 2001). Alliances are positively associated with firm growth (Baum et al., 2000) and competitive performance (Anand & Khanna, 2000), particularly in high-velocity environments where rapid access to complementary assets is essential (Eisenhardt & Schoonhoven, 1996). They also improve organizational learning and the development of dynamic capabilities through repeated collaborative experience (Kale et al., 2002; Zollo & Winter, 2002). Furthermore, alliances serve as mechanisms for affecting firms' strategic flexibility (Sarkar et al., 1998; Yayavaram et al., 2018) and shaping strategic positioning in evolving industries (Dyer & Singh, 1998; Lavie, 2006). Collectively, this body of work demonstrates that alliances are not merely relational arrangements but critical vehicles for value creation, capability development, and strategic adaptation.

A central concern in alliance research is how firms create value through collaborations by combining complementary resources and leveraging interorganizational relationships (Doz & Hamel, 1998; Eisenhardt & Schoonhoven, 1996). Alliances help firms access capital, technological expertise, and markets, particularly when key assets are controlled by external organizations (Pfeffer & Nowak, 1976; Pfeffer & Salancik, 1978; Powell et al., 1996). Studies on stock market reactions to alliance announcements provide evidence that investors view alliances as signals of future growth potential, influencing firm valuation and shareholder returns (Kale et al., 2002).

Value creation in alliances often relies on the exchange of tacit knowledge, which is difficult to codify and transfer, increasing the risk of misalignment in learning processes (Lane & Lubatkin, 1998). Effective alliances tend to evolve through ongoing cycles of mutual learning, periodic reassessment, and strategic adjustment (Doz, 1996; Koza & Lewin, 1998). Conversely, alliances that break down often suffer from insufficient learning or misalignment between how partners interpret the alliance and how they act on it, ultimately resulting in friction and potential failure (Doz, 1996).

Alliances provide firms with unique benefits relative to other strategic options. Unlike internal R&D, they enable quicker access to external expertise and resources, helping firms respond more flexibly and cost-effectively to technological and market shifts (Eisenhardt & Schoonhoven, 1996). Compared to mergers and acquisitions, alliances are especially preferrable under uncertainty, as they allow firms to test new capabilities, engage in time-bound collaborations, and adjust their level of involvement without incurring the substantial costs and risks associated with full integration (Hagedoorn & Duysters, 2002; Hoffmann & Schaper-Rinkel, 2001). In sum, alliances have emerged as a widely preferred strategic option due to their unique ability to facilitate access to external resources, knowledge, and markets while preserving organizational flexibility. Although not a substitute for internal R&D or mergers and acquisitions, alliances offer distinct advantages—particularly under uncertainty—by enabling firms to experiment with capabilities, share tacit knowledge, and adapt to changing environments without the high costs and risks of full integration. This strategic versatility underscores their central role in contemporary competitive dynamics.

2.1.3 Drivers of Alliance Formation

The decision to form an alliance is a multifaceted strategic choice influenced by a range of interdependent factors. These motivations are often grouped into three broad categories: agency-based, network-based, and external drivers (Ahuja et al., 2012). Unpacking these categories helps clarify why firms turn to alliances—to expand their resource base, mitigate uncertainty, and strengthen their competitive position.

From an agency perspective, firms pursue alliances as a deliberate strategy to access and combine resources and capabilities that they lack internally (Galaskiewicz, 1985; Oliver, 1990). Agency reflects firms' intentional efforts to access resources and knowledge held by others in the network (Emirbayer & Mische, 1998; Tasselli & Kilduff, 2021; Vissa, 2012). Agency-based explanations encompass multiple theoretical perspectives that emphasize firms' strategic motives to access and mobilize resources beyond their internal boundaries. From a resource-based view, alliances are formed to acquire and leverage complementary assets that firms lack internally, particularly in dynamic industries where innovation, speed, and access to specialized knowledge are critical for competitive advantage (Eisenhardt & Schoonhoven, 1996; Lavie, 2006). For example, banks form alliances to gain access to established payment systems, enabling credit card transactions through retail networks already developed by Visa or MasterCard (Johnson et al., 2008). This perspective views alliances as vehicles for resource recombination and capability enhancement. Hagedoorn (1993), for instance, identifies sector-specific differences in technology cooperation as key agency-related motivations for alliance formation. Similarly, Rothaermel and Boeker (2008) show that firm age, technological complementarities, and capability gaps significantly drive biotech–pharmaceutical partnerships.

From a transaction cost economics perspective, firms form alliances to economize on the costs of transacting in uncertain and opportunistic environments (Williamson, 1985). Here, the decision to ally is guided by considerations of governance efficiency—firms seek to reduce search, bargaining, and enforcement costs by partnering with reliable and known actors, especially when dealing with high asset specificity or appropriability hazards (Kogut, 1988; Oxley, 1997). Alliances, from this view, represent an intermediate governance form that balances flexibility with control. Both perspectives illuminate different aspects of the agency logic: while resource-based view emphasizes strategic opportunity and value creation, transaction cost economics focuses on cost minimization and risk mitigation in structuring interfirm collaboration.

Network-based explanations emphasize the structural context in which alliance decisions unfold. A firm's position within broader interorganizational networks can shape its access to potential partners and the quality of available information (Ahuja et al., 2012; Powell et al., 1996; Walker et al., 1997). Existing relationships help firms manage uncertainty and reduce search costs, with trust and reputational signals playing a central role in partner selection (Gulati, 1995a, 1995b). Firms structurally embedded in densely interconnected networks benefit from social capital, which supports coordination, learning, and efficient knowledge transfer (Coleman, 1988; Powell et al., 1996). These embedded ties are often formed with organizations that are geographically or technologically proximate, reinforcing the role of similarity in alliance formation (Rosenkopf & Padula, 2008). Both Powell et al. (1996) and Walker et al. (1997) demonstrated that centrality and structural holes within biotech networks facilitate partner selection and knowledge exchange. Sytch et al. (2012) further showed that existing bridging and local ties jointly shape firms' ability to form new alliances across community boundaries in the global computer industry.

External conditions play a critical role in shaping firms' alliance strategies. Organizations often form alliances in response to shifts in technology, competitive intensity, and regulatory frameworks that redefine industry boundaries (Beckman et al., 2004; Pfeffer & Salancik, 1978; Schilling, 2015). According to the resource dependence view, competitive pressures influence the external interdependence of organizations. Interdependence primarily concerns two fundamental issues: acquiring essential resources and managing uncertainty (Pfeffer & Salancik, 1978). By forming alliances, firms can mitigate external risks, share costs, and gain access to critical resources, enhancing their ability to adapt and compete in dynamic environments (Beckman et al., 2004). Technological disruptions, while opening space for new entrants, also introduce high levels of uncertainty regarding innovation trajectories and future growth (Fleming, 2001). To navigate this unpredictability, firms frequently turn to alliances as a means of accessing specialized knowledge, building adaptive capabilities, and leveraging the competencies of more experienced partners to accelerate both innovation and market reach (Rothaermel & Deeds, 2004; Schilling, 2015). Lastly, institutional pressures and industry norms also influence alliance formation by encouraging firms to adopt cooperative strategies to enhance legitimacy and comply with evolving standards (DiMaggio & Powell, 1983; Oliver, 1990).

Table 2.1 summarizes key contributions across these domains and illustrates the breadth of empirical support for various drivers of alliance formation.

Table 2.1 Empirical Studies on Drivers of Alliance Formation

Study	Key Drivers	Alliance Types	Industry Context
Hagedoorn (1993)	Motives for cooperation, sectoral differences, technology cooperation	Strategic technology partnerships	Multi-industry
Gulati (1995a)	Repeated ties, trust, transaction costs, governance structure	Interfirm alliances	Multi-industry
Powell et al. (1996)	Past interorganizational collaboration, centrality	Strategic alliances	Biotechnology
Eisenhardt and Schoonhoven (1996)	Strategic position, management team experience, social position	Product development alliances	Semiconductor
Walker et al. (1997)	Social capital, structural holes	R&D collaborations	Biotechnology
Oxley (1997)	Appropriability hazards, governance properties, transaction costs	Interfirm alliances	Multi-industry
Gulati (1999)	Network resources, firm capabilities, material resources	Strategic alliances	Multi-industry
Gulati and Gargiulo (1999)	Interdependence, prior alliances, network structure, centrality	Interorganizational alliances	Three industries
Chung et al. (2000)	Resource complementarity, status similarity, social capital, prior deals	Syndication in underwriting corporate stock offerings	US investment banks
Beckman et al. (2004)	Market and firm-specific uncertainty	Strategic alliances	Multi-industry

Continued on next page

Table 2.1 (continued)

Study	**Key Drivers**	**Alliance Types**	**Industry Context**
Baum et al. (2005)	Performance feedback	Nonlocal syndication in underwriting corporate stock offerings	Canadian investment banks
Rothaermel and Boeker (2008)	Complementarities, similarities, firm age, capabilities	Alliances between pharmaceutical and biotech firms	Pharmaceutical, biotechnology
Rosenkopf and Padula (2008)	Technological/geographic proximity, status homophily	Strategic technology alliances	Mobile communications
Lee (2010)	Past performance, heterogeneity in past performance	Patent collaboration	U.S. biotech inventors
Gulati et al. (2012)	Macro-level social structure, homogenization of the information space	Strategic technology alliances	Global computer industry
Sytch et al. (2012)	Existing local and bridging ties	Strategic technology alliances	Global computer industry
Schilling (2015)	Technological shocks	Strategic technology alliances	Technology-intensive sectors
Stadtler and Lin (2017)	Environmental networks, regulatory pressures, risk-taking propensity, industry concentration, prior experience	Environmental alliances	Multi-industry
Soda et al. (2019)	Organizational hierarchy, network neighborhood cohesion, knowledge base diversity	Intraorganizational co-patenting triads (brokerage ties)	Innovation-intensive Chinese manufacturing sectors

Continued on next page

Table 2.1 (continued)

Study	**Key Drivers**	**Alliance Types**	**Industry Context**
Vantaggiato and Lubell (2023)	Coordination and co-operation problems, bonding social capital, bridging social capital, actor characteristics (e.g., scale of operation, and strategic goals)	Different collaborative ties (information exchange, joint planning, resource sharing)	Public and non-profit sectors dealing with climate adaptation policy

2.2 Clusters in Alliance Network

2.2.1 Clusters as Structural Patterns

Clusters represent one of the foundational structural features in networks of all kinds—from personal social relationships to interfirm collaborations and broader economic systems (Easley & Kleinberg, 2010; Newman, 2003). In social network analysis (SNA), clusters are typically defined as groups of nodes—whether individuals, organizations, or firms—that are densely interconnected (Wasserman & Faust, 1994). These tightly knit structures are central to shaping information circulation, the development of trust, and how actors influence one another (Ahuja, 2000; Powell et al., 1996).

In the context of alliance networks, clustering arises as firms tend to form partnerships with others that are geographically nearby, operate in similar industries, or possess complementary technological capabilities (Baum et al., 2003). This preference is partly driven by the uneven distribution of information in markets and the advantages of reducing search and coordination costs by partnering within familiar circles (Gulati & Gargiulo, 1999). Thus, in interfirm alliance networks, clusters often form through repeated partnerships or third-party referrals, reinforcing localized network structures.

Clustering behavior is also visible at the individual level, where people gravitate toward others with whom they share mutual acquaintances, resulting in tightly bonded social or professional groups (Levine & Kurzban, 2006; Newman, 2003).

2.2.2 Clusters and Knowledge Transfer

Clusters serve as catalysts of knowledge transfer within alliance networks by enabling the frequent exchange, interpretation, and integration of information across organizational boundaries. Dense interconnections among firms promote the development of shared understandings and norms of trust and reciprocity, which facilitate particularly the transfer of tacit knowledge—knowledge that is experiential, situated, and socially embedded (Coleman, 1988; M. T. Hansen, 1999; Kogut & Zander, 1995). Such environments are conducive to joint problem-solving and coordinated learning, foster coordination, and allowing firms to align their interpretations and routines more efficiently (M. T. Hansen, 1999), which ultimately supporting innovation (Ahuja, 2000; Smith-Doerr & Powell, 2005).

Building on this foundation, Powell and colleagues have shown that interorganizational networks within clusters function as "learning networks," particularly in the biotechnology and pharmaceutical industries (Owen-Smith & Powell, 2004; Powell et al., 1996, 2005). These studies emphasize that while geographical proximity facilitates interaction, it is the structure and quality of alliances—rather than geography alone—that determine the efficacy of knowledge transfer. Local ties embedded in dense networks can become channels of trust-based exchange or, when highly open, "sprinklers" of knowledge diffusion (see Owen-Smith & Powell, 2004, p. 7). They also highlighted the role of informal mechanisms, such as labor mobility and social embeddedness, which operate alongside formal partnerships to enable collective learning and innovation (Powell et al., 1996, 2005).

Gulati and colleagues (2012) similarly highlight how network structure shapes knowledge access and innovation, particularly through alliance behavior in the global computer industry. In interfirm networks, small-world structures—characterized by high local clustering combined with short average path lengths—facilitate both trust-based coordination and efficient access to distant knowledge (Uzzi & Spiro, 2005; Watts & Strogatz, 1998). Gulati and Gargiulo (1999) demonstrated that firms select partners based on prior ties and network position, reducing search costs and governance risks. The broader structure of interfirm networks—particularly their small-world properties—affects how knowledge circulates and where innovation occurs. Gulati, Sytch, and Tatarynowicz (2012) showed that as small-world networks densify, initial advantages in local connectivity can lead to diminishing returns due to information redundancy. In such contexts, access to non-redundant, novel knowledge increasingly depends on bridging ties across clusters.

Further supporting this, Rosenkopf and colleagues show that firms drawing on geographically and technologically distant knowledge are more likely to introduce recombinant innovations, especially when embedded in networks that support such bridging behavior (Rosenkopf & Almeida, 2003; Rosenkopf & Nerkar, 2001). Their work confirms that clustered structures alone are insufficient for long-term innovation if firms are not simultaneously connected to diverse knowledge sources. Zaheer and Bell (2005) also reinforce this logic, showing that firms benefit not only from being a central actor in a network but also from their structural autonomy—that is, their ability to access non-redundant knowledge through less constrained ties that cut across clusters that are not connected otherwise. While their argument is grounded in structural hole theory, it does not account for conditions under which multiple between-cluster ties can connect distinct clusters. This point will be further elaborated in the following section.

In summary, these studies converge on a critical point: while clustered networks foster efficient knowledge transfer through trusted local ties and shared norms, their value for outcomes like innovation is contingent on firms' ability to complement cohesion with external connectivity. Structural over-embeddedness generally leads to homogeneity, redundancy, and reduced adaptability (Burt, 1992; Granovetter, 1985; Uzzi & Spiro, 2005). Thus, the capacity to bridge between network communities is essential for accessing novel knowledge, enabling exploratory learning, and sustaining innovative performance. From this perspective, alliance networks are structured, historically embedded, and dynamically evolving arenas, where a firm's access to knowledge depends both on its position within the network and on the overall structure of the network in which it is embedded (Gulati & Gargiulo, 1999; Powell et al., 2005; Gulati et al., 2012; Sytch et al., 2012).

2.3 Between Cluster Ties (BCTs) in Clustered Alliance Network

2.3.1 Definition of a BCT

Alliance networks often take a clustered form, with firms densely connected within clusters and fewer ties linking them across clusters (Gulati, 1995b; Gulati et al., 2012; Rosenkopf & Padula, 2008; Schilling, 2015; Sytch et al., 2012). Between-cluster ties (BCTs) refer to the alliances that firms form across clusters in interfirm alliance networks. These ties provide access to nonlocal knowledge that is unlikely to be found within a firm's immediate cluster (Gulati et al., 2012). While BCTs are structurally defined by their span across network clusters, their strategic value lies in the access they provide to novel, tacit, and often hard-to-reach knowledge and relational opportunities.

Compared to within-cluster ties (WCTs), BCTs are more likely to channel diverse, novel, and nonroutine knowledge, making them valuable for exploratory learning and strategic search. Searching for partners across clusters and forming BCTs is relatively costly compared to WCTs which imply that firms are more likely to pursue them deliberately. However, not all BCTs arise from planned exploration; some may emerge through informal channels—such as personal ties among senior managers—and serve exploitation objectives (Ahuja et al., 2012; Baum et al., 2003; Gulati et al., 2012). In contrast, WCTs connect firms within the same cluster, reinforcing shared routines and mutual familiarity. These ties are typically suited for exploitation-oriented activities, such as incremental innovation and operational refinement.

While this study adopts the term BCTs, prior research has conceptualized similar structures under various names: Baum et al. (2005) refer to them as nonlocal ties; Gulati et al. (2012) and Sytch et al. (2012) describe them as bridging ties between network communities; Rosenkopf and Padula (2008) identify them as ties between clusters (shortcuts); Schilling (2015) labels them shortcuts to formerly distant clusters; and Chang (2023) characterizes them as bridges between isolated subgroups. Despite the diversity in terminology, there is a common theoretical emphasis on ties that span structurally distant or otherwise weakly connected parts of a network, which are understood to facilitate access to novel and diverse knowledge.

2.1 provides an illustrative view of the clustered alliance network among major firms in the North American computer industry in 1997. Several dense regions of interfirm connections are visually enclosed in circles to represent apparent clusters. While precise cluster boundaries require detection through community-detection algorithms, the marked areas highlight visibly dense clusters for illustrative purposes. BCTs, such as those linking IBM-Dell and HP-Compaq, are shown with thick lines to demonstrate how certain firms connect across clusters. Note that not all clusters or BCTs are shown; only those that are visually salient have been marked to support conceptual clarity rather than empirical precision.

Figure 2.1 An Illustrative Clustered Alliance Network of the Computer Industry in 1997

Firms may or may not be aware when they form BCTs, as cluster boundaries are not always clearly defined by like geographic demarcations (cf., Gilding et al. 2020) or formal agreements such as strategic and business group affiliations (cf., Nohria and Garcia-Pont 1991). In small, highly dense clusters—such as cliques, where all members are directly connected—firms are more likely to recognize that they are forming an alliance with an external partner. However, in larger, less densely connected clusters, firms may form alliances with partners who possess distinct knowledge and routines compared to their existing collaborators, without necessarily perceiving them as belonging to a different cluster. These partnerships often stem from firms' efforts to explore new opportunities and conduct distant searches for valuable knowledge across the broader network (Baum et al., 2005; Gulati et al., 2012).

From a structural perspective, clusters are defined not by firm attributes but by the relative density of intra- and interfirm ties (Newman, 2004). When the density of ties between clusters rises to match or exceed internal density of at least one of the clusters that these ties connect them, structural boundaries blur and may disappear. BCTs are the ties that drive this integration, and their accumulation increases the likelihood that detection algorithms will no longer distinguish the original clusters as separate entities. Figure 2.2 illustrates this process, showing how two distinct clusters at time 1 become structurally integrated at time 2 due to the formation of multiple BCTs, ultimately increasing the overall network density and eroding their initial separation.

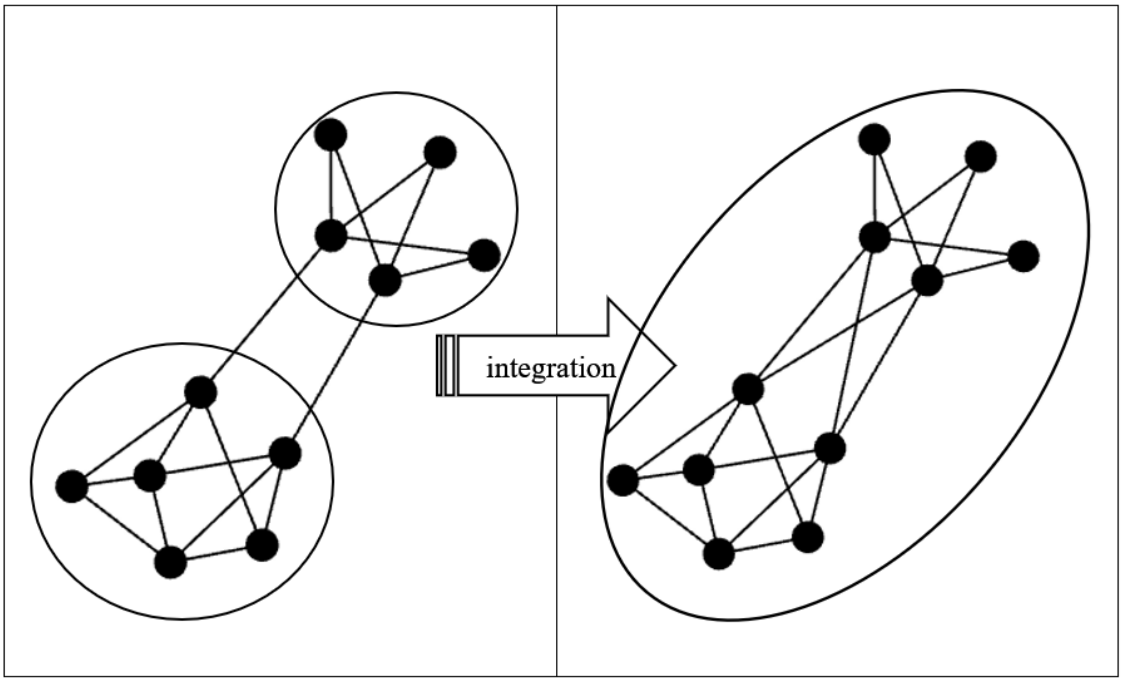

Figure 2.2 Integration of Distinct Clusters through BCT Formation

Even if firms do not structurally recognize that they are forming BCTs, they are more likely to face challenges in assessing the capabilities and behaviors of partners outside their cluster. They are also more likely to notice differences in routines, standards in knowledge creation and application, and relational norms when collaborating with distant partners. Consider the case of Merck and AstraZeneca: in 2017, Merck, centrally positioned in a cluster focused on immuno-oncology and targeted cancer therapies, formed a strategic alliance with AstraZeneca, which occupied a central position in a distinct cluster specializing in hormone-based and DNA damage response treatments (See Figure 2.3). Their collaboration, centered on the integration of therapeutic approaches using AstraZeneca's PARP inhibitor, exemplifies a BCT—transmitting highly nonredundant knowledge across clusters with distinct scientific and clinical routines.

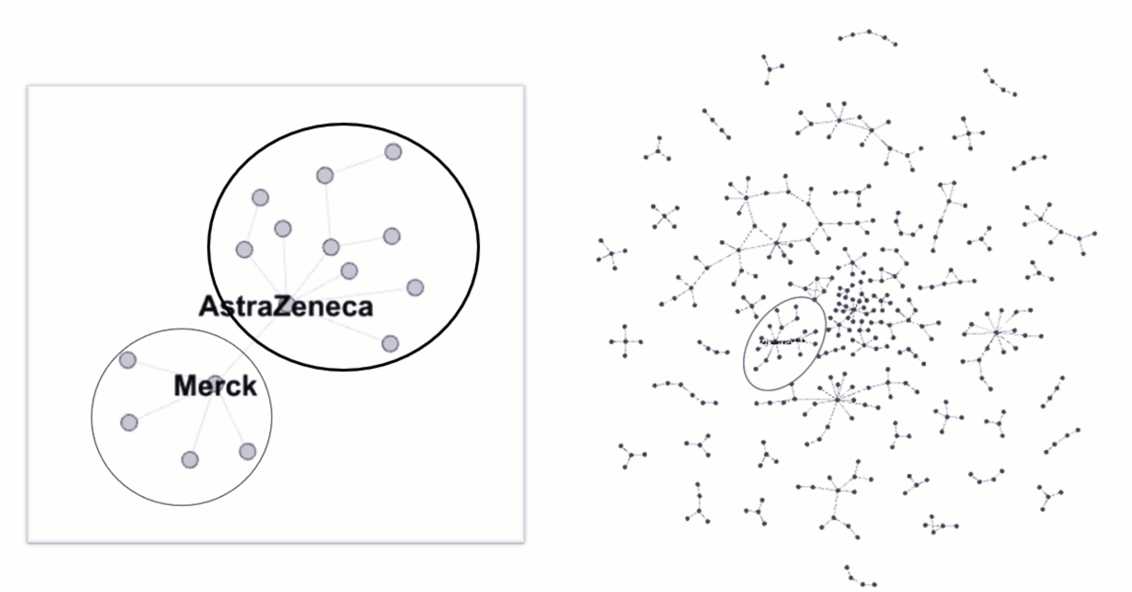

Figure 2.3 Clustered Alliance Network of Pharmaceutical Industry in 2017 and the BCT between Merck and AstraZeneca

As another example from earlier research, consider the emerging alliance network of mobile communication in Rosenkopf and Padula (2008) as shown in Figure 2.4) and Figure 2.5. In the early 1990s, Microsoft had only one alliance with central players in the network (See Figure 2.4). Over time, more firms clustered around Microsoft, focusing on emerging software technologies with mobile communication capabilities. Although Microsoft's alliance with Motorola may have indirectly benefited its immediate partners, it neither prevented nor replaced the need for other firms in Microsoft's cluster to establish direct ties with Microsoft or form their own BCTs to Motorola's cluster to gain firsthand exposure to Motorola's practices (See Figure 2.5).

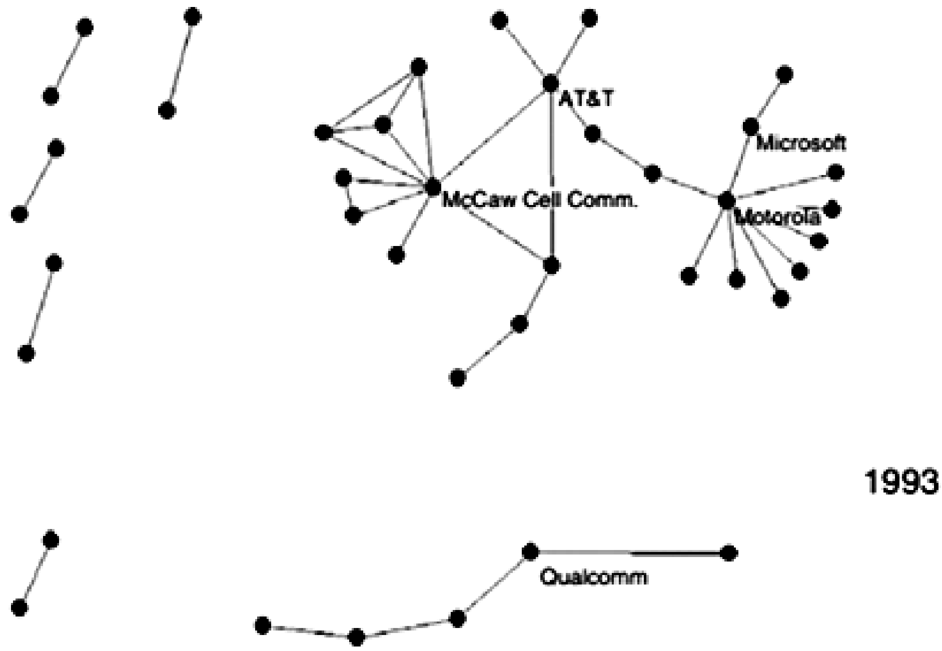

Figure 2.4 Emerging Alliance Network in Mobile Communication Industry 1993 (Rosenkopf & Padula,2008)

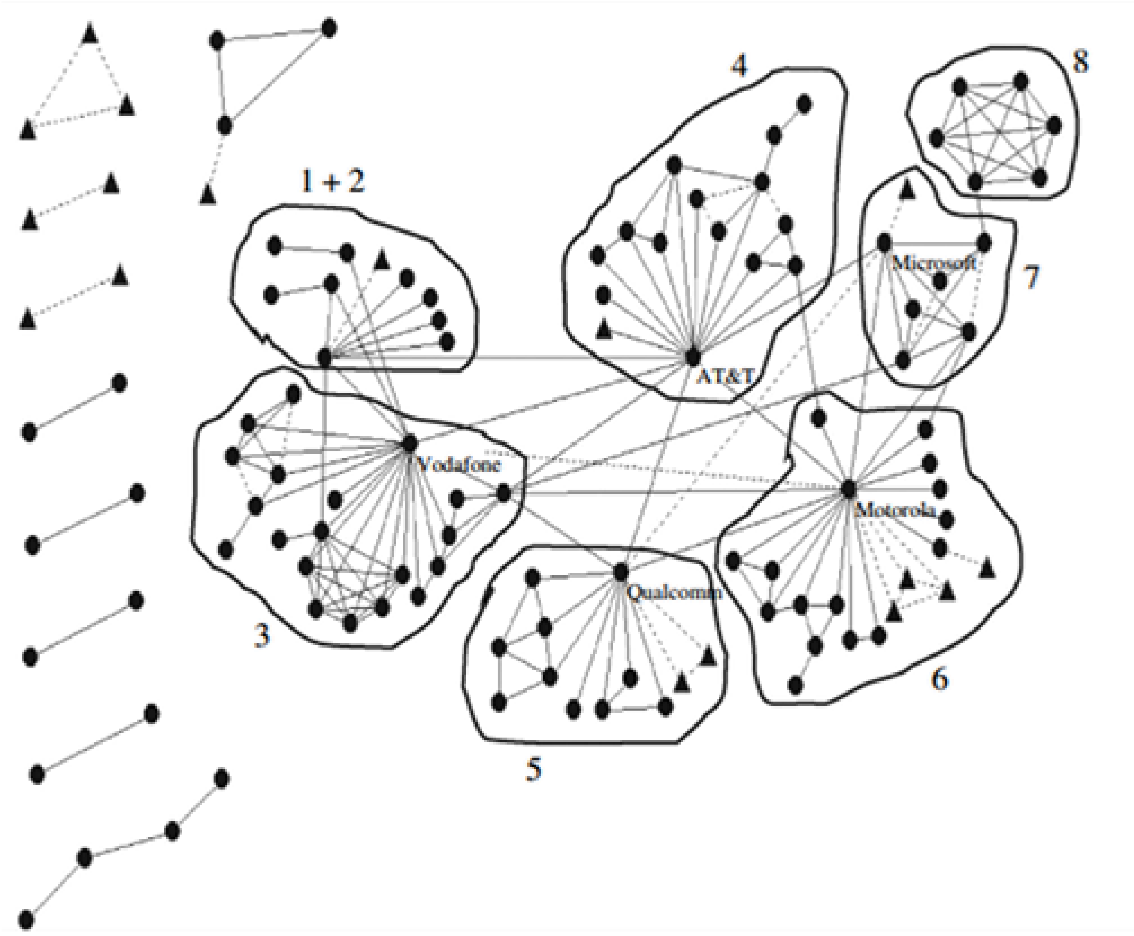

Figure 2.5 Clustered Alliance Network in Mobile Communication Industry 1998 (Rosenkopf & Padula,2008)

2.3.2 Significance of BCTs

BCTs serve important functions within interorganizational alliance networks, offering advantages and trade-offs at both the firm and network levels. In contrast to WCTs—which often circulate redundant information and knowledge due to high levels of cohesion (Granovetter, 1973)—BCTs enable firms to bypass these constraints and tap into diverse and novel knowledge sources that is otherwise inaccessible through localized connections (Baum et al., 2005; Kogut & Walker, 2001; Nohria & Garcia-Pont, 1991; Tortoriello et al., 2012). BCTs, in the context of this study as alliances across clusters, are often essential for accessing deeply embedded tacit knowledge—technological routines, market-specific insights, or governance capabilities—that cannot be transferred easily through indirect ties or secondhand channels (Gulati et al., 2012).

Beyond facilitating access to diverse knowledge pools, BCTs also support knowledge recombination and innovation. By linking firms from different technological or market domains, they create spaces for integrating heterogeneous expertise, which can spur creative problem-solving and the development of new ideas (Fleming, King III, & Juda, 2007; Fleming, Mingo, & Chen, 2007). Firms situated at the intersection of multiple clusters often act as brokers, leveraging their unique positions to synthesize diverse knowledge flows and drive innovation (Obstfeld, 2005; Tasselli & Caimo, 2019).

Strategically, BCTs enhance firms' adaptability and potential for competitive advantage. These connections enable early access to emerging technologies, trends, and strategic shifts across domains (Levine & Kurzban, 2006). While prolonged engagement within a single cluster may lead to knowledge convergence and limit learning potential, BCTs offer a pathway to escape these boundaries (Hagedoorn et al., 2011).

Firms in the position of brokering across clusters have the opportunity to timely access and even affect the emerging knowledge and standards across clusters in technological dynamic conditions. As clusters increasingly compete to shape technological standards, firms that occupy bridging positions can exert greater influence in setting industry norms and guiding technological evolution (Vanhaverbeke & Noorderhaven, 2001; Wen et al., 2020).

Empirical research underscores the impact of network position on firm outcomes. Firms embedded in densely interconnected structures—especially those within the core component of an industry's alliance network—tend to enjoy broader access to resources, knowledge, and partners, while peripheral firms remain disadvantaged (Rosenkopf & Schilling, 2007). McEvily and Zaheer (1999) demonstrated that firms in networks rich in bridging ties were better able to access novel information and opportunities, strengthening their competitive positions. Similarly, Uzzi and Spiro (2005) found that networks combining cohesive ties with occasional BCTs enhanced creative performance by balancing trust and novelty.

This pattern is also evident in industry-level studies. In the global computer industry, Schilling and Phelps (2007) found that firms embedded in small-world networkswere better positioned to recombine knowledge and innovate. Eisingerich et al. (2010), studying regional clusters, observed that high-performing firms often belonged to open networks characterized by frequent interactions with external partners. Schilling (2015) noted that the growth of the internet and digital connectivity spurred a wave of alliance formation that connected previously isolated clusters, thereby strengthening knowledge flows and supporting industry-wide innovation.

Beyond firm-level outcomes, BCTs reshape network structures by influencing tie formation patterns and altering the speed and reach of information circulation across the broader alliance network. Large-scale social networks often exhibit a scale-free property, where a few highly connected hubs link to many actors, resulting in a power-law distribution of connections and disproportionate influence by a few central firms (Uzzi, 2008). As firms form BCTs, the average path length between organizations in large social networks decrease, meaning most actors are reachable through a smaller number of intermediaries (Gulati et al., 2012). This phenomenon aligns with the small-world property, where networks maintain high local clustering while preserving global connectivity through a limited number of BCTs (Baum et al., 2003; Newman, 2000; Watts, 1999). Research has shown that even a small proportion of BCTs in a structured network can significantly reduce average path lengths, allowing for efficient knowledge exchange across otherwise fragmented groups (Chang et al., 2023). In a simulation study using email communication data from Samsung, Chang et al. (2023) found that when BCTs surpassed 1% of total network ties, there was a sharp increase in the diffusion of information.

However, BCTs also involve important trade-offs. Compared to WCTs, they tend to incur higher search costs, greater uncertainty about partner reliability, and more complex coordination. Identifying suitable partners across clusters often requires significant time and resources, particularly because firms have limited information about organizations outside their familiar network (Gulati & Gargiulo, 1999). Within clusters, multiple overlapping ties typically provide firms with more reliable signals about potential partners' capabilities and trustworthiness. In contrast, when evaluating partners from other clusters, firms often lack the informational depth needed to make well-grounded judgments.

Firms within the same cluster are often embedded in similar technological or market contexts (Gulati et al., 2012), which fosters alignment in capabilities (L. Wang & Zajac, 2007). Dense interconnections reinforce shared norms and social monitoring, which reduce the risk of opportunistic behavior through reputational pressures and informal sanctions (Coleman, 1988). Misconduct is more visible—and thus more costly—within tightly knit groups, making norm violations less likely (Gulati et al., 2012). BCTs, by linking firms across structurally distant parts of the network, lack such embedded safeguards. This makes them more vulnerable to opportunism and coordination breakdowns.

As firms develop relationships within clusters, they often establish shared routines and norms for collaboration, which smoothens knowledge exchange. But crossing cluster boundaries tends to introduce frictions, due to misaligned governance structures, different organizational routines, and unfamiliar institutional contexts (Bechky, 2003; M. T. Hansen, 1999). Cultural and cognitive distances between firms in different clusters further complicate communication and reduce the efficiency of knowledge absorption (Gilsing et al., 2014; Nooteboom et al., 2007). In contrast, firms embedded in dense clusters benefit from multiple knowledge pathways, which enhance the accuracy, reliability, and interpretability of information, making intra-cluster knowledge transfer more effective (Reagans & McEvily, 2003).

2.3.3 What BCTs Are Not

The idea that bridging ties play a central role in accessing novel knowledge has been developed across three influential streams of network theory: weak ties, structural holes, and range. While each highlights a different mechanism, they share the common assumption that ties connecting different parts of a network provide access to more diverse and nonredundant resources. BCTs are closely related to these ideas, but are best understood as ties that span distinct network communities—groups of actors that are densely connected internally and sparsely connected to the rest of the network. Granovetter (1973) introduced the theory of weak ties, defining tie strength in terms of emotional intensity, reciprocity, and frequency of contact. He argued that weak ties are more likely to connect people across social groups and thus function as "bridges" that shorten paths through the network. Because strong ties tend to cluster, weak ties play a crucial role in exposing individuals to information not circulating within their immediate group. Although this idea was originally developed in the context of interpersonal networks, it has been widely applied to organizational networks (e.g., M. T. Hansen,1999;McEvily and Zaheer,1999). However, interfirm alliances are typically not weak in this sense. They are formal, often resource-intensive agreements that involve high levels of coordination and governance (Gulati, 1998; Reuer & Ariño, 2007). Still, the idea that bridging structurally distant parts of a network increases access to novel information remains highly relevant, especially in alliance contexts where firms are structurally embedded in cohesive subgroups.

Structural hole theory, developed by Burt (1992), specifies that structural hole exists when two of a focal actor's contacts are not connected to each other otherwise. The actor can benefit from this position by gaining early access to information and controlling its flow between otherwise disconnected parts of the network (Ahuja, 2000; Burt, 1992, 2000). Burt emphasized that such ties are particularly valuable when they span different social worlds, stating that "nonredundant ties are your bridges to other clusters" (Burt, 1992, p. 28). While the formal definition allows the two disconnected contacts to belong to the same or different communities, the theoretical intuition often relies on the latter. In practice, however, structural holes can occur between clusters and within a single cluster to the extent that two actors are disconnected (see the node marked with an empty circle in Cluster 3 of Figure 2.6). Gulati et al. (2012) emphasized that BCTs offer access not only to a disconnected actor but to an entirely new network community with its own knowledge base and norms. This makes them especially important for accessing diverse and potentially transformative knowledge.

In alliance networks, clusters often form around shared technologies, routines, or geographic proximity (Gulati et al., 2012; Powell et al., 2005). While these clusters exhibit internal cohesion, firms within them may still differ significantly in strategic orientation, capabilities, or absorptive capacity (Phelps, 2010). Thus, the existence of a single bridging tie across clusters does not necessarily render additional cross-cluster ties redundant, even if these bridging ties close likely structural holes. Each BCT may offer access to distinct knowledge and learning opportunities—not only by linking different clusters, but also by connecting to firms whose knowledge bases are less likely to overlap with that of the focal firm.

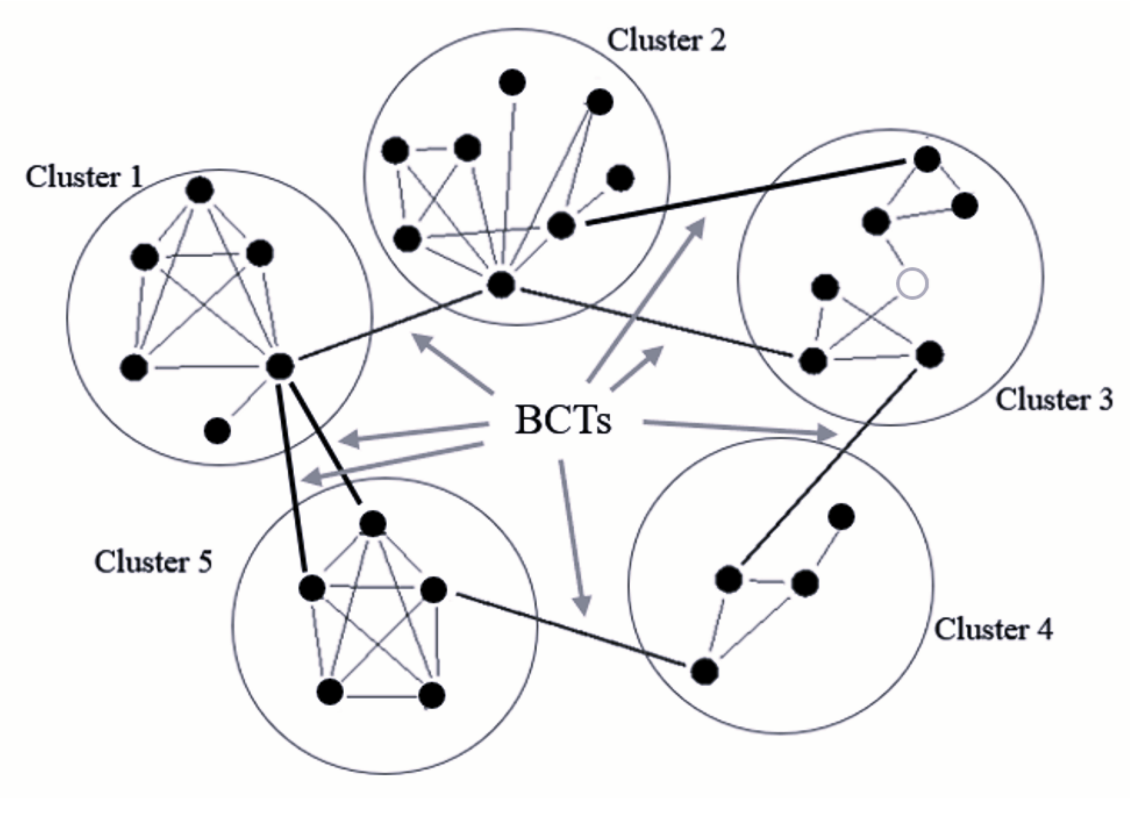

Figure 2.6 A Clustered Network with BCTs highlighted in bold

This is particularly important because much of the knowledge exchanged in alliances is tacit, context-dependent, and difficult to transfer through indirect ties (Hansen, 1999; Dyer & Singh, 1998). The distinction between information and knowledge is critical here (Polanyi, 1966; Sorenson et al., 2006). While information can often flow through sparse or indirect connections, tacit knowledge typically accumulates within tightly knit communities through repeated, embedded interactions (Owen-Smith & Powell, 2004). Clusters in alliance networks thus function as repositories of collective know-how, developed through shared routines and mutual adjustment. Although co-location can facilitate the transfer of such knowledge via face-to-face interaction (Operti & Kumar, 2023), complex knowledge may resist diffusion—even within the social networks where it originates (Sorenson et al., 2006).

When a firm from another cluster forms an alliance with a single member of a target cluster, it may gain access to that partner's expertise, but not necessarily to the distributed tacit knowledge embedded across the entire community. Such a tie may help identify "who knows what" (Hansen, 1999), but is less effective for transferring "how to" knowledge, which depends on multilateral engagement and shared practices (Owen-Smith & Powell, 2004; Uzzi, 1997). Because indirect ties are limited in their ability to transmit this form of knowledge, direct connections to multiple firms in a cluster remain valuable. Even after a structural hole is formally bridged, additional BCTs across the same boundary can provide differentiated access to complementary expertise, reinforcing the distinctive value of BCTs beyond the logic of bridging structural holes (see BCTs between Clusters 1 and 5 in Figure 2.6).

The third construct, range, captures the cognitive or functional diversity spanned by a tie (Reagans & McEvily, 2003). A tie is said to have high range if it connects actors with different areas of expertise, problem-solving approaches, or organizational routines. Unlike structural holes, which emphasize the absence of connections between actors, range focuses on the content of what is exchanged across a tie. While range is typically defined at the ego-network level—reflecting the diversity of a focal actor's direct ties—it can also describe structural diversity at the network level. In alliance contexts, BCTs often coincide with high range, as they tend to link firms embedded in distinct technological or institutional domains (Gulati et al., 2012). However, BCTs and range are not conceptually equivalent. BCTs are structurally defined by spanning network communities, regardless of the cognitive similarity or difference between the partners. By contrast, range refers to knowledge diversity and does not require that ties span network clusters. Thus, while BCTs often exhibit high range, not all high-range ties are BCTs. This distinction is important because it shows that BCTs reflect a specific structural form of bridging, whereas range captures a functional property of tie content.

Together, weak ties, structural holes, and range each contribute to understanding the logic of BCTs. But BCTs, as used in this study, are defined more precisely as formal alliances that interconnect structurally cohesive network communities. They are best understood as a stronger form of bridging that combines structural distance and strategic intent. This cluster-level conceptualization allows for a more accurate account of how firms pursue exploration through alliance networks.

2.3.4 Drivers of BCT Formation

There is limited research on the drivers of BCT formation. Prior work on inter-firm alliance networks has predominantly followed two distinct perspectives: the behavioral perspective, which focuses on firm-level motivations such as performance feedback, and the network perspective, which emphasizes structural features like position, embeddedness, and prior ties.

2.3.4.1 The Behavioral Perspective on BCT Formation

The behavioral perspective has its roots in the Behavioral Theory of the Firm (Cyert & March, 1963). Baum et al. (2005) were the first to link BCT formation to performance feedback, conceptualizing it as a risk-taking strategy. They argued that firms are more likely to pursue BCTs when their performance deviates from aspiration levels. This framing suggests that firms use BCTs as a means of adaptive search, particularly when routine strategies prove inadequate. It is thus useful to briefly review the key assumptions and mechanisms of this behavioral approach.

Behavioral Theory of The Firm (BTOF) History. The Behavioral Theory of the Firm (BTOF) emerged as a response to the limitations of classical economic models of firm behavior. Between the late 1940s and early 1960s, foundational works such as Simon's Administrative Behavior (1945), March and Simon's Organizations (1958), and Cyert and March's A Behavioral Theory of the Firm (1963) established a behavioral framework for understanding organizational decision-making (Argote & Greve, 2007; Gavetti et al., 2007). These scholars, often associated with the Carnegie School, focused on organizations as the unit of analysis, decision-making as a key driver of behavior, and theory development based on behavioral plausibility rather than abstract mathematical modeling.

Among these works, "A Behavioral Theory of the Firm" (Cyert & March, 1963) was particularly influential, challenging the core assumptions of neoclassical economics. It rejected the notions of profit maximization and perfect information, arguing instead that managers operate under bounded rationality, set aspiration levels rather than optimizing profits, and make decisions based on limited information and organizational routines. This perspective positioned firms as coalitions of actors governed by rules and procedures, rather than as unitary, perfectly rational entities—laying the foundation for decades of research on organizational learning, decision-making, and adaptation (Hagen et al., 2023).

Core Concepts. BTOF revolves around three interrelated concepts: bounded rationality, imperfect environmental adaptation, and unresolved internal conflict (Cyert & March, 1963). Here is a brief description of these concepts: (1) Bounded Rationality: Unlike the rational choice theory in economics, which assumes that firms have unlimited cognitive capacity and perfect information, Cyert and March (1963) argued that decision-makers face cognitive limitations and operate with imperfect information. Rather than optimizing, firms "satisfice", meaning they seek satisfactory solutions that meet aspiration levels rather than an absolute maximum. (2) Imperfect Environmental Adaptation: Organizations do not respond instantly or perfectly to external conditions. Instead, they rely on historical routines, learned heuristics, and feedback mechanisms to adjust their behavior over time (Levitt & March, 1988). (3) Unresolved Internal Conflict: Unlike classical economics, which assumes firms have a singular profit-maximizing objective, BTOF recognizes that organizations are coalitions of multiple stakeholders (e.g., managers, employees, shareholders), each with different and often conflicting goals (Cyert & March, 1963). Because conflicts cannot be fully resolved, firms rely on temporary compromises, political bargaining, and sub-goal prioritization.

Decision-Making Mechanisms in BTOF. The theory explains firm decision-making through the interaction of three key variables and four relational concepts (Cyert & March, 1963). The key variables are as below: (1) Organizational Goals: These are shaped by internal coalitions and past performance comparisons. Instead of a single profit goal, firms pursue multiple, evolving objectives influenced by historical performance (e.g., historical aspirations based on a weighted average of past outcomes) and peer benchmarking (e.g., social aspirations based on the average performance of comparable firms, such as industry competitors). (2) Organizational Expectations: Decision-makers infer future outcomes from incomplete information, often relying on theorizing and heuristic-driven inference. (3) Organizational Choice: Firms do not evaluate all possible alternatives but rely on standard operating procedures to structure decision-making.

The relational concepts upon which BTOF is based are outlined as follows (Cyert & March, 1963): (1) Problemistic Search: Firms engage in problem-solving search only when performance falls below aspiration levels. Rather than broad exploration, search is localized near the problem symptoms. (2) Uncertainty Avoidance: Firms try to eliminate uncertainties through establishing contracts and routines. They do not have foresight and avoid long-term planning that include unforeseen uncertainties. Instead, they rely on routines and try to resolve problems through local search. (3) Organizational Learning: Firms adjust their aspiration levels based on historical performance and peer comparisons, shaping future decisions (Greve, 2002). They learn from performance feedback relative to their aspirations and change their routines to adapt more effectively as problems emerge. (4) Quasi-Resolution of Conflict: Organizations manage conflicting goals by delegating decisions, applying local rules, and prioritizing issues sequentially rather than resolving all conflicts at once (Cyert & March, 1963).

A persistent theoretical tension exists over how organizations weigh historical versus social aspirations, resulting in varied assumptions and limited empirical consensus (Shinkle, 2012). Advocates of the salience of social aspirations argue that under uncertain conditions, firms are more likely to compare themselves to peers facing similar external constraints, as these comparisons offer cues for action when internal benchmarks lose validity (Bromiley, 1991; Greve, 2003b; Wiseman & Bromiley, 1996). Such social comparisons help firms interpret ambiguous outcomes and identify adaptive responses observed in the behavior of others (Banerjee et al., 2019). Thus, uncertain conditions can increase the salience of social aspirations—performance relative to comparable others—because peer outcomes offer more contextually grounded signals. This logic is supported by social learning theory (Lieberman & Asaba, 2006), competitive visibility (Festinger, 1954), and studies showing that firms under uncertainty often emulate successful peers (Yu & Lindsay, 2016).

Others have argued that firms favor self-referent feedback for its stability and interpretability (cf., Bromiley and Harris, 2014). Recently, Berchicci and Tarakci (2022) drawing on the attention-based view (Ocasio, 1997), found evidence that market volatility makes it cognitively and practically difficult to identify appropriate reference groups and interpret peer performance (Audia et al., 2022; Levinthal & March, 1981). As a result, firms reduce reliance on social aspirations and instead give more weight to historical ones, which are based on internal routines and known performance patterns (Posen & Levinthal, 2012). However, their findings may be context-specific: the study focuses on toxic waste reduction targets in U.S. manufacturing, a domain where firms seek legitimacy by signaling continuous improvement against their own historical benchmarks—possibly overperforming both social aspirations and their own past to project environmental responsibility.

Review of empirical research. Empirical research grounded in the BTOF has extensively examined how firms respond to performance feedback relative to aspiration levels. Numerous studies support the link between performance below aspirations and increased innovative activity. Greve (2003a) found that Japanese shipbuilders were more likely to initiate innovation projects and increase R D expenditure when performance fell below aspiration levels. Chen and Miller (2007) reported that negative attainment discrepancies led to higher R D intensity, consistent with the idea that firms search for technological solutions when underperforming. However, results for performance above aspirations have been mixed, with some studies finding reduced R D intensity due to complacency (Cabral et al., 2024), and others observing increased exploratory investments when resources permit (Xu et al., 2019).

Iyer and Miller (2008) examined acquisition behavior in U.S. firms and found that acquisition probability did not increase monotonically as performance fell below aspiration levels. Instead, acquisition activity declined at very low performance, possibly due to constrained resources or conservative managerial responses. Kuusela et al. (2017) extended this by showing that firms are more likely to divest underperformance units when facing negative performance feedback, while acquisitions occur nearer to aspiration thresholds. Ref and Shapira (2017) found an inverted U-shaped relationship: firms with moderate shortfalls were more likely to enter new markets, but when performance fell too far below aspirations, entry rates declined. This suggests declining capability or risk appetite at extreme shortfalls.

Posen et al. (2018) suggested that inconsistent results in empirical studies of the BTOF relate to several critical issues. These issues include an over-reliance on the initial conceptualization of problemistic search, which portrays it as overly routinized and automatic, with a limited role for cognition. Furthermore, empirical research frequently black boxes the search process itself, often conjoining distinct elements such as triggering search, the search process, and the resulting change, making it difficult to observe the actual search for solutions. The authors also note that the mixed empirical findings can be attributed to the ambiguity in aspiration construction, where various performance metrics and social reference groups can be combined in myriad ways, as well as conflicts with alternative theories that predict different organizational responses to performance shortfalls. Greve (2018) emphasized that outcomes depend on where search occurs (e.g., alliances vs. acquisitions vs. R&D), and on the firm's capabilities and constraints. Very low performance may constrain action due to resource limitations, even when motivation is high. This interplay of motivation and capability has emerged as a key factor in understanding behavioral responses to feedback. Bromiley and Harris (2014) tested alternative aspiration models and concluded that historical and social aspirations should be modeled separately rather than averaged or switched based on thresholds. While historical aspirations are often predictive in R& D and innovation contexts (Greve, 2003a), social aspirations may be stronger predictors in competitive, performance-visible domains such as alliances or market entry (Baum et al., 2005; Ref& Shapira, 2017). Nonetheless, empirical findings on the relative salience of each aspiration type remain mixed, partly due to measurement challenges.

BTOF and interorganizational Alliances. Research applying the BTOF to interorganizational alliances began with Koza and Lewin (1998), who introduced the idea that alliances serve as vehicles for either exploration or exploitation. Building on March's (1991) seminal exploration-exploitation framework, they framed alliances as adaptive learning mechanisms: some are formed to discover new opportunities and experiment with novel knowledge (exploration), while others aim to refine and leverage existing capabilities (exploitation). Thus, exploration entails more uncertainty and trial-and-error learning, whereas exploitation focuses on increasing efficiency and consistency. A substantial body of work has expanded on this distinction, highlighting the strategic importance of maintaining a balance between the two for long-term performance (e.g., Fang et al. 2010; He and Wong 2004; Zhang et al. 2024).

Rothaermel and Deeds (2004) advanced this perspective by showing that firms often shift from exploration to exploitation alliances as they accumulate knowledge. Early-stage alliances are typically exploratory, aimed at absorbing new insights, while subsequent alliances prioritize integration and commercialization. Similarly, Beckman et al. (2004) suggested that firms' choice of partners reflects this learning logic: alliances with new partners support exploration, while repeated collaborations with known partners reflect exploitation.

More recent research has refined the link between performance and alliance formation by incorporating contingency factors. Tyler and Caner (2016) found that unmet expectations from new product launches led firms to increase their R&D alliances, particularly when they had slack resources. W. Li and Wang (2019)) focusing on U.S. biotechnology firms, observed that firms with ample slack pursued exploration alliances under moderate market uncertainty, but as uncertainty intensified, they pivoted toward exploitation alliances to avoid excessive risk. In a similar vein, Zhang et al., (2024) showed that performance shortfalls increase the likelihood of forming exploration alliances—especially under the leadership of overconfident CEOs, who are more willing to engage in risky, uncertain ventures.

Beyond the exploration-exploitation lens, research drawing from problemistic search and organizational learning has examined how performance feedback shapes firms' alliance behavior. Baum et al. (2005) showed that firms falling short of their aspirations are more likely to seek out nonlocal ties—alliances with partners outside their existing direct or indirect networks. These ties represent a risk-taking strategy, enabling firms to explore new avenues beyond the familiar. In their study of investment banks, Baum and colleagues found that firms engaged in syndication with distant partners when performance was either below or above aspiration levels, suggesting that performance feedback triggers an expansion in search scope aimed at accessing new opportunities.

2.3.4.2 The Network Perspective on BCT Formation

The network perspective on BCT formation conceptualizes it as an outcome shaped by the evolving structure of the network itself. This perspective focuses on how a firm's structural position in the alliance network shapes its opportunities and constraints for forming new ties, particularly those that span clusters. Network perspective starts by arguing that firms do not operate in isolation (Granovetter, 1985); they are embedded in webs of prior relationships that provide access to resources, shape reputational signals, and influence future collaboration patterns (Gulati, 1998; Kumar et al., 2022).

From this view, alliance formation, in general, is conditioned by a firm's existing network structure and its embeddedness in the broader alliance network (Ahuja et al., 2012; Gulati & Gargiulo, 1999; Powell et al., 1996). Not all structural advantages translate equally to within- and between-cluster ties. For instance, firms located at the periphery of dense clusters may have fewer repeated ties but more freedom to explore bridging positions, while central firms possess the legitimacy and visibility required to connect distant clusters (Baum et al., 2003; Gulati et al., 2012; Sytch et al., 2012).

While the general principles of the network perspective were discussed in Section 2.1.3 with reference to alliance formation more broadly (cf., Ahuja et al., 2012), here I focus specifically on how these principles apply to the formation of BCTs. One key mechanism is structural embeddedness. Firms embedded in cohesive local networks develop trust and reputation that reduce coordination costs, but this embeddedness can also constrain search by reinforcing local preferences (Uzzi, 1996; Coleman, 1988). Therefore, forming BCTs may be more difficult for firms in densely connected clusters due to inertia, informational homogeneity, and lock-in effect (Gulati et al., 2000; Mossig & Schieber, 2016). However, network density can also lead to knowledge redundancy, which—in dynamic markets—may incentivize firms to seek out novel information beyond their clusters (Gulati et al., 2012).

Historical evidence from the computer industry illustrates this dynamic. During the early 1990s, a shift from vertically integrated firms to a disaggregated model—where firms specialized in either hardware or software—created clusters of technological specialization. As firms sought complementary capabilities, BCTs emerged between these clusters. Over time, these inter-cluster ties formed a large, connected component, enabling widespread knowledge diffusion. However, once redundancy increased at this component level, the network began fragmenting again into smaller, more specialized clusters (Gulati et al., 2012).

The other mechanism is network learning: firms with greater alliance experience—especially in forming bridging ties—accumulate knowledge on how to manage complexity, navigate unfamiliar domains, and extract value from non-redundant relationships (Sytch et al., 2012). This learning can reduce the cognitive and operational barriers to BCT formation, particularly in fast-moving or uncertain environments. Sytch and colleagues (2012) test this logic in the context of the global computer industry and find support for the role of experience.

Empirical research supports the view that structural position shapes the likelihood of BCT formation. Baum et al. (2003) examined the emergence of clique-spanning ties (i.e., BCTs) in the Canadian investment bank syndicate network (1952–1990), testing whether such ties arise by chance, through insurgent partnering by peripheral firms, or via control partnering by central firms. Their findings showed that peripheral firms—characterized by low betweenness centrality—were more likely to initiate BCTs, aiming to improve their network position by linking otherwise disconnected cliques. Although central firms also participated, the dominant mechanisms were chance and insurgent partnering, suggesting that structurally disadvantaged actors play a central role in the genesis of small-world structures. Similarly, Rosenkopf and Padula (2008) found that firms lacking prominence or extensive ties can still form BCTs (referred to as shortcuts). Their analysis also showed that within the main network component, BCTs often arise between structurally similar firms—suggesting that bridging ties are shaped by homophily.

In sum, the network perspective offers valuable insights into the structural opportunities and constraints influencing alliance formation, it does not fully account for why some firms choose to form BCTs while others, facing similar network positions, do not. To develop a more complete understanding of BCT formation, it is necessary to integrate structural mechanisms with firm-level behavioral drivers and external environmental conditions—an integrative approach that this thesis aims to advance.

2.3.5 External Drivers of BCTs

Recent research has increasingly emphasized the role of external conditions in shaping alliance formation decisions (Koka et al., 2006). As Ahuja et al. (2012) argued, in addition to internal drivers such as agency, opportunity, and inertia, exogenous factors—like external uncertainty—play a crucial role in influencing whether and how firms initiate new alliances. The behavioral theory of the firm (Cyert & March, 1963) highlights that firms operate in uncertain environments and tend to mitigate this uncertainty through structured mechanisms, including formal contracts and relying on internal routines. Building on this, contingency theory posits that firms adjust their organizational structures and strategic choices in response to external uncertainty, often opting for more flexible and adaptive arrangements—such as strategic alliances—when uncertainty is high (Thompson, 1967). Similarly, power dependence theory suggests that organizations are constrained by their reliance on external entities for critical resources. To reduce dependency and gain greater control over their environments, firms form interorganizational ties, particularly when facing instability or resource scarcity (Pfeffer & Salancik, 1978). From this perspective, alliances are viewed as strategic tools for managing uncertainty, securing resources, and navigating volatile external conditions.

Recent developments in the network perspective suggest that external uncertainties not only constrain firms but also create new opportunities for strategic action. For example, Koka et al. (2006) argue that uncertainty expands the range of interfirm options available, opening space for entrepreneurial actions with potentially high future payoffs. Schilling (2015) observed that the surge in alliances in the technology sector during the 1990s followed the emergence of the internet and widespread technological disruption. In this context, firms formed alliances with both incumbents and new entrants to access emerging knowledge and adapt to a rapidly changing environment.

While these perspectives underscore the role of alliances in managing uncertainty, both the type of uncertainty and the structural type of alliance matter for generalizing these arguments. For example, power dependence theory primarily focuses on uncertainty stemming from market structure, where moderate competition generates the most uncertainty in resource acquisition (Pfeffer & Salancik, 1978). Yet, contemporary markets face multiple forms of uncertainty—such as demand volatility or rapid technological change—that go beyond the scope of structural competition (Jalonen, 2012). Not all alliances are equally suited to navigating uncertainty. BCTs, in particular, often involve significant uncertainty regarding the capabilities and reliability of partners from distant clusters, along with added costs and complexity—such as coordination challenges and higher risks due to unfamiliar partners or knowledge domains. Thus, similar to explorative alliances (Li & Wang, 2019), BCTs can amplify uncertainty rather than mitigate it.

2.4 Uncertainty

2.4.1 The Concept of Uncertainty

Uncertainty is a foundational concept in organizational theory, capturing a persistent feature of the external environment that firms must navigate to survive and compete effectively (Cyert & March, 1963; Thompson, 1967). Early treatments—most notably Knight (1921)—drew a distinction between risk, where probabilities are known, and uncertainty, where such probabilities are indeterminate. Building on this, Cyert and March (1963) emphasized bounded rationality, arguing that organizations respond to uncertainty not through optimal calculation, but through heuristics and satisficing behaviors shaped by cognitive and informational limitations. Milliken (1987) later proposed a multidimensional view, identifying state, effect, and response uncertainty to capture the complexity of organizational environments. Recent contributions, including Griffin and Grote (2020), further highlight that while understandings of uncertainty have become more nuanced—incorporating cognitive filters, temporal dynamics, and subjective perception—unpredictability remains the concept's defining characteristic. Below is a chronological overview of key definitions of uncertainty, illustrating how the concept has evolved across different theoretical perspectives and time periods.

- Knight (1921): *"'Risk' means in some cases a quantity susceptible of measurement, while at other times it is something distinctly not of this character... We shall accordingly restrict the term 'uncertainty' to cases of the non-quantitative* *type."*

- Alchian (1950): *"[T]he phenomenon that produces overlapping distributions of potential outcomes."*
- Duncan (1972): *"(1) the lack of information regarding the environmental factors associated with a given decision- making situation, (2) not knowing the outcome of a specific decision in terms of how much the organization would lose if the decision were incorrect, and (3) inability to assign probabilities with any degree of confidence with regard to how environmental factors are going to affect the success or failure of the decision unit in performing its function."*
- Galbraith (1977): *"[T]he gap between the amount of information required to perform the task and the amount of information already possessed by the organization"* (as cited in Jalonen, 2012).
- Milliken (1987): *"[A]n individual's perceived inability to predict something accurately. An individual experiences uncertainty because he/she perceives himself/herself to be lacking sufficient information to predict accurately or because he/she feels unable to discriminate between relevant data and irrelevant data."*
- Beckman et al. (2004): *"Uncertainty is the difficulty firms have in predicting the future, which comes from incomplete knowledge."*
- Jurado et al. (2015): *"[T]he conditional volatility of a disturbance that is unforecastable from the perspective of economic agents."*
- Griffin and Grote (2020): *"[A]ny departure from absolute determinism... pointing to unpredictability as the core of uncertainty."*
- Kozyreva and Hertwig (2021): *"[A] property of the organism-environment system", emerging from both environmental unpredictability and the mind's limitations."*

Understanding the dimensions and types of uncertainty is essential for analyzing how managers interpret uncertainty and determine their strategic responses (Sutcliffe & Zaheer, 1998; Wernerfelt & Karnani, 1987). For instance, if firms are primarily uncertain about the behavior of their partners, they can mitigate this through governance mechanisms (Teng & Das, 2008). However, uncertainty regarding broader external factors—such as market trends, emerging technologies, competitors' decisions, and the innovation process—may necessitate different adaptive strategies, including increased exploration through strategic alliances or even wait until uncertainty subsides (Beckman et al., 2004; Mone et al., 1998).

Beckman et al. (2004) distinguished between (1) firm-specific uncertainty, which is unique to a particular firm, and (2) market level uncertainty, which affects multiple firms within an industry. This distinction is critical because firm-specific uncertainties are often more controllable through deliberate strategic actions and typically arise from internal factors, such as operational failures or managerial decisions. Firm specific uncertainties can also stem from external disruptions like supplier failures, though they remain unique to the firm. In contrast, external uncertainties, such as fluctuations in market demand, extend beyond firm-specific concerns, affecting entire industries and remaining largely beyond managerial control (Beckman et al., 2004).

This research focuses on external uncertainty, which despite extensive study in the economic and management literature, has gained increasing significance in recent years (Schoemaker et al., 2018). This growing attention stems from the rising prevalence of uncertainty in business environments and the need for a deeper understanding of its implications (Alvarez et al., 2018). While there is broad consensus on the core definition of uncertainty and its various dimensions, how market actors respond to different types of uncertainty remains an open question.

One of the earliest attempts to examine the dimensions of perceived uncertainty was made by Milliken (1987) who conceptualized uncertainty as comprising three distinct dimensions. State uncertainty refers to the unpredictability of environmental components and the interrelationships between them, making it difficult for firms to anticipate changes. Effect uncertainty captures the challenge of predicting how environmental shifts will impact the organization. Response uncertainty reflects the difficulty in determining appropriate strategic responses and assessing their potential outcomes. Milliken also emphasized that '[i]t is not change per se, or even a fast rate of change, that creates uncertainty about the environment; rather, it is unpredictable change that will be associated with this [environmental] uncertainty' (1987, p. 135). For instance, while markets exhibit regular volatility, sudden and unexpected shifts in market trends (e.g., demand or stock prices), constitute uncertainty. Moreover, unexpected changes not only capture the temporal aspect of external uncertainties but also disrupt established cause-and-effect relationships (Folta, 1998; Milliken, 1987). This disruption heightens unpredictability, making it more challenging for managers to rely on past experiences and historical data when making decisions (Artinger et al., 2015; Dess & Beard, 1984).

Wernerfelt and Karnani (1987) emphasized that developing effective competitive strategies requires a clear understanding of both the sources and characteristics of the uncertainties organizations encounter. Without this clarity, firms may misjudge the nature of threats and opportunities, leading to suboptimal strategic responses. Research in management has classified external uncertainties based on their sources, consistently identifying four major types: demand structure, supply structure, competitors, and externalities (Sutcliffe & Zaheer, 1998; Wernerfelt & Karnani, 1987). These uncertainties affect strategic decisions by shaping how firms assess market trends, secure critical inputs, anticipate rival moves, and respond to institutional or regulatory shocks.

Among these, market and technological uncertainty have emerged as particularly salient forms of environmental unpredictability (Jalonen, 2012). Market uncertainty refers to volatility in customer preferences, pricing, and demand patterns, while technological uncertainty stems from rapid innovation and the unpredictability of technological trajectories. These two dimensions are especially influential in shaping firms' strategic behavior and risk-taking tendencies. The next section examines each in turn, exploring their implications for alliance formation and positioning within interorganizational networks.

2.4.2 Types of Uncertainty

2.4.2.1 Market Uncertainty

Market uncertainty refers to the unpredictability of market trends (e.g., market demand), which complicates managers' efforts to anticipate customer preferences and plan accordingly (Beckman et al., 2004; W. Li & Wang, 2019; Martin et al., 2015). Market uncertainty is especially acute in industries characterized by rapid changes in consumer behavior, frequent technological disruption, and heightened exposure to macroeconomic volatility—including recessions, trade restrictions, or abrupt regulatory changes (Segal et al., 2015). Although firms adopt various strategies to adapt to and buffer against market uncertainty, this type of uncertainty remains largely unavoidable and affects most firms to some degree (Beckman et al., 2004). However, exposure does not necessarily imply uniform impact. Not all firms are equally affected by market uncertainty, and our understanding of this variation remains limited. For example, research in organizational ecology highlights the liabilities of smallness and newness, suggesting that smaller and younger firms often lack the resource buffers, routines, and established relationships needed to stabilize their task environments and absorb external shocks. While these firms because of limited suck costs and less inertia can act more boldly (Mintzberg, 1973). Thus, while market uncertainty is a common external force, its consequences can vary widely depending on firm characteristics.

Moreover, market uncertainty can create strategic opportunities for some firms, particularly those that are well-positioned to respond quickly and decisively. For instance, during the COVID-19 pandemic, lockdown regulations and the shift to remote work significantly increased demand for digital communication tools, creating rapid growth opportunities for companies like Zoom (Stecuła & Wolniak, 2022). However, not all firms are equally able to capitalize on these changes. Firms that have strong performance, established reputations, and scalable capabilities were more likely to respond aggressively and seize emerging opportunities (Helfat & Winter, 2011).

Beyond being external to firms and shared by actors within an industry, market uncertainty has two notable characteristics. First, as Bloom (2014) emphasizes, it is cyclical—typically intensifying during economic downturns at both the industry and macroeconomic levels. This cyclical pattern implies that firms with market experience can anticipate that periods of high uncertainty are often followed by more stable phases. During these stable periods, the task environment—including factors such as technology, customer demand, regulatory conditions, and competitive dynamics—tends to remain relatively unchanged. This recognition allows experienced firms to adjust their strategies accordingly, balancing short-term caution with longer-term opportunity seeking.

Another key feature of market uncertainty is that since it is rooted in external shocks firms can rarely control. While some firms—particularly those with ample slack, political capabilities, or strategic agility—can partially insulate themselves (Drnevich & West, 2023; Pfeffer & Salancik, 1978), most remain vulnerable and reactive. For example, during the global financial crisis that began in late 2007, many firms suffered severe disruptions regardless of their strategic competence. While some large financial institutions leveraged their political influence to secure government bailouts under the "too big to fail" rationale (Baron et al., 2023), and during COVID-19 a few adaptive businesses such as some restaurants collaborated with open-space venues or with online shopping platforms to circumvent lockdown constraints (Sharma et al., 2020), most firms could not adapt effectively, resulting in widespread failures (Coibion et al., 2020). As a result, research have suggested that firms often respond with caution, delaying or scaling back strategic moves rather than pursuing opportunity-driven initiatives (Beckman et al., 2004; Podolny, 1994).

Yet, the results are not consistent. For example, Howard et al. (2016) replicated the study by Beckman et al. (2004) using an extended time frame and found that firms continued to form ties with new partners—or what Beckman and colleagues termed explorative connections—even after experiencing market uncertainty. Therefore, the effect of market uncertainty on the formation of inherently uncertain alliances still requires further investigation.

Thus, market uncertainty is an external, cyclical, and largely uncontrollable condition that compels firms to respond and adapt in ways shaped by their internal characteristics—such as size, resources, and performance feedback.

2.4.2.2 Technological Uncertainty

Tushman and Anderson (1986) define technology as "those tools, devices, and knowledge that mediate between inputs and outputs´´ (p. 440). Technological uncertainty arises when firms cannot determine whether their chosen technologies will remain viable, whether new technological trajectories will supersede current paradigms, or whether complementary technologies will co-develop in time (Dosi, 1982; Fleming & Sorenson, 2004; Rosenberg, 2009). Thus, technological uncertainty refers to the difficulty in predicting how technologies will evolve, whether they will become dominant, and what their implications are for firm competitiveness (Jalonen, 2012; Toh & Kim, 2013).

A major source of technological uncertainty are radical and disruptive innovations, which can undermine established competencies and create unpredictable competitive dynamics (Anderson & Tushman, 1990; Christensen, 2013). Such changes often follow a pattern described by the punctuated equilibrium model: long periods of incremental improvement are disrupted by short bursts of radical innovation, which redefine the technological landscape (Afuah, 1998; Tushman & Anderson, 1986). During these periods of technological ferment, firms experiment with competing designs, seeking to influence the dominant design that eventually stabilizes the market (Suarez & Utterback, 1995; Utterback & Abernathy, 1975). Until a dominant design emerges, firms operate under heightened ambiguity and cannot rely on prior experience or routines to guide action.

These periods of technological ferment present both significant risks and strategic opportunities for firms. Aligning early with emerging technological trajectories can offer competitive advantages, such as shaping industry standards, gaining first-mover or second-mover benefits, and capturing new market segments. However, misalignment—whether through failure to adapt or investing in the wrong trajectory—can lead to technological obsolescence, eroded competencies, and loss of market relevance. Firms that are slow to respond may find their existing capabilities rendered obsolete, while more adaptive firms can reposition themselves to thrive in the new technological order.

A critical aspect of technological uncertainty is that it is partially shaped by firms themselves. While technological changes at the industry level are not under a firm's control—since other competitor, regulators, consumer preferences, and societal pressures also play a role— a typical firm can actively contribute to the evolution of technological landscapes. Firms participate in path creation by investing in R&D, shaping standards, experimenting with new technologies, and forming alliances that influence the evolution of the technological landscape (Drnevich & West, 2023; Tushman & Rosenkopf, 1992). Examples include OpenAI's disruptive role in generative AI (Treiber, 2023), or Tesla's influence over electric vehicle platforms and charging infrastructure (Associated-Press, 2023). These cases illustrate that even relatively young or small firms can shape—rather than merely adapt to—technological uncertainty. However, despite such interventions, the trajectories that emerging technologies ultimately follow often remain unpredictable.

Thus, technological uncertainty is an external and largely uncontrollable condition, but unlike market uncertainty, it does not follow a cyclical pattern. Instead, it unfolds through discontinuous shifts that can render existing technologies and capabilities obsolete (Tushman & Anderson, 1986). This distinction is critical: falling behind in the face of rapid technological change can expose firms to the risk of obsolescence. Once a dominant design emerges or regulatory ambiguity around a new technology resolves, only firms that have developed aligned and adaptive capabilities are likely to survive, while others may be pushed to the margins of the industry or exit altogether. The dual threat of falling behind and the emergence of new growth opportunities under technological uncertainty incentivizes firms to proactively search for and build capabilities that align with evolving technological trajectories.

2.4.3 Decision Making Under Uncertainty

In organizational theory, uncertainty avoidance is a foundational theme (Cyert & March, 1963; Thompson, 1967). Cyert and March (1963) emphasize that organizations manage uncertainty by shaping their environments—primarily through negotiated contracts and stable interorganizational arrangements that buffer against external shocks. Similarly, Pfeffer and Salancik (1978) argue that firms seek to reduce environmental dependence and uncertainty by controlling access to critical resources, often through alliances, board interlocks, or acquisitions. These strategies allow organizations to stabilize access to inputs, manage volatility, and maintain internal consistency (Beckman et al., 2004). Additionally, under uncertainty, firms tend to fall back on established routines and heuristics to manage complexity and cognitive limits (Nelson & Winter, 1982).

Yet, despite this extensive focus on structural responses, less is known about how decision-makers interpret ambiguous environments and adjust their strategic choices. In response to this gap, I drew on a growing body of research on decision-making under uncertainty to examine how firms respond behaviorally—through alliance formation across network clusters (BCTs)—when market and technological uncertainties increase in their environment.

2.4.3.1 Attribution Theory and Uncertainty

Attribution theory was originally developed in social psychology to explain how people make sense of the causes of events and behaviors (Heider, 1958; Kelley & Michela, 1980). Fritz Heider (1958) argued that individuals act as naïve psychologists, attributing outcomes either to internal factors (such as effort or ability) or external factors (such as context or luck). His key insight was that people seek causal explanations to understand their environment and maintain a sense of control. Harold Kelley later extended these ideas with the covariation model (Kelley, 1967, 1973), suggesting that people use cues of consistency, distinctiveness, and consensus to determine whether outcomes are caused by internal traits or external conditions (Kelley & Michela, 1980). These contributions established the concept of locus of causality—internal versus external causes—as central to attributional reasoning.

A major development came with Bernard Weiner's work on achievement motivation. Weiner (1985) added two further dimensions to the attribution framework: stability (whether the cause is constant over time) and controllability (whether the actor can influence the cause). He proposed that people explain success and failure using three core dimensions: locus, stability, and controllability. These shape how individuals respond emotionally (e.g., pride, guilt) and behaviorally (e.g., persistence, withdrawal). Attribution theory thus became a general model for understanding how individuals process outcomes and adjust behavior accordingly.

In the 1980s and 1990s, organizational scholars began applying attribution theory to examine managerial sensemaking and strategic response. Bettman and Weitz (1983) analyzed CEO letters and found that managers often claim credit for success and deflect blame for failure. Clapham and Schwenk (1991) argued that these attributional patterns can foster strategic rigidity by masking internal weaknesses. A self-serving CEO may ignore early signs of decline by attributing them to uncontrollable external factors. Similarly, Lant (1992) showed that framing poor performance as externally caused can reduce motivation for internal learning and change. Mone et al. (1998) argued that managers tend to attribute the causes of organizational decline to external crises which decrease their likelihood of responding with innovation. When decline is seen as stemming from stable and controllable causes, such as strategic flaws, managers are more likely to pursue adaptive change. In contrast, attributing decline to temporary or uncontrollable causes, such as crises, tends to reinforce passivity.

Later studies examined how self-esteem motives shape (bias) attributional judgments. Audia and Brion (2007) showed that managers confronted with conflicting feedback often emphasize favorable signals, reinforcing a self-enhancing narrative. Jordan and Audia (2012) proposed a model in which decision-makers move from problem-solving to self-protection when they interpret negative feedback as threatening. Recently, Audia and Brion (2023) reviewed the literature and showed that individuals with high self-esteem tend to externalize blame when faced with failure, particularly when their competence is threatened. These studies suggest that attribution serves as a psychological buffer—enabling managers to protect their self-image, but at the cost of delayed learning and misaligned strategic responses.

Overconfidence is another attribution-driven bias that shapes strategic decisions. When managers interpret repeated success as evidence of their own skill or insight, they develop an inflated sense of control. This can lead to excessive risk-taking, poor judgment, and misreading of performance signals. Hayward and Hambrick (1997) showed that overconfident CEOs tend to overpay in acquisitions, driven by an inflated belief in their ability to generate value. Mezias and Starbuck (2003) also suggested that attributional distortions, including overconfidence, lead managers to misalign their perceptions with objective indicators. Recently, Schumacher et al. (2020) found that such executives discount negative feedback and resist strategic change.

Uncertainty increases the difficulty of making accurate attributions. In ambiguous settings, causal clarity is low (Milliken, 1987), and managers rely on heuristics to interpret performance (Mousavi & Gigerenzer, 2017). This can lead to superstitious learning when success occurs—a process where leaders infer causality based on coincidental success (March & Olsen, 1975). Success in such environments often reinforces beliefs in personal competence and control, encouraging riskier strategies without clear causal justification (Levinthal & March, 1993). In contrast, when causal links are hard to verify, managers in underperforming firms tend to attribute failure to external volatility while still claiming credit for limited successes (Audia & Brion, 2023). Attribution thus becomes a flexible tool for justifying both persistence and change.

Attributions shape not only how past outcomes are explained but also how future expectations and actions are formed. When poor performance is attributed to external and unstable causes, managers would delay necessary changes. Conversely, internal and stable attributions for failure can prompt corrective action. Similarly, attributing success to internal, stable causes reinforces confidence and strategic persistence, while attributing it to external or unstable factors can lead to opportunistic, proactive behaviors. Through these mechanisms, attribution processes influence learning, risk-taking, and strategic inertia, offering a cognitive foundation for understanding firm behavior in behavioral strategy.

2.4.3.2 Heuristics and Uncertainty

An elemental characteristic of external, market-level uncertainties is that under such conditions, firms can hardly access reliable information about market trends (Sutcliffe & Zaheer, 1998). This leads to ineffectiveness of regular risk analysis (e.g., calculation of expected value) (Bloom, 2007; Mousavi & Gigerenzer, 2014). Managers are, therefore, confronted with complex conditions that impede their ability to make informed project selections and accurately determine appropriate investment levels. Under such circumstances, managers use heuristics to make decisions (Mousavi & Gigerenzer, 2017). Two dominant traditions have shaped research on heuristics in decision-making. The first, known as the heuristics-and-biases tradition, views heuristics as sources of systematic error and cognitive bias, highlighting how decisions often deviate from rational models due to limited information processing capacities (Kahneman & Tversky, 1979; Tversky & Kahneman, 1974; Tversky et al., 1982). This approach emphasizes the fallibility of intuitive judgments and the potential for miscalculation under uncertainty. In contrast, the second tradition argues that heuristics can be effective, adaptive strategies, especially under real-world constraints where information is incomplete or ambiguous (Gigerenzer & Todd, 1999; Mousavi & Gigerenzer, 2014). Rather than labeling deviations from rational choice as errors, this view assesses heuristics based on how well they align with specific environmental conditions.

I draw on the second approach, which defines heuristics as mental shortcuts or "rules of thumb that bypass exhaustive information search and complex calculations," offering managers simplified tools to make decisions under uncertainty (Mousavi & Gigerenzer, 2017, p. 367). Managers frequently rely on heuristics as fast and frugal tools for decision-making, particularly in uncertain environments (Gigerenzer & Goldstein, 1996). For instance, Cisco employed a rule-based acquisition strategy, targeting companies with no more than 75 employees, with approximately 75% of them being engineers (Gigerenzer et al., 2022). Similarly, research shows that managers often draw on analogous past experiences to guide decisions in uncertain conditions, using similar contexts as a key source of knowledge (Artinger et al., 2015). In financial decision-making, a portfolio manager may allocate funds across various investment opportunities using a 1/N strategy—distributing capital equally among all available options—rather than relying on complex optimization models (Gigerenzer & Gaissmaier, 2011).

Heuristics are widely used in both everyday decision-making and organizational settings, providing simple yet effective strategies for navigating complex environments. Gigerenzer and Gaissmaier (2011) has categorized heuristics into three main classes: recognition-based, one-reason decision, and trade-off heuristics. Recognition-based heuristics rely on familiarity—if only one option is recognized and the others are not, the recognized option is chosen. This heuristic assumes that recognition is a valid predictor of quality or relevance in a given context (Gigerenzer & Gaissmaier, 2011; Gigerenzer & Todd, 1999). One-reason decision heuristics base choices on a single, highly relevant cue while ignoring all other available information (Mousavi & Gigerenzer, 2017; Todd & Gigerenzer, 2000). These heuristics follow a non-compensatory strategy, meaning that no amount of additional evidence from other cues can override the selected cue's influence. Trade-off heuristics involve weighing multiple attributes but do so in a simplified manner, avoiding exhaustive comparisons (Gigerenzer & Gaissmaier, 2011; Todd & Gigerenzer, 2000). Instead of complex calculations, decision-makers use straightforward rules to make choices efficiently while balancing competing factors.

Rather than being judged by internal consistency, heuristics are evaluated based on how well they fit specific environmental conditions (Mousavi & Gigerenzer, 2017;

Todd & Gigerenzer, 2012). The alignment between heuristics and the structure of the environment which determines their effectiveness in decision-making is called Ecological rationality (Gigerenzer, 2002; Todd & Gigerenzer, 2012). Identifying key environmental structures, such as market and firm conditions, helps predict which heuristics firms will adopt and their implications for behavior under uncertainty. The ecological rationality involves analyzing environmental structures, heuristic structures, and their interaction to determine when certain heuristics outperform others. People learn by time and experience that which heuristic is more suited to which environment and conditions (Gigerenzer & Gaissmaier, 2011; Niittymies, 2020). This experience-based learning helps them to minimize the variance of errors while it may not necessarily decrease the bias in their selection (Gigerenzer, 2016; Gigerenzer & Gaissmaier, 2011).

In organizational settings, managers frequently rely on heuristics to navigate complex decisions. Niittymies (2020), through an inductive case study on firms' early internationalization, found that managers developed heuristics after accumulating contextual experience—often shaped by early setbacks—which then guided strategic choices in unfamiliar environments. In marketing, the "hiatus heuristic"—classifying customers as inactive based solely on the time elapsed since the last purchase—has been widely adopted by airline and retail managers, and has outperformed machine learning models across 35 companies (Gigerenzer et al., 2022). Yet, the application of recognition-based and single-reason heuristics is less likely in complicated situations such as organizational strategic decision-making. Recognition heuristics rely on a simple feeling of familiarity to make quick choices, while single-reason heuristics depend on one key piece of information (Todd & Gigerenzer, 2000). Organizational decision making processes, however, often involve extensive information gathering, weighting and integration of information, comparing alternative cues and outcomes considering their trade-offs, and discussions across various units and levels by professionals (Artinger et al., 2015; Atanasiu et al., 2023; Gigerenzer & Goldstein, 1996; Todd & Gigerenzer, 2000). As such, compensatory heuristics—especially inclusive ones like 1/N or tallying—that integrate multiple cues become more applicable. For instance, the 1/N rule is used to distribute resources or outcomes equally when individual contributions cannot be easily isolated (Artinger et al., 2015; Gigerenzer et al., 2022).

Empirical studies have documented such practices in various industries. Managers frequently apply compensatory heuristics—such as tallying and 1/N rules—in real-world strategic decisions under uncertainty. Managers in Cisco, for example, used a tallying rule for acquisition decisions (Gigerenzer et al., 2022). Similarly, in resource allocation and financial diversification, the 1/N heuristic—allocating resources equally across alternatives—has been widely applied by managers to ensure fairness and robustness under ambiguity (Messick, 1999).

Beyond identifying their use, a growing body of empirical work has tested the effectiveness of heuristics, often by comparing them to more complex models (Gigerenzer & Brighton, 2009; Gigerenzer & Gaissmaier, 2011; Vuori et al., 2024). Using simulations, experiments, and real-world data, researchers have found that simple heuristics can sometimes outperform more elaborate decision strategies. This "less-is-more" effect illustrates that ignoring certain information can actually improve predictive accuracy under the right conditions (Atanasiu et al., 2023; Gigerenzer & Todd, 1999). However, the literature is not uniformly optimistic: some studies have pointed to the potential for bias or inconclusive outcomes, underscoring the need for careful conceptualization and context-specific validation (Vuori et al., 2024).

In highly uncertain environments—where analytic models often fall short due to incomplete information and outcome ambiguity—heuristics offer managers a practical means of making timely decisions. Among the most relevant in organizational contexts are trade-off and compensatory heuristics, which allow decision-makers to weigh multiple cues without relying on exhaustive analysis. These heuristics strike a balance between cognitive efficiency and strategic responsiveness, offering a viable framework for action when complexity or speed renders optimization infeasible. Building on these insights, the next chapter introduces a theoretical framework that links heuristic decision-making to alliance formation under varying conditions of market and technological uncertainty.

3. THEORY AND HYPOTHESES

3.1 Performance Feedback and BCT Formation

The performance feedback model of the BTOF (Cyert & March, 1963; Greve, 2003a) posits that managers are boundedly rational and set aspiration levels for performance rather than optimizingoutcomes. These aspirations are typically based on the firm's own past performance (historicalaspirations) or the performance of similar others (social aspirations). When performance falls belowaspiration levels, organizations initiate problemistic search—a targeted effort to find solutions andmodify routines to close the performance gap (Cyert & March, 1963; Posen et al., 2018). In contrast, when performance exceeds aspirations, the motivation to search declines (Ref & Shapira, 2017). Overperformance, however, generates excess resources and confidence, which can facilitate experimentation and lead to increased search and risk-taking (Baum et al., 2005; Ref & Shapira, 2017). Drawing on these logics and following Baum et al., (2005) I developed two baseline hypotheses predicting that a firm's likelihood of forming BCTs as a search strategy depends on its performance relative to its aspiration levels.

Problem-Driven Search. When a firm performs close to its aspiration level, managers are less likely to initiate search, assuming that minor adjustments will suffice to address performance issues (Baum et al., 2005; Cyert & March, 1963). However, as performance falls further below aspirations, incremental changes become inadequate, and managers are more likely to engage in exploratory search behaviors to address the shortfall—such as increasing R&D spending (Cabral et al., 2024; Choi et al., 2019; Greve, 2003a, 2003b), pursuing product innovation (Angus, 2019; Greve, 2003a, 2007), entering new markets (T. Kim & Rhee, 2017; Ref & Shapira, 2017), or forming connections with distant partners (Baum et al., 2005). This search myopically begins locally, relying on familiar routines and trusted collaborators (Cyert

& March, 1963; Levinthal & March, 1993). But when the performance gap is large or persistent, local solutions may fail, prompting managers to explore more distant and uncertain areas beyond their established network (Ref & Shapira, 2017). BCTs, as broader search tools, enable firms to go beyond local routines and access tacit capabilities, strategic knowledge, and collaborative opportunities not available through within-cluster ties—particularly when local search fails to address performance shortfalls.

Thus, I hypothesize that poor performance relative to both historical and social aspiration levels increase the firm's willingness to search and to take risks in pursuit of novel solutions by forming new BCTs (Baum et al., 2005; Greve, 2003a). This leads to the first hypothesis:

> *Hypothesis 1a. The further a firm's performance is below historical aspirations, the more likely it is to engage in search by forming between-cluster ties (BCTs).*

> *Hypothesis 1b. The further a firm's performance is below social aspirations, the more likely it is to engage in search by forming between-cluster ties (BCTs).*

Slack-Enabled Search. While performance below aspiration levels is widely understood to trigger problemistic (problem-driven) search, the relationship between performance above aspiration levels and search behavior remains contested (Ref & Shapira, 2017). Two main perspectives, both grounded in the BTOF, offer competing predictions.

The first view extends the logic of problemistic search, arguing that overperformance relative to aspirations reduces the motivations to explore and change (Greve, 1998). When firms meet or exceed their goals, managers face less pressure to act, and performance feedback no longer signals a need for improvement (Greve, 2003b). As a result, managers in such firms become complacent, reduce their risk-taking, and avoid deviating from proven routines (Greve, 1998; Kahneman & Tversky, 1979). Empirical studies support this interpretation. Greve (2003a) found that in the shipbuilding industry, R&D intensity declined more sharply when performance rose above aspirations than when it improved from below. Audia and Greve (2006) observed similar reductions in risk-taking among Japanese firms. Other studies show that exceeding aspirations is linked to fewer new product introductions (Joseph & Gaba, 2015) and reduced innovation efforts (Parker et al., 2017).

The second view emphasizes slack-enabled search. Here, overperformance generates slack—excess resources beyond what is required to maintain the organization—that can be channeled into exploration (Cyert & March, 1963). Slack provides the capacity to pursue new initiatives and encourages experimentation, even in the absence of immediate performance problems (Baum & Dahlin, 2007; Cyert & March, 1963; Ref & Shapira, 2017). Success also enhance managerial confidence and strategic ambition (Lim, 2024; Xu et al., 2019). For example, Baum et al. (2005) found that investment banks exceeding their aspiration levels were more likely to form BCTs. Similarly, L.-H. Lu and Fang (2013) showed that overperforming firms increased their R&D spending, even after controlling for available slack. Wennberg et al. (2016) suggested that younger ventures are more likely to grow in size than older firms when their performance exceeds social and historical aspiration levels.

Both perspectives capture important facets of organizational behavior. The problem-driven view focuses on motivation: overperformance reduces the urgency for change. The slack-enabled view focuses on capability: high performance equips firms with the resources and legitimacy to explore new opportunities. I adopt the slack-enabled search perspective to explain why firms pursue BCTs when performance exceeds aspiration levels. My rationale is that, while positive performance feedback typically reduces the motivation to search (Greve, 2003a; Audia & Greve, 2006), it also generates slack resources that enable exploration of nonessential yet strategically valuable opportunities. In clustered alliance networks—where BCTs are costly, uncertain, and have long-term outcomes—overperformance, particularly relative to the industry average, has two implications that are especially salient in such contexts. First, slack resources generated through overperformance are essential for enabling exploratory BCTs. They allow managers to loosen budgetary constraints and justify riskier initiatives that enhance the firm's status and facilitate access to novel knowledge and opportunities beyond the local cluster. Second, it attracts the attention of other firms by signaling reliability, competence, and strategic value as a cross-cluster partner. Thus, even if overperformance does not stimulate broad search, BCT formation reflects a selective, opportunity-driven form of exploration enabled by the discretion and resources associated with exceeding aspirations (Baum et al., 2005).

Hypothesis 2a. The further a firm's performance is above historical aspirations, the more likely it is to engage in search by forming between-cluster ties (BCTs).

Hypothesis 2b. The further a firm's performance is above social aspirations, the more likely it is to engage in search by forming between-cluster ties (BCTs).

3.2 External Uncertainties and Responses to Performance Feedback

While the BTOF offers a foundational account of how firms adapt to performance feedback through search (Cyert & March, 1963), its core logic overlooks conditions in which outcomes cannot be reliably interpreted. This complexity is intensified under uncertainty and is particularly salient in the context of BCT formation, which involves ambitious, nonlocal exploration with less familiar partners. Under such conditions, marked by market volatility or technological disruption, managerial responses become more contingent and difficult to predict. In the following sections, I argue that external uncertainty alters how performance feedback is processed compared to stable conditions, and shapes how firms formulate BCT search strategies in response. Different types of uncertainty affect both the interpretation of performance signals and the strategic logic of BCT formation. Under such conditions, multiple cognitive and environmental mechanisms interact to shape how firms respond to both positive and negative performance feedback. Attribution processes influence whether outcomes are explained as the result of internal capabilities or external circumstances, affecting how managers interpret both success and failure. Heuristics provide simplifying rules for action when causal clarity is limited, guiding decisions based on a trade-off rule. The nature of uncertainty itself is also critical: market and technological uncertainties differ in how they affect signal reliability, interpretive demands, and the perceived controllability of outcomes. These dimensions jointly influence how firms assess their performance and decide on search behavior. I extend the BTOF framework by introducing these contingencies as moderating mechanisms that condition the relationship between performance feedback and BCT formation. Moreover, I argue that the salience of historical versus social aspirations varies systematically with the type of uncertainty and the firm's relative performance, influencing which reference point managers rely on when formulating search strategies.

3.3 Market Uncertainty and BCT Formation

Market uncertainty refers to the unpredictability and instability of market demand, pricing, and customer preferences (Sutcliffe & Zaheer, 1998; Oriani & Sobrero, 2008). It is often shaped by macroeconomic conditions, regulatory shifts, and broader geopolitical dynamics, and tends to intensify during periods of economic downturn or crisis (Bloom, 2014). The cyclical nature of market uncertainty suggests that periods of instability are often followed by phases of relative stability—particularly when underlying factors such as technology and consumer preferences remain largely unchanged (Bloom, 2014). For example, following the COVID-19 pandemic lockdowns, many businesses resumed their pre-pandemic operations and strategies, reflecting the temporary nature of market disruptions in certain sectors (Canton et al., 2021).

When a firm's performance falls below its aspiration level, under low market uncertainty, managers are more likely to attribute the shortfall to internal causes—such as inefficient routines, flawed execution, or weak offerings—since external conditions appear stable and predictable. In such settings, attributions to internal deficiencies are harder to deflect, which increases motivation to search for corrective solutions, including through new alliances with partners in other clusters. However, under high market uncertainty, attribution patterns shift. Faced with ambiguous or conflicting cues, managers tend to rely on compensatory heuristics and consider both internal and external explanations (Mousavi & Gigerenzer, 2017). This cognitive adjustment serves not only as a way to navigate complexity but also as a mechanism to protect self-esteem (Audia & Brion, 2023; Audia & Locke, 2003). In this context, performance shortfall relative to aspiration is attributed partly to temporary and uncontrollable external forces—such as demand shocks. A typical attribution might be: "We could have done better, but the market turned against us."

This broader attribution of failure to both internal and external causes reduces the clarity of the problem and weakens the sense of agency required to trigger ambitious, distant search. When performance signals are interpreted as reflecting external, temporary disruptions rather than internal shortcomings, the perceived need for strategic change is diminished. As a result, firms become less likely to pursue exploratory responses such as forming new BCTs, which require committing resources and navigating unfamiliar relational terrain. Instead, they delay such strategies.

> Hypothesis 3. Market uncertainty weakens the negative relationship between performance below (a) historical and (b) social aspiration levels and the formation of between-cluster ties (BCTs).

When performance is evaluated against social aspirations—that is, relative to the performance of other firms—external attributions become less credible. If peer firms are performing well despite high market uncertainty which is shared among actors, managers cannot easily blame external conditions for their own underperformance. This makes internal causes more salient and sustains the motivation for corrective action, such as forming new BCTs. In contrast, when performance is evaluated against historical aspirations, managers can more readily attribute shortfalls to changes in the external environment. This allows them to externalize blame, protect their self-image, and reduce the urgency to engage in ambitious search. Therefore, the weakening effect of market uncertainty on BCT formation in response to performance below aspiration is expected to be more pronounced when aspirations are based on a firm's own historical performance.

> Hypothesis 3c. The weakening effect of market uncertainty on the negative relationship between performance below aspiration and the formation of between-cluster ties (BCTs) is stronger when aspirations are based on historical performance rather than social comparisons.

When a firm's performance exceeds its aspiration levels, a different moderating effect of market uncertainty emerges. While strong performance typically reduces the need for change, it also generates slack resources that can enable exploratory behavior (Ref & Shapira, 2017), such as forming alliances with partners in other clusters. Under low market uncertainty, managers are more likely to attribute this success to internal capabilities—such as superior execution, innovation, or strategic foresight—reinforcing confidence in their current trajectory and encouraging further bold actions (Schumacher et al., 2020; Zhang et al., 2024). However, under high market uncertainty, causal ambiguity increases. Managers heuristically attribute part of their success to external, transient factors—such as favorable market shifts—leading to a more cautious stance. At the same time, to maintain a positive self-image and preserve self-enhancement, they are still inclined to emphasize internal strengths (Audia & Brion, 2023). Together, these dynamics allow managers to preserve self-esteem by acknowledging external factors, while simultaneously justifying bold actions through overconfidence—interpreting temporary success as confirmation of enduring strength, even under uncertain conditions. As a result, managers not only persist in their current strategy but also extend it through additional investments or risky alliances, including BCT formation, under the belief that their capabilities are well-aligned with the environment—even if that alignment is short-lived.

Thus, rather than becoming passive, managers will view uncertain yet favorable conditions as an opportunity to act while the window remains open. Research suggests that myopic managers try to "harvest" short-term gains while they last, investing quickly to maximize returns before conditions shift (Levinthal & March, 1993). In such cases, forming new BCTs can serve as a way to extend the current advantage by accessing complementary knowledge or entering new domains ahead of competitors. Market uncertainty, then, increases the tendency of firms performing above aspiration levels to engage in exploratory activities such as BCT formation (see Figure3.1).

> Hypothesis 4. Market uncertainty strengthens the positive relationship between performance above (a) historical and (b) social aspiration levels and the formation of between-cluster ties (BCTs).

This effect is especially pronounced for firms exceeding social aspiration levels, as their superior performance is externally visible. Outperforming peers under shared external uncertainty enhances a firm's reputation, legitimacy, and perceived reliability, making it a more attractive partner across the alliance network—particularly to other high-performing firms seeking to enhance their status (Rosenkopf & Padula, 2008). Moreover, high performance relative to peers signals capability and resilience in turbulent conditions, reinforcing confidence in the firm's strategic direction. In contrast, when performance exceeds historical aspirations, the firm lacks this external comparative signal, and success will be more easily discounted as situational or temporary. Thus, the strengthening effect of market uncertainty on the positive relationship between performance above aspirations and BCT formation is expected to be stronger when aspirations are socially rather than historically defined.

Hypothesis 4c. The strengthening effect of market uncertainty on the positive relationship between performance above aspiration and the formation of between-cluster ties (BCTs) is stronger when aspirations are based on social comparisons rather than historical performance.

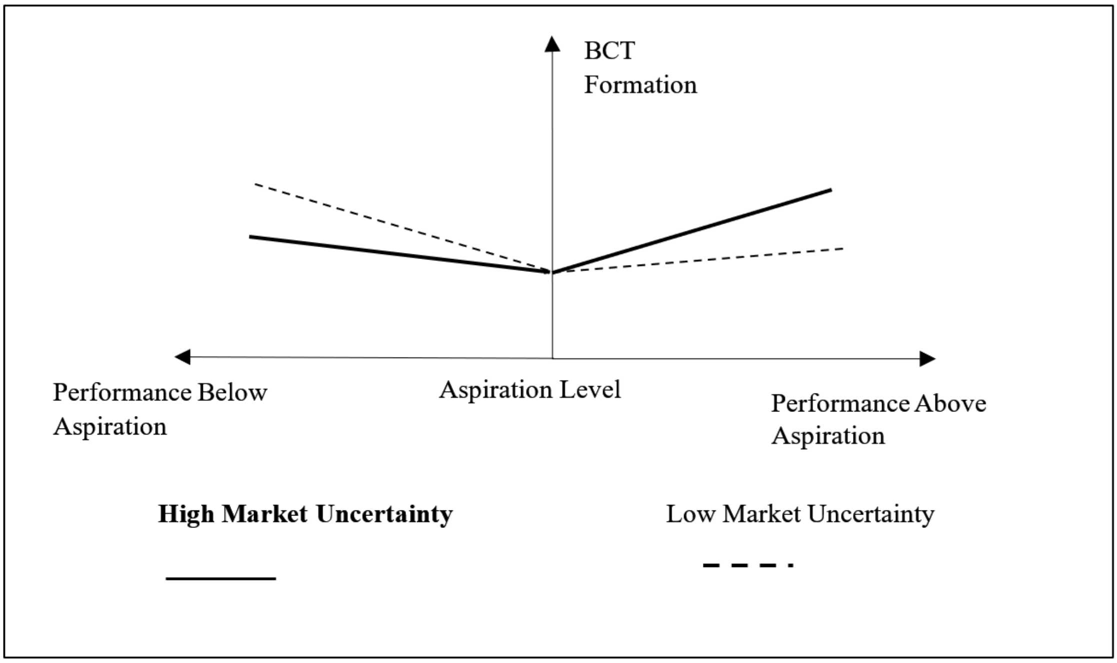

Figure 3.1 Moderating Effect of Market Uncertainty on the Relationship Between Performance Below and Above Aspiration Levels and BCT Formation

3.4 Technological Uncertainty and BCT Formation

Technological uncertainty refers to the ambiguity firms face about the development, diffusion, and eventual dominance of new technologies (Jalonen, 2012). Unlike market uncertainty—typically cyclical and temporary—technological uncertainty follows a different pattern, often marked by abrupt and discontinuous shifts. As Tushman and Anderson (1986) argue, technological change is punctuated by periods of stability interrupted by radical innovations that disrupt existing competencies and industry structures. These technological discontinuities create breaks from prior trajectories, rendering accumulated experience and established routines less valuable or even obsolete. Firms must therefore not only adapt but anticipate and shape emerging technologies to remain competitive. The unpredictability of when and how these shifts occur makes technological uncertainty particularly challenging and consequential for strategic decision-making. When a firm's performance falls below its aspiration level, technological uncertainty complicates causal attributions and intensifies concerns about long-term competitiveness. In such environments, managers struggle to determine whether underperformance results from internal inefficiencies or from misalignment with shifting technological trajectories. As the direction and pace of technological change become less predictable, performance shortfalls are increasingly interpreted as signs that existing capabilities are not only underdeveloped but potentially misaligned with emerging technologies (Oriani & Sobrero, 2008; Utterback, 1996). Even when self-enhancing biases are present, managers rely on compensatory heuristics, integrating both internal and external explanations into their diagnosis. When underperformance is attributed solely to internal shortcomings, firms are likely to respond by refining existing routines. However, if managers interpret the shortfall as reflecting a broader technological shift, they perceive a need for more fundamental adaptation—requiring access to new knowledge, tools, and capabilities. In this context, local search and incremental change appear inadequate. Instead, firms turn to distant search strategies that involve forming ties with partners beyond their existing cluster. These BCTs provide access to non-redundant knowledge, unfamiliar domains, and emerging technologies that may not be available within local networks. Therefore, technological uncertainty heightens the perceived urgency and breadth of search, strengthening the link between negative performance feedback and BCT formation. However, two caveats apply. First, firms performing far below their aspiration levels may lack the resources needed to invest in new technologies or initiate distant alliances. Second, severe underperformance can diminish a firm's attractiveness as a partner in fast-moving technological ecosystems, further constraining its ability to form valuable BCTs (Ref & Shapira, 2017). Despite these constraints, the heightened salience of external threats under technological uncertainty increases the likelihood that underperforming firms will seek to realign their capabilities through nonlocal exploratory ties (see Figure 3.23.2).

> Hypothesis 5. Technological uncertainty strengthens the negative relationship between performance below (a) historical and (b) social aspiration levels and the formation of between-cluster ties (BCTs).

The moderating effect of technological uncertainty on the relationship between performance shortfall and BCT formation is especially pronounced when aspirations are socially derived, as underperformance relative to peers intensifies concerns about technological misalignment. In highly uncertain environments, such underperformance signals not just operational weakness but a failure to keep pace with emerging technologies. This perceived lag increases the risk of exclusion from dominant designs or evolving industry standards, particularly in ecosystems where early participation helps shape future trajectories (Tripsas, 1997). The urgency to respond is amplified when a firm is underperforming both historically and socially. However, firms that fall below their own historical aspirations but still outperform peers would perceive less risk of falling behind, whereas those performing poorly in comparison to others—despite meeting their past benchmarks—face stronger pressure to act. To avoid being locked out of these developments, firms are more likely to initiate bold exploratory moves, such as forming nonlocal alliances that grant access to novel and complementary technological capabilities when they perform below their social aspiration levels.

> Hypothesis 5c. The strengthening effect of technological uncertainty on the negative relationship between performance below aspiration and the formation of between-cluster ties (BCTs) is stronger when aspirations are based on social comparisons rather than historical performance.

For firms performing above their aspiration levels, the dynamics shift. Although high performance reduces the immediate pressure to change, performance above aspirations result in some slack resources that enables exploratory initiatives by loosening budget constraints and lowering the perceived cost of experimentation (Greve, 2003a). Under high technological uncertainty, managers may begin to doubt whether current success can be sustained. They may worry that future technological changes could render existing capabilities less relevant or obsolete. As a result, part of the firm's strong performance is heuristically attributed to favorable but temporary external conditions. While internal capabilities remain a central part of their narrative reinforced by self-esteem, a sense of overconfidence would also emerge, reinforcing the belief that the firm can maintain or extend its advantage despite volatility. This confidence, coupled with available resources, can motivate risk-taking behavior aimed at leveraging transient gains and expanding influence in the alliance network—both to strengthen the firm's position and to shape the direction of technological evolution.

Moreover, as a firm performs above aspiration levels, it gains both legitimacy and resources that can be leveraged to influence emerging technological trajectories in ways that reinforce its existing capabilities. This enhanced position increases the firm's attractiveness as a partner within the industry and can expand its centrality and reach within alliance networks. By aligning external developments with internal strengths, high-performing firms are better positioned to shape the direction of technological evolution. For example, the success of VHS was not solely due to technical superiority but also to strategic alliances and an open architecture approach—demonstrating that shaping dominant designs often depends on collaborative engagement as much as internal innovation (Utterback, 1996).

Thus, technological uncertainty moderates the effect of above-aspiration performance on BCT formation by amplifying both the opportunity and strategic rationale for proactive exploration and influence over emerging standards. Under such conditions, firms use BCTs not out of immediate necessity, but as a proactive hedge against future technological obsolescence (see Figure 3.2).

> Hypothesis 6. Technological uncertainty strengthens the positive relationship between performance above (a) historical and (b) social aspiration levels and the formation of between-cluster ties (BCTs).

Finally, the type of aspiration matters as firms experience technological uncertainty. Firms exceeding social aspirations perceive less urgency to change, as their relative advantage suggests alignment with current technological trends. In contrast, firms that exceed only their historical aspirations would still feel pressure to adapt and expand, particularly under high technological uncertainty, where past success offers little assurance of future relevance. Accordingly, the moderating effect of technological uncertainty on the relationship between above-aspiration performance and BCT formation is expected to be stronger when aspirations are historically rather than socially defined.

> Hypothesis 6c. The strengthening effect of technological uncertainty on the positive relationship between performance above aspiration and the formation of between-cluster ties (BCTs) is stronger when aspirations are based on historical performance rather than social comparisons.

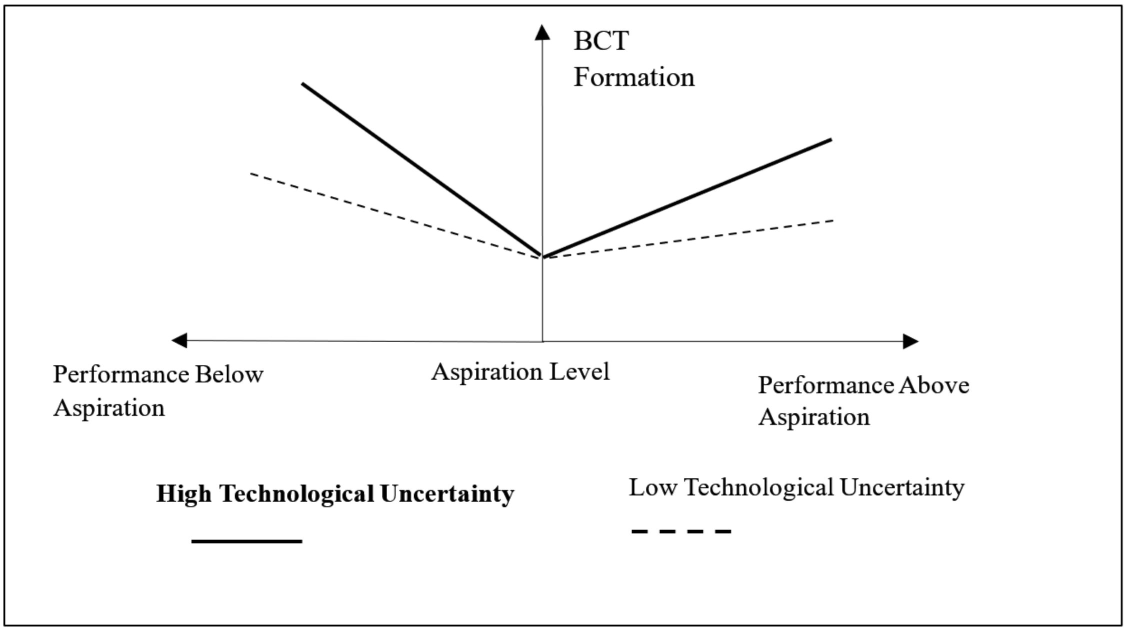

Figure 3.2 Moderating Effect of Technological Uncertainty on the Relationship Between Performance Below and Above Aspiration Levels and BCT Formation

4. METHOD

4.1 Data and Sample

4.1.1 Study Context

This study investigates a specific type of strategic alliance by focusing on the structure of alliance networks. Structurally, alliances can be classified into two types: within-cluster ties—collaborations among firms that are densely connected in the same cluster—and between-cluster ties (BCTs), which link firms across distinct network clusters. This structural classification highlights the different strategic roles alliances can play in knowledge access and network positioning.

Beyond structural distinctions, this study includes all alliance types to provide a comprehensive view of the alliance landscape. Equity alliances, such as joint ventures, involve shared ownership and resource commitment, while non-equity alliances are contractual in nature, including arrangements like licensing and co-marketing Reuer and Ariño (2007). These alliances vary in purpose and scope, spanning R&D, marketing, manufacturing, and technology exchange. Each type serves distinct strategic objectives—ranging from accessing new markets and capabilities to sharing risks and leveraging complementary resources.

The dataset comprises strategic alliances formed by North American public companies within manufacturing industries and the computer software service industry, covering the period from 1990 to 2020. The decision to begin the analysis in 1990 reflects a conservative approach, given that comprehensive and reliable alliance data only became available since the 1980s Schilling (2009). This research includes firms within the following Standard Industrial Classification (SIC) categories: Chemicals (281), Pharmaceuticals (283), Oil Products and Refining (29-), Computer Hardware (357), Household Electronic Equipment (365), Telecommunications Equipment and Services (366), Electronic Components (367), Aerospace Equipment (371), Automobiles and Parts (372), Medical Equipment (382), Measuring and Controlling Devices (384), and Computer Software (737). These industries were selected due to their extensive and active engagement in strategic alliances, allowing for direct comparison with prior studies that have examined alliance dynamics within these contexts Kogan et al. (2017); Schilling (2015). The industries included in the study are listed in Table 4.1.

Table 4.1 Industries Included in the Study

Industry	**SIC Code**
Chemicals	281
Pharmaceuticals	283
Oil Products and Refinery	29-
Computer (Hardware)	357
Household Electronic Equipment	365
Telecommunication Equipment & Services	366
Electronic Components	367
Aerospace Equipment	371
Medical Equipment	382
Measuring & Controlling Devices	384
Automobile and Parts	372
Computer (Software)	737

4.1.2 Data Sources

This study leverages multiple data sources. Alliance data were obtained from the Securities Data Corporation (SDC) Platinum database, which provides detailed information on alliance formation, including dates, partner identities, and alliance types (Schilling, 2009). Financial data was collected from COMPUSTAT, a database maintained by Standard & Poor's, which offers comprehensive historical financial records for publicly traded companies. Patent data, including filings, grants, and citations, were drawn from the United States Patent and Trademark Office (USPTO) database. In subsequent sections, I detail how these databases were used to operationalize and measure the variables employed in this study.

4.2 Variables

4.2.1 Dependent Variable

The dependent variable is the number of new between-cluster ties (BCTs) that each firm formed each year. A new BCT is defined as a newly established alliance between the focal firm and a partner in a different cluster within the same industry network. Two main phases were executed to get a reliable network and clusters.

In the first phase, after defining the industries, time period, and company nationalities, a thorough data cleaning process was carried out, including the removal of alliances involving unidentified partners. While preparing the edge lists (files with two columns indicating alliance partners), I split multi-partner alliances into separate dyadic ties. Previous research has either focused specifically on multi-partner alliances (e.g., Lavie, 2006), separated them from dyadic alliances (Rahman & Korn, 2014), or excluded them entirely due to the different mechanisms that govern these collaborations (Klossek et al., 2015; Lavie, 2006; Teng & Das, 2008). This is because multi-partner alliances might follow distinct dynamics compared to dyadic alliances. For instance, companies may join an association-type partnership primarily to enhance their status, as the collaboration typically involves low levels of risk, and outcomes tend to be more generalized with a larger number of partners. Additionally, the composition of partners may change over the course of the collaboration. Despite these complexities, I followed prior research that includes all types of alliances in the analysis, as any form of collaboration can contribute to information exchange and knowledge transmission (Schilling, 2015; Schilling & Phelps, 2007).

Further, network boundaries were defined at the industry level, such that if at least one firm in an alliance belonged to a given industry, the alliance was included in that industry's network. Following Rosenkopf and Padula (2008), I tracked firms over time using their CUSIP numbers to ensure consistent firm identification. When a firm was a subsidiary, its parent company was treated as the primary actor in the alliance. In cases of mergers or acquisitions, the alliances of the target firm were reassigned to the acquiring firm. Because alliance termination dates are not systematically recorded, prior studies assume fixed alliance durations. Following Schilling (2015), I assumed a three-year duration, meaning that the alliance network in each year consists of alliances formed during the previous three years.

Cluster detection. The other major step in identifying BCTs involved detecting clusters—a task with a long-standing tradition in social network analysis, where various algorithms have been developed to uncover densely connected groups within larger networks. Classic block modeling techniques, such as CONCOR and hierarchical clustering based on structural equivalence, have been widely applied in strategic management and social network research to identify network partitions (Nohria & Garcia-Pont, 1991; Rosenkopf & Padula, 2008; Walker et al., 1997). These methods conceptualize clusters (blocks, in their terminology) as groups of actors with similar relational profiles—typically defined by identical or near-identical patterns of connections. However, structural equivalence is a stringent criterion, making such approaches less suitable for large-scale, sparse networks where limited nodes may exhibit such uniformity (Schaub et al., 2023). As a result, these earlier methods often relied on manual refinement and validation of small, predefined groups—e.g., six to eight clusters in earlier studies—where researchers could monitor inter- and intra-cluster densities directly (Rosenkopf & Padula, 2008). While effective for small or mature industries with clear alliance patterns, these techniques struggle to detect meaningful structures in more complex, longitudinal datasets like the one used in this study.

In contrast, my use of community detection methods builds on more recent approaches that identify clusters as emergent structural formations based on network cohesion (Gulati et al., 2012; Kumar et al., 2022). This approach allows for the detection of densely connected subnetworks—without assuming homogeneity in relational profiles or strategic intent—making it particularly suited for analyzing evolving alliance networks across multiple industries. Therefore, the clustering algorithm used here does not seek to recover “strategic blocks” or “intentional coalitions,” but rather uncovers the structural architecture of interfirm connectivity. This methodological distinction reflects both the scale of the dataset and the theoretical orientation of this study—where clusters are treated not as strategy-aligned units, but as dense subnetworks shaped by alliance behavior.

To detect clusters, I employed the Louvain community detection algorithm (Blondel et al., 2008), which has been applied in organizational network studies (Bilgili et al., 2022; Kumar et al., 2022). Clusters were identified using the louvain.community package in Python. The algorithm optimizes modularity—a measure of the quality of a network’s division into clusters—by comparing the observed density of ties within clusters to what would be expected in a randomized network with the same degree distribution. High modularity indicates that more edges fall within clusters than expected by chance, suggesting a well-partitioned structure (Newman, 2004). Figure 4.1 illustrates this concept: both clusters and random networks have the same number of nodes and edges, but the left network exhibits clear clustering, whereas the right represents a random configuration. Modularity Q is calculated as:

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta\left(c_i, c_j\right) \tag{4.1}$$

where, A_ij is 1 if there is an edge between node i and node j (adjacency matrix element), k_i is the number of the edges attached to node i (degree of node i), c_i is the cluster to which node i is assigned, the δ function δ (u, v) is 1 if u = v and 0 otherwise and m is the total edges in the network. The more edges that exist between nodes $\sum_{i,j} A_{ij}$ which are also assigned to the same cluster ($\delta = 1$), the higher the modularity index.

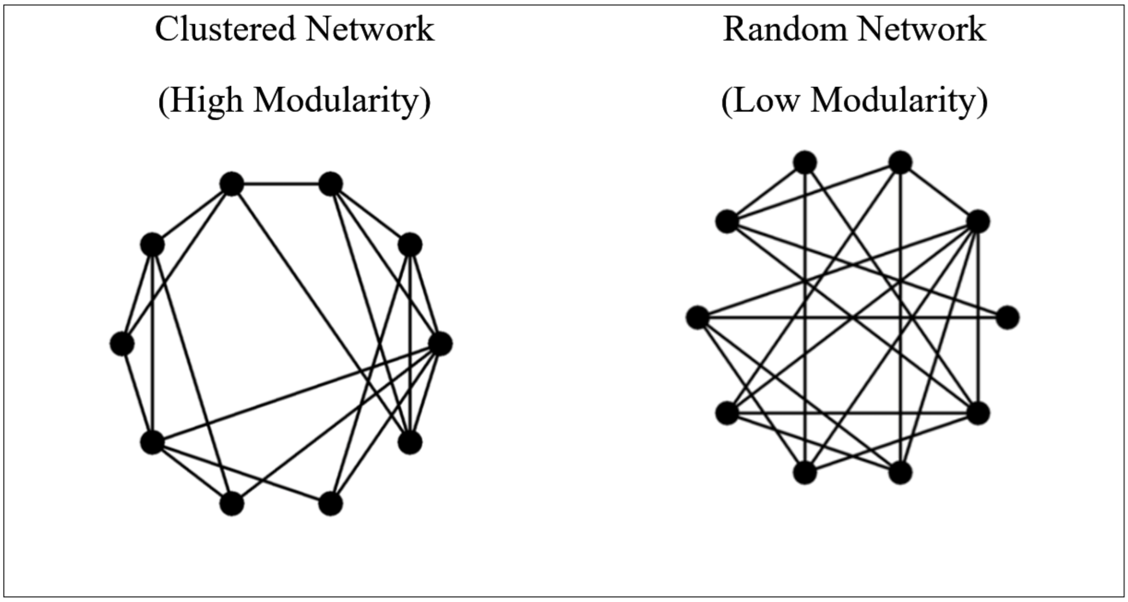

Figure 4.1 Comparison of Clustered and Random Networks

The Louvain method proceeds in two iterative phases. In the first phase, each node begins in its own cluster, and the algorithm evaluates whether moving a node to a neighboring cluster increases modularity. Reassignments continue until no further improvement is possible. In the second phase, each cluster becomes a single node, and the algorithm repeats on this aggregated network. This process continues until modularity can no longer be improved, producing a hierarchical partitioning of the network into cohesive communities.

To distinguish between different strategic intents behind alliances, I classified alliances as either marketing-related or technological using the alliance type flags provided in the SDC database. Marketing alliances included those marked with the Marketing Agreement, Supply Agreement, and Manufacturing Agreement flags, reflecting partnerships focused on distribution, procurement, or production. Technological alliances were identified using the following flags: Cross Licensing Agreement, Cross Technology Transfer, Exclusive Licensing Agreement, Licensing Agreement, Research & Development Agreement, and Technology Transfer. These categories capture alliances aimed at sharing, co-developing, or accessing technologies. Once BCTs were identified, each was labeled according to whether it fell under a marketing or technological alliance type.

After detecting clusters, I calculated relevant firm-level and network-level measures, including the count of BCTs and WCTs, cluster size and density, each firm's degree and betweenness centrality within its cluster, and the total number of clusters within each industry. Table 4.2 shows substantial variation across industries in the formation of new BCTs. The software industry exhibits the highest figures across all metrics, with an average of 3168 firms per year, 489 clusters, and 133 new BCTs—suggesting a highly fragmented yet densely interconnected ecosystem conducive to alliance formation. Pharmaceuticals and electronic components also show strong inter-cluster activity, with over 150 and 149 BCTs per year, respectively.

In contrast, industries such as oil products, automobile, and medical equipment operate in significantly smaller and less connected networks. These sectors report fewer than 100 firms and less than 4 new BCTs annually, indicating a relatively insular network structure. The data reflects both scale effects and industry-specific collaboration norms: sectors characterized by high technological complexity or modular innovation (e.g., software, pharma) tend to support more frequent and structurally diverse alliances.

My analysis on annual data shows that BCT formation peaked in the early 1990s, particularly in 1991 (mean = 0.304; max = 32), then declined steadily after 1995. The post-2000 period reflects a marked downturn, with annual averages falling below 0.05 and near-zero activity between 2010 and 2015. The data suggests that inter-cluster alliance formation was a concentrated phenomenon both sectorally and temporally, driven largely by a few active industries during a narrow window of time.

As an illustrative example, I selected the computer software industry—both due to its active involvement in BCT formation and because its leading firms are widely recognized. Figure 4.2 illustrates the clustered interfirm alliance network in the computer software industry in 2017. Each component represents a distinct cluster of firms. The zoomed-in view highlights a BCT between Amazon and Microsoft.

Table 4.2 Descriptive Statistics of New BCTs Formed by a Firm per Industry.

Industry	Mean	SD	Min	Max
Chemicals	0.027	0.226	0.000	4
Pharmaceuticals	0.056	0.434	0.000	18
Oil Products and Refinery	0.023	0.182	0.000	2
Computer (Hardware)	0.193	1.404	0.000	32
Household Electronic Equipment	0.005	0.107	0.000	4
Telecommunication Equipment & Services	0.050	0.569	0.000	18
Electronic Components	0.073	0.594	0.000	16
Aerospace Equipment	0.008	0.097	0.000	2
Medical Equipment	0.004	0.102	0.000	5
Measuring & Controlling Devices	0.008	0.129	0.000	4
Automobile and Parts	0.012	0.109	0.000	1
Computer (Software)	0.072	0.811	0.000	30

Figure 4.2 Clustered Alliance Network in the Computer Software Industry (2017)

4.2.2 Independent Variables

Performance below and above aspiration suggest the extent to which performance deviates from desired or aspirational levels. Measurement of performance relative to aspiration levels requires explaining three essential elements: performance measure and two aspiration measures, which include both historical and social aspirations.

Firm performance is measured using return on assets (ROA), calculated as the ratio of net income to total assets, a widely accepted proxy for performance in studies of aspiration-based research (O'Brien & David, 2014; Ref & Shapira, 2017). Consistent with prior studies (e.g., Hu et al., 2022; Miller & Chen, 2004), I used a spline function to split the performance feedback measure into two variables: performance below aspirations and performance above aspirations.

Aspiration levels refer to the benchmarks or reference points that organizations set to evaluate their performance. In behavioral research, aspiration levels are typically measured in two ways. Historical aspiration is based on the organization's past performance. It reflects an internal standard, capturing how well the firm expects to perform based on its own historical outcomes. Social aspiration compares the focal firm's performance to that of its peers or competitors. This external benchmark allows firms to evaluate their standing relative to others in the industry or market. The BTOF posits that managers assess performance as a deviation—positive or negative—from a target or aspiration level, and this evaluation shapes their behavior (Cyert & March, 1963; Greve, 2003b). Historical aspiration level is calculated as an exponentially weighted average of a firm's past performance and its prior aspiration level. The general formula is:

$$HA_{it} = aP_{it-1} + (1-a)HA_{it-1} \tag{4.2}$$

where HA_{it} represents the historical aspiration level of firm i at time t, P_{it-1} is the firm's performance in the previous period, HA_{it-1} is the firm's aspiration level in the previous period, and a is the weight assigned to past performance. Following Kuusela et al. (2017), I tested different values of a (0.75, 0.5, and 0.25) and selected $a = 0.25$, as the AIC and BIC values for the base models—including all variables but excluding interaction terms—were lowest at this level. Social aspiration level was measured as the average performance of firm's industry group (Hu et al., 2022).

Switching Model of Aspiration. Some studies choose the most salient aspiration level, assuming that firms shift their focus between historical and social aspirations based on their performance (March & Shapira, 1992) and follow upward-striving behavior (Bromiley, 1991). For example, firms underperforming relative to the industry aim to meet industry standards, while those outperforming the average focus on surpassing their own historical benchmarks (K. M. Park, 2007). This perspective has informed switching models, where firms dynamically alternate between aspiration types depending on relative performance. A typical representation of such models is:

$$\text{Aspiration}_{it} = I(P_{it} < \text{SA}_{it}) \cdot \text{SA}_{it} + I(P_{it} \geq \text{SA}_{it}) \cdot (1.05) \cdot \text{HA}_{it} \tag{4.3}$$

where the index function I returns 1 when the condition holds and 0 otherwise. When a firm performs below its social aspiration (SA), it sets its goal to match the SA level. If performance exceeds SA, the firm instead targets an improvement over its historical aspiration by a fixed adjustment factor of 1.05. This 1.05 value, commonly used in behavioral theory models, reflects a standard 5% upward revision in aspirations when firms exceed their reference point (Bromiley, 1991). This study employs the switching model of aspiration as a robustness check.

Performance relative to historical and social aspirations are operationalized as the difference between the firm's current performance (ROA at time t-1) and its historical and social aspirations. Following others, I split the variables indicating performance gaps into four using spline specification — two for when performance falls below historical and social aspirations, and two for when it exceeds them, capturing both directions separately (Goyal & Goyal, 2022; Greve, 2003a).

While both aspiration types reflect meaningful benchmarks, their behavioral salience may vary with environmental context. As argued in Section 3.2, uncertainty reduces the reliability of historical performance as a basis for decision-making. In volatile environments, firms are more likely to monitor peers and compare outcomes to others facing similar external challenges. This makes social aspirations particularly relevant for strategic decisions like alliance formation. Accordingly, I include both types of aspiration in the analysis but expect social aspiration discrepancies to exert stronger influence under uncertainty. For firms performing above their aspirations, the value of performance below aspiration was set to 0. Similarly, for firms performing below their aspirations, the value of performance above aspiration was set to 0. The expectation is that as a firm's performance improves, its negative attainment discrepancy will decrease if it is below aspiration and increase if it is above aspiration, reflecting its movement relative to its targets.

4.2.3 Moderators

I examine how market and technological uncertainty moderate the relationship between performance feedback and BCT formation. These moderators are operationalized using industry-level proxies—sales volatility and patent citation age, respectively. While these measures capture external volatility, uncertainty in a behavioral sense also involves how decision-makers perceive and interpret ambiguous conditions. Research in behavioral strategy suggests that uncertainty is cognitively constructed and may affect decision-making through attributional framing, selective attention, and heuristic reasoning (Gavetti et al., 2007; Jackson & Dutton, 1988; Milliken, 1987). While I do not directly observe how managers interpret uncertainty, I follow prior research in behavioral strategy by interpreting variation in responses to volatility as reflective of underlying cognitive processes such as attribution and heuristic reasoning (Barr, 1998; Maitland & Sammartino, 2015).

4.2.3.1 Market Uncertainty

Market uncertainty refers to the unpredictability of market trends and the inability of managers to forecast future industry demand levels based on available information (Oriani & Sobrero, 2008). Research typically measures market uncertainty using the standard deviation of market indicators like stock prices (Beckman et al., 2004; Howard et al., 2016). I did not adopt the conventional approach to measuring market uncertainty because it overlooks the role of trends that may reduce perceived unpredictability. For instance, a clear trend—such as a steady increase or decrease in stock prices—can provide directional information that helps firms anticipate future market conditions, thereby lowering perceived uncertainty. To account for this, I operationalized market uncertainty as the variance of residuals from AR(1) regressions on quarterly industry revenues, (Moon & Phillips, 2021). This approach isolates the unexplained fluctuations after accounting for historical trends, offering a more accurate measure of uncertainty as experienced by decision-makers. A higher residual variance indicates greater deviation from expected trends, and thus, greater market uncertainty.

4.2.3.2 Technological Uncertainty

Technological uncertainty was measured using the average age of patent citations in an industry (Laursen et al., 2017; Oriani & Sobrero, 2008). Using utility patent data from USPTO, I calculated the average age (in months) of backward citations for all patents within each industry. Shorter citation ages reflect faster knowledge turnover, indicating greater technological change and uncertainty. I applied a logarithmic transformation to reduce skewness and improve comparability across industries. Following Laursen et al. (2017), I inverted this measure by multiplying the average citation age by (-1) to align it with the logic of technological uncertainty—higher values indicate greater uncertainty.

Patents serve as externally validated indicators of novel invention, assessed through a formal examination process (Griliches, 1998). Patent counts have been shown to correlate with measures of innovation such as new product introductions (Basberg, 1987), and are widely regarded as robust proxies for knowledge creation (Trajtenberg, 1987). Research in strategic management also extensively use patents as measures of innovation outcome (Schilling, 2015) and to measure technological change (Oriani & Sobrero, 2008). However, patent data do not align neatly with industry classifications like SIC codes, since patents represent the underlying technology (like IPC, which is function-oriented) rather than the specific industry of application. Although several methods have attempted to assign patents to industries, such as concordance tables, have been criticized for being arbitrary or based on specific data sources (Griliches, 1998). To overcome this limitation, I adopt the approach of Oriani and Sobrero (2008), who started with firms classified by industry, linking patents to those firms to which they were granted and then mapped those firms to their respective industries, using this as a proxy for industry-level technological change.

4.2.4 Control Variables

To ensure robust analysis, I included several firm- and industry-level control variables that could influence BCT formation. I control for firms' R&D intensity, calculated as R&D expenditures divided by total sales, to account for differences in firms' innovation orientation and absorptive capacity that may influence their tendency to form BCTs. Firms with higher R&D intensity are generally more proactive in exploring novel knowledge (Cohen & Levinthal, 1990) and may be more likely to seek alliances beyond their current cluster, regardless of performance feedback. *Firm Size* is measured as the natural logarithm of total employees (Rosenkopf & Padula, 2008). Research suggests that firm size positively affects alliance formation (Stuart, 1998). Larger firms are typically more capable of absorbing coordination costs and leveraging existing networks, making them more likely to initiate or participate in alliances. *Organizational slack* refers to resources that exceed the minimum necessary to maintain operations and can be used to support adaptation, innovation, or search activities (Cyert & March, 1963; Nohria & Gulati, 1996). It allows firms to experiment without immediate performance pressure (Greve, 2003c). In this study, I focus on unabsorbed slack, measured as current assets minus current liabilities, scaled by total assets. This reflects liquid resources available for discretionary use that are not tied up in ongoing operations. This measure has been frequently employed in BTOF studies to operationalize a firm's search capacity (Greve, 2003a; Hu et al., 2022; Ref & Shapira, 2017). *Financial Health* is controlled using Altman's Z-score, a composite index of financial ratios that has been widely adopted to measure financial distress (Kuusela et al., 2017). Firms with lower Z-scores are more likely to face financial difficulties, which may make them less attractive as alliance partners or lead them to avoid risky initiatives (Iyer et al., 2019; Ref & Shapira, 2017).

I also included three network-related control variables. *Cluster density* is the normalized ratio of actual to possible ties within a cluster, reflecting the cohesion of local network structures; denser clusters may reduce the marginal value of forming external ties (Gulati et al., 2012). *Betweenness centrality* is calculated by identifying all shortest paths between every pair of firms in the network and counting how many of those paths pass through a given firm. Specifically, for each pair of nodes i and j, the proportion of shortest paths that pass through node k is summed across all pairs where $i \neq j \neq k$. The resulting measure reflects the extent to which a firm serves as an intermediary or broker, indicating its potential control over information flow (Borgatti & Everett, 2006). Both metrics have been used in alliance network studies to account for structural positioning effects on alliance formation (Cuypers et al., 2020; H. D. Kim et al., 2014).

At the industry level, *industry R&D intensity*—measured as the median R&D spending across all firms— captures the level of innovation-driven competitiveness of the industry and has been linked to greater alliance activity (Chen & Miller, 2007; O'Brien & David, 2014). *Industry Growth Opportunities*, proxied by the average market-to-book ratio, indicate the attractiveness and expansion potential of the industry, which can shape firms' strategic search and alliance formation patterns (O'Brien & David, 2014).

To account for *firm-specific uncertainty*, I followed Beckman et al. (2004) in controlling for idiosyncratic risk. I measured firm-specific uncertainty as the variance of residuals from AR(1) regressions on each firm's quarterly revenues, capturing fluctuations unexplained by historical trends. This method isolates unpredictable revenue shifts at the firm level and offers a more behaviorally meaningful proxy for the uncertainty faced by individual decision-makers. Finally, to account for temporal dynamics and significant external shocks to markets and the economy, I included controls for time trends (year) and specific events such as the Dot-Com bubble burst (2001), the Financial Crisis (2007-2008), and the COVID-19 (2019-2020) pandemic.

These dummies took value 1 for the even year(s) and 0 otherwise.

Outlier Treatment. Several financial variables—such as performance feedback (above and below aspiration levels), unabsorbed slack, and growth opportunities—showed extreme outliers. To reduce their influence, I chose to winsorize these variables at ± 4 standard deviations from the mean, replacing the extreme values with the nearest value within that range. Unlike studies that eliminate outliers entirely (e.g., Chen and Miller & 2007; Miller and Chen & 2004), this approach retains data integrity while minimizing the impact of extreme values (see for example Bromiley & Harris, 2014; Kuusela et al., 2017).

4.3 Analysis Process

Since the dependent variable—the number of new BCTs formed by each firm—is count-based, it exhibited a non-normal distribution, violating the assumptions of ordinary least squares (OLS) regression and resulting in inefficient estimates (W. H. Greene, 2000). In such cases, negative binomial (NB) regression is preferred, particularly when the count data display over-dispersion, where the variance exceeds the mean (Hausman et al., 1984). NB models improve upon Poisson regression by allowing the variance to differ from the mean. However, NB models rely on assumptions such as a moderate proportion of zeros, the absence of severe clustering (as seen in panel data), and no endogeneity.

Given the considerable number of firms that did not form any BCTs, this first assumption may not be fully met. One potential remedy is the zero-inflated negative binomial (ZINB) model, which accounts for excess zeros while addressing over-dispersion (Hilbe, 2011). However, Allison (2012) cautions against ZINB when over-dispersion caused by excess zeros can be adequately addressed using a standard NB model, which is simpler and often yields better fit. ZINB models are most appropriate when there is a clear two-stage data-generating process, which is not applicable here. Moreover, ZINB does not handle panel data structures well. In panel settings with repeated measures, other approaches such as fixed-effects, random-effects, generalized estimating equations (GEE), or multilevel models are more suitable for addressing firm-specific heterogeneity and time-related dependencies.

Nonetheless, NB models estimated through conditional likelihood may still fail to control for all time-invariant firm-level characteristics (Allison & Waterman, 2002;

W. Greene, 2007; Guimaraes, 2008). Therefore, I employed Poisson quasi-maximum likelihood (PQML) regression with robust standard errors. PQML produces consistent estimates under weaker distributional assumptions and is well suited for panel data settings (Cameron & Trivedi, 2005; Wooldridge, 2008).

For hypothesis testing involving interaction terms, I used moderation analysis. The interpretation of interaction effects in non-linear models differs from OLS, where interaction effects may still exist even when the coefficient on the interaction term is not statistically significant (Ai & Norton, 2003). In non-linear models such as negative binomial or Poisson regressions, the marginal effect of an interaction must be calculated directly, rather than inferred from coefficient estimates alone (Hilbe, 2011; Karaca-Mandic et al., 2012). Relying solely on the interaction term's coefficient can be misleading, as it does not capture the actual conditional effect of the focal variable at different levels of the moderator. Therefore, I used margins postestimation analysis in STATA SE 18.0 to compute predicted values and marginal effects across values of the moderator While some studies address this by splitting samples based on dichotomized moderators (e.g., Alcácer and Chung & 2007), such an approach introduces artificial cutoffs and measurement error (Aiken et al., 1991). Instead, I followed recommended best practices and used STATA's margins command to compute average marginal effects across a range of moderator values (Williams, 2012). This method provides a clearer interpretation of interaction effects by showing how the relationship between the independent and dependent variables changes at different levels of the moderator. The resulting plots illustrate whether the effect strengthens, weakens, or reverses under varying conditions of market or technological uncertainty.

Additionally, to assess potential multicollinearity, I conducted variance inflation factor (VIF) diagnostics. None of the VIF values exceeded the commonly accepted threshold of 5, indicating that multicollinearity was not a concern. Even after including interaction terms, all VIFs remained below 5, which falls well within acceptable limits according to established guidelines (Kennedy, 1992; Kutner et al., 2005).

Finally, to mitigate potential endogeneity concerns, I followed O'Brien and David (2014) and lagged all independent variables in the estimations. Moreover, applying fixed effects panel regressions helps control for time-invariant unobserved heterogeneity at the firm level, reducing omitted variable bias in estimating within-firm effects over time (Antonakis et al., 2010; Wooldridge, 2010). While alternative methods such as two-stage instrumental variable regressions can address endogeneity by isolating causal effects, they often result in less efficient estimates due to inflated standard errors (Wooldridge, 2016).

4.4 Results

4.4.1 Descriptive and Correlation Analysis

Table 4.3 presents summary statistics and Table 4.4 shows pairwise correlations for all variables included in the analysis. The dependent variable, BCT formation, has a highly skewed distribution (mean = 0.06, SD = 0.62), consistent with the rarity of BCTs. Additionally, the variance substantially exceeds the mean (SD/mean > 10), indicating overdispersion, which supports the use of Poisson models for estimating count outcomes (Cameron & Trivedi, 2013). Independent variables representing performance feedback relative to historical and social aspirations (PAHA, PBHA, PASA, PBSA) exhibit low to moderate intercorrelations, with the strongest being between PBHA and PBSA (r = 0.62), reflecting potential overlap in negative performance signals.

Moderators—market and technological uncertainty—are weakly correlated with both the performance feedback variables and the dependent variable, suggesting distinct variance contributions. Market uncertainty shows moderate correlation with firm size (r = 0.30) and cluster density (r = 0.35), and correlates negatively with technological uncertainty (r = –0.32). Some control variables, notably size, R&D intensity, and financial health, display moderate correlations with each other. For example, size is negatively correlated with R&D intensity (r = –0.45) and slack (r = –0.40), consistent with larger firms having relatively more stable financial structures but less unabsorbed slack. Financial health is positively correlated with PBSA (r = 0.60), indicating that underperforming firms with stronger financial positions (i.e., farther from bankruptcy) are more likely to perform near their social aspirations.

To mitigate potential multicollinearity, particularly in models with interaction terms, all continuous variables were mean-centered prior to estimation (Zhang et al., 2024). Following that, variance inflation factor (VIF) diagnostics confirmed that multicollinearity was not a significant concern for any of the models estimated, with all VIF values well were below 2.

Table 4.3 Descriptive Statistics

Variables	Mean	SD	Min	Max
1. BCTs	0.06	0.62	0.00	32.00
2. Performance Below Historical Aspiration (PBHA)	-0.07	0.14	-0.76	0.00
3. Performance Above Historical Aspiration (PAHA)	0.06	0.14	0.00	0.70
4. Performance Below Social Aspiration (PBSA)	-0.10	0.22	-1.08	0.00
5. Performance Above Social Aspiration (PASA)	0.11	0.14	0.00	0.72
6. Market Uncertainty (MU)	2.71	1.10	0.33	6.29
7. Technological Uncertainty (TU)	-4.71	0.25	-5.60	-4.25
8. R&D intensity	0.15	0.17	0.00	0.92
9. Size	-0.47	2.20	-6.91	6.76
10. Slack	4.21	4.74	0.00	34.73
11. Financial Health (FH)	1.06	3.81	-17.06	19.24
12. Firm-Specific Uncertainty (FSU)	24.74	119.83	0.00	1199.69
13. Cluster Density (CD)	0.21	0.23	0.01	1.00
14. Betweenness Centrality (BC)	0.34	0.39	0.00	1.00
15. Industry Growth Opportunities (IGO)	2.36	1.11	0.01	7.15
16. Industry R&D Intensity (Ind R&D)	4.53	1.16	-0.02	8.14

Table 4.4 Pairwise Correlations

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. BCTs	1															
2. PBHA	0.02***	1														
3. PAHA	-0.02***	0.21***	1													
4. PBSA	0.03***	0.62***	0.04***	1												
5. PASA	0.03***	0.24***	0.14***	0.36***	1											
6. Market U.	-0.06***	0.07***	-0.06***	0.07***	-0.11***	1										
7. Tech. U.	0.07***	-0.03***	0.03***	0	0.01**	-0.32***	1									
8. R&D intensity	-0.01**	-0.40***	0.09***	-0.57***	-0.20***	-0.17***	-0.01**	1								
9. Size	0.13***	0.23***	-0.22***	0.33***	0.10***	0.30***	-0.04***	-0.45***	1							
10. Slack	-0.03***	0.03***	0.10***	0.06***	0.10***	-0.11***	-0.09***	0.09***	-0.40***	1						
11. Fin. Health	0.03***	0.36***	-0.13***	0.60***	0.29***	0.00	0.08***	-0.53***	0.22***	0.40***	1					
12. Firm-Spec. U.	0.06***	0.06***	-0.06***	0.08***	0.01**	0.27***	-0.13***	-0.12***	0.42***	-0.11***	0.04***	1				
13. Cluster Density	-0.16***	0.05***	-0.03**	0.03**	-0.05***	0.35***	-0.28***	-0.16***	0.12***	-0.10***	-0.04**	0.12***	1			
14. Betweenness Cent.	0.16***	0.07***	-0.09***	0.08***	0.05***	0.23***	-0.18***	-0.21***	0.39***	-0.19***	0.03**	0.24***	0.45***	1		
15. Industry Growth Opp.	0.02***	-0.03***	0.11***	-0.08***	0.13***	-0.36***	0.19***	0.24***	-0.29***	0.20***	-0.07***	-0.15***	-0.23***	-0.20***	1	
16. Industry R&D Int.	-0.01	-0.02***	0.02***	-0.03***	0.07***	0.37***	-0.11***	0.05***	0.14***	-0.01**	-0.12***	0.22***	0.15***	0.15***	-0.02***	1

Note. *** p<0.01, ** p<0.05, * p<0.1

4.4.2 Main Effects and Interaction Results

Table 4.5 presents PQML regression estimates predicting new BCT formation across nine models. Model 1 includes only control variables. Models 2 and 3 estimate the baseline effects of attainment discrepancy to evaluate Hypotheses 1 and 2. Model 2 includes performance relative to historical aspirations, while Model 3 includes performance relative to social aspirations. Hypothesis 1 predicts that the coefficients on performance below aspiration— performance below historical aspiration (PBHA) in Model 2 and performance below social aspiration (PBSA) in Model 3—should be negative, indicating that as performance falls further below aspirations, the likelihood of forming BCTs increases (problemistic search). Conversely, Hypothesis 2 predicts positive coefficients on performance above aspiration— performance above historical aspiration (PAHA) and performance above social aspiration (PASA)—indicating slack-enabled search. Models 4 and 6 introduce market uncertainty to test its moderating effect. Hypotheses 3a and 3b predict that market uncertainty weakens the negative effect of PBHA and PBSA, respectively, with Hypothesis 3c expecting a stronger weakening effect for historical comparisons. Models 4 and 6 also allow evaluation of Hypotheses 4a and 4b, which state that market uncertainty strengthens the positive relationship between PAHA and PASA and BCT formation, with Hypothesis 4c predicting this strengthening is stronger for social than for historical comparisons. Models 5 and 7 examine technological uncertainty's moderating role. Hypotheses 5a and 5b propose that it strengthens the negative relationship between PBHA/PBSA and BCT formation, with 5c anticipating stronger effects for social comparisons. Finally, Models 8 and 9 include both uncertainty variables with historical and social comparisons, respectively, to assess potential joint influences and compare the relative strength of moderating effects.

The models are estimated on a sample of 3,398 firm-year observations, and log-likelihood values show improvement across specifications, with Model 1 at -4993.34 and the best-fitting models (7 and 9) reaching -2171.82 and -2171.29, respectively. Because the PQML model is nonlinear, coefficient signs alone cannot be used to evaluate interaction effects. Formal testing of moderation hypotheses relies on margins analysis, with graphical displays used to interpret the conditional marginal effects.

Table 4.5 PQML Regression Results (N=3,398)

DV: New BCTs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R&D intensity	0.05	0.57	0.42	0.49	0.59	0.23	0.39	0.50	0.29
	(0.33)	(0.48)	(0.48)	(0.49)	(0.48)	(0.49)	(0.48)	(0.50)	(0.48)
Size	0.09	0.08	0.07	0.07	0.08	0.08	0.15*	0.07	0.15*
	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)
Slack	-0.01	-0.02	-0.02	-0.01	-0.01	-0.02	-0.00	-0.01	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Financial Health	0.03	0.05	0.05	0.05	0.05	0.05	0.03	0.05	0.03
	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Firm-Specific Uncertainty	-0.00	-0.00	-0.00	-0.00*	-0.00	-0.00	-0.00	-0.00*	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Industry Growth Opportunities	-0.11***	-0.07	-0.07	-0.07	-0.07	-0.07	-0.06	-0.07	-0.06
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)
Industry R&D Intensity	0.24*	0.37**	0.37**	0.37**	0.38**	0.35**	0.23	0.38**	0.23*
	(0.14)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.14)	(0.16)	(0.14)
Cluster Density	0.29	-1.09***	-1.08***	-1.09***	-1.07***	-1.00***	-0.84**	-1.08***	-0.82**
	(0.18)	(0.38)	(0.38)	(0.38)	(0.38)	(0.37)	(0.35)	(0.38)	(0.35)
Betweenness Centrality	0.17	0.73***	0.72***	0.74***	0.74***	0.73***	0.69***	0.74***	0.69***
	(0.11)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.14)	(0.15)	(0.14)
year	-0.11***	-0.20***	-0.20***	-0.20***	-0.20***	-0.20***	-0.21***	-0.20***	-0.21***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Dummy DOTCOM	-0.85***	-0.89***	-0.92***	-0.89***	-0.90***	-0.89***	-0.71***	-0.89***	-0.71***
	(0.13)	(0.21)	(0.21)	(0.20)	(0.21)	(0.21)	(0.21)	(0.20)	(0.21)
Dummy FINCRS2007	-0.65***	-1.04***	-1.04***	-1.05***	-1.05***	-1.06***	-1.04***	-1.06***	-1.05***
	(0.10)	(0.20)	(0.21)	(0.20)	(0.20)	(0.21)	(0.21)	(0.20)	(0.21)
Dummy Covid19	0.72***	1.03***	1.02***	1.01***	1.04***	0.97***	0.81***	1.02***	0.79***
	(0.16)	(0.29)	(0.29)	(0.29)	(0.29)	(0.27)	(0.24)	(0.29)	(0.24)

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Table 4.5 (continued)

DV: New BCTs (t+1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Market Uncertainty (MU)		0.17*	0.18*	0.11	0.17*	0.09	0.14	0.11	0.10
		(0.09)	(0.09)	(0.10)	(0.09)	(0.11)	(0.09)	(0.10)	(0.10)
Technological Uncertainty (TU)		-2.82***	-2.88***	-2.78***	-2.91***	-2.63***	-1.97***	-2.87***	-1.90***
		(0.49)	(0.52)	(0.49)	(0.49)	(0.52)	(0.47)	(0.49)	(0.49)
Performance Below Historical Aspiration (PBHA)		0.84*		1.34**	0.78			1.33*	
		(0.43)		(0.63)	(0.64)			(0.78)	
Performance Above Historical Aspiration (PAHA)		-0.35		-1.47**	0.15			-0.95	
		(0.39)		(0.73)	(0.56)			(0.84)	
Performance Below Social Aspiration (PBSA)			0.31			0.45	-0.52		-0.25
			(0.38)			(0.56)	(0.63)		(0.79)
Performance Above Social Aspiration (PASA)			0.19			0.86**	2.32***		2.45***
			(0.34)			(0.41)	(0.50)		(0.50)
PBHA × MU				0.69				0.73	
				(0.64)				(0.64)	
PAHA × MU				-1.46**				-1.44**	
				(0.71)				(0.73)	
PBHA × TU					0.32			0.19	
					(2.03)			(2.02)	
PAHA × TU					-2.62			-2.65	
					(2.08)			(2.13)	
PBSA × MU						0.16			0.28
						(0.63)			(0.58)
PASA × MU						1.13***			0.29
						(0.41)			(0.47)
PBSA × TU							4.42**		4.19**
							(1.87)		(1.90)
PASA × TU							-10.24***		-10.01***
							(1.32)		(1.43)
Log pseudolikelihood	-4993.34	-2214.46	-2217.04	-2211.36	-2213.44	-2212.06	-2171.82	-2210.34	-2171.29

Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses.

The analysis of control variables reveals several consistent and theoretically meaningful patterns. Industry-level R&D intensity shows a robust positive association with new BCT formation across models, suggesting that technological dynamism at the sectoral level stimulates inter-cluster search. In contrast, firm-level R&D appears less consequential, with small and statistically insignificant coefficients.

Network characteristics show stronger and more consistent effects. Cluster density negatively predicts BCT formation, supporting the idea of a lock-in effect where high internal cohesion may constrain outward search by reducing the perceived need or capacity to connect across clusters (Gulati et al., 2012). Conversely, betweenness centrality has a consistently positive and highly significant effect, aligning with the expectation that structurally advantaged firms are more likely to initiate or attract inter-cluster ties due to their brokerage position (Gulati et al., 2012; Sytch et al., 2012).

Among temporal and contextual controls, all year dummies are negative and highly significant, suggesting a long-term decline in BCT formation over time, potentially due to market maturation or shifts in alliance strategies (Gulati et al., 2012; Schilling, 2015). The negative and significant coefficients for the Dotcom and Financial Crisis dummies indicate that macroeconomic disruptions suppress BCT activity, likely due to resource constraints or strategic retrenchment. Interestingly, the Covid-19 dummy is positive and significant, possibly reflecting a reactive broadening of search during a systemic shock that forced firms to look beyond existing ties.

Market and technological uncertainty show contrasting effects on BCT formation. Market uncertainty has a weakly positive effect in early models, suggesting that demand-side ambiguity may prompt broader search, though the significance does not persist consistently. In contrast, technological uncertainty exerts a large, negative, and robust effect across all models, indicating that high technological volatility deters average firms from forming between-cluster alliances—likely due to increased coordination costs and strategic risk under rapid technological change.

Model 2 provides a test of the baseline BTOF hypotheses without interaction effects. Here, PBHA is positively associated with BCT formation ($\beta = 0.84$, $p < 0.10$), contrary to the core prediction of problemistic search. A positive sign implies that higher performance (i.e., a smaller gap from aspirations) increases the likelihood of forming BCTs, inconsistent with the notion that search intensifies under shortfalls. PAHA is negatively associated with BCT formation but the effect is not significant even at the 90% confidence level in Model 2 ($\beta =$ ˘$0.35, p > 0.10$).

Model 3 introduces social aspiration variables. PBSA has a small, positive, and insignificant coefficient ($\beta = 0.31, p > 0.10$), offering no support for problemistic search. PASA's effect is also positive ($\beta = 0.19, p > 0.10$) and insignificant at the 90% confidence level. Thus, based on these models, there is no support for H1 (a & b) and H2 (a & b).

Model 4 includes both performance relative to historical aspiration and their interaction term with market uncertainty (MU). PBHA's effect is positive ($\beta = 1.34, p < 0.05$), again inconsistent with problemistic search. PAHA's effect is significantly negative ($\beta =$ ˇ$1.47, p < 0.05$), suggesting that firms exceeding historical aspirations reduce BCT activity, inconsistent with my slack-enabled predictions, supporting the decrease in motivation of problemistic search. In Model 5, where the interaction term with technological uncertainty (TU) is introduced, the effect of two measures of performance relative to historical aspiration remain statistically non-significant. In Model 6, PASA's effect is positive and significant ($\beta = 0.86, p < 0.05$), indicating that high performers relative to peers are more likely to engage in structural search, supporting a slack-enabled explanation, a support for H2.b. In Model 7, PASA's effect is strongly positive and significant ($\beta = 2.32, p < 0.01$), and PBSA is negative ($\beta =$ ˇ$0.52, p > 0.10$) but not significant. Models 8 and 9 replicate the significant positive effect of PASA, while the effects of PBHA and PBSA remain statistically insignificant.

Across specifications, the strongest and most consistent result is the positive effect of PASA, suggesting that BCTs are more likely when firms outperform their peers, consistent with slack-enabled behavior rather than search triggered by underperformance. Therefore, I find partial support for H2.b, while other baseline hypotheses receive no support.

To test the remaining hypotheses, I rely on marginal effects analysis based on average marginal effect estimates derived from Models 4 to 9. The marginal effects analysis reveals several significant interactions. The effect of PAHA on BCT formation becomes more negative as market uncertainty increases (Figure 4.3). Because the 95% confidence intervals in the margins plots overlapped at the extreme values of the uncertainty moderators, it was not possible to determine from the plots alone whether the marginal effects differed significantly across conditions. To formally test these differences, I conducted linear contrast tests comparing the marginal effects at the lowest and highest levels of uncertainty. A linear contrast test comparing the marginal effects of PAHA across low and high market uncertainty levels revealed a significant decline in effect size. Specifically, the effect was 3.02 units smaller under high uncertainty (z = –2.22, p = 0.026, 95% CI [–5.67, –0.36]), suggesting that firms are less likely to pursue exploratory alliances when exceeding their historical targets under high market volatility, a finding against the prediction of H4.a. Conversely, the effect of PASA strengthens with market uncertainty (Figure 4.4), indicating that high-performing firms relative to peers are more inclined to expand their search scope when facing external demand-side unpredictability. This finding supports H4.b.

Turning to technological uncertainty, the effect of PBSA increases with technological uncertainty: although mostly negative at low uncertainty, the effect approaches zero as uncertainty rises. This pattern may reflect reduced responsiveness to peer-based shortfalls when the technological environment renders performance aspirations less salient (Figure 4.5). A linear contrast test comparing the marginal effects of PBSA under low versus high technological uncertainty showed a significant increase in effect size under high uncertainty. Specifically, the marginal effect was 2.20 units larger in high uncertainty contexts ($z = 2.27$, $p = 0.023$, 95% CI [0.30, 4.11]), indicating that the positive consequences of underperformance diminish substantially under high technological uncertainty, contrary to the prediction stated in H5b. In contrast, the effect of PASA on BCT formation diminishes as technological uncertainty rises, becoming indistinguishable from zero at high levels (Figure 4.6). This suggests that firms exceeding their historical aspirations are less likely to engage in cross-cluster search when facing technological turbulence, potentially due to a preference for exploiting existing capabilities rather than exploring uncertain external opportunities.

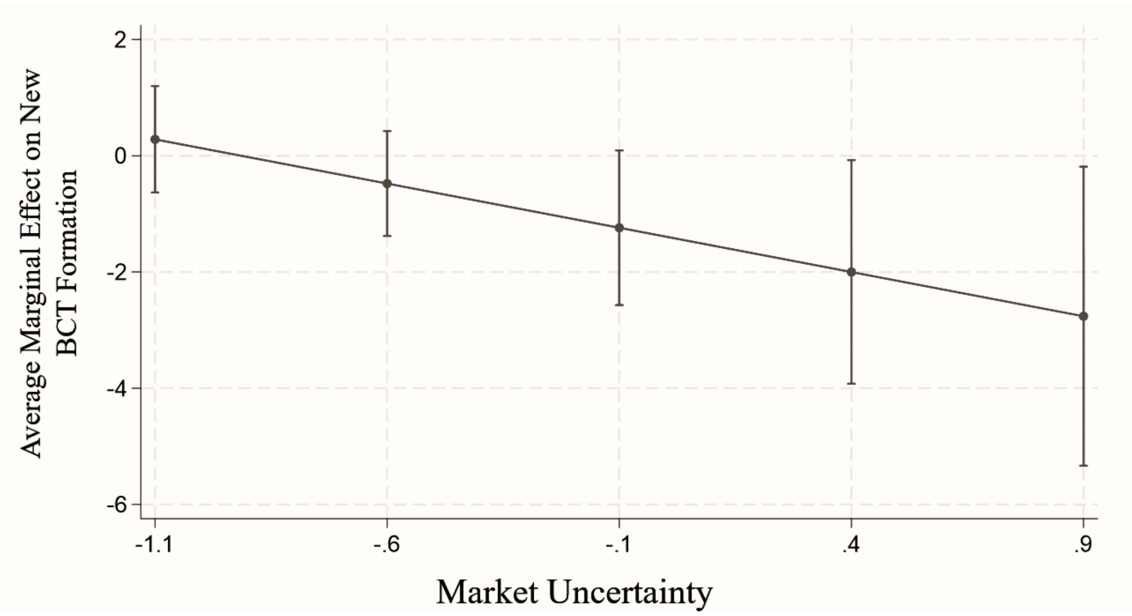

Figure 4.3 Marginal Effect of Performance Above Historical Aspirations on New BCT Formation at Varying Levels of Market Uncertainty

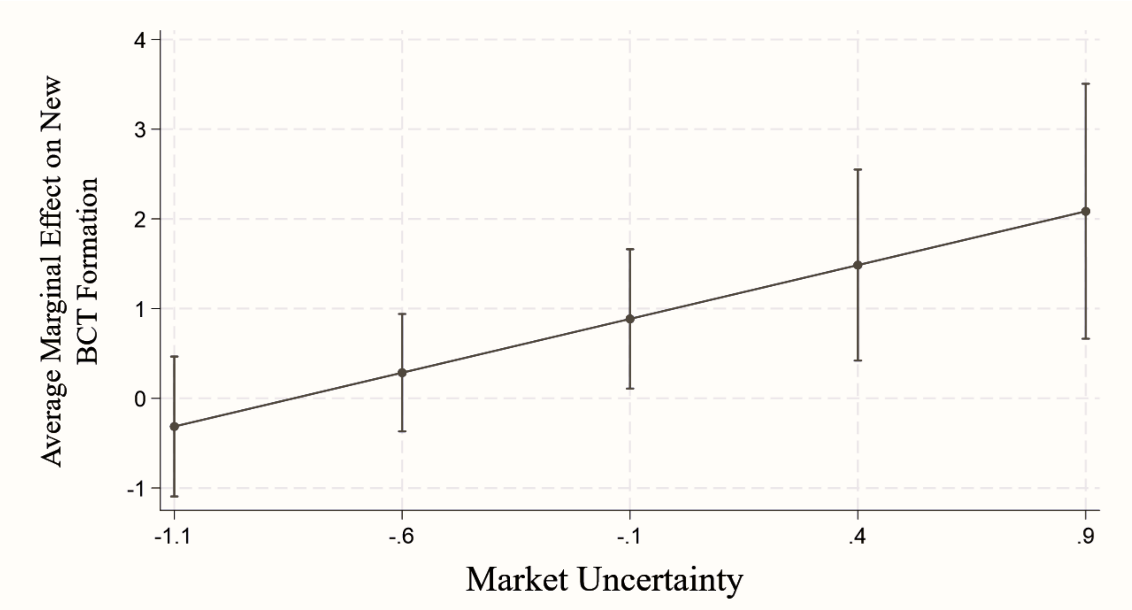

Figure 4.4 Marginal Effect of Performance Above Social Aspirations on New BCT Formation at Varying Levels of Market Uncertainty

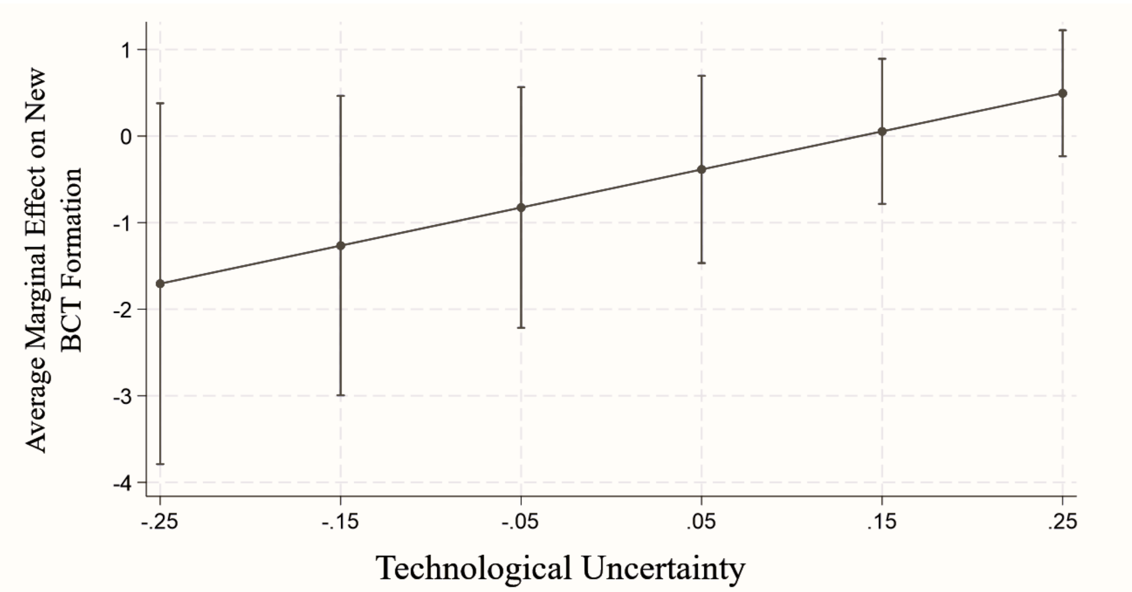

Figure 4.5 Marginal Effect of Performance Below Social Aspirations on New BCT Formation at Varying Levels of Technological Uncertainty

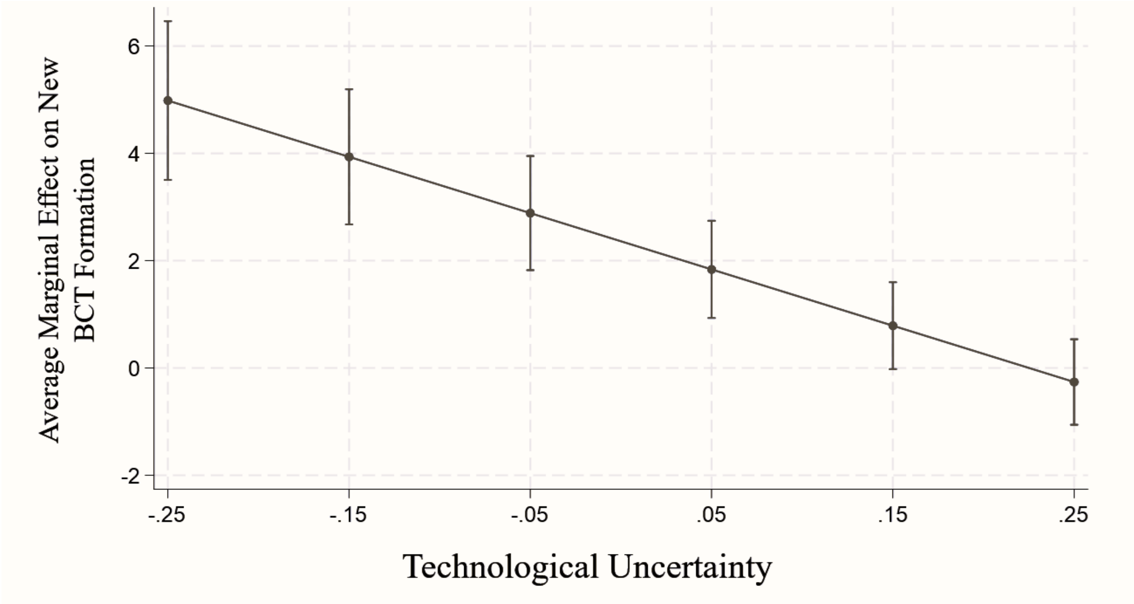

Figure 4.6 Marginal Effect of Performance Above Social Aspirations on New BCT Formation at Varying Levels of Technological Uncertainty

In sum, the analysis provides empirical support for H2b and H4b, indicating that firms performing above their social aspiration levels are more likely to form BCTs, and that this effect strengthens under high market uncertainty. In contrast, H1a, H1b, and H2a are not supported: performance below aspiration levels, whether historical or social, does not increase BCT formation, and performance above historical aspirations is either insignificant or negatively associated with BCTs. Among the interaction hypotheses, H4a, H5a, H5b, H6a, and H6b are not supported, with some effects reversing direction relative to theoretical expectations. These results suggest that positive deviations from social aspirations—especially in uncertain market conditions—are more reliable triggers for structural search than negative performance gaps, challenging the core prediction of problemistic search.

The comparative hypotheses (H3c, H4c, H5c, and H6c), which predict differences in the strength of moderation effects across aspiration referents, were not uniformly testable. In most cases—particularly for H3c and H6c—the underlying interaction effects were statistically insignificant or unstable, making formal comparisons theoretically and empirically inappropriate. However, two cases warrant further reflection. First, H4c is supported: the positive effect of PASA on BCT formation strengthened significantly under market uncertainty, whereas the effect of PAHA became more negative—clearly indicating a stronger motivational role for social comparisons in uncertain market environments. Second, H5c is more ambiguous. While only PBSA showed a significant response to technological uncertainty, the effect moved in the opposite direction of the prediction—becoming more positive rather than more negative. Thus, although H5c is not supported, the results suggest that peer-based performance gaps may remain behaviorally salient under technological uncertainty, even if they do not motivate search in the way problemistic theories anticipate. Table 4.6 provides a summary of the hypotheses and the corresponding empirical results.

Table 4.6 Summary of Hypotheses and Empirical Findings

Hypothesis	Predictor / Interaction	Expectation	Result
H1a	PBHA	Negative	Not supported (non-significant)
H1b	PBSA	Negative	Not supported (non-significant)
H2a	PAHA	Positive	Not supported (non-significant or negative)
H2b	PASA	Positive	Supported
H3a	PBHA × MU	Positive	Not supported
H3b	PBSA × MU	Positive	Not supported
H3c	PBSA vs. PBHA × MU	Social < Hist.	Not supported (interactions not significant)
H4a	PAHA × MU	Positive	Not supported (negative interaction)
H4b	PASA × MU	Positive	Supported
H4c	PASA vs. PAHA × MU	Social > Hist.	Supported
H5a	PBHA × TU	Negative	Not supported
H5b	PBSA × TU	Negative	Not supported (effect reversed)
H5c	PBSA vs. PBHA × TU	Social > Hist.	Not supported
H6a	PAHA × TU	Positive	Not supported
H6b	PASA × TU	Positive	Not supported (effect reversed)
H6c	PASA vs. PAHA × TU	Social < Hist.	Not supported

Note. PBHA: Performance Below Historical Aspiration; PBSA: Performance Below Social Aspiration; PAHA: Performance Above Historical Aspiration; PASA: Performance Above Social Aspiration; MU: Market Uncertainty; TU: Technological Uncertainty

4.5 Robustness Analysis

To assess the robustness and generalizability of the baseline findings, I conduct a series of complementary analyses. These include testing an alternative aspiration model, revising the measure of technological uncertainty, exploring disaggregated outcomes for BCT types, and extending the analysis to within-cluster ties (WCTs). Each serves to validate or qualify the main results by probing their sensitivity to modeling assumptions and operationalizations.

4.5.1 Lagged BCTs

There are three main reasons why I did not include lagged BCTs as explanatory variables in the main models. First, including a lagged dependent variable can absorb a substantial portion of the variance that would otherwise be explained by performance feedback, potentially obscuring the behavioral mechanisms central to the theory. Second, incorporating lagged outcomes raises endogeneity concerns, particularly due to the correlation between past values and unobserved firm-specific effects. Addressing such concerns typically requires more complex estimation strategies beyond the scope of the current analysis. Third, postestimation margins analysis cannot be conducted in STATA for dynamic panel models.

In this robustness check, I included both prior new BCTs and existing BCTs as additional explanatory variables in the models to account for the possibility that BCT formation is influenced by firms' past BCT decisions—that is, that the system exhibits memory. The results indicate that the coefficients of the lagged BCT variable and existing BCTs are not statistically significant, likely due to the relatively low frequency and limited variance of BCTs compared to other types of alliances. Importantly, the coefficients of the key explanatory variables and their interactions with the moderators remained largely unchanged (see Table 4.7).

Table 4.7 PQML Regression Results Including Lagged and Existing BCTs (N=3,287)

DV: New BCTs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged New BCTs	0.02**	0.01*	0.01*	0.01*	0.01*	0.01	0.01	0.01*	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Existing BCTs	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R&D intensity	0.14	0.61	0.46	0.53	0.63	0.28	0.41	0.54	0.32
	(0.40)	(0.47)	(0.46)	(0.48)	(0.47)	(0.47)	(0.47)	(0.49)	(0.47)
Size	0.02	0.07	0.06	0.07	0.07	0.08	0.14*	0.06	0.14*
	(0.10)	(0.09)	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)
Slack	-0.03	-0.02	-0.02	-0.01	-0.01	-0.02	-0.00	-0.01	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Financial Health	0.07**	0.05	0.05	0.05	0.05	0.05	0.03	0.05	0.03
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Firm Specific Uncertainty	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Industry Growth Opportunities	-0.13**	-0.08*	-0.07*	-0.08*	-0.08*	-0.07	-0.06	-0.08*	-0.06
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Industry R&D Intensity	0.39***	0.33**	0.33**	0.33**	0.33**	0.32**	0.21	0.34**	0.21
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)	(0.14)	(0.13)
Cluster Density	-0.59	-0.97***	-0.97***	-0.97***	-0.95***	-0.91**	-0.78**	-0.96***	-0.77**
	(0.38)	(0.36)	(0.36)	(0.36)	(0.36)	(0.36)	(0.33)	(0.36)	(0.34)
Betweenness Centrality	0.67***	0.69***	0.69***	0.70***	0.70***	0.69***	0.66***	0.71***	0.67***
	(0.13)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
year	-0.19***	-0.19***	-0.20***	-0.19***	-0.19***	-0.20***	-0.21***	-0.19***	-0.21***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Dummy DOTCOM	-0.95***	-0.88***	-0.90***	-0.87***	-0.88***	-0.89***	-0.71***	-0.87***	-0.71***
	(0.21)	(0.20)	(0.21)	(0.20)	(0.20)	(0.20)	(0.21)	(0.20)	(0.21)
Dummy FINCRS2007	-0.82***	-1.03***	-1.03***	-1.04***	-1.04***	-1.05***	-1.04***	-1.05***	-1.04***
	(0.21)	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)	(0.21)	(0.20)	(0.21)
Dummy Covid19	1.65***	1.00***	0.99***	0.98***	1.01***	0.95***	0.80***	0.99***	0.78***
	(0.34)	(0.29)	(0.29)	(0.29)	(0.29)	(0.28)	(0.24)	(0.29)	(0.24)

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Table 4.7 (continued)

DV: New BCTs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Market Uncertainty (MU)		0.20**	0.20**	0.14	0.20**	0.12	0.16*	0.14	0.12
		(0.08)	(0.09)	(0.10)	(0.08)	(0.10)	(0.09)	(0.10)	(0.10)
Technological Uncertainty (TU)		-2.73***	-2.80***	-2.69***	-2.81***	-2.58***	-1.95***	-2.78***	-1.89***
		(0.48)	(0.50)	(0.47)	(0.47)	(0.51)	(0.47)	(0.47)	(0.49)
Performance Below Historical Aspiration (PBHA)		0.90**		1.38**	0.88			1.42*	
		(0.43)		(0.63)	(0.64)			(0.79)	
Performance Above Historical Aspiration (PAHA)		-0.37		-1.49**	0.12			-0.98	
		(0.39)		(0.74)	(0.56)			(0.83)	
Performance Below Social Aspiration (PBSA)			0.35			0.51	-0.49		-0.21
			(0.38)			(0.56)	(0.63)		(0.79)
Performance Above Social Aspiration (PASA)			0.21			0.81**	2.27***		2.37***
			(0.32)			(0.39)	(0.50)		(0.51)
PBHA × MU				0.67				0.72	
				(0.64)				(0.64)	
PAHA × MU				-1.46**				-1.45**	
				(0.71)				(0.72)	
PBHA × TU					0.14			0.02	
					(2.04)			(2.03)	
PAHA × TU					-2.61			-2.64	
					(2.07)			(2.13)	
PBSA × MU						0.18			0.29
						(0.64)			(0.58)
PASA × MU						1.02**			0.23
						(0.41)			(0.47)
PBSA × TU							4.35**		4.13**
							(1.88)		(1.90)
PASA × TU							-9.99***		-9.81***
							(1.45)		(1.53)
Log pseudolikelihood	-2252.02	-2209.70	-2212.51	-2206.59	-2208.65	-2208.43	-2170.56	-2205.53	-2170.15

Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses.

4.5.2 Switching Aspiration Model

The switching aspiration model (Bromiley, 1991; Deephouse & Wiseman, 2000; K. M. Park, 2007; Wiseman & Bromiley, 1996) defines a single aspiration level that shifts based on performance relative to industry. Firms performing below the industry average adopt the industry level as their aspiration, while those above it set aspirations at a modest improvement over their own past performance (e.g., 1.05× prior performance). This rule-based approach avoids the arbitrariness of weighted models, reflects attention-switching logic central to BTOF (Ocasio, 1997), and reduces information-processing demands while retaining theoretical grounding in both self- and socially-referent benchmarks (Bromiley & Harris, 2014). As this model blends social and historical reference points into a single benchmark, hypotheses based on distinct aspiration gaps no longer apply. The analysis instead evaluates whether overall performance feedback effects and their moderation by uncertainty persist under this unified aspiration framework.

The switching aspiration model (Table 4.8) yields no significant performance feedback effects on BCT formation. Neither performance below nor above the switching aspiration shows robust associations, and none of the interaction terms with market or technological uncertainty reach significance using margins post estimation analysis. These null effects may reflect the limited applicability of threshold-based rules in contexts characterized by ambiguity and volatility (see Dong, 2021). Rather than following fixed switching logics, firms may rely on contextual cues, ad hoc reasoning, or perceived partner visibility when deciding whether to form BCTs.

Table 4.8 PQML Regression Results Using the Switching Aspiration Model (N=3,398)

DV: New BCTs	(1)	(2)	(3)	(4)	(5)
R&D intensity	0.14	0.43	0.30	0.39	0.27
	(0.42)	(0.47)	(0.47)	(0.47)	(0.48)
Size	-0.02	0.02	0.01	0.02	0.01
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Slack	-0.02	-0.02	-0.02	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Financial Health	0.06*	0.05	0.05	0.05	0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Industry Growth Opportunities	-0.11**	-0.06	-0.06	-0.06	-0.06
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Industry R&D Intensity	0.35**	0.30*	0.30*	0.30*	0.30*
	(0.15)	(0.16)	(0.16)	(0.16)	(0.16)
Cluster Density	-0.78*	-1.11***	-1.11***	-1.11***	-1.12***
	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)
Betweenness Centrality	0.75***	0.76***	0.76***	0.76***	0.77***
	(0.15)	(0.16)	(0.16)	(0.16)	(0.16)
year	-0.19***	-0.20***	-0.20***	-0.20***	-0.20***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Dummy DOTCOM	-0.90***	-0.82***	-0.82***	-0.82***	-0.82***
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
Dummy FINCRS2007	-0.83***	-1.02***	-1.02***	-1.02***	-1.02***
	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)
Dummy Covid19	1.64***	0.98***	0.97***	0.98***	0.97***
	(0.34)	(0.30)	(0.30)	(0.30)	(0.30)
Market Uncertainty (MU)		0.16*	0.11	0.17*	0.11
		(0.10)	(0.11)	(0.10)	(0.12)
Technological Uncertainty (TU)		-2.73***	-2.70***	-2.87***	-2.83***
		(0.46)	(0.46)	(0.47)	(0.47)
Performance Below Switching Aspiration (PBSWA)		0.35	0.82	-0.02	0.44
		(0.34)	(0.58)	(0.54)	(0.71)
Performance Above Switching Aspiration (PASWA)		-0.14	-0.57	0.04	-0.38
		(0.52)	(0.84)	(0.77)	(1.00)
PBSWA × MU			0.63		0.56
			(0.63)		(0.63)
PASWA × MU			-0.55		-0.53
			(0.86)		(0.86)
PBSWA × TU				1.82	1.64
				(1.70)	(1.68)
PASWA × TU				-0.99	-0.97
				(2.74)	(2.78)
Log pseudolikelihood	-2323.78	-2284.48	-2283.65	-2283.80	-2283.11

Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses.

4.5.3 An Alternative Measure of Market Uncertainty

To evaluate the robustness of the market uncertainty effect, I replaced the baseline measure with the variance of residuals from AR(1) regressions on monthly average industry stock prices. This approach captures idiosyncratic volatility after removing autocorrelated trends, offering a detrended and temporally stable indicator of market uncertainty. Stock return volatility, is widely used as a proxy for market uncertainty in strategic and financial research (e.g., Beckman et al., 2004; Liang and Mei, 2019), and this specification ensures that short-term fluctuations are not conflated with long-term trends or seasonality.

The baseline results of PMQL regressions with the alternative market uncertainty measure remain largely consistent. The positive effect of PASA on BCT formation persists, while other performance feedback variables remain insignificant or directionally inconsistent. The most notable change appears in the market uncertainty moderation results: under the alternative market uncertainty measure, the effect of PAHA on BCT formation shifts from negative to positive in high-uncertainty conditions, aligning more closely with the contingency logic proposed in H4a (Figure 4.7). I expected that overperforming firms, under such conditions, would act opportunistically by expanding their network to pursue opportunities aligned with their capabilities and external conditions.

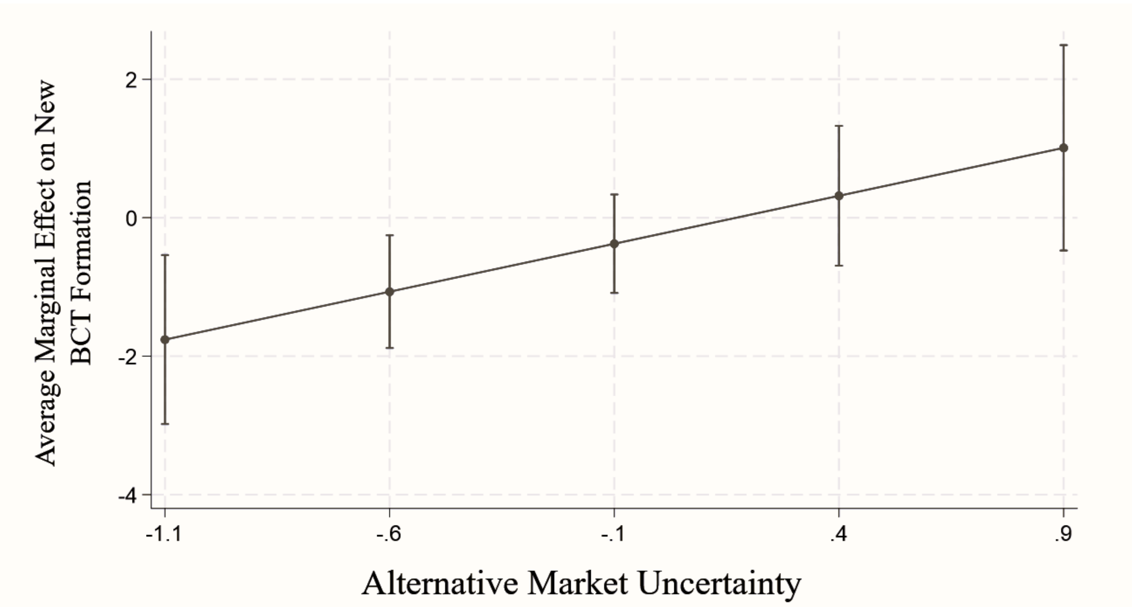

Figure 4.7 Marginal Effect of Performance Above Historical Aspirations on New BCT Formation at Varying Levels of Alternative Market Uncertainty

4.5.4 Marketing and Technological BCTs

Here, I decompose the dependent variable to examine new BCTs oriented toward marketing and technological domains separately. This allows assessment of whether performance feedback and uncertainty differentially affect strategic search in distinct knowledge areas, reflecting domain-specific exploratory logics. Disaggregating BCTs into marketing and technological domains reveals that several previously significant interactions lose significance, likely due to reduced statistical power as fewer firms form each specific type of BCT. Table 4.9 and Table 4.10 present the corresponding PQML regression results. Marginal effects analysis was used to draw final conclusions about interaction patterns.

For marketing-oriented BCTs, performance feedback variables such as PBHA and PBSA are not statistically significant. However, the interaction between PASA and market uncertainty remains positive and significant, a result confirmed by the margins analysis. Similarly, interactions between performance feedback relative to social aspirations and technological uncertainty mirror the patterns observed in the baseline models (see Table 4.9).

For technological BCTs, performance effects are even less pronounced—PBHA, PAHA, and PBSA show no significant associations. Only PASA remains significant in models that include technological uncertainty, consistent with a slack-enabled search under stable technological conditions. Additionally, the interaction between PAHA and market uncertainty is significant, as confirmed by the margins analysis (see Table 4.9 and Table 4.10). Overall, these findings suggest that the relationship between performance feedback and BCT formation under market and technological uncertainties is domain-specific, depending on the type of knowledge being pursued and the strategic logic underlying each BCT type.

Table 4.9 PQML Regression Results Using New Marketing BCTs as Dependent Variable (N=2,640)

DV: New Marketing BCTs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R&D intensity	0.35	0.60	0.54	0.56	0.61	0.19	0.33	0.56	0.09
	(0.62)	(0.65)	(0.65)	(0.66)	(0.65)	(0.64)	(0.67)	(0.66)	(0.65)
Size	-0.01	0.01	0.03	0.01	0.01	0.05	0.10	0.01	0.11
	(0.12)	(0.11)	(0.11)	(0.12)	(0.11)	(0.11)	(0.12)	(0.11)	(0.11)
Slack	0.01	0.01	0.01	0.01	0.01	0.02	0.03	0.01	0.03
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Financial Health	0.04	0.03	0.03	0.02	0.03	0.02	0.01	0.02	0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Industry Growth Opportunities	-0.08	-0.02	-0.02	-0.02	-0.02	-0.01	-0.00	-0.02	-0.00
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)
Industry R&D Intensity	0.48***	0.42***	0.45***	0.42***	0.43***	0.41***	0.32*	0.43***	0.31*
	(0.16)	(0.15)	(0.16)	(0.15)	(0.15)	(0.16)	(0.19)	(0.15)	(0.19)
Cluster Density	-0.14	-0.50	-0.48	-0.51	-0.49	-0.40	-0.35	-0.50	-0.30
	(0.52)	(0.49)	(0.49)	(0.50)	(0.49)	(0.49)	(0.47)	(0.50)	(0.47)
Betweenness Centrality	0.55***	0.56***	0.55***	0.57***	0.56***	0.55***	0.53***	0.57***	0.53***
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.18)	(0.19)	(0.18)
year	-0.23***	-0.24***	-0.24***	-0.24***	-0.24***	-0.24***	-0.25***	-0.24***	-0.25***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Dummy DOTCOM	-0.55***	-0.49**	-0.57***	-0.49**	-0.49**	-0.55***	-0.40*	-0.49**	-0.41*
	(0.20)	(0.20)	(0.21)	(0.20)	(0.20)	(0.21)	(0.22)	(0.20)	(0.21)
Dummy FINCRS2007	-0.38*	-0.67***	-0.66***	-0.68***	-0.67***	-0.70***	-0.68***	-0.68***	-0.70***
	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)	(0.24)	(0.24)	(0.23)	(0.24)
Dummy Covid19	2.15***	1.31**	1.32**	1.29**	1.31**	1.27***	1.11***	1.29**	1.07***
	(0.60)	(0.52)	(0.52)	(0.51)	(0.52)	(0.49)	(0.42)	(0.51)	(0.41)

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Table 4.9 (continued)

DV: New Marketing BCTs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Market Uncertainty (MU)		0.25**	0.27**	0.20*	0.25**	0.15	0.22**	0.20*	0.14
		(0.11)	(0.11)	(0.11)	(0.11)	(0.13)	(0.11)	(0.12)	(0.12)
Technological Uncertainty (TU)		-2.92***	-3.12***	-2.88***	-2.96***	-2.78***	-2.60***	-2.90***	-2.40***
		(0.56)	(0.58)	(0.56)	(0.56)	(0.60)	(0.62)	(0.56)	(0.65)
Performance Below Historical Aspiration (PBHA)		0.63		1.08	0.67			1.21	
		(0.55)		(0.86)	(0.82)			(1.17)	
Performance Above Historical Aspiration (PAHA)		-0.81*		-1.65*	-0.56			-1.44	
		(0.48)		(0.86)	(0.63)			(1.07)	
Performance Below Social Aspiration (PBSA)			-0.09			0.31	-1.16		-0.69
			(0.41)			(0.78)	(0.79)		(1.15)
Performance Above Social Aspiration (PASA)			0.71*			1.50***	2.65***		3.00***
			(0.40)			(0.53)	(0.57)		(0.62)
PBHA × MU				0.65				0.69	
				(0.78)				(0.81)	
PAHA × MU				-1.15				-1.13	
				(0.88)				(0.88)	
PBHA × TU					-0.19			-0.49	
					(2.72)			(2.83)	
PAHA × TU					-3.98			-3.78	
					(2.50)			(2.55)	
PBSA × MU						0.48			0.46
						(0.79)			(0.77)
PASA × MU						1.40**			0.84
						(0.60)			(0.68)
PBSA × TU							4.77**		4.31*
							(2.37)		(2.47)
PASA × TU							-9.17***		-8.52***
							(2.33)		(2.32)
Log pseudolikelihood	-1539.67	-1514.38	-1514.27	-1513.25	-1514.25	-1509.37	-1496.76	-1513.11	-1494.83

Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses.

Table 4.10 PQML Regression Results Using New Technological BCTs as Dependent Variable (N=2,825)

DV: New Technological BCTs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R&D intensity	0.18	0.44	0.13	0.44	0.48	0.00	0.07	0.46	0.05
	(0.44)	(0.52)	(0.52)	(0.54)	(0.53)	(0.55)	(0.53)	(0.55)	(0.56)
Size	-0.00	0.03	0.03	0.03	0.03	0.04	0.12	0.03	0.12
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)	(0.11)	(0.11)	(0.10)
Slack	-0.02	-0.01	-0.02	-0.01	-0.01	-0.02	-0.01	-0.01	-0.00
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)
Financial Health	0.04	0.03	0.04	0.03	0.03	0.04	0.02	0.03	0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)
Industry Growth Opportunities	-0.12**	-0.07	-0.08*	-0.07	-0.07	-0.07	-0.06	-0.07	-0.06
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Industry R&D Intensity	0.24	0.17	0.16	0.17	0.18	0.15	-0.01	0.18	-0.01
	(0.23)	(0.27)	(0.26)	(0.27)	(0.26)	(0.25)	(0.20)	(0.27)	(0.20)
Cluster Density	-1.85***	-2.17***	-2.17***	-2.18***	-2.15***	-2.07***	-1.86***	-2.16***	-1.83***
	(0.46)	(0.51)	(0.50)	(0.51)	(0.50)	(0.49)	(0.47)	(0.51)	(0.46)
Betweenness Centrality	0.85***	0.84***	0.84***	0.85***	0.85***	0.84***	0.82***	0.85***	0.82***
	(0.18)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
year	-0.18***	-0.19***	-0.18***	-0.19***	-0.19***	-0.19***	-0.19***	-0.19***	-0.19***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Dummy DOTCOM	-1.26***	-1.20***	-1.17***	-1.18***	-1.20***	-1.16***	-0.96***	-1.19***	-0.97***
	(0.31)	(0.31)	(0.32)	(0.31)	(0.31)	(0.32)	(0.33)	(0.31)	(0.32)
Dummy FINCRS2007	-1.24***	-1.43***	-1.42***	-1.43***	-1.43***	-1.44***	-1.39***	-1.44***	-1.40***
	(0.29)	(0.28)	(0.28)	(0.28)	(0.28)	(0.29)	(0.29)	(0.28)	(0.29)
Dummy Covid19	1.55***	0.95***	0.96***	0.94***	0.96***	0.87***	0.68***	0.95***	0.63**
	(0.31)	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)	(0.25)	(0.27)	(0.25)

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Table 4.10 (continued)

DV: New Technological BCTs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Market Uncertainty (MU)		0.17	0.16	0.15	0.17	0.08	0.11	0.15	0.09
		(0.12)	(0.13)	(0.14)	(0.12)	(0.15)	(0.13)	(0.14)	(0.15)
Technological Uncertainty (TU)		-2.30***	-2.26***	-2.30***	-2.42***	-1.97***	-1.19**	-2.42***	-1.10**
		(0.58)	(0.61)	(0.58)	(0.58)	(0.61)	(0.54)	(0.58)	(0.56)
Performance Below Historical Aspiration (PBHA)		0.41		0.35	0.52			0.49	
		(0.48)		(0.70)	(0.72)			(0.89)	
Performance Above Historical Aspiration (PAHA)		-0.20		-1.00	0.51			-0.24	
		(0.48)		(0.94)	(0.63)			(1.07)	
Performance Below Social Aspiration (PBSA)			-0.18			-0.41	-0.87		-1.11
			(0.42)			(0.68)	(0.70)		(0.90)
Performance Above Social Aspiration (PASA)			-0.20			0.74	2.05***		2.40***
			(0.40)			(0.50)	(0.62)		(0.67)
PBHA × MU				-0.09				-0.02	
				(0.79)				(0.78)	
PAHA × MU				-1.00				-0.89	
				(0.88)				(0.90)	
PBHA × TU					-0.45			-0.39	
					(2.37)			(2.33)	
PAHA × TU					-3.98			-3.78	
					(2.50)			(2.55)	
PBSA × MU						-0.30			-0.26
						(0.77)			(0.69)
PASA × MU						1.43**			0.61
						(0.64)			(0.68)
PBSA × TU							3.87*		4.02*
							(2.11)		(2.08)
PASA × TU							-11.50***		-11.13***
							(1.63)		(1.76)
Log pseudolikelihood	-1853.77	-1832.45	-1832.73	-1831.29	-1830.53	-1828.13	-1793.70	-1829.66	-1792.91

Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses.

4.5.5 Within-Cluster Ties as Dependent Variable

I examined whether performance and external uncertainty also influence the formation of within-cluster ties (WCTs). By comparing results with the BCT models, this analysis clarifies whether structural search is contingent not just on motivation and context, but also on the spatial configuration of alliances.

The analysis of WCTs reveals a strategic shift toward internal collaboration under high market uncertainty (see Table 4.11), contrasting with the outward-oriented behavior observed in BCTs. As shown in Figure 4.8, the marginal effect of performance below historical aspirations becomes negative as market uncertainty increases, indicating that underperforming firms prefer the relative safety of local partnerships during volatile conditions. In Figure 4.9, the marginal effect of performance above social aspirations becomes increasingly positive with rising market uncertainty, suggesting that firms outperforming peers also reinforce internal ties in uncertain markets.

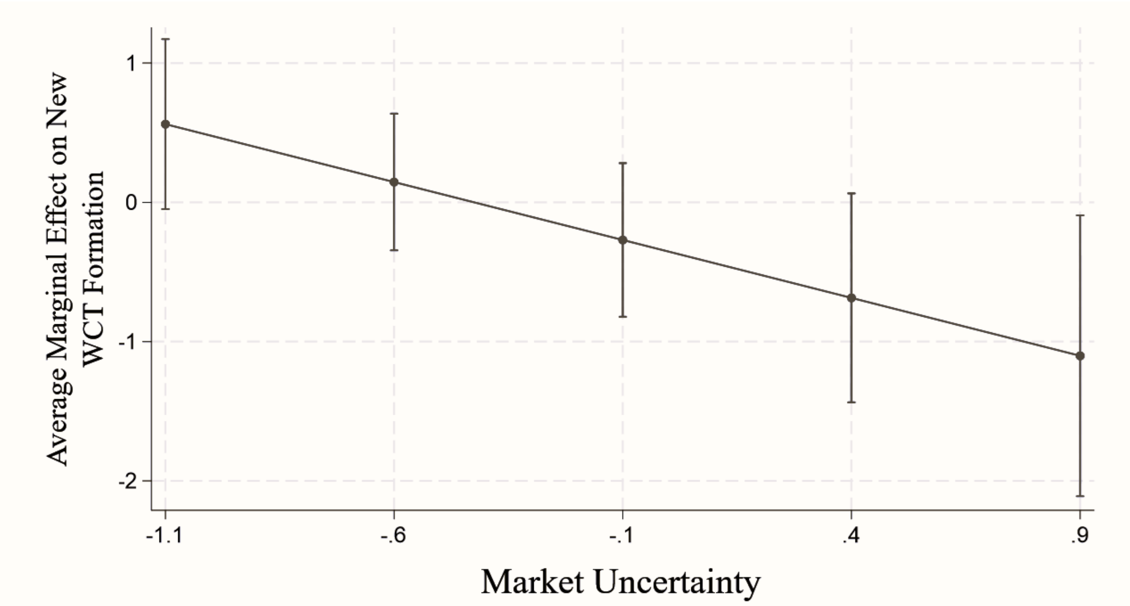

Figure 4.8 Marginal Effect of Performance Below Historical Aspirations on New WCT Formation at Varying Levels of Market Uncertainty

Under technological uncertainty, the pattern diverges. As illustrated in Figure 4.10, the marginal effect of performance above social aspirations declines as technological uncertainty increases, becoming negligible at higher levels. This suggests that in technologically dynamic environments, high-performing firms rely less on within-cluster alliances, possibly due to limited adaptability of local partners. Performance below and above historical aspirations show no significant moderation by technological uncertainty, and performance below social aspirations remains insignificant across conditions.

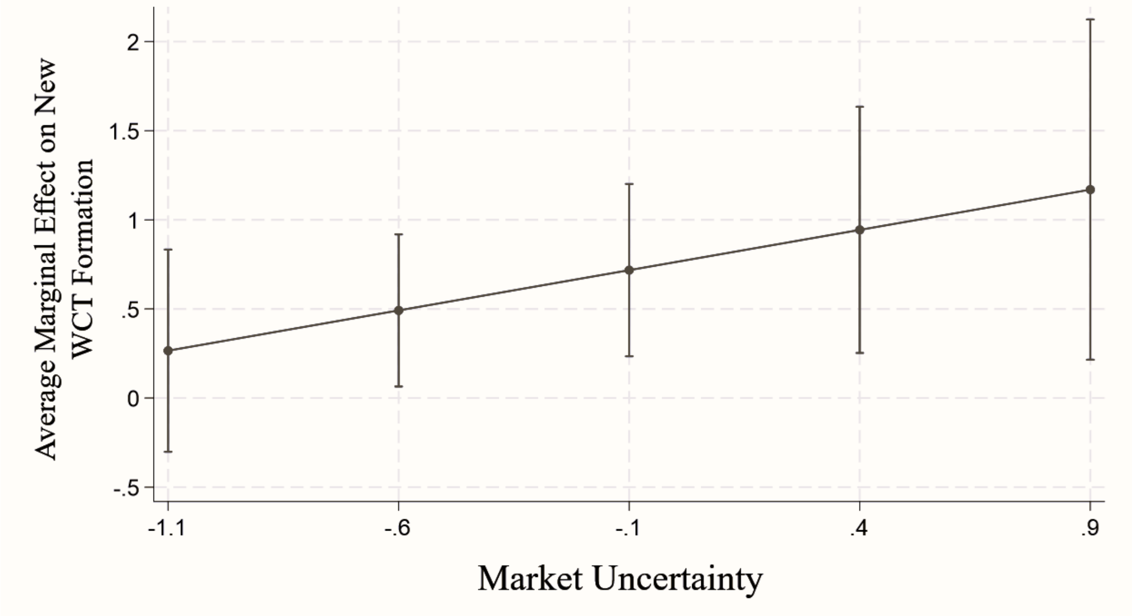

Figure 4.9 Marginal Effect of Performance Above Social Aspirations on New WCT Formation at Varying Levels of Market Uncertainty

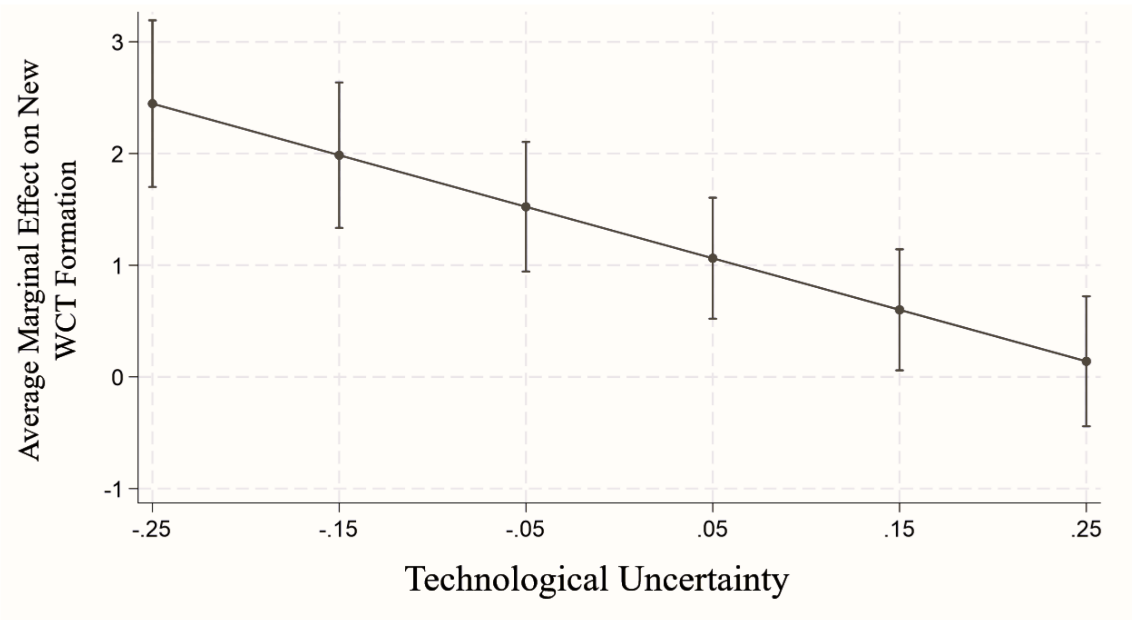

Figure 4.10 Marginal Effect of Performance Above Social Aspirations on New WCT Formation at Varying Levels of Technological Uncertainty

Table 4.11 PQML Regression Results Using WCTs as Dependent Variable (N=3,398)

DV: New WCTs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R&D intensity	-0.06	0.07	0.20	0.16	0.06	0.25	0.20	0.15	0.27
	(0.31)	(0.32)	(0.32)	(0.32)	(0.32)	(0.31)	(0.31)	(0.32)	(0.31)
Size	0.18***	0.21***	0.22***	0.21***	0.21***	0.22***	0.23***	0.21***	0.23***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Slack	0.01	0.01	0.02	0.01	0.01	0.02	0.02	0.01	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Financial Health	0.01	-0.00	-0.01	0.00	-0.00	-0.01	-0.02	-0.00	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Firm-Specific Uncertainty	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Industry Growth Opportunities	-0.13***	-0.10***	-0.10***	-0.10***	-0.10***	-0.10***	-0.10***	-0.10***	-0.10***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Industry R&D Intensity	0.27***	0.17**	0.19**	0.17**	0.17**	0.19**	0.17**	0.17**	0.17**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)
Cluster Density	0.76***	0.65***	0.67***	0.65***	0.66***	0.67***	0.71***	0.65***	0.70***
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Betweenness Centrality	0.14	0.16	0.15	0.16	0.16	0.15	0.14	0.16	0.14
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
year	-0.06***	-0.07***	-0.08***	-0.07***	-0.07***	-0.08***	-0.08***	-0.07***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Dummy DOTCOM	-0.70***	-0.70***	-0.76***	-0.69***	-0.70***	-0.75***	-0.72***	-0.69***	-0.71***
	(0.13)	(0.12)	(0.13)	(0.12)	(0.12)	(0.13)	(0.13)	(0.12)	(0.13)
Dummy FINCRS2007	-0.49***	-0.56***	-0.57***	-0.56***	-0.56***	-0.58***	-0.57***	-0.56***	-0.57***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Dummy Covid19	0.26**	0.07	0.04	0.07	0.08	0.04	0.01	0.07	0.01
	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)

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Table 4.11 (continued)

DV: New WCTs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Market Uncertainty (MU)		0.26***	0.28***	0.29***	0.26***	0.30***	0.28***	0.29***	0.30***
		(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)
Technological Uncertainty (TU)		-0.95***	-1.10***	-1.00***	-1.01***	-1.08***	-0.91***	-1.04***	-0.93***
		(0.33)	(0.33)	(0.33)	(0.33)	(0.34)	(0.32)	(0.33)	(0.33)
Performance Below Historical Aspiration (PBHA)		0.28		-0.22	0.09			-0.36	
		(0.26)		(0.31)	(0.27)			(0.32)	
Performance Above Historical Aspiration (PAHA)		-0.21		0.14	0.04			0.29	
		(0.26)		(0.36)	(0.30)			(0.36)	
Performance Below Social Aspiration (PBSA)			0.22			-0.06	0.04		-0.18
			(0.27)			(0.35)	(0.29)		(0.37)
Performance Above Social Aspiration (PASA)			0.54**			0.63**	0.89***		0.86***
			(0.21)			(0.26)	(0.26)		(0.27)
PBHA × MU				-0.84**				-0.81**	
				(0.33)				(0.33)	
PAHA × MU				0.60				0.52	
				(0.41)				(0.41)	
PBHA × TU					1.00			0.82	
					(1.06)			(1.04)	
PAHA × TU					-1.53			-1.22	
					(1.11)			(1.10)	
PBSA × MU						-0.40			-0.32
						(0.28)			(0.28)
PASA × MU						0.15			-0.10
						(0.28)			(0.31)
PBSA × TU							1.05		1.00
							(0.88)		(0.89)
PASA × TU							-2.13***		-2.21***
							(0.73)		(0.78)
Log pseudolikelihood	-4853.86	-4824.56	-4818.61	-4818.36	-4822.69	-4817.11	-4810.90	-4817.19	-4809.63

Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses.

4.5.6 Alternative Samples and Model Specifications

Additional robustness checks were conducted using various sample restrictions to assess the stability of the baseline results. Given the relative rarity of BCT formation, restricting the sample—whether by industry activity, performance distance from aspirations, or levels of uncertainty—reduces the number of qualifying observations and weakens statistical power. This is particularly important when analyzing interaction effects, which requires sufficient variance across conditions.

First, I restricted the sample to industries that are highly active in BCT formation—specifically pharmaceuticals, computer hardware/software, and electronic components. In this subsample, only one finding holds: technological uncertainty continues to negatively moderate the relationship between performance above social aspirations and BCT formation, consistent with baseline results (Figure 4.11).

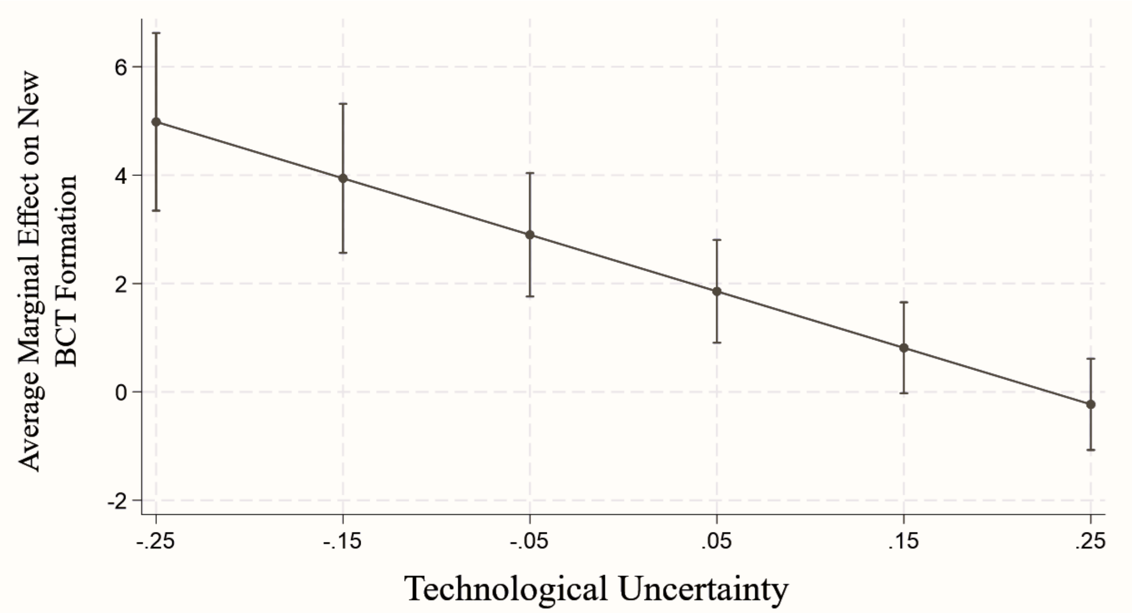

Figure 4.11 Marginal Effect of Performance Above Social Aspirations on New BCT Formation at Varying Levels of Technological Uncertainty (Restricted to BCT-Active Industries)

Second, I applied a restriction on the range of aspiration gaps to include only firms with performance values above the mean (m = 0.11) for performance above aspirations and below the mean (m = -0.9) for performance below aspirations. These cutoffs are calculated across the full sample and held constant across all firms. This approach focuses on firms experiencing more substantial deviations from their targets. The results here were less conclusive: due to a considerable drop in observations, most effects became statistically insignificant. However, some key patterns—such as the negative moderation of technological uncertainty on performance above social aspirations—remained directionally consistent. Third, I restricted the sample to firms simultaneously exposed to high market and high technological uncertainty (i.e., above the mean on both dimensions) to address the slight negative correlation (r = 0.31) between the two types of uncertainty, which raised concerns about potential confounding effects. This restriction was intended to limit the potentially contradicting effects of one type of uncertainty on the influence of the other. The results remained consistent, indicating that the main findings are not an artifact of extreme or isolated subsamples.

Finally, I used a one-period lead of the dependent variable to account for potential time lags in BCT formation. Given the cost, coordination, and contractual complexity involved, firms may take longer than a year to respond to performance feedback and external uncertainty. In this temporally adjusted model, market uncertainty continued to exhibit a positive effect (Table 4.12). Performance below social aspirations showed a significant negative effect, while its interaction with technological uncertainty became positive, indicating that the previously negative marginal effect, contrary to the predictions, attenuates under high uncertainty (Figure 4.12). A similar shift was observed for performance below historical aspirations (Figure 4.13), where the negative effect also weakened in high technological uncertainty. These results suggest that technological turbulence may delay and dampen the structural search response of underperforming firms.

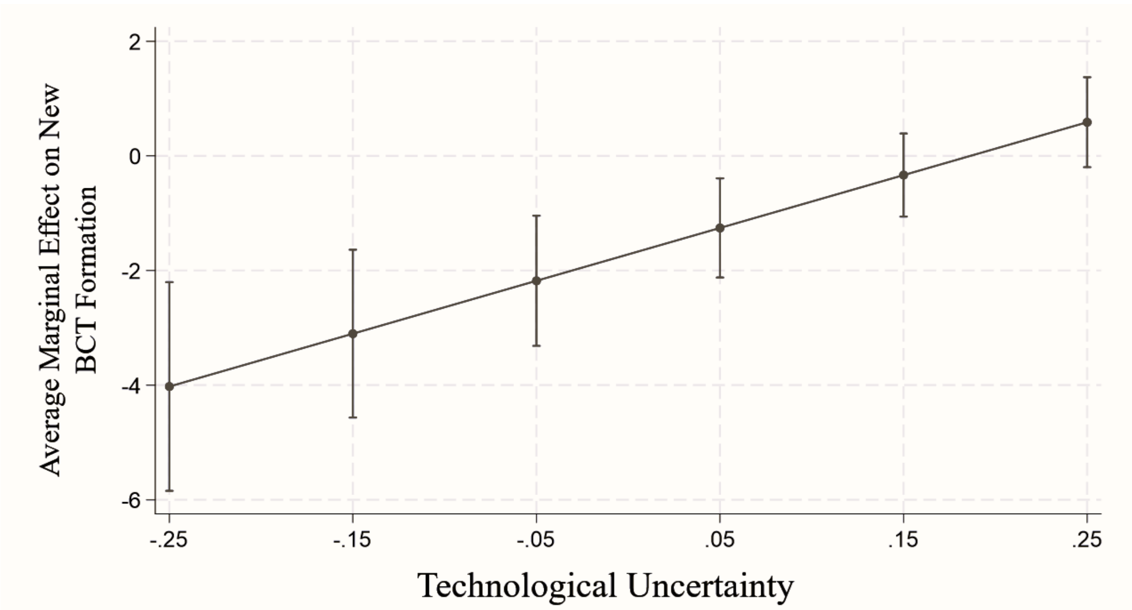

Figure 4.12 Marginal Effect of Performance Below Social Aspirations on New BCT (t+1) Formation at Varying Levels of Technological Uncertainty

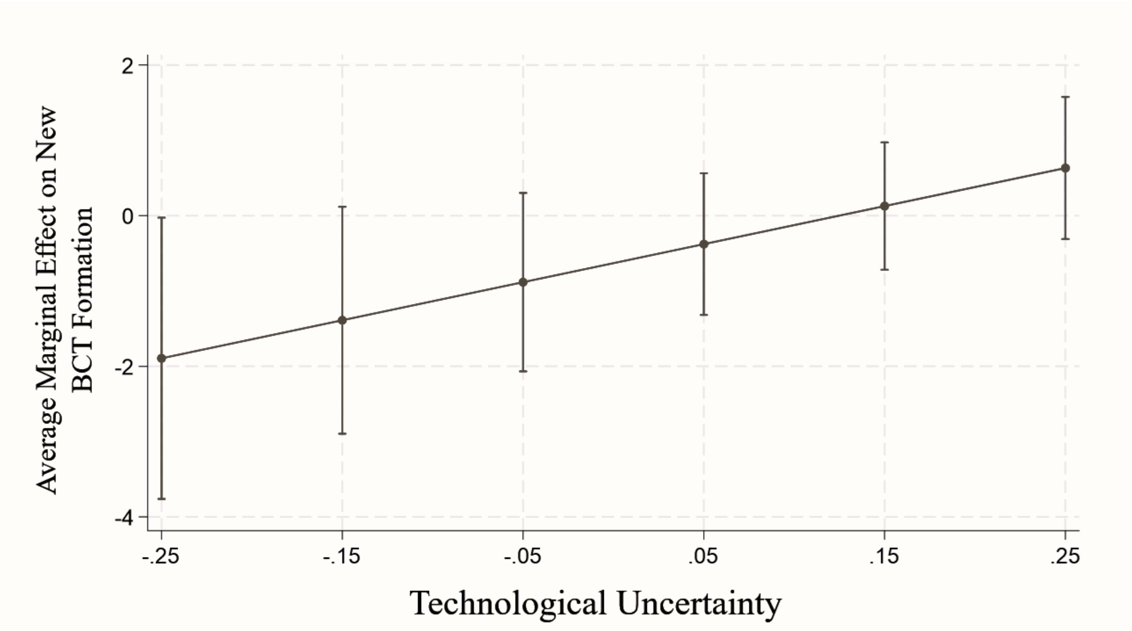

Figure 4.13 Marginal Effect of Performance Below Historical Aspirations on New BCT (t+1) Formation at Varying Levels of Technological Uncertainty

Table 4.12 PQML Regression Results Predicting Future BCTs (t+1) (N=3,398)

DV: New BCTs (t+1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R&D intensity	0.56	0.69	0.61	0.56	0.62	0.28	0.45	0.52	0.27
	(0.71)	(0.72)	(0.74)	(0.71)	(0.71)	(0.78)	(0.70)	(0.71)	(0.73)
Size	-0.07	-0.01	0.00	-0.02	-0.01	0.01	0.07	-0.01	0.07
	(0.10)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Slack	-0.03	-0.03	-0.03	-0.03	-0.02	-0.03	-0.02	-0.02	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)
Financial Health	0.08**	0.07*	0.08**	0.07*	0.06	0.07*	0.05	0.06	0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Industry Growth Opportunities	-0.17***	-0.10**	-0.10***	-0.10**	-0.10***	-0.10**	-0.10**	-0.10***	-0.09**
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Industry R&D Intensity	0.48***	0.34*	0.32*	0.35*	0.34*	0.31*	0.18	0.34*	0.18
	(0.17)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.15)	(0.18)	(0.15)
Cluster Density	-0.20	-0.82**	-0.81**	-0.83**	-0.81**	-0.75**	-0.62*	-0.82**	-0.60*
	(0.38)	(0.38)	(0.38)	(0.38)	(0.39)	(0.38)	(0.36)	(0.39)	(0.36)
Betweenness Centrality	0.62***	0.62***	0.62***	0.63***	0.62***	0.62***	0.61***	0.63***	0.61***
	(0.17)	(0.19)	(0.18)	(0.19)	(0.19)	(0.19)	(0.18)	(0.19)	(0.18)
year	-0.19***	-0.20***	-0.20***	-0.20***	-0.20***	-0.20***	-0.21***	-0.20***	-0.21***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Dummy DOTCOM	-1.20***	-1.09***	-1.07***	-1.09***	-1.10***	-1.07***	-0.91***	-1.10***	-0.92***
	(0.25)	(0.27)	(0.28)	(0.27)	(0.27)	(0.28)	(0.28)	(0.27)	(0.28)
Dummy FINCRS2007	-2.02***	-2.29***	-2.28***	-2.29***	-2.30***	-2.31***	-2.29***	-2.30***	-2.30***
	(0.37)	(0.36)	(0.36)	(0.36)	(0.36)	(0.36)	(0.37)	(0.36)	(0.37)
Dummy Covid19	0.98**	0.08	0.09	0.06	0.08	0.02	-0.08	0.07	-0.13
	(0.38)	(0.31)	(0.31)	(0.31)	(0.31)	(0.32)	(0.30)	(0.31)	(0.31)

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Table 4.12 (continued)

DV: New BCTs (t+1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Market Uncertainty (MU)		0.33***	0.32***	0.26***	0.33***	0.18*	0.29***	0.27***	0.22**
		(0.09)	(0.09)	(0.09)	(0.08)	(0.10)	(0.09)	(0.10)	(0.10)
Technological Uncertainty (TU)		-3.84***	-3.85***	-3.79***	-4.05***	-3.64***	-3.60***	-3.99***	-3.48***
		(0.53)	(0.57)	(0.52)	(0.50)	(0.55)	(0.51)	(0.50)	(0.51)
Performance Below Historical Aspiration (PBHA)		0.25		1.04	-0.63			0.06	
		(0.44)		(0.74)	(0.54)			(0.86)	
Performance Above Historical Aspiration (PAHA)		-0.90*		-1.74***	-0.37			-1.23	
		(0.46)		(0.67)	(0.78)			(0.94)	
Performance Below Social Aspiration (PBSA)			-0.10			0.72	-1.72***		-1.15
			(0.32)			(0.58)	(0.51)		(0.83)
Performance Above Social Aspiration (PASA)			-0.16			0.43	1.53**		1.76***
			(0.37)			(0.51)	(0.62)		(0.64)
PBHA × MU				1.10				0.88	
				(0.73)				(0.75)	
PAHA × MU				-1.13				-1.09	
				(0.76)				(0.76)	
PBHA × TU					5.05**			4.77**	
					(2.13)			(2.15)	
PAHA × TU					-2.56			-2.35	
					(2.95)			(3.00)	
PBSA × MU						0.97			0.57
						(0.61)			(0.69)
PASA × MU						0.99*			0.46
						(0.55)			(0.62)
PBSA × TU							9.22***		8.69***
							(2.03)		(2.16)
PASA × TU							-9.06***		-8.76***
							(1.80)		(1.86)
Log pseudolikelihood	-1923.17	-1851.00	-1853.21	-1848.97	-1847.71	-1848.56	-1822.08	-1846.17	-1820.92

Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses.

4.5.7 Industry-Specific Robustness Check: The Case of Pharmaceuticals

To enhance the robustness of the main findings, this subsection focuses on the pharmaceutical industry as a single-industry case. An industry-specific analysis offers the opportunity to examine how alliance formation—particularly between-cluster ties (BCTs)—responds to a more homogeneous institutional and market context. The pharmaceutical sector is especially relevant for such an analysis due to its long-standing exposure to intense regulatory scrutiny, patent regime shifts, and pricing pressures (Kavusan & Frankort, 2019; Penner-Hahn & Shaver, 2005; Rothaermel, 2001; Xia & Dimov, 2019).

Among several major regulatory events between 1990 and 2022—such as the Hatch-Waxman Act adjustments in the 1990s and the Medicare Modernization Act of 2003—the Affordable Care Act (ACA) of 2010 stands out as the most salient and widely examined in management research (Tan, 2023; Zhou et al., 2023). The ACA introduced sweeping reforms to drug pricing, coverage expansion, and compliance requirements, creating significant strategic ambiguity for pharmaceutical firms as they navigated new reimbursement models and uncertain demand forecasts (Grabowski et al., 2014). Firms faced unclear long-term revenue implications due to fluctuating enrollment levels and variability in Medicaid expansion across states (Handel & Kolstad, 2022).

To better capture the regulatory uncertainty surrounding the ACA, I introduce two separate dummy variables: one for the debate period (2009–2010), reflecting heightened uncertainty during legislative negotiations and lobbying, and another for the implementation period (2010–2014), covering the law's enactment, phased roll-outs, and ongoing legal challenges. Including these dummies alongside the main market uncertainty measure allows a clearer comparison of how regulatory versus unpredictable revenue fluctuations as the measure of market uncertainty influences BCT formation.

The direct effects of both dummies on BCT formation were negative overall, indicating that ACA-related regulatory uncertainty broadly discouraged new alliance formation across clusters (see Table 4.13). Notably, there was no significant moderating effect of performance relative to historical aspirations, but results revealed that regulatory uncertainty during the ACA debate period had differentiated effects depending on firms' performance relative to social aspirations. Specifically, while firms performing below their social aspirations reduced BCT formation—likely due to perceived risk and resource constraints—firms performing above their social aspirations increased BCT formation, consistent with the pattern observed under market uncertainty in the broader sample. This suggests that even when facing regulatory ambiguity, relatively successful firms may leverage their stronger position to pursue exploratory, cross-cluster partnerships, while underperforming firms retreat from such uncertain commitments. These findings reinforce the idea that performance feedback and uncertainty interact in complex ways, and that the type of uncertainty—regulatory vs. market—can shape firm behavior differently depending on performance reference points.

Table 4.13 PQML Regression Results for the Pharmaceutical Industry with ACA Regulation Uncertainty Dummies (N = 1,099)

DV: New BCTs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R&D intensity	0.03	0.48	0.21	0.49	0.32	0.20	0.19	0.31	0.15
	(0.48)	(0.67)	(0.62)	(0.66)	(0.66)	(0.62)	(0.63)	(0.63)	(.)
Size	0.32	0.41**	0.39**	0.40**	0.41**	0.39**	0.42**	0.41**	0.43
	(0.20)	(0.18)	(0.18)	(0.19)	(0.18)	(0.18)	(0.17)	(0.18)	(.)
Slack	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(.)
Financial Health	-0.01	-0.02	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(.)
Firm Specific Uncertainty	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(.)
Industry Growth Opportunities	-0.32***	-0.34***	-0.32***	-0.34***	-0.35***	-0.33***	-0.31***	-0.31***	-0.28
	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.06)	(.)
Industry R&D Intensity	-1.69***	-1.45***	-1.44***	-1.47***	-1.52***	-1.47***	-1.44***	-1.49***	-1.42
	(0.52)	(0.51)	(0.50)	(0.51)	(0.52)	(0.50)	(0.50)	(0.54)	(.)
Cluster Density	-1.26	-1.22	-1.27*	-1.36*	-1.21	-1.32*	-1.14	-1.29*	-1.15
	(0.77)	(0.76)	(0.76)	(0.77)	(0.76)	(0.77)	(0.75)	(0.75)	(.)
Betweenness Centrality	0.62***	0.56***	0.56***	0.57***	0.53***	0.56***	0.57***	0.54***	0.58
	(0.16)	(0.16)	(0.16)	(0.16)	(0.15)	(0.16)	(0.16)	(0.16)	(.)
year	-0.02	-0.07**	-0.07**	-0.07**	-0.07**	-0.07**	-0.08**	-0.07**	-0.07
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(.)
Dummy DOTCOM	-0.04	0.03	0.07	0.03	0.02	0.07	0.06	0.11	0.16
	(0.34)	(0.38)	(0.38)	(0.38)	(0.38)	(0.38)	(0.38)	(0.32)	(.)
Dummy FINCRS2007	-0.95***	-1.08***	-1.06***	-1.07***	-1.05***	-1.04***	-1.01***	-1.01***	-0.95
	(0.29)	(0.30)	(0.29)	(0.33)	(0.29)	(0.33)	(0.29)	(0.32)	(.)
Dummy Covid19	0.90***	0.66***	0.65***	0.66***	0.62***	0.66***	0.45**	0.66***	0.51
	(0.21)	(0.19)	(0.20)	(0.19)	(0.20)	(0.20)	(0.18)	(0.18)	(.)
Dummy_BEFOREACA	-0.95**	-1.18**	-1.11**	-1.13*	-1.11**	-1.14	-1.13**	-1.11*	-1.20
	(0.45)	(0.49)	(0.49)	(0.64)	(0.49)	(0.75)	(0.51)	(0.67)	(.)
Dummy_AFTERACA	0.57	0.25	0.24	0.25	0.20	0.22	0.25	0.11	0.11
	(0.35)	(0.34)	(0.34)	(0.42)	(0.34)	(0.39)	(0.32)	(0.44)	(.)

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Table 4.13 (continued)

DV: New BCTs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Market Uncertainty (MU)	0.10	0.14	0.11	0.14	0.15	0.11	0.19	0.14	0.15
	(0.21)	(0.22)	(0.21)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
Technological Uncertainty (TU)	-3.16***	-3.14***	-3.15***	-3.07***	-2.40**	-3.10***	-0.48	-2.63***	-0.87
	(0.95)	(0.95)	(1.03)	(0.94)	(0.98)	(1.02)	(1.21)	(0.99)	(.)
Performance Below Historical Aspiration (PBHA)		0.33		0.29	1.08		1.01		
		(0.64)		(0.64)	(0.74)		(0.74)		
Performance Above Historical Aspiration (PAHA)		0.90*		0.95*	0.20		0.24		
		(0.53)		(0.54)	(0.55)		(0.56)		
Performance Below Social Aspiration (PBSA)			0.05			0.04	0.24		0.20
			(0.61)			(0.61)	(0.72)		(.)
Performance Above Social Aspiration (PASA)			-0.03			-0.05	-0.07		-0.12
			(0.59)			(0.62)	(0.53)		(.)
PBHA × Dummy_BEFOREACA				3.57				1.15	
				(6.01)				(5.55)	
PAHA × Dummy_BEFOREACA				-61.87**				-58.03**	
				(30.12)				(29.33)	
PBHA × Dummy_AFTERACA				27.86				24.63	
				(26.74)				(26.57)	
PAHA × Dummy_AFTERACA				-4.10				-1.22	
				(4.79)				(4.76)	
PBHA × TU					-14.48***			-13.85***	
					(4.77)			(4.51)	
PAHA × TU					14.86***			13.93***	
					(4.92)			(4.93)	
PBSA × Dummy_BEFOREACA						252.20***			244.00
						(42.03)			(.)
PASA × Dummy_BEFOREACA						-0.77			-1.66
						(2.84)			(.)
PBSA × Dummy_AFTERACA						72.78***			71.50
						(13.82)			(.)
PASA × Dummy_AFTERACA						4.18			2.83
						(3.66)			(.)

Continued on next page

Table 4.13 (continued)

DV: New BCTs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PBSA × TU							-11.19***		-10.62
							(3.40)		(.)
PASA × TU							-0.48		-0.44
							(6.29)		(.)
Log pseudolikelihood	-738.66	-736.15	-738.65	-733.02	-729.43	-737.77	-731.08	-727.55	-731.21

Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses. (.) indicates standard errors not computed.

5. DISCUSSION

This study sets out to understand why firms form strategic alliances across clusters, focusing on how performance feedback interacts with external uncertainty to shape search behaviors. Building on the Behavioral Theory of the Firm (BTOF), I examined the role of both historical and social aspiration deviations in motivating the formation of between-cluster ties (BCTs), and how these effects are moderated by market and technological uncertainty. The overarching theoretical ambition was to enrich problemistic and slack-enabled search perspectives by embedding them within uncertain environments driven by heuristic decision-making. In doing so, this research contributes to contemporary debates about organizational learning, alliance formation, and strategic adaptation in complex interfirm networks.

5.1 Summary of Findings

The findings offer no support for the baseline predictions of BTOF regarding performance below aspiration levels. Contrary to the logic of problemistic search (Greve, 2003a), neither historical nor social aspiration shortfalls reliably predicted increased BCT formation. Additional analyses restricting the sample to industries actively forming BCTs yielded similar null results, indicating that the lack of association is not driven by inactivity in alliance formation. In some specifications, the direction of the relationship was even reversed, suggesting that underperformance not only fails to trigger distant partnerships but also discourages them. This pattern, while counterintuitive, aligns with a growing body of evidence highlighting the conditional nature of feedback responses. For instance, Greve (2003b) found no significant effect of historical underperformance on asset changes in shipbuilding firms, and Iyer and Miller (2008) reported that performance shortfalls did not increase the likelihood of acquisitions, but instead delayed them—pointing to financial constraints or managerial hesitation in the face of uncertainty. These findings suggest that motivation alone is insufficient; firms must also possess the resources and confidence to pursue ambitious responses like BCTs.

Moreover, as Greve (2018) argues, it matters not only whether firms search, but where they search. As results indicate, underperformance does not lead firms to invest in forming costly and uncertain interfirm between cluster alliances. This is in not necessarily in contrast to the most research that has found negative relationship between performance below aspirations and R&D investments as internal and local search strategies (Goyal & Goyal, 2022; Greve, 2003a). In the context of interfirm collaboration, performance shortfalls may indeed prompt search beyond local clusters, especially if existing partnerships are perceived as part of the problem. However, the resource demands, coordination complexity, and relational uncertainty associated with BCTs limit their feasibility for underperforming firms. These findings reinforce the need for context-sensitive interpretations of BTOF predictions, recognizing that the impact of aspiration shortfalls depends on the nature of the search response, the firm's resource position, and the broader alliance environment.

The results provide partial support for the baseline hypotheses regarding BCT formation in response to performance above social aspirations (PASA). While the baseline models—excluding interaction terms of the market and technological uncertainties—did not show a significant effect for PASA, the effect became significant and in the expected direction once the interaction terms were included in the models. This result partially supports a slack-enabled interpretation: as firms can gain surplus resources when they perform their above aspirations, they are more enabled to engage in riskier, nonlocal search (Baum et al., 2005). This pattern remained evident in disaggregated analyses of both technological and marketing BCTs, reinforcing the view that slack-enabled search operates across different strategic domains. Crucially, this effect is further moderated by market uncertainty. The interaction between PASA and market uncertainty was significantly positive, indicating that firms performing above their social aspirations are even more likely to form BCTs under demand-side ambiguity. This interaction pattern supports H4b and aligns with the argument that managers exploit the opportunities in the environment by extending their search across the network under market uncertainty.

Contrary to the prediction of H6b, technological uncertainty weakens the positive effect of PASA on BCT formation. This result is not explained by a shift toward local partnerships: high-performing firms also reduce WCT formation under high technological uncertainty (see Figure 16). A more tailored explanation may lie in the nature of overperformance itself. Firms that outperform their peers in highly dynamic technological environments may view their position as fragile or difficult to sustain, especially if success depends on proprietary knowledge or speed (Srivastava & Frankwick, 2011). In such contexts, engaging in new alliances—particularly across clusters—may be seen as diluting focus, increasing exposure, or risking misalignment. Rather than leveraging their success outward, these firms may have opted to consolidate internally to protect what is seen as a temporary advantage.

The interaction effects for performance below aspirations and uncertainty were generally weak or insignificant, suggesting that negative attainment discrepancies become less behaviorally salient in volatile environments when the desired strategy was forming between cluster alliances. These patterns are inconsistent with predictions of problemistic search and point instead to a more bounded and asymmetric responsiveness to performance signals. Consistent with threat-rigidity theory (Staw et al., 1981), underperformance may trigger conservatism, internal retrenchment, or a narrowing of strategic attention rather than external search. Moreover, legitimacy concerns arise as firms performing poorly lack the reputational credibility or partner attractiveness necessary to initiate structurally distant collaborations (Beckman et al., 2004; Howard et al., 2016; Suchman, 1995). These constraints can help explain why BCT formation appears more sensitive to overperformance and resource availability than to shortfalls against aspiration levels.

5.2 Theoretical Contributions

This thesis contributes to social network theory by extending the behavioral perspective on BCT formation. While the pioneering study of Baum et al., (2005) showed how performance feedback influences nonlocal partner selection, the current study advances this line of research by examining how firms form between-cluster alliances in response to aspiration attainment and external uncertainty. By integrating environmental contingencies into the behavioral logic of problemistic and slack-enabled search, the study shows that network evolution is shaped by firms' responses to performance feedback and managers' interpretations of volatile external conditions. This expands the scope of behavioral approach to network theory to account for how uncertainty moderates the influence of performance feedback, especially when a firm performs above its social aspiration levels.

Specifically, this study contributes to research on network dynamics by identifying when a firm is more likely to affect network evolution under varying types of external uncertainty. Under market uncertainty, when a firm outperforms its peers, it is more likely to form BCTs, thereby connecting clusters and influencing the broader network structure. Moreover, when a firm outperforms its peers under low technological uncertainty, it is more likely to form BCTs. In contrast, a firm that performs above its aspiration levels under high technological uncertainty is less active in forming BCTs—suggesting that moderate performers were more attuned to exploratory learning and cross-cluster collaboration in the face of technological change. This nuanced view highlights how the behavioral drivers of network change differ across environmental contexts.

This research also extends the BTOF literature in several directions. First, it offers a domain-specific application of performance feedback theory to search via distant alliance formation. Most prior BTOF applications have focused on internal actions such as R&D (Goyal & Goyal, 2022; Greve, 2003a; Han, 2023; Xu et al., 2019), innovation (Greve, 2003c; Lu & Wong, 2019; Z. Zhang et al., 2024), new market entry (Ref & Shapira, 2017), and acquisitions (Iyer et al., 2019; Iyer & Miller, 2008); this study expands the scope by analyzing external, interorganizational behavior in the context of clustered alliance networks and by introducing BCTs as a form of distant search strategy.

Second, the findings challenge the generalizability of problemistic search by showing that underperformance does not universally lead to broader or riskier strategies. In fact, overperformance—especially relative to peers—appears to be a more reliable trigger for between-cluster alliance formation. This refines the traditional view of problemistic search by highlighting the capability perspective, suggesting the enabling role of overperformance relative to peers as firms loosen resource constraints and make distant search across clusters.

Third, the results demonstrate that external uncertainty shifts firms' reliance from historical to social benchmarks. When uncertainty weakens the predictive value of past performance, firms look outward to assess their relative standing (Dong, 2021). Social aspirations thus become more salient, offering contextually grounded cues that shape behavioral responses to performance signals. This insight adds nuance to BTOF by linking aspiration salience to external volatility and the perceived informativeness of reference points.

Forth, the study integrates uncertainty into BTOF models in a theoretically grounded manner. Rather than treating uncertainty as noise or avoided (Cyert & March, 1963; Greve, 2018), I demonstrate how market and technological uncertainty differentially affect the attribution process, moderating the impact of performance feedback on slack-enabled responses. This also extends behavioral theory in organizational settings and responds to calls to theorize how ambiguity shape decision-making under uncertainty (Alvarez et al., 2018; Audia & Brion, 2023; Mousavi & Gigerenzer, 2017). The results of this study indicate that firms performing above their social aspiration levels are more likely to form BCTs under market uncertainty, but less likely to do so when faced with heightened technological uncertainty.

Finally, this study contributes to behavioral strategy by showing that BCT formation is not a search option triggered by performance below aspiration levels—neither under low nor high external uncertainty. This finding suggests that firms do not pursue structurally distant and risky alliances as a form of problemistic search in uncertain environments. In doing so, the study extends Greve's (2018) argument that research on performance feedback should move beyond whether firms search to consider where they search. BCTs appear to be more viable as search options when a firm performs above its aspiration levels, particularly under high market uncertainty and low technological uncertainty.

5.3 Practical Implications

This study provides insights into the conditions under which firms are more or less likely to pursue structurally expansive search. Rather than prescribing specific actions, the findings clarify how performance feedback and uncertainty jointly shape firms' strategic posture. This can inform managerial judgment by identifying when certain alliance behaviors are likely to emerge—and when they may not.

First, managers may recognize that the likelihood of forming between-cluster alliances depends not just on objective performance but on how that performance compares to reference points and is interpreted under uncertainty. Understanding these behavioral triggers can help managers assess when their organizations and other firms may be more inclined to form BCTs.

Second, the finding that firms are more likely to form BCTs in response to performance relative to social rather than historical aspirations under market uncertainty suggests that managers place greater emphasis on peer comparison than on internal benchmarks when evaluating strategic responses. In uncertain environments, internal reference points may be less informative, and strategic decisions are guided more by relative standing in the industry than by isolated firm-level performance. This is important as firms actively monitor competitors' strategies. The results show that under market uncertainty, firms that perform above the industry average are more likely to form BCTs. These moves can potentially strengthen their position in both the alliance network and the industry by connecting the firms to distant areas that might provide novel knowledge and opportunities.

Third, the findings offer practical insights for managers navigating alliance decisions under uncertainty. In volatile environments, forming alliances—especially between clusters—requires more than structural opportunity or resource availability; it hinges on how decision-makers interpret ambiguous performance signals and attribute outcomes. Managers often lack clear feedback about whether their current strategies are effective or whether external conditions are driving results. As this study suggests, those who interpret performance through a broader lens—accounting for both internal capabilities and shifting external conditions—may be better positioned to form strategic alliances that extend beyond their immediate network. Firms can benefit from institutionalizing processes that challenge overly internal or overly external attributions, especially in turbulent markets where causal ambiguity is high.

Ultimately, the differential effects of market and technological uncertainty offer a cautionary note. While market volatility opens opportunities for ambitious search, technological uncertainty appears to suppress it, even among high-performing firms. Managers should therefore be aware that between cluster alliance formation is not only shaped by internal performance assessments, but also by the specific type of uncertainty they face. Technological uncertainty, in particular, reduce the attractiveness or feasibility of forming BCTs, as competitors might also hesitate to initiate new distant alliances when innovations are rapidly evolving and outcomes are difficult to anticipate.

5.4 Boundary Conditions, Limitations, and Future Research

Several boundary conditions arise from the assumptions of the conceptual model and the scope of the research design. Conceptually, the model builds on the behavioral theory of the firm, assuming that firms engage in search guided by performance relative to aspiration levels. This logic presumes that aspiration levels are given, performance signals are salient, and that managers interpret them consistently—conditions that may not hold uniformly across firms or environments. Firms often rely on multiple performance metrics, though some provide more salient signals than others. As one CEO noted in a SMS webinar, as long as the company maintains sufficient cash reserves, underperformance on most other metrics is not a major concern. If aspiration levels shift rapidly or are poorly benchmarked, or if attribution biases distort how performance feedback is processed, the mechanisms theorized may not function as expected (cf. Berchicci & Tarakci, 2022). Future research should explore how dynamic aspiration formation and cognitive biases interact with alliance decisions, possibly by incorporating real-time performance monitoring, managerial cognition, or alternative benchmark structures.

Although slack and financial health are included as controls, prior research suggests they also can moderate how firms respond to performance feedback (for review, see Mount et al., 2024). Financial slack can buffer risk and enable search following both underperformance and overperformance, while bankruptcy risk can constrain managerial discretion and suppress behavioral responses to feedback (Chen & Miller, 2007; Kuusela et al., 2017). Testing these hypotheses would require a research design incorporating three-way interactions, which falls outside the methodological scope of the present study.

Another limitation of this study is that it does not explicitly account for firms' varying capabilities to form BCTs. Beyond the limited studies in this area, my analysis emphasizes the strategic drivers of BCT formation under performance feedback and external uncertainty, but it overlooks potential heterogeneity in firms' alliance-building capacities and the dyadic feature of alliance formation. Factors such as prior alliance experience, reputation, or absorptive capacity may influence whether a firm can access and benefit from nonlocal partners. Future research could incorporate these firm-level alliance capabilities to provide a more nuanced understanding of how and when firms are able to respond to performance feedback through BCTs.

From a methodological standpoint, the analysis relies on standard approximations of aspiration gaps (Greve, 2003b; Hu et al., 2022; Kuusela et al., 2017). However, it remains unclear which reference points managers prioritize in practice or how aspiration levels are cognitively formed and adjusted across organizations (Bromiley, 1991; Greve, 1998). The ambiguity surrounding aspiration identification allows for varied interpretations of performance, some of which may deviate from BTOF predictions. Greve (2002) notes that aspirations tend to be sticky—adjusted slowly even in the face of new information. Future studies could explore how firms interpret and act on short-term versus sustained feedback deviations in the context of clustered alliance networks in general, and BCT formation in particular.

A related issue concerns how firms identify their social reference group when forming social aspirations. While Cyert and March (1963) do not offer clear guidance, subsequent work typically uses industry or regional averages as proxies (for review see Bromiley & Harris, 2014). Yet, as Posen et al. (2018) argued, this choice may vary systematically across firms, and may itself be influenced by competitive structure or firm identity. Audia et al. (2021) highlighted that high environmental volatility further complicates this process by obscuring the actions and performance of rivals, making reference group formation both ambiguous and unstable. Others, have suggested that relying on social references under uncertain conditions provide better benchmarks and result in higher performance outcomes (Dong, 2021). This suggests a promising avenue for future research: examining how firms construct and adapt their reference groups under uncertainty, and how variation in reference group selection affects strategic decisions such as alliance formation. This study's findings are most applicable to contexts where interfirm collaboration and network strategies are viable. They may not generalize to sectors with limited alliance activity or institutional support for network-based coordination. Measurement of external uncertainty also presents important limitations. While I relied on established volatility metrics, uncertainty can emerge from varied sources—macroeconomic instability, regulatory change, or geopolitical risk—with differing effects (Bloom, 2014). These factors may influence not only the magnitude but also the persistence of uncertainty (Berchicci & Tarakci, 2022), affecting how firms interpret and respond to performance signals. To reduce heterogeneity, the sample focused on North American firms and specific industries, with robustness checks at extreme uncertainty levels. However, limitations in sample size may have reduced statistical power at those extremes.

There is an ongoing debate about whether managers perceive market uncertainty in line with objective indicators, such as demand volatility or unpredictability in market trends, or whether their perceptions are shaped by cognitive filters and organizational routines (Milliken, 1987; Sutcliffe & Weber, 2003). While objective volatility measures are commonly used in empirical research, several scholars argue that perceived uncertainty is often decoupled from external conditions and instead reflects interpretive processes influenced by experience, framing, and internal information systems (Daft et al., 1988; Maitland & Sammartino, 2015). This distinction matters because behavioral responses, such as BCT formation, may be driven more by perceived than actual environmental volatility. Future research might investigate how discrepancies between perceived and objective uncertainty shape strategic choices, possibly by integrating managerial cognition data with external volatility indicators to assess their relative influence on BCT formation.

Technological uncertainty remains especially difficult to capture. While the age of citations is a meaningful proxy—indicating the pace of technological change—it may not necessarily reflect different dimensions of technological uncertainty, such as the success rate of R&D projects, the market acceptability of new innovations, or regulatory uncertainty surrounding emerging technologies. Future research may benefit from more complicated measures that reflect the complexity of this type of uncertainty. For instance, compound measures that reflect both the pace of innovation and corresponding market reactions may offer a more nuanced view of uncertainty stemming from both technological development and adoption outcomes.

More work is needed to unpack the cognitive mechanisms underlying attribution and aspiration setting under uncertainty. Mixed-method designs combining archival data with field experiments or qualitative interviews could shed more light on how managers construct performance feedback in uncertain environments. For example, J. A. Hansen and Nielsen (2022) showed aspiration levels can be cognitively primed using performance cues from both the focal firm and its peers. Moreover, future research could examine how a firm's status influences the weight placed on social versus historical aspirations—particularly in shaping alliance behavior (Rosenkopf & Padula, 2008).

This study does not distinguish between different governance modes of alliances. All alliance types—whether equity-based or non-equity-based—are treated uniformly, provided they involve formal interfirm agreements. This broad definition captures the diversity of strategic purposes and governance structures typical of alliance activity in manufacturing and high-tech service industries. However, this inclusive approach may obscure meaningful differences in how various alliance forms operate under uncertainty and respond to performance feedback. For example, equity-based alliances often involve stronger commitment and deeper resource integration, whereas non-equity alliances may offer greater flexibility but lower stability.

Future research could refine this approach by differentiating between alliance governance forms and examining how each type interacts with market and technological uncertainties, as well as with firms' performance relative to their aspirations. In addition, exploring the content of alliances—whether focused on R&D, market access, or production—may shed light on how strategic intent moderates the effects of uncertainty on alliance behavior. Although a robustness test using technological and marketing-related BCTs showed consistent results, it is possible that a more fine-grained classification or an industry-specific focus could reveal different patterns, offering deeper insight into alliance formation and adaptation under uncertainty.

Lastly, the unit of analysis in this study was BCT formation by a focal firm. While this approach effectively captures one side of alliance initiation, it overlooks the role of potential partners in shaping alliance outcomes. Alliances, including BCTs, are the result of mutual agreement, meaning that both firms' aspirations, resources, and perceptions of uncertainty play a role in their formation. Adopting a dyadic perspective could offer deeper insights into how performance symmetry or asymmetry between firms affects the likelihood of forming BCTs—especially in uncertain environments where risk perceptions and strategic priorities may differ. For instance, a firm performing above its aspirations may prefer to ally with similarly successful firms, while one underperforming may be more open to risk-taking or may struggle to attract desirable partners. Future research could explore how these relational dynamics unfold and how mutual evaluation processes influence the structure and direction of alliance networks.

5.5 Conclusion

This thesis contributes to the behavioral theory of strategic alliances by showing that firms are more likely to form between-cluster alliances when they perform above their social aspiration levels. This effect is stronger under market uncertainty and weaker under technological uncertainty. These findings extend the predictions of BTOF by showing how different types of uncertainty shape how firms respond to performance feedback.

This thesis contributes to our understanding of network dynamics by applying the behavioral theory of the firm to explain when and why firms initiate alliances across cluster boundaries. By integrating aspiration-driven behavior with external uncertainty, the study shows that alliance decisions—particularly the formation of BCTs—are shaped not only by firm performance but by how that performance is interpreted under different environmental conditions. Market and technological uncertainty affect whether firms treat performance signals as triggers for exploration or restraint. These findings advance behavioral research by moving beyond static explanations of partner selection and showing how firm behavior under uncertainty contributes to the evolution of interorganizational networks.

A key insight is that firms do not always search through distant partners for knowledge and opportunities in the network when they underperform. Instead, high-performing firms—those exceeding their peers—are more likely to explore and form new ties across clusters. This suggests that slack-based, rather than problem-driven, search is more common in uncertain and complex networks. The findings also show that not all uncertainty types work the same way. Market uncertainty encourages exploration for firms performing above the industry average, while technological uncertainty tends to limit it. While this may seem counterintuitive, it may reflect the different cognitive and strategic demands posed by each type of uncertainty.

Overall, this study shows that BCT formation is not only a response to performance feedback, but also depends on how firms interpret that feedback relative to reference points under conditions of external uncertainty. By applying behavioral theory to alliance behavior across different types of uncertainty, the study offers a more nuanced understanding of when firms are likely to reach beyond their local networks and engage in structurally ambitious collaborations.

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