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Knowledge-Based Assets in Business Groups: A Dynamic Capabilities View of Complementarity and Rents

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We extend the business group (BG) literature by combining the knowledge-based perspective and the dynamic capabilities view to explain the benefits of group affiliation. In the BG context, group affiliates can use not only their own firm-level knowledge-based assets (KBAs), but also group-level KBAs. While prior research examines the efficiencies of BG affiliation by comparing BG affiliates to non-affiliated firms, we ask to what extent affiliate-specific rents from group-level KBAs vary among affiliate firms and why. To explain this variation, we identify affiliate-specific rents generated by the complementarity between firm- and group-level KBAs. Drawing from the dynamic capabilities view, we developed a framework to explain the sources of such complementarity and tested a series of hypotheses. This study provides empirical evidence using firm-level data on 524 affiliates of keiretsu groups in Japan from 1985 to 2015. To measure KBAs and their characteristics, we use data on 11.5 million patents matched to the sample firms. This study provides a knowledge-based perspective to explain BG affiliation benefits and the persistence of BGs as an organizational form of economic activity.

Keywords: *knowledge-based assets; business groups; complementarity; dynamic capabilities; rents*

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Introduction

Business groups (BGs) are an important form of organizing business activity in many countries around the world (Aoki & Wilhelm, 2017; Dau, Morck, & Yeung, 2021; Kinger-Hans, Chittoor, Vissa, & Chen, 2024; R. Wang, Heugens, & Wijen, 2024). Although studies have identified a significant effect of BGs on the financial performance of BG-affiliated firms (Carney, Gedajlovic, Heugens, Essen, & Oosterhout, 2011; Chang & Hong, 2002; Joe & Oh, 2018; Yang & Schwarz, 2016), the literature has primarily conceptualized BGs as a means of circumventing institutional voids (Carney, Essen, Estrin, & Shapiro, 2018). This focus presents some limitations. First, the institutional voids approach is less suitable for explaining the persistence of BGs in institutionally developed environments (Liang & Carney, 2020; Shapiro, Estrin, Carney, & Liang, 2024; L. Zhang, Sjögren, & Kishida, 2016). Moreover, institutional reforms in emerging economies have reduced the relevance of this approach, requiring alternative explanations (Gopal, Manikandan, & Ramachandran, 2021; Hoskisson, Johnson, Tihanyi, & White, 2005; Poczter, 2018). Second, prior explanations of affiliation have sought to identify how BG-affiliated firms outperform (or underperform) standalone firms, leading to a focus on the BG-level benefits of affiliation. However, the group-average effect may hide substantial *intra-group* variation because BGs consist of affiliates with varying abilities to use group-level assets. Surprisingly, the literature has paid limited attention to this *intra-group* variation in the benefits of BG affiliation.

We focus on BG affiliates' access to group-level knowledge-based assets (KBAs), such as patented proprietary technology and know-how, because prior literature identifies KBAs as a major source of value (He & Wang, 2009; Teece, 2007), and BGs are at the forefront of investing in proprietary knowledge (Belenzon & Berkovitz, 2010; Wu, Wei, & Wang, 2021). Although BG affiliates can benefit from group-level KBAs, the benefits are likely to vary across affiliates. To explain the sources of such variation, we build on two theoretical propositions. First, BG affiliates create joint value from complementarity between group- and firm-level KBAs, constituting a major source of affiliate rents. Second, the level of such complementarity varies across affiliates because of variations in the structure of group-level KBAs and the knowledge generation (reconfiguring) processes. To develop these propositions, we integrate knowledge-based literature on the complementarities of external knowledge (Foss, Lyngsie, & Zahra, 2013; Grant & Baden-Fuller, 2004; Grigoriou & Rothaermel, 2017) with the dynamic capabilities view (DCV) (Teece, 2007; Wilden, Devinney, & Dowling, 2016). While the two perspectives align in placing knowledge assets as key elements, the DCV also includes the role of the continuous reconfiguration of technological assets in dynamic environments (Easterby-Smith & Prieto, 2008). By applying the principles of DCV to KBAs in BGs, we hypothesize and test for whether the *decentralization* and *relatedness* of group-level KBAs, along with firms' ability to *sense* and *seize* in-group (as opposed to out-group) knowledge opportunities, influence the complementarity between firm- and group-level KBAs.

Explaining inter-affiliate variation in the benefits of KBAs in BGs is important for several reasons. First, without a clear understanding of the sources of the *affiliate-specific* benefits of BG affiliation and the conditions that facilitate affiliate rents, we cannot fully grasp the strategic opportunities available to firms from BG affiliation. This is particularly important for environments in which BG is the dominant organizational form (Kinger-Hans et al., 2024; R. Wang et al., 2024). Second, intra-group variation in rents implies variation in incentives for BG affiliation. This approach refocuses attention from historical and institutional factors contributing to the persistence of BGs (Hoskisson et al., 2005; L. Zhang et al., 2016) toward affiliate-specific, rent-induced motives for persistent affiliation.

To test our framework, we used a longitudinal analysis of 524 affiliates within 13 Japanese keiretsu groups during 1985–2015. To measure KBAs, we identified 11.5 million patents owned by the firms in our sample. Furthermore, by tracing exits from keiretsu groups, we show that drivers of rents from group-level KBAs also significantly explain the likelihood of firms maintaining their affiliations, providing evidence that joint value creation from group-level KBAs explains the persistence of BG ties. The Japanese economy represents a knowledge-intensive environment within which BGs maintain a persistently important role (Aoki & Lennerfors, 2013a), providing a suitable context for testing knowledge-based insights regarding BGs. We also conducted three interviews with managers of keiretsu-affiliated firms to provide insider evaluations of the nature of inter-affiliate relations and access to group-level KBAs.

This study makes three main contributions to the literature. First, by focusing on KBAs, we complement prior approaches that interpret BGs as mechanisms to circumvent institutional voids (Khanna & Rivkin, 2001; Khanna & Yafeh, 2007; Yiu, Lu, Bruton, & Hoskisson, 2007) as sources of information and reputation signaling (Bothello, Ioannou, Porumb, & Zengin-Karaibrahimoglu, 2023; Lamin, 2013), as facilitators of entrepreneurial market-entry capabilities (Guillén, 2000; Yiu, Bruton, & Lu, 2005), or in terms of their organizational characteristics (Manikandan & Ramachandran, 2015). Departing from prior approaches, we place the role of complementarity between group- and firm-level knowledge as central to explaining BG affiliation benefits. Our findings contribute to understanding the mechanisms binding BG affiliates together (Dau et al., 2021; L. Zhang et al., 2016), as this complementarity represents value that is jointly created across affiliates.

Second, we contribute to the long-standing literature that has investigated the performance effects of BG affiliation (Carney et al., 2011; Chang & Hong, 2000; Faccio & O'Brien, 2021; Joe & Oh, 2018; Rhee, Ocasio, & Kim, 2019) by focusing on group-level effects, but overlooked inter-affiliate heterogeneity in those effects. By identifying affiliate-specific rents earned from group-level KBAs, we explain the within-group variation of affiliation benefits. Previous attempts to explain such differential benefits assumed value creation at the group level, relying on control- and power-based explanations of value distribution (Brouthers, Gao, & Napshin, 2014; Keum, 2023; Kim, Hoskisson, & Wan, 2004; Yang & Schwarz, 2016). In contrast, our explanation shifts the focus towards affiliate-level differences in value creation.

Finally, integrating DCV with the knowledge-based approach (Easterby-Smith & Prieto, 2008) in the context of BGs paves the way for another contribution. This approach explains the interplay between a firm's dynamic capabilities – specifically its ability to integrate, build, and reconfigure knowledge-based competences – and the decentralized, diverse KBAs in BGs. By applying DCV, this study uncovers nuanced sources of complementarity that are important for understanding joint value creation by BG affiliates, thus, extending the BG literature on the determinants of financial performance benefits for affiliate firms. Specifically, the contribution consists of hypothesizing and demonstrating how the *decentralization* of KBAs can influence knowledge combination opportunities, how *technological relatedness* can influence joint value creation, and how *in-group* opportunities can create *sensing* and *seizing advantages* for BG affiliates. As such, group membership and group-level KBAs facilitate affiliates' *dynamic capabilities* because they *enable* a reconfiguration of the affiliate's knowledge base, an enhancement of technological (*ordinary*) capabilities, and effect change in strategy (Schilke, Hu, & Helfat, 2018; Schulze & Brusoni, 2022; Teece, 2014; Wilden et al., 2016).

Theoretical Background and Hypotheses

Defining Business Groups

BGs are defined as "collections of firms bound together in some formal and/or informal ways" (M. Granovetter, 1995: 95). This definition excludes "on the one hand, a set of firms bound merely by short-term strategic alliances, and on the other, a set of firms legally consolidated into a single entity" (Granovetter, 1995: 95) Carney et al. (2018) distinguish BGs from multidivisional hierarchical firms, emphasizing that "It is the loose ties among BG-affiliated firms that distinguish them from the typical Western corporation. . . Coordination in the M-form occurs through the unified internal control of multiple business units, but in BGs it relies on an intricate network of formal and informal control mechanisms" (Carney et al., 2018: 493–494). Indeed, many BG affiliates are large and diverse firms with a multidivisional (M-form) structure (Rhee et al., 2019; Yoshikawa, Tsui-Auch, & McGuire, 2007). Each affiliate has its own shareholders and board of directors, to whom it is accountable (Manikandan & Ramachandran, 2015).

The conceptualization of BGs has roots in the network embeddedness perspective (Luo & Chung, 2005; Uzzi, 1996). Structural embeddedness in BGs creates a context for inter-affiliate relationships that differs significantly from the relationships outside the BG (Granovetter, 1985, 1995). Both strong and weak ties can coexist within BG networks (Granovetter, 1973; Luo & Chung, 2005). Strong ties, such as regular interactions over products and technologies, facilitate the intensive exchange of complex knowledge, while weak ties (e.g., intra-group ties among affiliates that do not interact directly) offer the option of activating knowledge opportunities as they emerge. Loose integration and network brokerage by managers facilitate dynamic capabilities by enabling the exploration, recombination, and redeployment of resources within and across network clusters (Burt & Soda, 2021).

Some characteristics of BG networks, such as complementarities between network members, may resemble those of ecosystems. Specifying conceptual differences between ecosystems and BGs helps to clarify the goals of our study. First, ecosystems typically have "open" membership based on self-selection, with flexible relationships that allow participants to join or exit depending on their interests, the evolution of technology, or market needs (Gulati, Puranam, & Tushman, 2012; Jacobides, Cennamo, & Gawer, 2018). By contrast, BGs feature enduring relationships that typically outlive specific technological waves or platforms. Second, coordination in ecosystems is generally centered around specific products, services, or platforms (Altman, Nagle, & Tushman, 2022; Chen, Yi, Li, & Tong, 2022). With BGs, however, inter-affiliate ties are not product- or platform-specific, as affiliates work across diverse industries, and knowledge sharing often spans multiple platforms, products, or services.

Prior Literature on Business Group Affiliate Performance

The dominant approach for explaining the existence and performance effects of BGs has been the institutional voids perspective, which suggests that BGs emerged to circumvent the lack of market intermediaries (Khanna & Rivkin, 2001; Khanna & Yafeh, 2007; Yiu et al., 2007). Several studies have applied a resource-based view to extend the institutional approach. For instance, Guillén (2000) focused on the entrepreneurial capabilities of accessing and combining key resources (capital, labor, technology, and market connections) as a mechanism to enable repeated industry entry in emerging economies. Yiu et al. (2005) focused on resource-accessing mechanisms such as government connections and acquisitions. Lamin (2013) proposes that BG networks can serve as an important source of information and reputation signaling for market entry opportunities, while Bothello et al. (2023) demonstrate how reputation from BG affiliation can protect firms from harmful perceptions. Several studies have extended the institution-based view by focusing on the organizational characteristics of BGs, which enhance diversification in environments with improved institutional conditions (Gopal et al., 2021; Manikandan & Ramachandran, 2015).

Despite the useful contributions of previous studies, two key limitations should be recognized. First, the BG organizational form persists and has even grown in importance despite institutional advances in many countries (Liang & Carney, 2020; Poczter, 2018; Shapiro et al., 2024). Second, the focus on institutional factors has steered prior empirical studies toward capturing the differences between BG-affiliated and independent firms, leading to a predominant focus on group-level effects (Carney et al., 2011). Given the intra-group diversity of affiliates and their distinct assets, however, it is likely that the BG-level average effect hides a large intra-group variation in the value that affiliates can create and capture. These limitations highlight the need for alternative explanations. We offer a knowledge-based perspective with a focus on complementarity between firm- and group-level KBAs. Complementarity is important for representing quasi-rents[1] that are jointly created across affiliates. The presence of such complementarity implies that each firm benefits from group-level KBAs to different extents. We focus on the heterogeneity of complementarity (Adegbesan, 2009) and examine its sources.

KBAs in Business Groups and Complementarity

Group-level KBAs. KBAs accumulate over time and become inimitable because imitating such knowledge would require replication of the entire accumulation path (Aliyev & Kafouros, 2023; Dierickx & Cool, 1989; Knott, Bryce, & Posen, 2003). In BGs, affiliates benefit from preferential access to KBAs, facilitated by common group identity and affiliation links (Manikandan & Ramachandran, 2015; Rhee et al., 2019; R. Wang et al., 2024). Consequently, we define *group-level KBAs* pertaining to a firm as the identifiable proprietary technological knowledge owned by firms in the BG. We refer to an affiliates' own KBAs as *firm-level KBAs*.

Although KBAs in multidivisional firms may resemble the characteristics of group-level KBAs (e.g., decentralization), there are critical differences. Divisions in the M-form are coordinated under unified internal control, whereas coordination in BGs relies on loose ties formed by an intricate network of formal and informal control mechanisms (Carney et al., 2018). Hence, knowledge within (multidivisional) firms is formed under a common hierarchy, in which managers aim to optimize the R&D process across divisions, while the firm's management strives to integrate knowledge across divisions (Argote, Guo, Park, & Hahl, 2022), as well as restructuring divisions to take advantage of synergies to maximize *firm-level* outcomes (Karim & Kaul, 2015). In a BG setting, there is no common hierarchy that seeks to optimize a group's total set of KBAs. Moreover, unlike firm-level KBAs, group-level KBAs form and evolve outside the focal firm's control. In essence, group-level KBAs combine features of external KBAs and internal KBAs, where the affiliate does not have direct control over the formation of other affiliates' KBAs but can benefit from preferential access. Embeddedness in a BG network allows affiliates to tap into knowledge pools in the group, characterized by short network distance and density (Ahuja, 2000). Access to such collective knowledge portfolios in dense inter-affiliate networks amplifies affiliates' opportunities to combine knowledge (Yang & Schwarz, 2016; Zheng, Ma, & Hong, 2022).

Complementarity. Complementarity exists if "doing more of one thing increases the returns to doing more of another" (Milgrom & Roberts, 1995: 181). Consequently, group-level KBAs are complementary to firm-level KBAs if firm-level KBAs enhance marginal returns from group-level KBAs. Complementarity and the associated quasi-rents (Q) can be represented as $v\left(G \cup F\right) = v\left(G\right) + v\left(F\right) + Q(F, G)$, where $v\left(G \cup F\right)$, the value of jointly using group-level KBAs (G) and firm-level KBAs (F), exceeds the individual use of these assets by the amount of Q when complementarity is present ($Q > 0$)[2] (Adegbesan, 2009). The focus of our study is not only the presence of Q but also how its value varies across affiliates, implying the presence of *heterogeneous* complementarity (Adegbesan, 2009). In other words, earnings from group-level KBAs vary across affiliates not only because of the variation in the level of F but also because the level of *complementarity* between a unit of G and a unit of F (the rate of joint value creation) differs across affiliates. Heterogeneous complementarity implies that there must be factors influencing the *rate* of earning quasi-rents. Consequently, to explain intra-group variation in rents, the central question becomes: *where does such complementarity come from?*

Complementarity Between Firm- and Group-Level KBAs

Generating rents from knowledge requires combining and integrating it with other knowledge (Kamuriwo & Baden-Fuller, 2016; Zahra, Neubaum, & Hayton, 2020). Knowledge integration can occur in two ways: integration within a product, where knowledge is combined to introduce new products or services (Grant & Baden-Fuller, 2004; T. Wang & Chen, 2018); and integration for generating new inventions, where a combination of knowledge leads to the discovery of new knowledge (Ahuja, Lampert, & Novelli, 2013). Novel combinations typically require knowledge from a wide range of technological domains, and firms rarely possess all the technology internally (Palomeras & Wehrheim, 2021). Hence, to realize new product or invention opportunities, firms must complement their knowledge with external knowledge (Foss et al., 2013; Roper, Du, & Love, 2008). An important feature of BGs is that intra-group relations evolve over long periods, in which affiliates become familiar with each other's specializations and technological trajectories. Such a co-evolution of specializations results in the ability to recognize and integrate knowledge from other affiliates more easily. Recent research on intra-organizational knowledge combinations identifies "architectural knowledge" as a distinct type of knowledge that firms possess about how to combine knowledge from various technological domains (Yayavaram, Srivastava, & Sarkar, 2018). Architectural knowledge can evolve across affiliates' technological specializations, enabling firms to learn how to combine each other's knowledge for complementary gains. Combined with information on "who knows what", architectural knowledge can turn BG affiliates into an inter-linked knowledge integration and development system through which legally independent firms benefit from preferential access[3] to each other's knowledge and realize opportunities for complementary knowledge combinations. Consequently, as our baseline hypothesis, we submit that, in addition to rents from the shared use of group-level KBAs (reflected as the *direct* effect), affiliates also earn quasi-rents emerging from complementarity.

Baseline hypothesis H1: There is complementarity between group-level KBAs and firm-level KBAs such that firm-level KBAs strengthen the positive relationship between group-level KBAs and the financial performance of an affiliate firm.

Sources of Complementarity: Knowledge Combinations and Dynamic Capabilities View

To identify the sources of complementarity, we integrate *the knowledge-based* and *dynamic capability* views. The knowledge-based view positions knowledge as a key resource for achieving competitive advantage (Grant, 1996). Its extension to the inter-organizational context focuses on creating value via complementary combinations of knowledge across firms (Grant & Baden-Fuller, 2004). Knowledge-based literature has also identified that firms can complement their internal knowledge with external knowledge to create value (Foss et al., 2013; Grigoriou & Rothaermel, 2017; Kamuriwo & Baden-Fuller, 2016). These views align with the DCV as it places knowledge assets at center stage (Teece, 2007), focusing on how knowledge is absorbed, processed, and retained (Schilke et al., 2018). However, DCV also adds the role of *dynamic* environments and highlights *asset reconfiguration* as an important adaptive mechanism (Easterby-Smith & Prieto, 2008; Wilden et al., 2016; J. Zhang, Chen, Li, & Li, 2023).

Dynamic capabilities are defined as "the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments" (Teece, Pisano, & Shuen, 1997: 516). Extending the key elements of DCV to KBAs in BGs uncovers important mechanisms of complementarity in combining knowledge across affiliates. Namely, DCV specifies the importance of decentralization for enabling flexibility and responsiveness to technological changes (Heaton, Teece, & Agronin, 2023; Pitelis, Teece, & Yang, 2024; Teece, 2007). Decentralization "involves decomposition and the devolution of decision rights to quasi-independent profit centers" (Teece, 2007: 1336). Decentralization is a characteristic feature of BGs as affiliates operate in diverse industries and develop KBAs in various technological domains. Group ties and common identity can foster knowledge integration and facilitate the co-evolution of group-level KBAs into a flexible web of knowledge assets and a dynamic knowledge-creation system in which affiliates can gain complementarities.

However, in a diverse set of group-level KBAs, cross-affiliate redeployability likely varies. This relates to the role of the alignment and redeployability of technological assets in DCV (Dickler & Folta, 2020; Teece, 2007). From the perspective of dynamic capabilities, maximizing complementarities requires "asset alignment, coalignment, realignment, and redeployment" (Teece, 2007: 1336). Affiliates can earn quasi-rents from complementary group-level KBAs by *redeploying* them in combination with their own. Nevertheless, the inter-affiliate redeployability of KBAs and the potential for complementary combinations may vary depending on the degree to which group-level knowledge is *related* to the focal affiliate's knowledge and combinatorial requirements. Consequently, we identify *the decentralization* of group-level KBAs and their *relatedness* to the affiliate's knowledge as two configurational characteristics influencing the complementarity between group- and firm-level KBAs.

Furthermore, the DCV specifies the *sensing* and *seizing* of new opportunities and the *reconfiguring* of key assets as core enablers of dynamic capabilities (Teece, 2007; Wilden et al., 2016). As BG affiliates *reconfigure* their KBAs by developing new knowledge, combining group-level knowledge can help realize complementarities, where group ties offer advantages for affiliates' sensing and seizing of new technological opportunities. To identify this process, we propose two factors: *in-group sensing advantage* and *in-group seizing intensity*.

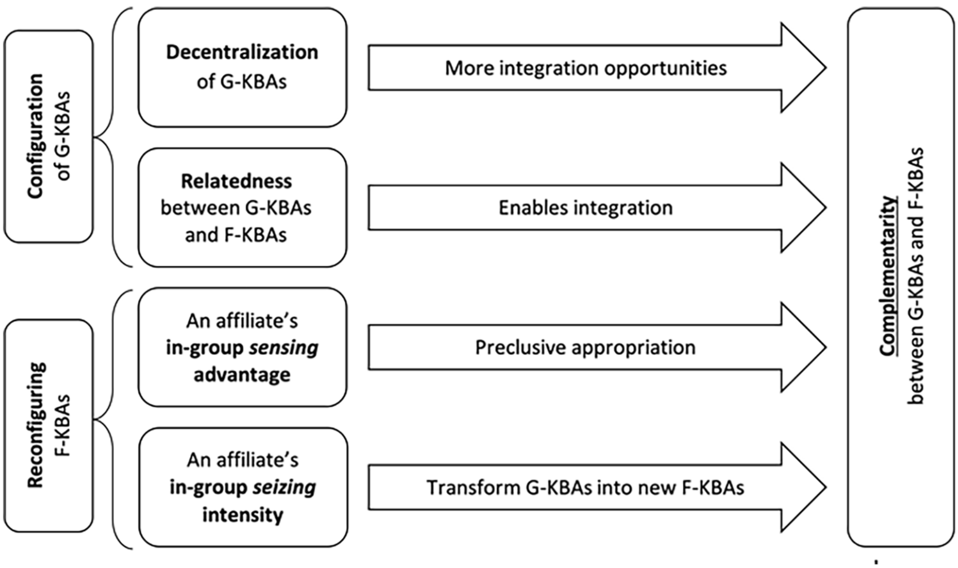
DCV defines *sensing* as a firm's ability to spot market and technological opportunities, emphasizing that the value-capturing properties of sensing are reflected in the firm's ability to position for first-mover advantage and determine desirable entry timing (Katkalo, Pitelis, & Teece, 2010). Hence, what matters is not only the incidence of sensing but mainly the ability to sense an opportunity and reconfigure the required assets *quickly*. With this logic, we define the *in-group sensing advantage* of knowledge-sourcing opportunities as time economies that an affiliate gains in sensing *in-group* opportunities relative to *out-group* ones.

Finally, sensed opportunities should be *seized* to create value (Teece, 2007). Seizing is reflected in investment disciplines, R&D choices, building relevant competencies, achieving new (re)combinations, and intellectual property protection (Katkalo et al., 2010). We expect complementarity between group- and firm-level KBAs to be realized when an affiliate seizes in-group knowledge combination opportunities by transforming the knowledge of other affiliates into firm-level knowledge. The key challenge in *seizing* is carefully selecting from multiple (competing) investment paths (Teece, 2007). Figure 1 summarizes the framework.

Decentralization of Group-Level KBAs

The decentralized organization of R&D offers both benefits and challenges (Ahuja et al., 2013; Eklund, 2022). In a decentralized form, R&D activity occurs in smaller units with more focused goals (Eklund, 2022; Leiponen & Helfat, 2011), enabling affiliates to specialize in their core competencies within their knowledge domain (Cassiman, Colombo, Garrone, & Veugelers, 2005). A decentralized structure can also make affiliates more sensitive to external changes and allow the flexibility to respond quickly to emerging opportunities (Heaton et al., 2023; Leiponen & Helfat, 2011), further helping affiliate firms to remain at the forefront of their field (Teece, 2007). However, increased specialization also means that, for knowledge needs beyond their core specialization, affiliates become increasingly reliant on the knowledge of other affiliates. In a BG with highly decentralized KBAs, an affiliate firm may have the opportunity to leave the development of complementary technology to a trusted affiliate if it falls within that affiliate's core competency. Additionally, affiliates can take advantage of their embeddedness in the inter-affiliate network to combine the KBAs dispersed across affiliates (Burt & Soda, 2021). The structural embeddedness of affiliates within

Figure 1
Sources of Rents from Complementary Knowledge Combinations Across BG Affiliates



BGs can facilitate trust, reciprocity, joint problem-solving, and rich information exchange (Uzzi, 1996). Such activities enable BG affiliates to capitalize on the benefits of dispersed KBAs. Hence, BG ties help to enhance efficiencies from the "division of labor" (Kavusan, Noorderhaven, & Duysters, 2016) and facilitate the evolution of complementary specialization across affiliates. In other words, group ties among affiliates foster modular decoupling of KBAs in the BG, where inter-affiliate ties enable the continuous bundling of KBAs across modules. This shifts knowledge combination activities (Ahuja et al., 2013; Xiao, Makhija, & Karim, 2022) from an *intra-affiliate* to an *inter-affiliate* process. Complementary specialization helps BG affiliates to individually develop technologies that can be combined across affiliates (Grant & Baden-Fuller, 2004).

Eklund (2022) notes that in hierarchical firms, decentralized R&D may optimize managerial incentives and increase the number of inventions, though often at the cost of reduced knowledge integration. In the context of BGs, affiliates operate as separate profit centers, preserving the incentive benefits associated with decentralization. At the same time, however, decentralized KBAs in BGs promote greater inter-affiliate knowledge integration, as each inter-affiliate tie creates more combinatorial opportunities. When KBAs are concentrated within a small number of affiliates, integration opportunities are facilitated within those affiliates but limit the potential for knowledge integration between them. Although higher KBA decentralization may still pose a challenge due to the more distant location of knowledge, BG ties and interactions evolved over time can mitigate this challenge by creating inter-affiliate knowledge exchange routines akin to group-level "transactive memory systems" (Argote & Ren, 2012). Affiliates are likely to know where to search for knowledge combination opportunities, as they remain aware of who is working on what.

In summary, we expect that the higher the decentralization of KBAs in a BG, the more opportunities for complementarity arise from the combined use of group- and firm-level KBAs that affiliates utilize via inter-affiliate channels of knowledge exchange established via BG ties.

Hypothesis H2: Decentralization of group-level KBAs across BG affiliates enhances the complementarity between group-level KBAs and firm-level KBAs.

Relatedness Between Firm-Level Kbas and Group-Level KBAs

Considering that group-level KBAs encompass knowledge from diverse technological domains, technological relatedness can facilitate the redeployability of group-level KBAs and their compatibility with firm-level KBAs (Dickler & Folta, 2020; Teece, 2007). Recent research supports this logic by showing that a patent is more likely to trade when it is technologically related to the potential buyer's technology stock (Kwon, Park, & Deng, 2022). Similarly, Makri, Hitt, and Lane (2010) found that firms can achieve complementary interfirm knowledge combinations if solutions to their problems reside within related knowledge domains. In a BG context, if one affiliate discovers a technology that resolves a specific engineering problem (or unlocks a new opportunity), other affiliates facing similar problems can benefit from the discovery and associated opportunities. Consequently, when group-level KBAs offer technological solutions in technology domains related to those of firm-level KBAs, there is a higher chance that the focal affiliate can benefit from the technological discoveries of other affiliates in the group. This is because the relatedness of group-level KBAs makes it easier for the focal affiliate to identify and apply complementary technological discoveries that can be combined with firm-level KBAs. By contrast, combining technologically distant KBAs may produce compatibility limitations and diverge in the types of problems they resolve.

In technologically dynamic environments, affiliate firms can benefit from adopting technological discoveries embedded in group-level KBAs, thereby upgrading their firm-level technologies. The technological relatedness between firm- and group-level KBAs can intensify such upgrades. Prior literature emphasizes that complementarity occurs when bundled assets complete, rather than substitute, each other (Zaheer, Castañer, & Souder, 2013). However, from the perspective of DCV, technological upgrades and reconfigurations are beneficial for firms operating in environments characterized by continuous technological change. In this sense, upgrading firm-level KBAs with group-level discoveries is more likely if they already use KBAs from related technological domains. The complementarity occurs between the new group-level knowledge and non-replaced firm-level KBAs. For instance, if we denote complementarity from firm-level KBAs $Q(F) = v(F_n, F_m)$, where $F_{n,m}$ are two firm-level technologies (knowledge sets) that are complementary to each other, the focal affiliate can replace F_m with a group-level upgrade of G_m, thus, realizing complementarity between F_n and G_m. Technological relatedness (between F_m and G_m in this example) can facilitate complementarity from such upgrades because of the pre-existing alignment between technology domains n and m in the focal knowledge combination.

Additionally, considering how the technologies of BG affiliates co-evolve dynamically under inter-affiliate interactions, we contend that affiliates evolve to become familiar with each other's technological knowledge bases, particularly if they work in related technological domains. Long-term cooperative behavior can create routine channels of communication, whereby affiliates learn "who is working on what," which can facilitate the coordination of consequent investments in knowledge. These effects facilitate group-level *co-alignment* of KBAs (Teece, 2007). A good understanding of the technological knowledge of other affiliates can help the focal firm evaluate the comparative advantages across affiliate firms and facilitate cross-affiliate combinations of upgrades from peer affiliates. In conclusion, we expect that:

> ***Hypothesis H3:*** Technological relatedness between group-level KBAs and firm-level KBAs enhances complementarity between them.

In-group Sensing Advantage

DCV proposes two classes of factors that emphasize the importance of sensing in the reconfiguration process (Teece, 2007). First, firms have differential access to existing information (Kirzner, 1973). Second, new knowledge can create new opportunities (Schumpeter, 1934). From the first perspective, a BG affiliate has more information about ongoing projects and discoveries within its BG than its competitors. This represents an advantage because of insider information accessible to BG affiliates but not accessible to outsiders. BG affiliates gain more information about these projects through their regular interactions with other affiliates. This implies that peer affiliates are also the first to *sense* new opportunities. For instance, when new concepts, designs, and knowledge are developed in a BG network, affiliates are first in line to evaluate how they can use those concepts or how they can contribute their knowledge to new designs.

From the Schumpeterian perspective, when new knowledge is created within a BG, fellow affiliates have early access to the discovery, allowing them to *sense* the consequent opportunities before their competitors. The *advantage* the affiliate gains by sensing *in-group* opportunities is important because out-group opportunities are accessible to any firm, while in-group opportunities become known to the focal affiliate *earlier* than they do to its competitors.

Potentially, any firm can build on a discovery made inside a BG as, in a knowledge-intensive setting, new discoveries are typically patented to obtain intellectual property rights. As a result, discoveries become open to all firms for subsequent inventions. Fellow BG affiliates, however, have an upper hand in sensing subsequent invention opportunities because of their early access to the new knowledge and associated combinatorial opportunities. This advantage arises because BG affiliates, through their continuous interactions with other affiliates, are exposed to novel developments and associated concepts emerging within the BG *before* the ideas turn into patentable discoveries.[4] While it takes time for a new concept to become an invention, BG affiliates can take advantage of such early access to these ideas and act before their competitors. This represents a preclusive mechanism of *generative appropriability*, where the firm that senses a new knowledge opportunity first precludes competitors (Ahuja et al., 2013). The advantage stemming from early access can be significant, considering that the idea-to-invention lead time may take months or years.[5] Such a long lead time between the inception of a conceptual idea and its public disclosure (becoming known outside the BG) poses advantages for BG affiliates in early sensing. Consequently, in-group knowledge combination opportunities enhance affiliates' chances of appropriating complementary inventions sensed through group-level discoveries.

Hypothesis H4: In-group sensing advantage of knowledge combination opportunities enhances the complementarity between group-level KBAs and firm-level KBAs.

In-group Seizing Intensity

In selecting which opportunities to seize, firms consider which paths generate the highest long-term rewards while accounting for the associated risks and uncertainty (Furr & Eisenhardt, 2021; Jung, Mallon, & Wilden, 2024). As firms sense new knowledge opportunities, seizing them often requires the presence of (or investments in) complementary knowledge. Firms must often make irreversible investment decisions, as they are co-specialized in a specific technology or product domain (Teece, 2007). This creates path dependency in the firms' scope of preferred investments. Given that in-group relations among affiliates evolve over time, path dependency and associated combinatorial opportunities are likely to be present across affiliates, facilitating cross-affiliate commitment to path-dependent investments. These advantages enable affiliates to satisfy their demand for external knowledge from in-group sources, rather than out-group.

Moreover, when a technological discovery is achieved, it typically becomes useful for additional purposes beyond the original intent (Hargadon & Sutton, 1997). The more frequently new knowledge or concept is bundled with other knowledge, the more often new uses for the initial idea or concept can be discovered (Ahuja et al., 2013). BG ties among affiliates can function as knowledge-processing mechanisms that facilitate extracting new discoveries taking place within the BG and recombining them with other knowledge to apply for subsequent inventions (Xiao et al., 2022). Network relations among BG affiliates evolve over time, where they not only get to know the specialization of other affiliates but also develop specific architectural skills by combining knowledge from the technological domains of peer affiliates (Yayavaram et al., 2018). Assuming some extent of continuity in firms' technological trajectories, BG affiliates should gain efficiencies when they build on in-group opportunities as compared to out-group ones.

Hypothesis H5: In-group seizing intensity of knowledge combination opportunities enhances complementarity between group-level KBAs and firm-level KBAs.

Empirical Context and Methodology

Japanese Keiretsu as Empirical Context for Knowledge-Intensive Business Groups

Keiretsu are commonly recognized groups of Japanese firms (Brouthers et al., 2014). Some of the *horizontal keiretsu* (e.g., Mitsubishi) are historical relics of the post-World War II dismantling of *zaibatsu*, while others formed around big banks (e.g., Sanyo) (Lincoln & Gerlach, 2004; Yoshikawa et al., 2007). *Vertical keiretsu* centers around a major industrial firm, its buyers, and suppliers (e.g., Toyota), whose member firms contribute to the value chain (Dyer & Nobeoka, 2000). Trust-based links are important for sharing financial resources and characterize the relationships in horizontal keiretsu. Vertical keiretsu affiliates are tied by buyer-supplier links (McGuire & Dow, 2009). Both types exhibit close strategic and operational relationships. Our analysis includes all seven major vertical keiretsu (Toyota, Honda, Toshiba, Nissan, Hitotsubashi/Shogakukan, Kodansha, and APA) and all leading horizontal keiretsu known as the "Big Six" (Fuyo, Sanwa, Sumitomo, Mitsubishi, Mitsui, and DKB).

After the Asian financial crisis, keiretsu relationships experienced adjustments throughout the 2000s with diminished bank debt, reduced cross-holdings, and reduced buyer-supplier ties (McGuire & Dow, 2009). Aoki and Lennerfors (2013a) describe the "new" keiretsu where companies (e.g., Toyota and Nissan) no longer rely exclusively on a set group of keiretsu suppliers and allow external suppliers to join the value chains to reduce costs. Despite restructuring, key keiretsu characteristics remain evident, with most core suppliers still providing integrated, critical systems. In these arrangements, trust and cooperation persist, with formal contracts remaining ambiguous, containing only general statements and non-binding targets (Aoki & Lennerfors, 2013a; Aoki & Wilhelm, 2017).

Keiretsu groups provide a suitable empirical setting for our analysis as they represent a knowledge-intensive environment. For instance, more than 13 million patents were registered in the Japanese patent office by the end of 2014 (our sample period). Our patent matching shows that the firms in our sample account for 87% of Japanese patents during this time. Keiretsu groups share many characteristics with BGs in other countries (Aoki & Lennerfors, 2013b; Granovetter, 1995; Lincoln & Gerlach, 2004; Yiu et al., 2007) and have underpinned numerous influential studies of knowledge and rents in BGs (Aoki & Wilhelm, 2017; Dyer & Hatch, 2006; Kim et al., 2004).

Interviews

To evaluate intra-group relations and the preferential access to group-level KBAs assumed for affiliates, we conducted three interviews with managers currently or formerly employed in keiretsu firms.[6] All respondents consistently described group ties as very strong. We asked how keiretsu firms utilize the KBAs of other affiliates, how these processes unfold, and whether they differ for non-affiliate firms. One respondent said "[Keiretsu company] *is a very old company and has a lot of know-how, so, if it's a similar field, you just snoop around and accumulate knowledge. 'We can do this, we can combine this, we can make a new battery'*, *You can do a lot of research that builds up knowledge like this, and most people do all of that . . . In the case of non-affiliate knowledge, it will be difficult for them to find a point of contact.*"

In addition, there were several examples from respondents regarding the nature of collaboration among keiretsu affiliates with clear signs of preferential partnerships: "*I think it's very simple and standard for business. Easier for keiretsu because it's the same network and we usually meet at some events. For example, when I worked at* [keiretsu company], *one time per month I'd usually meet with* [keiretsu network] *group companies' people, discuss with them about new technology or write papers together with all of them and drink after that. So we know each other and every month we meet and discuss. So this relationship is strong*." One respondent referred to 'nemawashi': "*Acquaintance is very important for business in Japan; we say nemawashi. Nemawashi means 'Making necessary arrangements'*, *In Japan, nemawashi is very tough work for managers. So, if they already know each other, its nemawashi is very easy.*"

Another respondent referred to existing collaborations as drivers of preferential partnership: *"Of course, it's easier among keiretsu companies. Easy to meet, especially via offline* *meetings because they are very close, and they have a lot of meetings so it's easy to communicate on other topics. Getting contacts and making contracts is also easy because they have a lot of them. For example, now* [keiretsu company] *have* [project name] *projects*, [project description] *project with keiretsu companies like* [another company in the same keiretsu] *and* [another company in the same keiretsu]. *So basically, even if it's a very difficult project, like* [nature of the project], *at first* [keiretsu company] *would like to put the emphasis on keiretsu." Confidentiality of information was another reason presented: "I think it's easy to get a contract because they have many contracts, so far, so contracting speed is very high and there is no need to worry about breaking confidential information in* [keiretsu supplier] *and* [keiretsu buyer]."

Overall, the interviews indicate that inter-affiliate relations in keiretsu groups feature strong preferences for keiretsu affiliates when undertaking projects requiring technological cooperation. In-group ties, such as managerial networks and contractual agreements, facilitate searches for technological solutions from peer affiliates, encourage knowledge and information exchange, and enable new projects.

Data and Sample

Financial data. We compiled data from the Worldscope database and Toyo Keizai's *Japan Company Handbooks*. The sample includes 524 keiretsu-affiliated firms traded on the Tokyo Stock Exchange (TSE) and the Japan Exchange Group (JPX) from 1985 to 2015. All observations with valid financial values are included unless the firm exits its BG.

We used firms within vertical and horizontal keiretsu as two separate samples because they operate in different ways. Although both fit our assumption of preferential access to group-level KBAs, the strength of the effects may vary between the two. We use vertical keiretsu as our primary sample because affiliates in these groups engage in more intensive technological cooperation and knowledge exchange than those in horizontal keiretsu (Lincoln & Gerlach, 2004; McGuire & Dow, 2009), which we use as our secondary sample. The consistency of results between the two tests the robustness and generalizability of the findings.

Patent data. To measure KBAs, we relied on patent data. Since patents document firms' intellectual property, they represent KBAs (Arora, Belenzon, & Sheer, 2021a; He & Wang, 2009). Patent data enable the measurement of KBA configurations and knowledge sourcing across affiliates, using details on patent technology domains, backward citations, and assignees.

We obtained patent data from the Institute of Intellectual Property (Japan) (IIP). The IIP Patent Database (IIP-DB) is based on standardized Japanese Patent Office (JPO) data. The JPO implements accurate patent attribution to firms, then the IIP conducts further cleaning before the release (Goto & Motohashi, 2007). These procedures minimize patent data errors. We accessed the IIP-DB 2020 version and extracted patents dated up to the end of 2014, totaling 13,268,490 patents. For accuracy, we manually searched for the names of the 524 firms in the "Name of applicant" field and visually verified the matched names. This process identified 11,517,496 patents associated with the firms in our sample.

Keiretsu classification. Classifying keiretsu membership, particularly for horizontal keiretsu, has been a daunting task in the literature (Kim et al., 2004). Prior studies have examined membership criteria such as a seat on the presidents' council that brings together the presidents of core group members (Gerlach, 1992) and other ties, such as ownership, director memberships, lending relationships, or historical relationships (Hundley & Jacobson, 1998). Similarly, we identified keiretsu member firms by relying on several published sources.[7] These sources documented keiretsu membership based on ownership structures, historical affiliations, debt structures, and other relevant characteristics (Kim et al., 2004). Our keiretsu attribution is time-variant. We traced 63 exits from vertical keiretsu and 107 from horizontal keiretsu (M&As, disassociations, and dissolutions). In total, 84% of the exits occurred in the post-2000 period.

Variable Measures

Dependent variable. We use return on sales (ROS) as the dependent variable, calculated as the percentage of net income to total sales. ROS measures profit on a revenue base and is widely used in prior literature (e.g., Zhao & Murrell, 2016). We also ran the analyses with return on assets and return on equity and found largely similar results.

Knowledge-based assets. We calculate *the firm-level KBAs* (F-KBAs) of a focal firm as the cumulative stock of firms' patents using the perpetual inventory method (Belenzon & Berkovitz, 2010). Formally, $\boldsymbol{S_t} = \boldsymbol{P_{t-1}} + (1-\delta)\boldsymbol{S_{t-2}}$, where S is the patent stock in year t, P represents the number of new patents of the firm, and δ is a depreciation rate of 0.15[8] (ibid.).

To calculate *the group-level KBAs* (G-KBAs) pertaining to the focal firm, we aggregated the patent stocks of all affiliates within each keiretsu for each year, excluding the focal firm's own patents. Formally, $GKBA_{ij} = \Sigma_{n-1} S_{aj}$, $(a \neq i)$, where S_{ij} represents the G-KBAs pertaining to firm i in group j,[9] n is the number of affiliates within the group, and affiliates a include all other affiliates (Aliyev & Kafouros, 2023; Chang & Hong, 2000). Both measures of KBAs enter the models in natural logs as $ln(1 + \text{patent stock})$, where observations without patents are set to zero (Arora, Belenzon, & Sheer, 2021b). Using patent stock in logs is an established practice in the literature because the original scale usually has a very large dispersion (Arora et al., 2021a; Belenzon & Berkovitz, 2010). The log transformation reduces the influence of extreme values.

Decentralization of group-level KBAs. To measure *the decentralization of group-level KBAs*, we used the Blau index (Harrison & Klein, 2007). In this context, the index represents the distribution of G-KBAs among affiliates. Formally, $D_{ij} = 1 - \Sigma_{n-1} s_{aj}^2$, $(a \neq i)$, where D_{ij} represents the decentralization of BG patents pertaining to firm i in group j, s_{aj} represents the share of the patent stock of affiliate a in group j, and n is the number of affiliates within the group. The index varies between 0 and 1, where high values represent decentralization.

Technological relatedness of the KBAs. To measure *the technological relatedness* of G-KBAs and F-KBAs, we use a technological overlap index based on the technological classification of pairs of patent portfolios (Belenzon & Berkovitz, 2010). Formally, $R_{ij} = \frac{(T_i T_j^{\mathrm{T}})}{(T_i T_i^{\mathrm{T}})^{1/2} (T_j T_j^{\mathrm{T}})^{1/2}}$, where *technological relatedness* R_{ij} for firm i in group j represents the level of technological overlap between the focal firm's patent portfolio and that of the BG (excluding the patents of the focal firm). T_i is a vector $T_i = (T_{i,1}, T_{i,2}, \ldots, T_{i,m})$, where $T_{i,m}$ represents the share of the patents of firm i in technology class m. To capture the technology class, we used the four-digit level of the International Patent Classification (IPC) codes. T_j is a similar vector for the group-level patent portfolio. For this variable, we used patents of the last five years (up to time $t-1$). The index TS_{ij} ranges from 0 to 1, with 1 representing the highest relatedness.

In-group sensing advantage. Following the emphasis on first-mover advantage and entry timing as the key mechanisms of capturing value from sensing (Katkalo et al., 2010), *in-group sensing advantage* should capture *how quickly* a firm can sense *in-group* knowledge opportunities relative to *out-group* ones. We treated the patent application date as an indicator of the time at which knowledge was created. Patented knowledge can be considered a combination of prior knowledge, traceable through backward citations in the patent. A shorter period between the elements of the combination (application dates of backward citations) and new knowledge (the focal patent's application date) indicates how quickly the affiliate sensed the knowledge combination opportunity and turned it into new knowledge (patent). A shorter lead time means a higher chance of appropriating the benefits of complementarity created from the combination. We should note that: first, the firm's sensing capability helps with sensing both in-group and out-group opportunities; second, the total lead time also includes patent "production" time after sensing. Therefore, our measure of in-group sensing *advantage* is calculated as the lead time of combining in-group opportunities relative to out-group opportunities. For a given level of sensing and patent production capability (after sensing the opportunity) of the firm, the difference in lead times captures the *in-group sensing advantage*.

The measure was calculated in five steps: (1) Using backward citations of each patent from the IIP database, we identified external (i.e., non-self) citations representing external knowledge sourcing opportunities; (2) External citations were categorized into in-group (to patents of other affiliates within the same BG) and out-group citations; (3) The average time (in days) between the application dates of the citing patent and cited patents was calculated; (4) A firm-year average was computed separately for in-group and out-group citations; (5) The average lead time for in-group citations was subtracted from that of the out-group citations. Formally, $A = \frac{1}{N_{out}} \Sigma L_{out} - \frac{1}{N_{in}} \Sigma L_{in}$, where $L_{out/in}$ represents the length of time (in days) between the citing and cited patent dates of the focal firm in each year, and $N_{out/in}$ is the number of citing-cited pairs per year. A larger difference between out-group and in-group averages indicates a higher advantage, as shorter lead times for in-group citations suggest time saved due to group affiliation. If the firm were not affiliated, it would require "*A*" additional days to sense those in-group opportunities because it would have sensed in-group opportunities at the same pace as it senses out-group opportunities. The variable enters the models with a lag of $t-1$.

In-group seizing intensity. This variable captures the extent to which the firm seizes *in-group* knowledge combination opportunities over *out-group* ones. By adapting prior uses of backward citation intensity to identify the sources of knowledge inflows (Katila & Ahuja, 2002), we calculated the ratio of in-group (non-self) backward citations to total *external* citations in patents filed each year. Formally, $Z_{ij} = \frac{B_{in}}{B_{ext}}$, where B_{in} is the firm-year count of *in-*

group backward citations, and B_{ext} is the firm-year count of total external (*in-* and *out-group*) backward citations. The variable enters the models with a lag of $t-1$.

Control variables. We include firm- and group-level controls. At the firm level, we control for capital availability using *liquidity* (current assets as a percentage of current liabilities) and financial *leverage* (long-term debt as a percentage of equity) (Jones, Johnstone, & Wilson, 2017). We control for firm size using the log of total assets in millions of Japanese yen.

At the group level, *the group liquidity* pertaining to the focal firm is the weighted average of the liquidity ratios of all other group affiliates, weighted by the proportion of each affiliate's current liabilities to the group's total (Chang & Hong, 2000). Group *leverage* is calculated as the weighted average of the leverage ratios, using the equity base as the weighting factor (Chang & Hong, 2000). To account for diversification, we use the entropy measure. G*roup unrelated diversification* is measured *across* two-digit Japanese Standard Industrial Classification (JSIC) codes, while *related diversification* is measured *within* two-digit (across three-digit) codes. *Group size* is controlled using the log of the total assets of all group affiliates. Finally, we control for industry and year effects using dummy variables for two-digit JSIC codes and years.

Analysis

Modeling and Statistical Approach

Given that the observations are nested within groups and firms, we employed a multilevel method of hierarchical linear modeling (HLM). HLM accounts for dependencies within groups by partitioning and modeling within- and between-group variances (Chang & Hong, 2002). We followed established approaches to multilevel performance estimation (Guo, 2017; Karniouchina, Carson, Short, & Ketchen Jr., 2013). Formally, the model is as follows:

Level 1: $ROS_{tij} = \alpha_{0ij} + e_{tij}$;
Level 2: $\alpha_{0ij} = \beta_{00j} + w_{0ij}$;
Level 3: $\beta_{00j} = \lambda_{000} + h_{00j}$

Here, the subscripts t, i, and j denote time, firm, and group, respectively. ROS_{tij} is the year t performance of firm i in group j. α_{0ij} is the over-time mean *ROS* of firm i. β_{00j} is the mean *ROS* of all firms in group j. λ_{000} is the grand-mean *ROS* of all firms in the dataset. Residuals e_{tij}, w_{0ij}, and h_{00j} represent within-firm, between-firm (within-group), and between-group variance components, respectively, and are normally distributed with a zero mean and variances of σ_e^2, σ_w^2, and σ_h^2. The equation for the full model is as follows:

$$ROS_{tij} = \lambda_{000} + h_{00j} + w_{0ij} + r_F F_{tij} + r_G G_{tij} + q_{FG} F_{tij} G_{tij} + \theta_k \sum_k Z_k + e_{tij}$$

F_{tij} and G_{tij} represent the *F-KBAs* and *G-KBAs*, respectively. The coefficient r_G represents the rate of rents from G-KBAs without complementarity. Testing baseline Hypothesis H1 requires estimating the complementarity between F_{tij} and G_{tij}. Formally, variables F and G are complementary with respect to ROS (π) if $\frac{\partial^2 \pi}{\partial F \partial G} > 0$ (Tanriverdi & Lee, 2008), yielding q_{FG}. A positive and statistically significant q_{FG} confirms Hypothesis H1, with the coefficient size representing the *rate of earning* quasi-rents (elasticities due to the logarithmic measure of KBAs). Hypotheses H2–H5 are tested via three-way interaction terms moderating q_{FG}. Formally, $\frac{\partial^3 \pi}{\partial F \partial G \partial U_m} > 0$ verifies that factors U (sources of complementarity in H2–H5) enhance the rate of earning quasi-rents q_{FG}. Z_k represent the remaining variables.

Results

Tables 1A and B present descriptive statistics and correlations for the two samples. There are no overly strong correlations that raise concerns. Several notable observations emerge from the means. *Decentralization* of group-level KBAs is, on average, higher for horizontal keiretsu (0.83) than for vertical keiretsu (0.62), as expected. Conversely, mean *relatedness* is higher for vertical keiretsu (0.08) than for horizontal keiretsu (0.03), reflecting the closer technological proximity of KBAs in vertical groups. *In-group sensing advantage* shows that vertical keiretsu affiliates economize an average of 307 days when sourcing knowledge within BGs, while horizontal keiretsu affiliates economize almost a year (360 days). This temporal advantage suggests that in-group knowledge sourcing contributes to the preclusive appropriation of inventions. Finally, *in-group seizing intensity* shows a mean of 0.40 for vertical and 0.27 for horizontal keiretsu, indicating that vertical keiretsu affiliates build on in-group knowledge more intensively than horizontal keiretsu affiliates.

Table 2 presents the vertical keiretsu sample results. Model M1 reports the direct effects of regressors, showing a positive and statistically significant relationship between G-KBAs and affiliate ROS ($r_G = 0.210$, $p = .002$). Model M2 adds two-way interactions, showing that the interaction between F-KBAs and G-KBAs is positive and significant ($q_{FG} = 0.263$, $p = .000$), supporting Hypothesis H1, which states that firm-level KBAs strengthen the positive relationship between group-level KBAs and financial performance.

Figure 2 illustrates the strength of complementarity by plotting the effect of G-KBAs on affiliate ROS at two values of F-KBAs (based on Model M7). The horizontal axis shows the full range of G-KBAs in natural logs. Solid and dashed lines represent two F-KBA levels: no patents and the 75th percentile (111 patents; $ln(111) = 4.71$). This value is well below the mean of the F-KBAs (787 patents) but offers conservative estimates given the positively skewed distribution. The solid line takes ROS from −1.32% to 2.21% for affiliates with no F-KBAs, while the dashed line moves from −0.17% to 14%. This difference highlights the large effect size of complementarity between G-KBAs and F-KBAs.

Model M3 introduces the three-way interaction between F-KBAs, G-KBAs, and *decentralization (D)*. The coefficient for the three-way interaction term (F × G × D) is positive and statistically significant ($q_{FGD} = 0.873$, $p = .000$), supporting Hypothesis H2, which states that decentralization enhances the complementarity between group- and firm-level KBAs. The coefficient q_{FGD} represents how a unit change in *decentralization* impacts the level of complementarity (rate of earning quasi-rents).

Model M4 includes the three-way interaction between F-KBAs, G-KBAs, and *relatedness* (R) (F × G × R). The positive and significant coefficient ($q_{FGR} = 0.571$, $p = .044$) supports

Table 1A
Descriptive Statistics for *Vertical* Keiretsu Sample (N=4,104)

		Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Firm ROS (%)	0.92	9.66	−65.27	87.49																
2	**Firm-level KBAs (log)***	786.59	504.43	0	4357	0.08															
3	Firm advertising (%)	3.07	2.61	0.00	62.70	0.07	0.18														
4	Firm liquidity (%)	1.74	5.59	0.00	662.06	0.10	−0.04	0.01													
5	Firm leverage (%)	1.8	9.05	−33.24	142.94	−0.05	−0.02	−0.04	0.00												
6	Firm size (log)	6,186	12,098	68	201,802	0.04	−0.01	0.23	0.00	−0.03											
7	**Group-level KBAs (log)**	13021.25	3039.44	11	22,013	0.06	0.44	0.11	−0.04	0.02	0.00										
8	Group advertising (%)	3.07	1.48	1.01	10.99	0.04	0.02	0.15	0.07	−0.05	0.03	0.04									
9	Group liquidity (%)	7.17	8.65	12.05	587.38	0.03	−0.07	−0.02	−0.01	−0.03	0.10	0.01	−0.05								
10	Group leverage (%)	1.3	6.3	1.98	342.94	−0.04	−0.02	−0.01	−0.01	0.29	−0.10	−0.07	−0.01	−0.08							
11	Group unrelated diversification	0.12	0.11	0.00	0.37	0.06	0.17	0.16	−0.02	−0.01	0.17	0.22	−0.04	0.23	−0.06						
12	Group related diversification	0.1	0.1	0.00	0.36	0.03	0.16	0.12	0.01	−0.01	0.34	0.17	0.00	0.09	−0.05	0.49					
13	Group size (log)	281,280	198,356	3,953	858,754	0.05	0.05	−0.04	−0.01	−0.06	0.21	0.09	−0.02	0.32	−0.25	0.20	0.12				
14	**Decentraliz. of group KBAs**	0.62	0.22	0	1	0.06	0.15	−0.05	0.01	0.06	−0.10	0.18	−0.03	−0.04	0.08	−0.01	−0.01	−0.01			
15	**Relatedness of KBAs**	0.08	0.17	0	1	0.05	0.33	0.13	−0.01	−0.01	0.02	0.15	0.04	−0.01	−0.02	0.00	0.06	−0.01	−0.09		
16	**In-group sensing adv. (log)**	307.32	372.17	75	957	0.09	−0.03	−0.15	0.10	0.01	−0.10	0.06	−0.23	0.17	−0.11	0.12	−0.00	−0.24	−0.06	0.09	
17	**In-group seizing intensity**	0.40	0.30	0	1	0.08	0.04	0.19	−0.06	0.08	0.49	0.06	0.08	0.02	0.11	−0.04	−0.17	0.09	0.07	0.03	0.14

Table 1B

Descriptive Statistics for *Horizontal* Keiretsu Sample (*N*=13,791)

		Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Firm ROS (%)	0.74	9.94	−141.82	85.24																
2	**Firm-level KBAs (log)**	736.37	406.62	0	4418	0.06															
3	Firm advertising (%)	2.76	4.59	0.00	136.05	0.03	0.03														
4	Firm liquidity (%)	1.69	4.91	0.00	977.96	0.03	0.03	−0.01													
5	Firm leverage (%)	2.89	31.36	−76.95	1037.15	0.01	0.02	−0.02	0.00												
6	Firm size (log)	8,258	14,785	873	203,442	0.13	−0.02	0.00	0.00	0.04											
7	**Group-level KBAs (log)**	32149.32	5023.97	27	37114	0.04	0.50	0.01	−0.05	0.03	−0.01										
8	Group advertising (%)	5.18	3.81	1.01	15.33	0.02	0.02	0.04	0.00	−0.02	−0.03	0.00									
9	Group liquidity (%)	8.33	3.03	21.11	604.03	−0.04	−0.03	0.01	0.03	−0.03	−0.02	−0.17	0.03								
10	Group leverage (%)	96.3	47.24	81.35	464.61	−0.03	0.06	−0.01	−0.01	0.02	−0.03	0.03	−0.07	−0.11							
11	Group unrelated diversification	0.13	0.11	0.00	0.37	0.02	0.17	0.14	−0.02	0.06	0.06	0.16	0.02	−0.03	−0.04						
12	Group related diversification	0.06	0.08	0.00	0.37	0.05	0.09	0.06	−0.02	0.03	0.30	0.07	−0.03	−0.01	−0.06	0.44					
13	Group size (log)	1,068,314	265,385	59,182	1,608,754	0.04	−0.03	0.02	0.03	−0.07	−0.03	−0.03	0.17	0.51	−0.46	−0.03	−0.02				
14	**Decentraliz. of group KBAs**	0.83	0.11	0.35	1	0.03	0.08	0.01	0.02	0.02	0.10	0.13	0.13	−0.24	0.06	0.02	−0.04	−0.03			
15	**Relatedness of KBAs**	0.03	0.07	0	1	0.04	0.40	−0.01	−0.01	0.04	−0.01	0.31	−0.02	−0.02	−0.01	0.04	0.04	−0.02	−0.02		
16	**In-group sensing adv. (log)**	359.98	216.59	76	968	0.09	−0.13	0.02	0.01	0.07	−0.06	0.19	0.12	0.68	−0.55	0.02	−0.02	−0.42	−0.27	0.08	
17	**In-group seizing intensity**	0.27	0.23	0	1	0.09	0.01	0.02	−0.02	0.01	0.57	0.02	0.05	−0.03	0.02	−0.12	0.38	0.02	0.07	0.02	0.03

*Variables entering the models in logs have means and standard deviations (SDs) reported *without* logs and correlations *with* logs. Measures of size (total assets) are reported in billions of Japanese yen to conserve space.

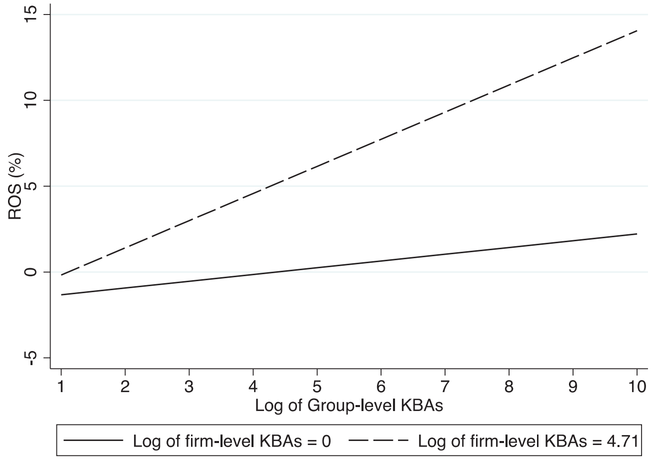
Table 2

Multilevel Analysis Results

		M1		M2		M3		M4		M5		M6		M7		M7(H)	
		Coef.	*(p-val)*	*Coef.*	*(p-val)*	*Coef.*	*(p-val)*	*Coef.*	*(p-val)*	*Coef.*	*(p-val)*	*Coef.*	*(p-val)*	*Coef.*	*(p-val)*	*Coef.*	*(p-val)*
	Intercept	4.664	(.037)	1.339	(.593)	4.827	(.063)	0.423	(.868)	1.334	(.595)	1.271	(.612)	4.493	(.086)	−37.117	(.000)
	Firm advertising (%)	0.070	(.278)	0.049	(.451)	0.014	(.836)	0.044	(.503)	0.050	(.447)	0.053	(.421)	0.101	(.124)	0.081	(.000)
	Firm liquidity (%)	0.158	(.000)	0.154	(.000)	0.157	(.000)	0.155	(.000)	0.154	(.000)	0.155	(.000)	0.163	(.000)	0.112	(.000)
	Firm leverage (%)	−0.070	(.002)	−0.092	(.000)	−0.093	(.000)	−0.092	(.000)	−0.092	(.000)	−0.092	(.000)	−0.092	(.000)	0.005	(.065)
	Firm size (log)	0.483	(.001)	0.487	(.001)	0.440	(.002)	0.498	(.001)	0.488	(.001)	0.502	(.001)	0.489	(.001)	2.312	(.000)
	Group advertising (%)	0.318	(.008)	0.207	(.086)	0.287	(.018)	0.166	(.174)	0.206	(.087)	0.200	(.097)	0.226	(.064)	0.006	(.015)
	Group liquidity (%)	0.080	(.000)	0.080	(.000)	0.077	(.000)	0.076	(.000)	0.080	(.000)	0.079	(.000)	0.064	(.002)	−0.351	(.000)
	Group leverage (%)	−0.008	(.836)	−0.084	(.023)	−0.076	(.040)	−0.086	(.019)	−0.084	(.023)	−0.085	(.022)	−0.078	(.034)	−0.004	(.078)
	Group unrelated diversification	6.330	(.001)	9.225	(.000)	9.022	(.000)	9.328	(.000)	9.229	(.000)	9.252	(.000)	9.205	(.000)	2.706	(.004)
	Group related diversification	6.546	(.003)	6.829	(.002)	8.074	(.000)	6.881	(.002)	6.804	(.003)	6.538	(.004)	7.769	(.001)	6.970	(.000)
	Group size (log)	0.215	(.037)	0.486	(.000)	0.349	(.003)	0.519	(.000)	0.487	(.000)	0.492	(.000)	0.365	(.002)	1.174	(.000)
	Firm-level KBAs (log) (F)	**0.362**	**(.002)**	**1.955**	**(.003)**	**2.735**	**(.003)**	**2.447**	**(.000)**	**2.482**	**(.011)**	**2.078**	**(.005)**	**5.010**	**(.000)**	**10.914**	**(.008)**
	Group-level KBAs (log) (G)	**0.210**	**(.002)**	**0.759**	**(.008)**	**0.718**	**(.014)**	**0.725**	**(.012)**	**0.774**	**(.008)**	**0.786**	**(.006)**	**0.774**	**(.010)**	**0.681**	**(.012)**
	Decentralization of group KBAs **(D)**	3.913	(.000)	6.173	(.000)	8.465	(.000)	5.744	(.000)	6.162	(.000)	5.917	(.000)	7.859	(.000)	4.466	(.000)
	Relatedness of KBAs **(R)**	3.131	(.005)	7.952	(.011)	8.811	(.005)	20.661	(.006)	8.032	(.013)	8.497	(.007)	31.610	(.000)	263.993	(.003)
	In-group sensing advant. (log) **(Sn)**	0.381	(.029)	0.488	(.023)	0.449	(.036)	0.479	(.026)	0.476	(.027)	0.491	(.023)	0.430	(.048)	2.637	(.000)
	In-group seizing intensity **(Sz)**	5.005	(.000)	2.484	(.003)	2.140	(.012)	1.977	(.019)	2.279	(.007)	2.078	(.017)	1.959	(.025)	1.617	(.017)
H1:	**F × G**			**0.263**	**(.000)**	**0.255**	**(.035)**	**0.298**	**(.000)**	**0.253**	**(.034)**	**0.203**	**(.010)**	**0.615**	**(.001)**	**0.833**	**(.075)**
	F × D			4.255	(.000)	10.080	(.000)	3.977	(.000)	4.257	(.000)	4.310	(.000)	12.343	(.000)	6.868	(.171)
	F × R			3.600	(.001)	3.266	(.004)	2.713	(.229)	3.609	(.001)	3.673	(.001)	3.760	(.104)	29.782	(.023)
	F × Sn			0.570	(.000)	0.571	(.000)	0.547	(.000)	0.552	(.009)	0.578	(.000)	0.578	(.023)	0.446	(.116)
	F × Sz			2.459	(.000)	2.629	(.000)	2.387	(.000)	2.457	(.000)	3.374	(.000)	5.655	(.000)	7.376	(.000)
	G × D			0.736	(.016)	0.202	(.530)	0.655	(.033)	0.737	(.016)	0.779	(.011)	0.538	(.100)	0.171	(.558)
	G × R			3.048	(.002)	3.187	(.001)	5.277	(.000)	3.067	(.003)	3.156	(.002)	7.619	(.000)	31.983	(.002)
	G × Sn			0.177	(.001)	0.179	(.001)	0.169	(.002)	0.179	(.002)	0.180	(.001)	0.173	(.003)	0.043	(.069)
	G × Sz			0.441	(.061)	0.451	(.057)	0.464	(.049)	0.429	(.069)	0.438	(.075)	0.467	(.058)	0.435	(.002)
H2:	**F × G × D**					**0.873**	**(.000)**							**1.261**	**(.000)**	**1.104**	**(.051)**
H3:	**F × G × R**							**0.571**	**(.044)**					**1.033**	**(.000)**	**3.629**	**(.013)**
H4:	**F × G × Sn**									**0.063**	**(.018)**			**0.062**	**(.057)**	**0.068**	**(.029)**
H5:	**F × G × Sz**											**0.329**	**(.001)**	**0.434**	**(.001)**	**0.863**	**(.000)**
		σ^2	*SE*	σ^2	*SE*	σ^2	*SE*	σ^2	*SE*	σ^2	*SE*	σ^2	*SE*	σ^2	*SE*	σ^2	*SE*
	Variance of group-level effects	84.615	2.017	82.190	1.932	81.573	1.903	81.356	1.902	81.127	1.901	81.285	1.905	81.069	1.892	60.784	1.166
	Variance of firm-level effects	73.189	1.885	70.453	1.745	69.904	1.735	69.898	1.733	70.015	1.732	69.950	1.734	68.432	1.715	70.195	1.235
	Residual variance	87.982	1.942	84.222	1.859	83.704	1.848	84.139	1.857	84.222	1.859	84.187	1.858	83.207	1.837	90.504	1.090
	Pseudo R^2	35.418		64.957		80.561		79.362		79.466		80.312		91.769		94.788	

Notes: Dependent variable: ROS. N=4,104 in models M1-M7 for the vertical keiretsu sample. N=13,791 in model M7H for the horizontal keiretsu sample. P-values in parentheses. Industry and year specific dummy variables are included but not reported.

Figure 2
Moderation of the Effect of Group-level KBAs on ROS by Firm-level KBAs



Hypothesis H3, which states that *relatedness* enhances the complementarity between group- and firm-level KBAs. Model 5 shows a statistically significant effect of *in-group sensing advantage* (Sn) (FxGxSn; $q_{FGSn}=0.063$, $p=.018$), corroborating Hypothesis H4, which states that *in-group sensing advantage* enhances complementarity between group- and firm-level KBAs. Model M6 supports Hypothesis H5 with a significant coefficient (FxGxSz; $q_{FGSz}=0.329$, $p=.001$), indicating that *in-group seizing intensity* enhances complementarity. Finally, Model M7 presents the full model, where most coefficients of interest remain statistically significant at the 0.1% level. While the coefficient of F × G × Sn weakens in statistical significance, the p-value is just above the traditional 5% threshold, implying the presence of the effect.

Model M7(H) presents the full model for the horizontal keiretsu sample (Table A1 in the online appendix provides the full set of models). While coefficient sizes differ due to variations in variable values and distributions, the pattern of coefficient signs and statistical significance supports the hypotheses, demonstrating the generalizability of the results to this setting. The only weakly significant coefficient is the effect of decentralization ($p=.051$).

Three-way Moderation Effect Sizes

We calculated how the three-way interactions strengthen complementarity. In the presence of a three-way interaction, F × G represents complementarity at zero for the three-way moderator. Complementarity changes can be estimated for specific values of moderators. For instance, in Model M3, F × G = 0.255 and F × G × D = 0.873. A one standard deviation (SD) increase in *decentralization* (from the mean of 0.62 by 0.22 SD) raises complementarity from 0.796 (=0.255 + 0.873 × 0.62) to 0.988 (=0.255 + 0.873 × (0.62 + 0.22)), a 24% increase in complementarity attributable to one SD change in *decentralization*. Table 3 presents effect sizes for each moderator. Panel A covers Models M3–M6, and Panel B covers Model M7. The effects are weaker in Panel B due to the simultaneous inclusion of all moderators. For *in-group sensing advantage* (Sn), which is in natural logs,

Table 3

Effect Sizes of Complementarity Moderation

Panel A (based on models M3-M6) Third-way moderator (U)	Mean	SD	Baseline complementarity $F \times G$ (U=0)	Coefficient of $F \times G \times U$	Moderated complementarity at U=mean	Moderated complementarity at U=mean + SD	Change in moderated complementarity: $\frac{q_{FGU\,(mean+SD)}}{q_{FGU\,(mean)}}$
Decentralization of group-level KBAs	0.62	0.22	0.255	0.873	0.796	0.988	1.241 (24.1% increase)
Relatedness of KBAs	0.08	0.17	0.298	0.571	0.344	0.441	1.282 (28.3% increase)
In-group sensing advantage	307.32	372.17	0.253	0.063	0.614	0.664	1.081 (8.1% increase)
In-group seizing intensity	0.40	0.30	0.203	0.329	0.334	0.434	1.297 (29.7% increase)

Panel B (based on model M7) Third-way moderator (U)	Mean	SD	Baseline complementarity $F \times G$ (U=0)	Coefficient of $F \times G \times U$	Moderated complementarity at U=mean	Moderated complementarity at U=mean + SD	Change in moderated complementarity: $\frac{q_{FGU\,(mean+SD)}}{q_{FGU\,(mean)}}$
Decentralization of group-level KBAs	0.62	0.22	0.615	1.261	1.397	1.674	1.199 (19.9% increase)
Relatedness of KBAs	0.08	0.17	0.615	1.033	0.698	0.873	1.252 (25.2% increase)
In-group sensing advantage	307.32	372.17	0.615	0.062	0.970	1.019	1.051 (5.1% increase)
In-group seizing intensity	0.40	0.30	0.615	0.434	0.788	0.919	1.166 (16.6% increase)

Figure 3a
Moderation of Complementarity by *Decentralization*

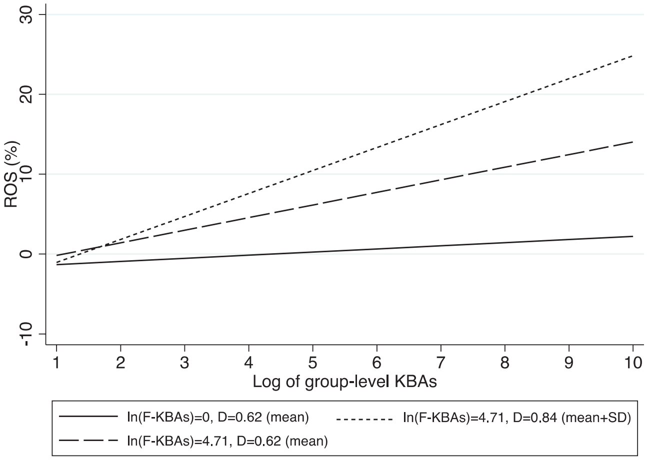
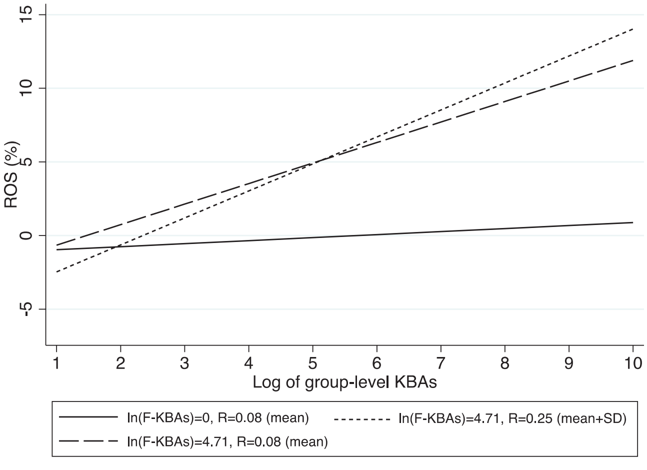


Figure 3b
Moderation of Complementarity by *Relatedness*



we transformed values into logs for calculations (e.g., the value at the mean was calculated as $0.253 + 0.063 \times ln(307.32) = 0.614$). Because of the logarithmic scale, the effects of each unit are different. For example, a move from 0 to the mean (307 days) increases complementarity from 0.253 to 0.614 – a 143% increase – while a move from the mean by 372 days (one SD) raises complementarity by 8.1%.

Figures 3a–d graph the moderation of complementarity as calculated from Model M7 in Table 2. Figure 3a plots the predicted ROS values for three scenarios. The solid line shows

Figure 3c
Moderation of Complementarity by *In-Group Sensing Advantage*

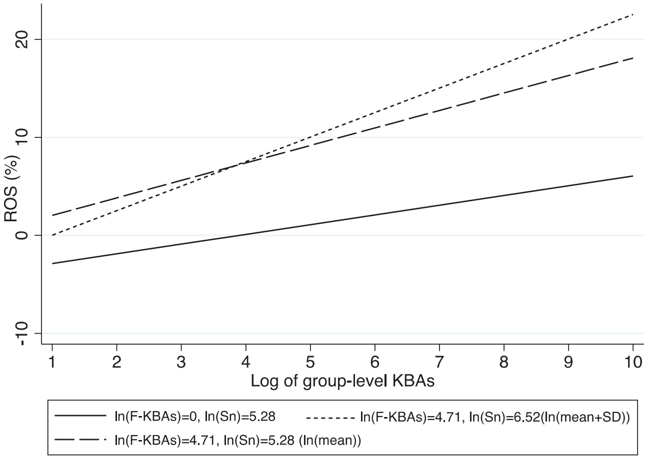
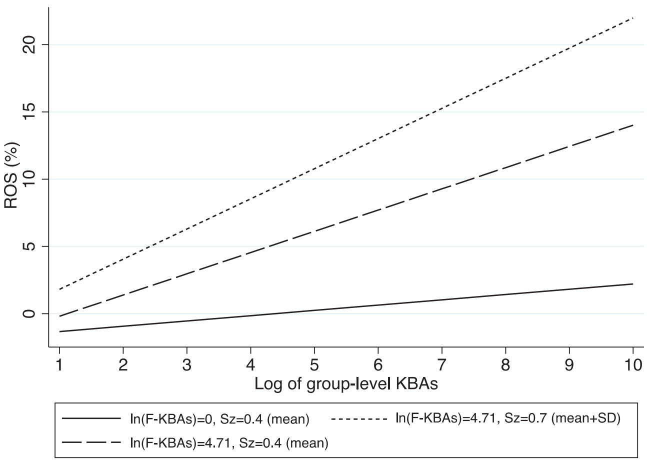


Figure 3d
Moderation of Complementarity by *In-Group Seizing Intensity*



the effect of G-KBAs when F-KBAs are zero, with *decentralization* at its mean (0.62). The long-dashed line represents the effect of G-KBAs when F-KBAs are at the 75th percentile, while *decentralization* remains at its mean. The short-dashed line adds the effect of increasing decentralization by one SD. The difference in steepness between the long-dashed and solid lines reflects complementarity at the mean level of decentralization, while the difference between the short- and long-dashed lines indicates the impact of decentralization on complementarity.

Figures 3b–d were created similarly. In all figures, the short-dashed lines are steeper than the long-dashed lines, demonstrating how the moderator increases complementarity between the G-KBAs and F-KBAs. It is important to note that the intercepts of the predicted lines are not stable due to the multilevel model used. Unlike linear models, where intercepts remain unchanged when predictor values are imputed, multilevel models first perform within-group regressions and then use the resulting parameter estimates in higher-level analyses. Consequently, when predicting ROS from the imputed predictor values, intercepts may shift due to lower-level regressions. Thus, the focus should be on the steepness of the lines.

Application of Mean-Centering Techniques

Methodological literature on HLM suggests that, depending on the purpose of the analysis, mean-centering the independent variables can resolve some analytical issues. For instance, *grand*-mean-centering (GMC) rescales predictors to make intercepts easier to interpret (Hoffman & Walters, 2022: 664; Hox, 2010), while *group*-mean-centering removes between-group variation in lower-level variables, enabling coefficients to capture the effect of within-group variation only (Enders & Tofighi, 2007). In our study, removing between-group variation is not desirable because the goal is to identify affiliate-specific heterogeneity in the effect of group-level KBAs. Nonetheless, we conducted robustness tests using both GMC and group-mean-centering. Due to the longitudinal structure of our data, we applied group-mean-centering in two ways. First, we mean-centered all variables within keiretsu-year clusters, where each firm-year observation is treated as clustered within the keiretsu-year (KYMC). Second, we mean-centered the firm-year observations of all variables within a firm (FMC). Results – provided in Table A2 in the online appendix – show coefficient signs and statistical significance levels, confirming the robustness of our inferences across various mean-centering specifications.

Analysis of Exits from Business Groups

Our dataset traces firm exits resulting from the keiretsu restructuring in the early 2000s. This provided an opportunity to investigate the impact of complementarity in KBAs on the likelihood of firms maintaining their keiretsu affiliations. We estimated the hazard rates of exit using Cox proportional hazards models, which assess the effects of independent variables on the risk of exiting the group. Table 4 reports the results. A negative coefficient indicates a lower probability of exit (i.e., a longer duration of affiliation). For vertical keiretsu, the coefficients corresponding to the hypothesized effects are statistically significant, except for the effect of *in-group seizing intensity* on complementarity in Model M6, which is significant only at the 6% level. For the horizontal keiretsu, most effects are strongly significant, though the effect of *in-group sensing advantage* in Model M7(H) is marginally significant ($p = .051$). Table A3 in the online appendix provides the full set of models for the horizontal keiretsu sample.

These results indicate that factors driving rents also predict the likelihood of firms maintaining their affiliations, suggesting that KBAs and the rents they generate are important in keeping group affiliates together. Factors of complementarity show evidence that incentives for remaining affiliated may vary across firms within BGs. This highlights the role of *affiliate-specific* joint value creation in explaining the persistence of keiretsu affiliations.

Table 4
Cox Proportional Hazard Model Analysis

		M1		M2		M3		M4		M5		M6		M7		M7(H)	
		Coef.	*(p-val)*	*Coef.*	*(p-val)*	*Coef.*	*(p-val)*	*Coef.*	*(p-val)*	*Coef.*	*(p-val)*	*Coef.*	*(p-val)*	*Coef.*	*(p-val)*	*Coef.*	*(p-val)*
	Firm advertising (%)	−0.041	(.012)	−0.042	(.014)	−0.036	(.037)	−0.047	(.005)	−0.043	(.011)	−0.042	(.014)	−0.039	(.022)	−0.001	(.875)
	Firm liquidity (%)	0.017	(.006)	0.017	(.008)	0.017	(.006)	0.017	(.008)	0.017	(.007)	0.017	(.008)	0.018	(.004)	−0.139	(.620)
	Firm leverage (%)	0.033	(.000)	0.028	(.000)	0.028	(.000)	0.028	(.000)	0.028	(.000)	0.028	(.000)	0.028	(.000)	0.001	(.353)
	Firm size (log)	−0.048	(.142)	−0.075	(.025)	−0.065	(.055)	−0.095	(.005)	−0.074	(.028)	−0.075	(.025)	−0.078	(.022)	−0.187	(.000)
	Group advertising (%)	0.023	(.425)	−0.005	(.859)	0.018	(.553)	−0.043	(.161)	−0.011	(.706)	−0.006	(.853)	−0.019	(.544)	−0.002	(.020)
	Group liquidity (%)	−0.012	(.035)	−0.025	(.000)	−0.025	(.000)	−0.029	(.000)	−0.025	(.000)	−0.025	(.000)	−0.030	(.000)	0.221	(.000)
	Group leverage (%)	−0.017	(.021)	−0.010	(.202)	−0.009	(.272)	−0.012	(.131)	−0.011	(.160)	−0.010	(.202)	−0.012	(.142)	0.013	(.000)
	Group unrelated diversification	−4.480	(.000)	−5.294	(.000)	−5.180	(.000)	−5.382	(.000)	−5.368	(.000)	−5.296	(.000)	−5.310	(.000)	1.344	(.000)
	Group related diversification	−3.297	(.000)	−3.783	(.000)	−3.947	(.000)	−3.596	(.000)	−3.743	(.000)	−3.777	(.000)	−3.702	(.000)	−0.723	(.106)
	Group size (log)	−0.017	(.427)	−0.026	(.301)	−0.006	(.814)	−0.058	(.023)	−0.030	(.240)	−0.026	(.302)	−0.033	(.212)	−0.351	(.000)
	Firm-level KBAs (logs) (F)	**−0.089**	**(.002)**	**−0.356**	**(.021)**	**−0.711**	**(.000)**	**−0.472**	**(.003)**	**−0.662**	**(.015)**	**−0.566**	**(.008)**	**−1.264**	**(.000)**	**−3.910**	**(.007)**
	Group-level KBAs (logs) (G)	**−0.047**	**(.001)**	**−0.169**	**(.011)**	**−0.167**	**(.016)**	**−0.168**	**(.010)**	**−0.181**	**(.007)**	**−0.176**	**(.008)**	**−0.186**	**(.007)**	**−0.437**	**(.000)**
	Decentralization of group KBAs **(D)**	−0.359	(.036)	−0.496	(.038)	−0.754	(.004)	−0.553	(.020)	−0.463	(.052)	−0.494	(.040)	−0.571	(.026)	−0.948	(.012)
	Relatedness of KBAs **(R)**	−4.002	(.000)	−9.070	(.000)	−7.481	(.000)	−28.091	(.000)	−10.066	(.000)	−9.121	(.000)	−30.584	(.000)	−140.208	(.000)
	In-group sensing advant. (logs) **(Sn)**	−0.092	(.027)	−0.123	(.034)	−0.139	(.018)	−0.120	(.036)	−0.134	(.022)	−0.123	(.034)	−0.139	(.020)	−0.495	(.000)
	In-group seizing intensity **(Sz)**	−1.096	(.000)	−1.092	(.000)	−1.149	(.000)	−1.142	(.000)	−1.071	(.000)	−1.086	(.000)	−1.143	(.000)	−2.557	(.000)
H1:	**F × G**			**−0.036**	**(.037)**	**−0.101**	**(.000)**	**−0.041**	**(.012)**	**−0.074**	**(.026)**	**−0.057**	**(.019)**	**−0.195**	**(.000)**	**−0.420**	**(.009)**
	F × D			−0.144	(.397)	−0.597	(.038)	−0.219	(.166)	−0.106	(.534)	−0.142	(.408)	−1.107	(.000)	−2.851	(.085)
	F × R			−2.122	(.000)	2.268	(.000)	−6.644	(.000)	−2.045	(.000)	−2.120	(.000)	−7.447	(.000)	−22.237	(.000)
	F × Sn			−0.067	(.003)	−0.078	(.001)	−0.066	(.003)	−0.130	(.012)	−0.067	(.003)	−0.160	(.007)	−0.118	(.150)
	F × Sz			−0.250	(.012)	−0.244	(.015)	−0.250	(.010)	−0.257	(.011)	−0.235	(.322)	−0.466	(.096)	−3.280	(.000)
	G × D			−0.155	(.046)	−0.261	(.002)	−0.198	(.007)	−0.140	(.073)	−0.154	(.050)	−0.361	(.000)	−0.472	(.000)
	G × R			−1.055	(.011)	−1.369	(.001)	−1.816	(.014)	−0.866	(.051)	−1.047	(.015)	−2.143	(.004)	−16.248	(.000)
	G × Sn			−0.045	(.000)	−0.048	(.000)	−0.048	(.000)	−0.040	(.001)	−0.045	(.000)	−0.046	(.000)	−0.025	(.001)
	G × Sz			−0.140	(.014)	−0.121	(.035)	−0.139	(.013)	−0.147	(.010)	−0.142	(.020)	−0.135	(.027)	−0.397	(.000)
H2:	**F × G × D**					**−0.129**	**(.002)**							**−0.224**	**(.000)**	**−0.374**	**(.042)**
H3:	**F × G × R**							**−0.636**	**(.000)**					**−0.736**	**(.000)**	**−2.543**	**(.000)**
H4:	**F × G × Sn**									**−0.015**	**(.025)**			**−0.019**	**(.015)**	**−0.017**	**(.051)**
H5:	**F × G × Sz**											**−0.058**	**(.057)**	**−0.072**	**(.050)**	**−0.295**	**(.001)**
	Wald $\chi 2$ (Prob)	337.74	(.000)	410.69	(.000)	420.40	(.000)	440.73	(.000)	415.47	(.000)	413.69	(.000)	474.85	(.000)	1142.79	(.000)

Notes: Dependent variable: BG membership. N=4,104 in models M1-M7 for the vertical keiretsu sample. N=13,791 in model M7H for the horizontal keiretsu sample. P-values in parentheses. Industry and year specific dummy variables are included but not reported.

Discussion and Conclusions

Theoretical Implications

The BG literature has established that understanding the existence of BGs and the benefits of affiliation is of theoretical and practical importance (Carney et al., 2011, 2018; Kinger-Hans et al., 2024; L. Zhang et al., 2016). This study investigates the role of complementarities between firm- and group-level KBAs in influencing the financial performance of group-affiliated firms. By combining *knowledge-based* and *dynamic capabilities* views, we identified four sources of such complementarity: *decentralization* of group-level KBAs, *relatedness* between group- and firm-level KBAs, *in-group sensing advantage*, and *in-group seizing intensity*. Our analysis shows that the complementarity between group- and firm-level KBAs significantly affects the profitability of group affiliates. The four factors representing the structure of KBAs and the reconfiguring process show statistically and economically significant moderating effects on the level of complementarity between group- and firm-level KBAs. Our analysis of the Cox proportional hazards model shows that group- and firm-level KBAs also have a complementary effect on the likelihood of firms maintaining their BG affiliations. In summary, this study makes three main contributions.

First, by applying a *knowledge-based perspective* to explain BG affiliation benefits and the persistence of BGs, this study supplements existing approaches that include institutional voids-based (Khanna & Yafeh, 2007; Yiu et al., 2007), diversification capability-based (Gopal et al., 2021; Manikandan & Ramachandran, 2015), internalization-based (Gaur, Pattnaik, Singh, & Lee, 2019), information/reputation-based (Bothello et al., 2023; Lamin, 2013), and control-based perspectives (Brouthers et al., 2014; Kim et al., 2004; Yang & Schwarz, 2016). Our approach shifts the focus to the role of complementarity between group- and firm-level KBAs as a driver of affiliation benefits and an important incentive mechanism for firms to remain affiliated. The focus on such complementarity is important for explaining affiliation incentives because the associated quasi-rents represent the value created *jointly* among group members. Using the effect of KBAs to explain the likelihood of firms to maintain their BG affiliations represents a shift from prior literature that focuses primarily on the historical and institutional forces behind the persistence of BGs (L. Zhang et al., 2016). While institutional explanations are valuable, institutional changes – such as those triggered by the Asian financial crisis, which led to the partial restructuring of keiretsu in the 2000s – can disturb historically evolved equilibria. Such disruptions may signify affiliate-specific motives based on joint value creation, which are important for explaining the persistence of BG links.

Second, we contribute to the BG literature that seeks to explain the performance effects of BG affiliation (Carney et al., 2011; Chang & Hong, 2000; Joe & Oh, 2018; Rhee et al., 2019; Yang & Schwarz, 2016) but does not consider how its benefits may vary across affiliates within a group. Most studies have compared group-affiliated and unaffiliated firms leading to a focus on group-level effects. One of our study motives was an expectation that the group-effect would likely hide significant cross-affiliate variation because affiliation benefits are unlikely to be uniform across affiliate firms. Our study fills this gap by specifying and testing sources of variation in affiliate-level earnings from group-level knowledge. Prior explanations of differential earnings within BGs predominantly adopted power- or control-based approaches, which assume that value is created at the group level and distributed based on the balance of powers (Brouthers et al., 2014; Keum, 2023; Kim et al., 2004; Yang & Schwarz, 2016). In contrast, we focus on variations in *affiliate-specific* value creation.

Third, the application of the dynamic capabilities approach (Schilke et al., 2018; Wilden et al., 2016) to explain the performance of BG affiliates conceptualizes KBAs in BGs as catalysts for integrating, building, aligning, and reconfiguring the KBAs of affiliate firms to enable them to navigate knowledge-intensive environments. This conceptualization allowed us to identify and validate nuanced sources of complementarity between affiliate- and group-level KBAs. The findings on the role of decentralization of KBAs, their relatedness, and the ways in-group opportunities create sensing and seizing advantages for BG-affiliates provide evidence that the microfoundations of the DCV can explain the ways in which BG-affiliated firms benefit from the KBAs in their group. In this regard, the benefits of BG membership are not only in gaining access to knowledge but also the associated mechanisms that foster the affiliate's ability to reconfigure its own knowledge base. As such, group-level KBAs embedded in the web of inter-affiliate relations extend affiliates' *dynamic capabilities* by enabling knowledge reconfiguration, enhancing technological competencies, and shaping new strategies (Schilke et al., 2018; Teece, 2014; Wilden et al., 2016).

Practical implications

Our results provide evidence that decentralization is important for creating opportunities for complementary knowledge integration in BGs. BG affiliates (particularly multidivisional affiliates) can structure their operations to align with what is more efficient to manage inside the firm (within the M-form subsidiary structure) and what is more efficient to be modularly linked across the affiliates. This offers extra flexibility for BG-affiliated firms. We also find that technological *relatedness* can facilitate the complementary redeployment of group-level KBAs. The knowledge of "who knows what" and the ability to identify the locations of "lowest hanging fruits" can facilitate complementary knowledge combinations.

Furthermore, we found that insider access to opportunities arising within BGs enables affiliates to capture additional quasi-rents. Findings on *in-group sensing advantage* imply that temporal advantage plays a role in capturing rents from complementarity. This is consistent with the mechanism of preclusive appropriation in the generative appropriability literature (Ahuja et al., 2013). Hence, what matters is not merely the incidence of sensing, but also the temporal advantage in sensing (enabled by in-group ties), which helps the affiliate to preclude competitors. Finally, our findings on the contributions to complementarity made by *in-group seizing intensity* signal that in-group ties among affiliates foster a commitment to complementary technological trajectories, enabling complementarity in KBAs. These results suggest that the act of leveraging inter-affiliate connections to sense and seize new knowledge-sourcing opportunities enables affiliates to not only respond to technological change but to also position themselves for first-mover advantages and to *shape* new market opportunities.

Limitations and future research

First, although BGs are an important economic activity in many countries around the world, BGs in each country have their own specific characteristics (Khanna & Yafeh, 2007; Yiu et al., 2007; L. Zhang et al., 2016). From a theoretical perspective, the only BG-specific assumption we make in our logic is that group affiliates have preferential access to KBAs within the group. The assumption of preferential access to resources, knowledge, and R&D processes is common in the BG literature and in country-specific empirical studies focused on India (Gopal et al., 2021), Taiwan (Mahmood, Zhu, & Zajac, 2011), Brazil (Gama & Bandeira-de-Mello, 2021), China (R. Wang et al., 2024), South Korea (Rhee et al., 2019), and Japan (Aoki & Wilhelm, 2017; Kim et al., 2004). In this sense, we contend that our theoretical framework is applicable across countries and that the results obtained from Japanese data are generalizable to BGs across countries. However, recognizing cross-country variations in certain characteristics of BGs (Yiu et al., 2007), there is potential to investigate how these characteristics influence the knowledge-based drivers of financial performance.

Second, we focus on knowledge-based assets that represent identifiable assets and *explicit* knowledge. While the representation of explicit knowledge by patents offers opportunities for econometric tests, patents do not directly capture *tacit* knowledge (Nonaka, 1991). On the one hand, we can expect a correlation between explicit and tacit knowledge, whereby an organization rich in explicit knowledge is also likely to possess tacit knowledge about using explicit knowledge. On the other hand, tacit knowledge is embedded in individuals, social networks, and organizational routines and processes, i.e., not in identifiable assets. Therefore, the mechanisms of complementarity in tacit knowledge may vary, limiting the applicability of our findings to complementarity in explicit knowledge.

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Notes

1. Quasi-rents explain earnings in which different firms earn rents at different rates from the same asset (Klein, Crawford, & Alchian, 1978; Peteraf, 1993). For instance, two affiliates may have access to the same set of patents, but one earns more rents than the other from that set of patents. This *difference* constitutes quasi-rents. The literature attributes quasi-rents to *complementarity* in combined assets (Panico, 2017; Stieglitz & Heine, 2007).

2. $Q < 0$ represents the substitution effect and $Q = 0$ represents independence.

3. Although the assumption of group ties enabling preferential access to group-level resources is common in the BG literature, we evaluated these assumptions with reference to group-level KBAs in the interviews we conducted with managers of keiretsu-affiliated firms (presented in the sub-section titled “Interviews” below).

4. For instance, in our interviews with managers, contributors pointed to how managers regularly and proactively share ideas, write collaborative papers, and how their existing ties enable formal agreements that may contain confidential knowledge and information.

5. In addition, even after a patent application is filed, there is an 18-month period from the application date to publication (if granted), which is common in most countries around the world, including Japan.

6. All three interviewed managers were directly involved in intellectual property-related positions or projects. Two were mid-level managers, and one was a senior manager in keiretsu-affiliated firms. One respondent worked for one horizontal keiretsu-affiliated firm. Two worked in multiple firms and both worked in vertical and horizontal keiretsu-affiliated firms. The interviews were conducted in English and were quoted directly with minimal syntactic editing. For ethical reasons, the company names in the quotes were anonymized.

7. Specifically, Toyo Keizai’s Modern Japanese Enterprise Groups (1987), The Newest Reality of Japanese “Big Six” Business Groups (1998), The Newest Edition of Business-World Map (2005–2015) and Japan Company Business-World Map (2007–2015), Nihon Keizai Hyronsha’s Modern Keiretsu (1992) and Nihon Keizai Business-World Map (2005–2015), Dobunkan Publishing’s Business Group Management (1993), Chuokeizai-Sha’s Japanese

Inter-Firm Relationships (1994), Sangakusha's The Newest Business-World Keiretsu Map (2003), and Dodwell's Industrial Groupings in Japan (1992).

8. To check the sensitivity of the results to alternative assumptions, we conducted robustness tests with the assumptions of 10% and 20%. While the coefficient sizes changed, the pattern of coefficient signs was as hypothesized, and the statistical significance levels repeated those of the main findings.

9. All independent variables are time variant but, in some formulae, we skip time subscripts *t* for simplicity.

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