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RESEARCH ARTICLE

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How much does the firm's alliance network matter?

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Abstract

Research Summary: Extant empirical work partitioning the variance in firm (business segment) profitability has identified industry, corporate parent, business segment, and time as key sources. However, this variance decomposition research stream has treated firms as atomistic, autonomous entities. We employ a fast-unfolding community-detection algorithm to detect firms' network memberships and use the Shapley Value method to isolate the effect of the firm's alliance network, in addition to industry, corporate parent, business segment, and year effects, on the variance in business unit performance. Our findings demonstrate that the effect of the firm's alliance network explains 11% of the variance in firm ROA among 16,381 business segments from 1979 through 1996. We also extend the time period through 2018 and find that our results broadly hold.

Managerial Summary: In the search for superior firm performance, managers typically focus their attention externally on profitable industries in which to operate, as well as internally on their firms' idiosyncratic and valuable resources and capabilities. In addition to these profitability sources, our work suggests another important, but heretofore overlooked, factor in the managerial quest for competitive advantage: the value-creating potential of alliance networks. We employ a machine-learning

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algorithm to detect firms' network memberships. Our findings indicate that as much as 11% of the variance in firm profitability (ROA) is explained by the network of alliances of which the firm is a part. Our study also implies that the emphasis on networks continues to be relevant in a technology age in which industry boundaries are blurring.

KEYWORDS

community detection, firm profitability, network effects, Shapley value, variance decomposition

1 | INTRODUCTION

A central theme in strategic management is identifying the origins of variation in firm performance. In this vein, core studies in a rich research stream have decomposed the variance of firm (strictly speaking, business segment) performance into industry, corporation, business segment, and year effects (e.g., Brush & Bromiley, 1997; Chang & Singh, 2000; McGahan & Porter, 1997; Rumelt, 1991; Schmalensee, 1985; Sharapov, Kattuman, Rodriguez, & Velazquez, 2020; Vanneste, 2017).[1] Although models of variance decomposition differ with respect to their underlying specifications, there is general agreement in most recent studies regarding the importance of all these effects, with the business segment explaining the lion's share of variance in performance but each industry, corporation, and year also having explanatory power (e.g., Guo, 2017; McGahan & Porter, 2002; Misangyi, Elms, Greckhamer, & Lepine, 2006; Sharapov et al., 2020). The empirical grounding of the roles of industry and firm effects, respectively, is motivated by the debate on the relative significance of theories of industrial organization (Porter, 1980), which emphasize industry structure, and the resource-based view, which underscores the firm's internal resources and capabilities (Barney, 1986; McGahan & Porter, 1997).[2]

Although both industry and firm effects are notably relevant for comprehending the sources of variation in firm performance, extant empirical studies have typically regarded firms as atomistic (Granovetter, 1985). In contrast, a vast body of research on interfirm alliances and networks emphasizes inter-organizational relationships as an important determinant of firm performance (e.g., Burt, 1992; Dyer & Singh, 1998; Galaskiewicz, 1985; Gulati, 1998; Gulati, Nohria, & Zaheer, 2000; Rowley, Greve, Rao, Baum, & Shipilov, 2005; Shipilov, 2006; Thorelli, 1986). Interfirm networks are composed of ties of strategic importance such as joint ventures and strategic alliances. The relational view (Dyer & Singh, 1998; Dyer, Singh, & Hesterly, 2018) and subsequently the networks view (e.g., Gulati, 1998; Gulati et al., 2000) have expanded the

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[1] Useful extensions to this literature in the international business setting have examined the business groups and country effects (e.g., Khanna & Rivkin, 2001; Majumdar & Bhattacharjee, 2014; McGahan & Victer, 2010).

[2] Following Rumelt's characterization of "difficult-to-imitate resources," scholars have more explicitly associated the business unit (segment) effect with valuable, rare, inimitable and nonsubstitutable (VRIN) resource characteristics. The "corporate effect" conceptualization can be generally linked to Peters and Waterman (1982) and Rumelt's work on corporate strategy.

lens of the strategy field and are viewed as critical extensions of the resource-based view. For example, Lavie (2006) integrates network theory with the resource-based view, emphasizing the relevance of shared resources in the extraction of network-based rents from alliances and their portfolios (see also Gulati, 1999). Furthermore, recent work in strategy has made a similar point about how a relational or network view offers a distinct source of value compared with the industrial organization (industry) or the resource-based view (atomistic firm; e.g., Feldman & Hernandez, 2021). Despite the salience of interfirm networks, surprisingly little work parsing out the variance in business segment performance has paid attention to the network of alliance relationships in which firms are embedded. As Gulati et al. (2000, p. 2003) point out, with the taking of a relational angle, “we can deepen our understanding of the sources of differences in firm conduct and profitability.”

Alliance and network scholars have underscored the performance benefits that firms derive from their access to external resources through network membership (Gnyawali & Madhavan, 2001; Gulati, 1998; Lavie, 2007; McEvily & Marcus, 2005). In this vein, firms' alliance network embeddedness becomes a salient determinant of firm performance (Gulati et al., 2000; Mowery, Oxley, & Silverman, 1996). Networks provide reliable, novel, and timely information (Burt, 1992), allow the pooling of interfirm resources and capabilities (Dyer & Singh, 1998; Uzzi, 1996), and enable inter-organizational endorsements needed to alleviate the liability of newness (Stuart, Hoang, & Hybels, 1999). Moreover, membership in a network of external alliance relations allows firms to generate additional opportunities by enabling new partner search under conditions of uncertainty and sanction member firms' opportunistic behaviors (Coleman, 1994; Gulati & Gargiulo, 1999; Rowley et al., 2005). Studies have shown that firms occupying superior structural positions exhibit vision advantages, enjoy resource-recombination opportunities, and engage in knowledge arbitrage, with firms' network-enabled capabilities enhancing their performance (Nohria & Eccles, 1992; Zaheer & Bell, 2005). Overall, a great deal of research has shown the benefits of networks for firm performance. On reviewing this literature, network effects seem to be a relevant and important factor for explaining aggregate firm performance variance.

Accordingly, in this article, we empirically tackle the question: how much of the variance in firm performance can be attributed to the firm’s alliance network? And by extension, how much explanatory power in firm performance has been left on the table by leaving networks out? Along the lines of prior work in this empirical research stream, we adopt a variance decomposition approach in which the variation in business-segment profitability is broken down into the variance ascribed to industry, year, corporate parent, and business segment. We seek to estimate whether a firm’s membership in a network explicates variance in business segment profitability over and above its industry membership, its year of operation, corporate parent affiliation, and its business segment.

Basing our study on the most recent empirical work in this domain, we employ the Shapley Value approach to parse out the variance in business segment profitability (Lundberg & Lee, 2017; Redell, 2019; Shalit, 2021; Sharapov et al., 2020). This variance decomposition method is robust to the nonorthogonality of regressors, the order in which the different sources of variance are considered, and assumptions regarding the fixed versus random nature of effects (Grömping, 2007; Shapley, 1953; Shorrocks, 2013). We deliberately deviate from using nested ANOVA and COV (component of variance) approaches, two dominant estimation tools used by earlier work, because they entail restrictive assumptions (see Guo, 2017, pp. 1328–1329, for a detailed discussion on their limitations). Additionally, as robustness checks, we use multilevel modeling estimation methods using the RMLE (restricted maximum likelihood estimator; Hough, 2006; Misangyi et al., 2006) and multilevel models based on the MCMC (Markov chain

Monte Carlo) method (Guo, 2017; Hadfield, 2010), which estimates the confidence interval of the proportion of variance attributed to different components.

Similar to prior work (Guo, 2017; McGahan & Porter, 1997; Vanneste, 2017), we find that business segment effects carry the most weight in explaining the performance variance (32%). Likewise, the industry (3%) and corporate parent (11%) are also salient as in prior work but exert effects of smaller magnitude than those of the business segment. However, the firm's network membership explains a sizeable 11% of the total variance in business-segment profitability.

The remaining paper is organized as follows. First, we review the prior empirical literature on the locus of business segment performance. We next discuss what it theoretically means to be a member of a network. We then elaborate on our data and sampling procedure and describe the methodology to determine the network to which a firm belongs. Thereafter, we explain our econometric procedure and results, followed by a discussion and conclusion.

2 | PRIOR EMPIRICAL LITERATURE ON VARIANCE DECOMPOSITION

The empirical origins of analysis of variance research to understand the sources of business unit profitability heterogeneity can be traced to the seminal work of Schmalensee (1985) who decomposed profit differences into variance related to industry membership, corporate parent membership, and business unit market shares using the 1975 FTC Line of Business Program data in manufacturing. The underlying rationale for Schmalensee's variance decomposition approach derived from three sources: the classic industrial economists' view which emphasized industry as the relevant unit of research and treated firm differences as insubstantial; the "managerial" view which highlighted corporate parent effects and treated better-managed firms as a relevant source of profitability differences; and the "anticlassical industrial economics" view which underscored business unit market shares as reflecting lasting scale-derived efficiency differences among firms. Schmalensee found support for industry effects (20%) but no support for corporate parent and business unit effects. A key limitation of the study was the use of only a single year's data which made difficult the identification of year and stable business-related effects.

Enlarging the scope of analysis and using FTC Line of Business data from 1974 to 1977 in manufacturing, Rumelt's (1991) decomposition analysis incorporated both stable (industry only) and transient industry effects (an industry × year interaction). Additionally, he used business unit dummies instead of the market share used by Schmalensee (1985). Using both COV and nested ANOVA analyses, Rumelt showed that business unit effects explain the largest proportion of variance (46%), compared to stable industry effects (8%). Additionally, corporate parent effects, though small, also existed (0.8%).[3]

Later empirical advances in this research domain further validated and refined Rumelt's findings by incorporating an expanded time horizon, examining a broader set of industries besides manufacturing, and updating estimation methods. More specifically, Roquebert, Phillips, and Westfall (1996) used the COMPUSTAT business segment dataset from 1985 to 1991 in the manufacturing sector and found results similar to Rumelt's (business segment = 37%; industry = 10%). One limitation of their study was the exclusion of single segment firms which

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[3] Table 3 Sample A in Rumelt (1991) and also reported verbatim in Table 3 of this paper for easy reference.

resulted in an increased corporate parent effect of approximately 18%. McGahan and Porter (1997) employed a considerably expanded dataset from the same COMPUSTAT business segment reports, spanning the period from 1981 to 1994 and including both manufacturing and nonmanufacturing sectors. Using both COV and nested ANOVA, McGahan and Porter (1997) identify business segment (32%), corporate parent (4%), and industry effects (19%), with business segment explaining the largest share of the variance. Though the authors generally retained Rumelt's (1991) estimation technique, a notable departure was not using industry-time interactions but instead allowing for residual serial correlations.

Around the same time, puzzled by the relatively low magnitude of the corporate parent effect in Rumelt (1991), Brush and Bromiley (1997), using simulations, highlighted the limitations of COV in its inability to detect effects, even when they actually exist, in the event of non-independence of components and correlated residuals with nonconstant variance. The authors suggested that Rumelt's findings do not necessarily reflect the unimportance of corporate parent effects. Consistent with this argumentation, Brush, Bromiley, and Hendrickx (1999) provide an alternative estimate employing a simultaneous equation model (2SLS). They treat corporate parent and business segment profitability as endogenous, where both are simultaneously determined with industry effects, with a firm's debt ratio being exogenous in the system of equations and find a corporate parent effect ranging from 6% to 23%, much larger than that of Rumelt (1991).

Similarly, Chang and Singh (2000) demonstrate that corporate parent effects are substantially greater than zero when business segments are more narrowly defined. They used market share instead of profitability as a response variable because of their use of the Trinet database. Bowman and Helfat (2001) point out the limitations of nested ANOVA, especially its sensitivity to the order in which different sources of variance are entered, and further confirm that corporate parent effects become more salient when one considers variance decomposition studies more comprehensively, as a group.

Overall, by the early 2000s scholars were generally agreed that industry, corporate parent, and business unit effects principally explained the variance in business segment profitability, with the business unit explaining the largest portion of variance. Studies thereafter shifted the focus to questioning the assumptions of COV and nested ANOVA and suggested alternative estimators such as OLS (Khanna & Rivkin, 2001), simultaneous equations (Brush et al., 1999), and simultaneous ANOVA (McGahan & Porter, 2002) as appropriate estimation techniques.

At the same time, some studies with extreme results appeared but were duly rebutted by other scholarly work. For example, Ruefli and Wiggins (2003) using a nonparametric approach found significant corporate parent effects but nonsignificant industry effects. However, McGahan and Porter (2005) provided a rebuttal against nonsignificant industry effects. Another study, Hawawini, Subramanian, and Verdin (2003), showed that firm-specific factors matter for only a few leaders and loser firms but for the rest, industry effects dominate. However, McNamara, Aime, and Vaaler (2005) in their rebuttal questioned the methods used to categorize the outliers by Hawawini et al. (2003).

Most recently, Vanneste (2017), in his meta-analysis, found the industry's portion of performance variance to be between 6 and 10%, the corporate parent's between 11% and 16%, and the business segment's between 30 and 42%, further confirming the dominance of business-segment effects in explaining the variance in performance.[4] This study underscored the role of

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[4] This meta-analysis found that corporate parent effects explain somewhat greater performance variance than industry effects.

effect size measures in evaluating the explanatory power of different sources of variance. For example, measures based on the sum of squares, such as those using ANOVA and 2SLS, are sensitive to sample dimensions (e.g., the total count of industries or business segments per industry), in contrast to variance-based measures, such as those using multilevel modeling (Vanneste, 2017).

In the same vein, scholars have proposed multilevel modeling as an alternative approach that overcomes the limitations of conventional COV, nested or simultaneous ANOVA, and simultaneous equations (2SLS) by taking advantage of the underlying multilevel character of business segment profitability data (Hough, 2006; Guo, 2017; Karniouchina, Carson, Short, & Ketchen, 2013; Majumdar & Bhattacharjee, 2014; Misangyi et al., 2006). As discussed earlier, COV may generate unreliable estimates of variance because the method may be unable to detect variance estimates even when they are present, while ANOVA is sensitive to order of entry in that, for example, if the two sources of variance covary, the contribution from the covariance is solely allocated to the source entered first in a fixed-effects ANOVA (Bowman & Helfat, 2001; Brush & Bromiley, 1997). This becomes problematic unless the variance sources are orthogonal to each other. Although a COV approach using random effects does not depend on the order in which the sources are entered, it makes strong distributional assumptions, for example, that the specified covariances are randomly distributed and the random effects are jointly normal.

Although simultaneous equation approaches such as 2SLS provide more traction in reliably detecting smaller variance effects, they impose restrictions on the estimation sample (Misangyi et al., 2006; for a detailed discussion of the limitations of these methods, see Hough, 2006, p. 46 and Guo, 2017, pp. 1328–1329). For example, Brush et al. (1999) use different models depending on whether the corporate parent has three or four business segments.[5] In contrast, multilevel modeling allows for the cross-nesting of business segments simultaneously within the corporate parent and industries, addressing the issue of non-independent observations (Hofmann, Griffin, & Gavin, 2000). It also accounts for collinearity between the business segment and the corporate parent by allowing for hierarchical cross-nesting as well as for interactions (Patterson, 2013; Rabe-Hesketh & Skrondal, 2012). However, despite the advantages of the multilevel model and its ability to incorporate both fixed and random effects, the estimates of variance explained are sensitive to the choice of *nesting*, as regards which source is assumed to be nested within which, and to the choice of effects as regards whether the cross-nesting effects are assumed to be random or fixed (Misangyi et al., 2006; Sharapov et al., 2020).

Lately, scholars have highlighted the Shapley Value method for variance decomposition which is agnostic to the nonorthogonality of variance sources, the order in which the different sources of variance are introduced and nested in the model, and the categorization of these sources as random or fixed effects (Sharapov et al., 2020). Along the lines of most recent work, in this article we use a Shapley Value approach to estimate the effect of the firm's network membership on business segment profitability. In robustness analyses, we employ a cross-classified multilevel modeling approach using the RMLE (restricted maximum likelihood estimator) and MCMC (Markov chain Monte Carlo) methods (Guo, 2017; Karniouchina, Carson, Short, & Ketchen Jr, 2013). We also include the results from a nested ANOVA for comparison purposes.

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[5] Brush et al. (1999) use of simultaneous estimation may not be a limitation of the simultaneous equation per se but reflects the need to have an appropriate data format to make valid comparisons with the COV estimation approach.

3 | NETWORK MEMBERSHIP

A first step in the examination of corporate network-level effects is to clearly delineate the network affiliation of a corporate parent firm. Unlike the well-defined *keiretsu* networks in Japan (Caves & Uekusa, 1976; Gerlach, 1992), most firms in the U.S. merely form alliances rather than business groups. Thus, in the absence of any obvious grouping construct, the networks to which firms belong need to be empirically determined through an examination of the patterns of their alliance relationships.

In this vein, network community detection for network identification provides unique benefits through its use of network boundary setting (e.g., Rowley et al., 2005; Sytch & Tatarynowicz, 2014). The demarcation of a community occurs when the firms are more densely connected to each other *within* a community than to firms *outside* their community (e.g., Knoke, 2009). A large number of interfirm networks have been described as small-world systems whose prominent attributes are nonoverlapping groups with densely connected member firms with only sparse connections to outsiders (e.g., Baum, Shipilov, & Rowley, 2003). Membership in a network community allows firms to tap into local knowledge pools using ties, marked by short network distance and density, to other member firms (Ahuja, 2000). Having easy access to such a collective knowledge scaffolding may amplify the recombinatorial opportunities available to the network members due to complementary knowledge inputs. Dense connections and the ensuing cooperative norms facilitate easier resource exchanges between members within network communities than across them (Gulati, Sytch, & Tatarynowicz, 2012; Rowley et al., 2005).

Broadly speaking, a parallel exists between network communities and strategic groups in industrial economics, which highlights groups of firms pursuing similar strategies (Hunt, 1972), in that both these theoretical approaches focus on groupings of firms to explicate firm-level performance over and above firm- and industry-specific influences. However, it is important to note that the network community-detection emphasis is distinct from Hunt's (1972) strategic groups. Strategic groups research attempts to identify groups of *rival* firms *within* an industry based on their similarity along various strategic dimensions, such as diversification, advertising, and geographic scope (Caves & Porter, 1977). In contrast, network community detection focuses on groups of densely connected *allying* firms, while remaining indifferent to whether the allying firms are rivals or not. Conceptually, from the vantage point of firms,[6] a "network community" may not be confined within an industry boundary, given that firms may have alliance relationships that transcend industry boundaries. A case in point would be the strategic alliance between Hewlett-Packard and the Walt Disney Company or that between Starbucks and Barnes and Noble bookstores. Thus, "network community" is a broader theoretical construct than strategic group. Network communities may include both—groups of rival firms that cooperate with one another and groups of firms that cooperate without competing. Here density, not rivalry, is a necessary criterion for determining community membership.[7]

Furthermore, studies on strategic groups assume that groups of firms that follow *similar strategies* exist within an industry, suggesting that member firms lack heterogeneity in strategically relevant aspects (Barney & Hoskisson, 1990). However, network community theorizing does not make any restrictive assumptions about whether a member firm is idiosyncratic or not in its strategy. In other words, rather than homogeneity within a network community, the

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[6] From a researcher's vantage point, a network boundary may be confined within an industry for simplicity.

[7] In the extreme, to the extent that rival firms may avoid forming ties with one another, structurally dense strategic groups are improbable, but the same is not the case for network communities (e.g., Madhavan, Koka, & Prescott, 1998).

defining criterion is intra-community density. In fact, interfirm heterogeneity may exist within a network community, and communities may, or may not, consist of firms possessing similar resource or product profiles (e.g., Rowley, Baum, Shipilov, Greve, & Rao, 2004), with firms typically seeking partners with complementary capabilities. Additionally, compared to strategic groups, network communities by design exhibit stronger levels of coordination because they derive from alliance ties rather than merely product-market similarities (Rowley et al., 2004).

Empirically, clustering algorithms to identify strategic groups are mostly designed to detect firms with similar performance because they use performance-based inputs such as sales and market share (Hergert, 1988), making the argument that strategic groups affect performance seemingly tautological. In contrast, network community detection does not derive from performance-based inputs but focuses instead on dense alliance relationships among its group members. Networks provide avenues for cooperation and resource sharing thus enabling value creation, allowing for firms from different industries and sizes to be part of the same network community.

Relatedly, the network community concept is distinct from cognitive communities. The work on cognitive communities emphasizes group boundaries based on the *perceptions* of firm managers and their cognitive categorization of *rivals* (e.g., Porac, Thomas, Wilson, Paton, & Kanfer, 1995). In contrast, the network community approach does not require socio-cognitive rivalry as a criterion to set group boundaries. Furthermore, because we use a wide range of interfirm relationships, both horizontal and vertical (e.g., Sytch & Tatarynowicz, 2014), it is worth pointing out that the notion of network community is also distinct from that of strategic blocks (Nohria & Garcia-Pont, 1991). Though strategic blocks are also based on connectivity, “in all cases, however, the partners continue to compete with each other” (Nohria & Garcia-Pont, 1991, p. 111) and thereby capture horizontal relationships among *rival* firms within an industry. Unlike strategic blocks, network communities derive from relational patterns among *all* firms and are agnostic as to whether the member firms compete or not. In sum, we chose the network community approach because it gels well with our broader focus that goes beyond groups within a focal industry or strategic blocks of rival firms.

Additionally, our rationale for network identification and the use of a nominal measure of network membership instead of a continuous measure (e.g., centrality or structural holes) is consistent with the existing convention in variance decomposition work. For example, Schmalensee in his use of a nominal industry measure argued that, “Conventional, classical industry-level variables [e.g., concentration] may thus perform poorly at least in part because they are poor, incomplete measures of the (classical and other) market effects present in available data” (Schmalensee, 1985, p. 343). In this regard, Schmalensee attempted to capture the relevance of *all* industry effects using industry dummies. Similarly, applying Schmalensee’s argument to the business unit, Rumelt states that “market-share is an imperfect measure of resource heterogeneity among businesses” (Rumelt, 1991, p. 172) and uses nominal business unit measures to measure *all* business-unit effects.

Applying the logic that both Schmalensee (1985) and Rumelt (1991) employed to the corporate-network level, we also believe that structural holes or other available network measures might be an imperfect representation of the network and apply nominal network measures to capture *all* corporate network effects rather than some specific portion captured by any particular network variable. Our emphasis here is neither prescriptive nor causal (i.e., what relevant network measures cause these effects?) but to explain network effects, *however generated*, over and above the well-documented sources of variance in business unit performance. Another advantage of the use of a nominal rather than a continuous measure in these studies is that different levels of an explanatory variable matter differently in explaining the total variance, allowing for the fact that the mechanism can be different for different networks (or different industries).

4 | DATA AND SAMPLE

4.1 | COMPUSTAT business segment data

To maintain consistency and comparability with both past and most recent work, we use COMPUSTAT business segment data from 1979 to 1996 (Guo, 2017; McGahan & Porter, 1997; Misangyi et al., 2006). Another rationale for limiting this study to 1996 is that, as Hough (2006) pointed out, in contrast to earlier Statement of Financial Accounting Standards (SFAS 14), a new standard (SFAS 131) came into force after 1997, which significantly modified how firms report their business segments. More specifically, the earlier focus derived from industry-based reporting about business segments, while the changes allowed firms to report based on their internally determined business segments. Additionally, the U.S. Office of Management and Budget (OMB) formally ended the use of the Standard Industrial Classification System (SICS) and adopted the North American Industrial Classification System (NAICS) in 1997.[8]

We used the selection criteria followed by McGahan and Porter (1997) to arrive at our estimation sample. Our original sample from the COMPUSTAT business segment dataset consisted of 483,335 observations during the 1979–1996 period. First, for the segment type (STYPE), a firm may report a business (BUSSEG), operating (OPSEG), geographic (GEOSEG), and/or state (STSEG) segments. We retain the observations pertaining to business segments and screen out the remaining three segments to minimize redundancy, thus dropping 275,818 records. Second, in order to ensure that the same segment data is not repeated multiple times (for example, because the 10-K filings for fiscal years 1994, 1995, and 1996 may all disclose segment data for 1994), we eliminated all 417 observations in which the source date (SRCDATE) differed from the data date (DATADATE). Third, we removed 6,722 duplicate observations to ensure that, for a specific year, each observation uniquely pertains to a single business segment. Fourth, we dropped 2,529 records without any primary SIC codes (SICS1). Fifth, we eliminated segment data, 36,311 observations, whose SIC classification pertain to "nonclassifiable establishments" (SICs in the 1999s). We also removed observations whose SIC classifications pertain to government through a keyword search (anything with the word "government") in the segment names (SNMS) provided in the COMPUSTAT segments database. Sixth, for consistency and comparability, we removed 17,532 business segment observations belonging to the financial sector (SICs in the 1960–1967s). Seventh, we dropped 2,625 records pertaining to monopolies in which, for any year, the business segments were the sole players in a specific industry. Eighth, we eliminated 61 singleton observations in which the business segments appeared for only 1 year. Ninth, we dropped 44,176 cases in which the business segments reported sales (SALES) or assets (IAS) number lower than $10 million. Tenth, we removed 2,078 observations that contained missing values for sales (SALES), operating income (OPS), and identifiable total assets (IAS). Finally, we repeat the seventh and eighth criteria to ensure no new monopolies and singleton observations resulted due to additional eliminations, dropping a further 1,210 observations. Following these screening criteria, our final usable sample contains 93,856

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[8] https://www.naics.com/hrf_faq/do-sic-codes-change-over-time/; https://dor.wa.gov/about/statistics-reports/sic-and-naics-codes.

observations with 16,381 unique business segments pertaining to 8,926 corporate parents in 808 industries during the 1979–1996 period. This number of observations is in line with Guo's (2017), McGahan and Porter's (1997), and Misangyi et al.'s (2006) samples.

Along with the lines of prior work (e.g., McGahan & Porter, 1997), we measure performance using return on assets (ROA), which is calculated by dividing the operating income (OPS) by identifiable total assets (IAS). The return on assets (ROA) in our estimable sample has a grand mean of 0.1085, a median of 0.1020, and a variance of 0.0269. The ROA mean per year varies from a minimum of 0.0859 to a maximum of 0.1578. In this regard too, our dataset compares well with prior work (Guo, 2017; McGahan & Porter, 1997; Misangyi et al., 2006).

4.2 | SDC Platinum alliance data

To create networks, we used the SDC Platinum data for joint ventures and alliances announced from 1975 to 1996 consisting of 48,104 distinct alliances.[9] The dataset covers a broad variety of interfirm relationships such as R&D alliances, supply alliances, manufacturing alliances, marketing and sales alliances, licensing and distribution alliances, and joint ventures. This wide range of both horizontal and vertical interfirm relationships allows us to take a more holistic approach to network identification by constructing a pan-industry partnership network for each year. A key benefit of the SDC database for our empirical context is that it reports alliances across the widest range of SIC codes, compared to other databases such as MERIT-CATI; that is, SDC reported at least one alliance across almost all of the four-digit SIC codes (Schilling, 2009).[10] Unlike the COMPUSTAT database which uses the most recent CUSIP, SDC Platinum also has historical CUSIP available at the time alliances were announced. We standardized the SDC CUSIP using the CRSP monthly stock files provided by WRDS.

To create a pan-industry network, we undertook the following steps. First, given our focus on the COMPUSTAT firms based in the U.S., we assess only those alliances in which at least one of the partner firms was headquartered in the U.S., resulting in 29,744 alliances among 21,358 firms. Second, in the case of alliances with more than two firms, we parsed them into all possible combinations of dyadic relationships, resulting in 38,074 alliances. Third, along the lines of extant work, we limited the lifespan of alliance relationships to five years (e.g., Gulati & Gargiulo, 1999; Sytch & Tatarynowicz, 2014). The reason is that alliance durations are rarely disclosed. As a result, to construct an alliance network for the year 1979 for example, we included all alliances from the 1975 to 1979 period. Overall, we created 18 separate networks based on rolling five-year windows for each year, corresponding to the 1979–1996 period.

5 | NETWORK DETECTION

After constructing the network of alliance relationships among firms, we employ a fast-unfolding community-detection algorithm to pin down the distinct, nonoverlapping network

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[9] The alliance data are sparse before 1985. We arrive at this number based on the total number of deals, that is, if a deal involved three firms, we count it as one distinct alliance.

[10] More specifically Schilling (2009, p. 235; additions in square brackets ours) points out, "Of the databases considered here [SDC, MERIT-CATI, CORE, RECAP, and Bioscan], the SDC database covers the widest range of sectors (SDC reports at least one alliance for each of 1,059 four-digit...SIC codes between 1985 and 2005)."

community membership to which a specific firm belongs in a given year (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). In fact, the standard approach to delineate the network-community boundary is to partition the relationships in such a way that the communities derived from the actual network are significantly different from a random network with the same degree distribution and size (Danon, Diaz-Guilera, Duch, & Arenas, 2005; Girvan & Newman, 2002; Tatarynowicz, Sytch, & Gulati, 2016). If we denote c_i to represent the network community to which $Firm_i$ belongs, then the modularity M captures a formally quantified measure to distinguish the actual community from a random community (e.g., Newman & Girvan, 2004):

$$M = \frac{1}{2e} \sum_{ij} \left[l_{ij} - \frac{d_i d_j}{2e} \right] \delta_{c_i, c_j},$$

where constant $\frac{1}{2e}$ normalizes modularity to calculate proportion of links or edges instead of the aggregate numbers and is built into the equation by convention but does not impact optimization; l_{ij} refers to the number of links between $Firm_i$ and $Firm_j$; $\frac{d_i d_j}{2e}$ represents the expected number of links between $Firm_i$ and $Firm_j$ in a random model[11]; δ_{c_i,c_j} reflects the Kronecker delta, taking a value of *1* if $Firm_i$ and $Firm_j$ belong to the same community (i.e., $c_i = c_j$ and *0* otherwise); Σ_{ij} essentially sums the differences between the actual links and the expected value of links in a random network over all pairs of firms that belong to the same network community. The modularity M exactly possesses the Hamiltonian form $\left(-\sum_{ij} J_{ij} \delta_{c_i,c_j}\right)$ of a Potts model.[12] Thus, the modularity maximization is analogous to determining the ground state (minimum modularity) of the Potts model.

However, we adopt a different approach to modularity maximization because studies have shown that direct modularity optimization is computationally intractable except for "the smallest of networks" (Newman, 2012, p. 28). Ours is a *large* network with a maximum of 32,665 alliances per year, in part because we do not limit the network boundary to contain only alliances between firms which belong to the same industry and in part because we consider *all* alliance types. For a large network, since exactly optimizing modularity represents a computationally hard problem (Brandes et al., 2006),[13] we use Blondel et al.'s (2008) Louvain community detection method as an approximate technique to detect reasonably good partitions (communities) based on large modularity values.[14] The Louvain approach is computationally

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[11] A most frequently used random model for the computation of modularity is the one that upholds the degree d of each $Firm_i$ of the original alliance network. In order to do so, we can generate the random network by "splitting" the existing links between $Firm_i$ and $Firm_j$, thus generating "half links" and relinking them to random firms in the original network. The splitting of *e* links creates *2e* half links. The probability of a $Firm_i$ with degree d_i to rewire with a random half link is $\frac{d_i}{2e}$, because the firm possesses d_i half links out of *2e* possible half links. Similarly, the probability of a $Firm_j$ with degree d_j to rewire with a random half link is $\frac{d_j}{2e}$. Assuming the half links are wired independently of each other, the probability that a link exists between $Firm_i$ and $Firm_j$ is $\left(\frac{d_i}{2e}\right) \times \left(\frac{d_j}{2e}\right)$. The expected number of links between $Firm_i$ and $Firm_j$ is $(2e) \times \left(\frac{d_i}{2e}\right) \times \left(\frac{d_j}{2e}\right) = \frac{d_i d_j}{2e}$ because of the presence of a total of *2e* number of half links in the network.

[12] The Potts model generalizes a system of interacting spins based on the relative angles between two nodes evenly distributed about a circle, with the line joining the center of the circle to the node acting as a vector (see Wu, 1982, p. 236 for a detailed description).

[13] Network modularity optimization is NP-hard (nondeterministic polynomial-time hard).

[14] Modularity in this case varies between −1 and +1, with values close to 1 representing a modular network.

efficient in finding communities in large networks and hence, has widely been adopted (Newman, 2012; Wu, Lou, & Hitt, 2019).[15]

The Louvain community detection method employs an unsupervised machine learning algorithm using modularity as an optimization (convergence) criterion (Wu et al., 2019). The algorithm uses unsupervised learning in that the "outcome is unsupervised," not needing either the community size or the number of communities as predetermined inputs. The algorithm repeatedly iterates between the modularity optimization phase and the community aggregation phase (Blondel et al., 2008). One iteration, consisting of two phases, is called a pass.

In the first phase, each $Firm_i$ is allocated a distinct community, with the initial number of communities being equal to the total number of firms in the original network. Next, for each $Firm_i$, the algorithm focuses on the $Community_j$ of $Firm_i$'s neighbor $Firm_j$ and calculates the gain in modularity if $Firm_i$ were to be moved to the $Community_j$ of neighbor $Firm_j$. $Firm_i$ is moved to the neighbor's community for which the modularity gain is maximum and positive, or else $Firm_i$'s community remains unchanged. This heuristic is applied to all firms in the original network in a repeated and consecutive fashion until no further gain in modularity can be obtained, marking the completion of the first phase. We note that a focal $Firm_i$ can be evaluated more than once in this process. Additionally, the results from the first phase reflect a *local* maximum because the algorithm moves firms in its *neighborhood*, and no further movement of an individual $firm_i$ to a different community can increase modularity.

In the second phase, using the communities identified in the first phase as a node, the algorithm constructs a new network. The self-loops for the "node" in the new network reflect the number of links between the members of the same community, and the links between nodes represent the number of links between the members of the two communities originally identified during the first phase. After the completion of the second phase, that is, one pass, the algorithm reevaluates the first phase using the new, weighted network. The passes are repeated until no further gains in modularity can be achieved (see Figure 1 below for a detailed visualization).

We used the igraph's *cluster_louvain* function of the *R* package to implement this algorithm.[16] The estimated modularity values in our data ranged from 0.4995 in 1983 to 0.9797 in 1985. The grand mean value for all 18 years was 0.7536, much above the suggested threshold of 0.3. The number of communities found varied from a minimum of five in 1979 to a maximum of 2,166 in 1996. The average size of a network community, that is, the average number of member firms in a specific network community, varied from 2.333 firms in 1981 to 8.705 in 1996.

Thus far, the network community detection algorithm identifies unique communities to which the firms belong in a given year but does not track community dynamics over time. For example, this algorithm does not predict whether a firm belongs to the same community over time, that is, whether two distinct network communities from two different years are identical or not. To find the community dynamics we used the following steps. First, for each community $C_{p,t}$ in the year t, we calculate a numerical overlap score with respect to every identified community $C_{q,t+1}$ in the year $t+1$ using the formula $(C_{p,t} \bigcap C_{q,t+1})/(C_{p,t} \cup C_{q,t+1})$, where the numerator represents the number of shared community members and the denominator

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[15] It can analyze 2 million nodes in less than 2 min and can handle 1 billion relational ties in less than 3 hr. Using a 5-year rolling window, our data for network identification has more than half a million alliances, including until 2018 which we need for further robustness checks.

[16] https://igraph.org/r/doc/cluster_louvain.html.

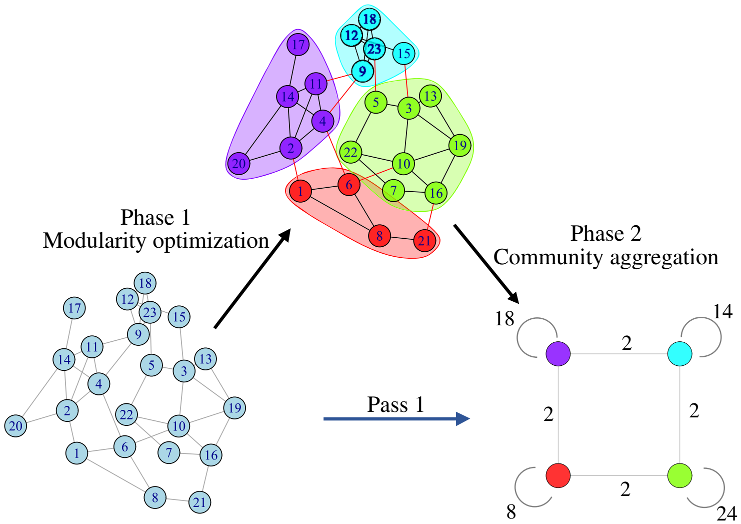

FIGURE 1 Visualization of the phases in machine-learning based network detection algorithm (a pass consists of two phases)

captures the total number of members in both communities. Second, we detect a one-to-one mapping between a community from time t and another community from time $t+1$ by solving the linear sum assignment problem (LSAP) applying the Hungarian method using the overlap scores from the previous step (Kuhn, 1955; Papadimitriou & Steiglitz, 1982). We used the solve_LSAP function of the *clue R* package.[17] The optimization problem here is to assign $C_{p,t}$ to $C_{q,t+1}$ so that the sum of the best one-to-one matched overlapping scores obtained is maximized. This step helps us identify the unique, best possible match between $C_{p,t}$ and $C_{q,t+1.}$ Last, following Sytch and Tatarynowicz (2014), we identified $C_{p,t}$ and $C_{q,t+1}$ as a single community if there was at least 30% overlap between their members.

Using these steps, we assigned 21,355 firms to 4,527 distinct dynamic communities during the 1979–1996 period. The lifespan of network communities has a mean of 2.83 years, and a range between one and 11 years. We matched the firms in the alliance dataset to those in the COMPUSTAT business segments data. Out of 8,926 firms from COMPUSTAT 2,318 were assigned networks using this process. For the remaining firms, we assigned an isolated network.

6 | METHODS

Our analytical approach draws on the models used by Schmalensee (1985), Rumelt (1991), McGahan and Porter (1997), and most recently by Sharapov et al. (2020):

$$ROA_{spint} = \mu + \propto_t + \beta_p + \gamma_i + \delta_n + \varphi_{pi} \text{ or } \varphi_s + \varepsilon_{spint} \tag{1}$$

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[17] https://rdrr.io/cran/clue/man/solve_LSAP.html.

where $\boldsymbol{ROA_{spint}}$ represents the return on assets of a corporate parent p's business segment s operating in industry i and belonging to network n in year t, μ reflects the grand mean ROA, $\propto_t$ captures the contribution to ROA by year effects, β_p captures the contribution to ROA by corporate parent p, γ_i captures the contribution to ROA by industry i, δ_n measures the contribution to ROA by network n, φ_{pi} or φ_s captures the independent contribution to the ROA by a business segment belonging to corporate parent p and operating in industry i, and ε_{spint} represents the error terms, which are not correlated with these effects and normally distributed. To decompose the total variance in profitability into unique proportions contributed by each source, we employ the Shapley Value method of variance decomposition (Shapley, 1953; Sharapov et al., 2020; Shorrocks, 2013), using the Shapley function in *R*.[18]

With coalitional game theory as its conceptual foundation, the Shapley Value method originated to solve the problem of how to justly divide the total surplus to players in a coalition who cooperate in a strategy to accomplish an intended outcome (Shapley, 1953). The key idea here is to assign the payout to each coalition player according to their marginal contributions to the joint cooperative task. To the extent that two players in a coalition are alike in their abilities to add to the desired outcome, the marginal contributions of each would be susceptible to prior existing contributions made by the other player. To offset this influence and assign gains in a fair manner to a coalition player, the Shapley Value uses the expectation (average) of a player's marginal contribution over all possible permutations of coalition formation, that is, all possible orderings in which the player can add value. Hence, the contribution of any player is not affected by who entered the game first because everyone gets an equal chance to be in the first and second positions and so on, eliminating the dependence of contributions on the entry order—a common problem in other variance decomposition methods. Another useful property of Shapley Value reflecting fairness is *symmetry* in that if two players contribute equally to the total payout, they will have the same Shapley Values. In fact, Shapley Value is the only assignment or decomposition method that meets the criteria of efficiency, symmetry, and monotonicity (Lundberg & Lee, 2017; Pintér, 2011; Young, 1985).[19]

But how can the Shapley Value rationale be used for variance decomposition using regression? In our paper, the regression of ROA is treated as a "game" in which regressors (e.g., industry, network, business segment, and corporate group) act as "players" and cooperate to produce a collective outcome, an adjusted R-square in the model (Grömping, 2007). Importantly, as discussed earlier, the Shapley Value method provides a *fair* payout to each regressor-player in the total adjusted R-square surplus generation process. Even when the regressors are nonorthogonal, the method is fair in its assignment of the proportion of R-square that arises from each specific regressor, all the while remaining agnostic to the order of entry of regressors in the model (Pintér, 2011).

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[18] https://github.com/elbersb/shapley [accessed on December 30, 2020].

[19] In addition, the solution is *efficient* or *locally accurate* in that the Shapley Values of each player sum to the model Shapley Value. The solution also satisfies *dummy* axiom or *missingness* in that if a player neither positively nor negatively contributes to a coalition (is absent), their Shapley Values are zero (Lundberg & Lee, 2017). Also, the solution exhibits *additivity* in that if two games at the same time, their joint value is the same as the sum of Shapley Values of these two games occurring at different times. Scholars have also used *monotonicity* or *consistency* instead of a dummy and additivity in that if the marginal contribution of a player in a second game is higher than or equal to that in the first game, then the Shapley Value of the player in the second game will be greater than or equal to the Value in first game (Lundberg & Lee, 2017; Young, 1985).

The conceptual extension of conventional Shapley Value from cooperative game theory to regression models with a total of k regressors is as follows:

$$\Phi_j\left(adj.R^2\right) = \underset{O\sim F}{\mathbb{E}}\left[adj.R^2\left(\left(O_{before\,j}\right)\cup\{j\}\right) - adj.R^2\left(O_{before\,j}\right)\right]$$
$$= \frac{1}{k!}\sum_{Allpermutationsofkregressors}\left[adj.R^2\left(\left(O_{before\,j}\right)\cup\{j\}\right) - adj.R^2\left(O_{before\,j}\right)\right],$$

where Φ_j ($adj.\ R^2$) is the proportion of adjusted R-square assigned to regressor-player j. $\boldsymbol{F}$ represents a universal set of all possible permutations or ordering of k regressors taken *all* at a time (i.e., $k!$ ways in which all k regressors can be arranged or entered to "form coalitions"). Permutations help determine whether the regressor j should be added right after the null model or after adding another specific regressor and so on for assessing the marginal contribution of regressor-player j compared to the set of prior added regressor-players. O represents a specific permutation consisting of all k regressors. For a specific regressor j within this permutation O, $O_{\text{before } j}$ represents a sequence of all regressors that precede the regressor j in the permutation. For each ordering O of regressors, a regressor-player j's marginal contribution is the difference in adjusted R-square when the regressor j is added to the regression which consists of all regressors *before* the regressor j in the permutation O. The Shapley Value is the expectation of regressor j's marginal contributions across all permutations in $\boldsymbol{F}$.

Alternatively, for computational efficiency, the Shapley Value can also be calculated in terms of the marginal contribution of a regressor-player j to all possible *subsets* of *combinations* of k regressors excluding regressor j taken one or two regressors at a time and so on, with a maximum of $k - 1$ regressors at a time:[20]

$$\Phi j\left(adj.R^2\right) = \sum_{C\subseteq T\setminus\{j\}}\frac{|C|!(k-|C|-1)!}{k!}\left[adj.R^2\left((C\cup\{j\}\right) - adj.R^2(C)\right],$$

where $T\setminus\{j\}$ represents the universal set, whose elements are subsets formed by all possible combinations of regressors other than j. Essentially, it captures the different combinations of regressors that may come *before* regressor j. Coalition C represents a specific combination. For example, to calculate the contribution of the regressor *network* (j = *network*), all possible coalitions (combinations) of regressors that may appear before *network* is entered are as follows: (1) intercept only or null model, (2) year, (3) business segment, (4) corporate parent, (5) industry, (6) year + business segment, (7) year + corporate parent, (8) year + industry, (9) business segment + corporate parent, (10) business segment + industry, (11) corporate parent + industry, (12) year + business segment + corporate parent, (13) year + business segment + industry, (14) year + corporate parent + industry, (15) business segment + corporate parent + industry, and (16) year + business segment + corporate parent + industry.

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[20] Previously, we considered only those regressors that appeared before the regressor j in a *permutation*. Say, two regressors a and b appear before the regressor j. Then (a, b) and (b, a) are two different permutations but just *one* combination. Here, in a combination, order is not important but just which regressors came before the regressor j.

For each coalition C, we calculate the marginal contribution of a regressor j to the coalition by taking the difference between the adjusted R-squares with and without the variable j (adj. $R^2((C \cup \{j\})$ – adj. $R^2(C))$. For example, for the year-only "coalition," we subtract the year-only adjusted R-square from the adjusted R-square obtained by the regression of performance on both *year* and *network*. We follow the same steps for all other coalitions.

In turn, we compute the Shapley Value by taking the weighted mean of these marginal contributions across combinations. The weights are given by $\frac{|C|!(k-|C|-1)!}{k!}$. Here, $|C|$ reflects the cardinality of C. $|C|!$ is the number of different permutations in which the regressors in a combination C could have appeared prior to the addition of regressor j, and $(k - |C| - 1)!$ reflects the different permutations in which the remaining (i.e., $k - |C| - 1$) regressors appear after regressor j in a regression. Overall, $|C|!\ (k - |C| - 1)!$ represents all possible permutations of k regressors in which the regressors present in C appear before the regressor j. $k!$ represents all possible permutations of k regressors, the order in which regressor j can appear. In this vein, the weight $\frac{|C|!(k-|C|-1)!}{k!}$ denotes the probability of selecting a specific subset C. The weights capture the probability that the regressors of C precede a regressor j in any permutation, allowing us to calculate the expected contribution.

7 | RESULTS

7.1 | Variance decomposition results

Table 1 presents the descriptive statistics of our estimation sample. To reiterate, our sample consists of 16,381 business segments belonging to 8,926 corporate parents operating in 808 industries and 9,849 communities over the 18-year period 1979-1996. In Table 2, we provide the results using the Shapley Value method. We first introduce the baseline result in which we report variance contributions by business segment, corporate parent, industry, and year. Then, in Model 2 of Table 2, we introduce the variance attributed to network effects. As seen in Model 2, network effects represent 11.19% of variance in the business segment's return on assets. The bootstrapped 95% confidence interval with 100 simulated samples for the network effect ranges from 4.26% to 18.11%.

In Table 3, we further confirm the validity of our results by comparing the main results from our multilevel models to those of Guo (2017), McGahan and Porter (1997), Misangyi et al. (2006), Rumelt (1991), Sharapov et al. (2020), and Vanneste (2017). As shown in Table 3, the variance attributed to the business segment, corporate parent, industry, and year effects in our data are 31.50, 10.60, 3.31, and 1.30%, respectively, of the total variance in business-segment ROA. These results generally support the findings of prior work and are consistent with work by Sharapov et al. (2020) and Vanneste (2017) in terms of the relative importance of business segment, industry, and corporate parent effects.

7.2 | Robustness checks

For robustness, we re-estimate Equation (1) using a cross-nested multilevel estimator with restricted maximum likelihood estimation (RMLE) in which the business segments are cross-

TABLE 1 Sample summary statistics

	Mean	Minimum	Maximum
Whole sample			
Corporate parents	8,926		
Business segments	16,381		
4-digit industries	808		
Network communities	9,849		
ROA	0.11		
Corporate parents per network community	1.70	1	250
Corporate parents (business segments) per industry[a]	20.27	2	521
Business segments (industries) per corporate parent[b]	1.84	1	19
Per year			
Corporate parents	3,589	3,045	4,764
Business segments	5,214.22	4,861	6,100
Industries	559.11	541	590
Network communities	3,175.06	2,912	3,370
ROA	0.11	0.09	0.16

[a] Following Misangyi et al. (2006, p. 575), we view business segments which switched industries (SICS1) during the sampling period as new business segments every time they entered a new industry.
[b] Same reasons as in a above.

TABLE 2 Shapley value results

Components	Model 1: Baseline	Model 2: Network
Business segment	35.23% [29.28, 41.18]	31.50% [25.55, 37.46]
Corporate parent	14.30% [11.68, 16.92]	10.60% [7.97, 13.22]
Industry	3.57% [2.53, 4.62]	3.31% [2.27, 4.36]
Year	1.42% [1.09, 1.75]	1.30% [0.97, 1.64]
Residual	45.48% [39.18, 51.78]	42.10% [35.79, 48.39]
Network		11.19% [4.26, 18.11]

Note: In brackets, 95% confidence intervals with variance estimated by bootstrapping 100 times.

nested within corporate parents, industries, networks, and time (Guo, 2017; Hough, 2006; Karniouchina et al., 2013); Misangyi et al., 2006; Sharapov et al., 2020).[21]

Equation 1 rephrased: Level 1: $ROA_{tspin} = \vartheta_{0spin} + u_{t000} + e_{tspin}$

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[21] Unlike the maximum likelihood (ML) procedure, which estimates variances assuming that the fixed components are accurately known or measured without any error, restricted estimation of maximum likelihood (RMLE) takes into consideration the possibility that fixed components are mere estimates. As such, compared to those based on maximum likelihood, in which standard errors may be generally downward biased (Hox, 2013), REML estimates are less biased because they account for the degrees of freedom used in estimating the fixed effects by separating the estimation of fixed and random components and maximizing the likelihood of a batch of residual contrasts (Raudenbush & Bryk, 2002; Snijders & Bosker, 2012).

TABLE 3 Comparison of this study with selected previous studies

	Our study	Guo (2017)[a]	McGahan and Porter (1997)[b]	Misangyi et al. (2006)[c]	Rumelt (1991)[d]	Sharapov et al. (2020)[e]	Vanneste (2017)[f]
Years covered	1979–1996	1979–1996	1981–1994	1984–1999	1974–1977	2002–2006	–
No. of observations	93,856	97,011	58,132	10,663	6,932	5,000	18 samples
Database	COMPUSTAT	COMPUSTAT	COMPUSTAT	COMPUSTAT	FTC	Amadeus	Meta-analysis
Year	1.30%	0.95%	0.30%	0.80%	–	0.06%	1.00%
Industry	3.31%	6.35%	9.40%	7.60%	8.32%	4.07%	8.00%
Corporate parent	10.60%	5.60%	9.10%	7.20%	0.80%	12.46%	14.00%
Business segment	31.50%	42.12%	35.10%	36.60%	46.37%	34.11%	36.00%
Residual	42.10%	44.98%	33.20%	47.80%	36.87%	48.94%	–

[a] Results of Model 1 in Guo (2017) paper without interaction or random linear/nonlinear year effect; year effect is estimated by adding a fixed linear year at Level 1 in Model 1 and calculating the amount of dynamic variance accounted for by fixed linear year effects.

[b] Nested ANOVA results in which the effects were added in the following order: year, industry, corporate parent, and business segment.

[c] Hierarchical linear modeling (HLM) results.

[d] Table 3 Sample A in Rumelt (1991) which includes the variance component estimates.

[e] Results using the Shapley Value method; 5,000 is not the number of observations but resampled firms.

[f] Results using the effect-size measure based on variance; Table 6 in Vanneste (2017).

TABLE 4 Robustness checks using alternate method and specification

Components	Model 1: MLM RMLE	Model 2: MLM MCMC with 95% confidence interval	Model 3: MLM with year fixed effect[a]	Model 4: ANOVA I, C[b]	Model 5: ANOVA C, I[c]
Business segment	36.96%	36.95% [35.62, 38.40]	37.83%	18.51%	18.51%
Corporate parent	2.26%	2.08% [1.18, 2.91]	2.31%	26.16%	29.58%
Industry	4.89%	4.91% [3.89, 5.90]	5.00%	8.18%	4.76%
Year	2.28%	2.61% [1.06, 4.66]	1.22%[c]	1.66%	1.66%
Residual	47.51%	47.35% [46.88, 47.88]	48.61%	42.10%	42.10%
Network	6.10%	6.10% [5.41, 6.78]	6.24%	3.39%	3.39%

[a] Year effect is estimated by adding fixed year dummies in our models with all other random effects (business segment, corporate parent, and industry) and calculating the amount of variance accounted for by fixed year dummies effects. $\left(\sigma^2_{e\,(unconditional\text{ model})} - \sigma^2_{e\,(full\text{ model})}\right) \div Total\text{ variance}_{(unconditional\text{ model})}$.

[b] Ordering of effects: year, industry, corporate-parent, business segment, and network.

[c] Ordering of effects: year, corporate-parent, industry, business segment, and network.

Level 2: $\vartheta_{0spin} = \theta_{00pin} + s_{0spin}$
Level 3: $\theta_{00pin} = \Delta_{00000} + w_{000p} + x_{000i} + z_{000n}$,
where
$e_{tspin} \sim N\left(0, \sigma^2_e\right), u_{t000} \sim N\left(0, \sigma^2_t\right), s_{0spin} \sim N\left(0, \sigma^2_s\right), w_{000p} \sim N\left(0, \sigma^2_p\right), x_{000i} \sim N\left(0, \sigma^2_i\right), z_{000n} \sim N\left(0, \sigma^2_n\right)$.

ϑ_{0spin} is the mean ROA of business segment s over the total duration, θ_{00pin} is the mean ROA across all business segments pertaining to corporate parent p, operating in industry i, and belonging to network n, Δ_{00000} the overall grand-mean ROA. $e_{tspin}, u_{t000}, s_{0spin}, w_{000p}, x_{000i}$, and z_{000n} represent within-business segment, between-year, between-business segment, between-corporate parent, between-industry, and between-network residuals, respectively. Furthermore, $\sigma^2_e, \sigma^2_t, \sigma^2_s, \sigma^2_p, \sigma^2_i$, and σ^2_n capture within-business segment, between-year, between-business segment, between-corporate parent, between-industry, and between-network variances, respectively. We use the *lmer* function in *lme4 R* package (Bates, Mächler, Bolker, & Walker, 2014; Freeman, Savva, & Scholtes, 2020; Riedl & Seidel, 2018; Sherf, Parke, & Isaakyan, 2020).[22]

In Table 4 (Model 1), network effects contribute 6.10% of the total variance explained in profitability. Though the effect is lower, our multilevel model, as discussed earlier, relies on strong assumptions pertaining to the distribution of random effects and the independence of network effects. In Table 4 (Model 2), we further check the robustness of our findings using multilevel modeling with the MCMC method which allows us to estimate the confidence interval of the variance attributed (Guo, 2017). We estimate the MCMC method using the *MCMCglmm* function in the *MCMCglmm R* package.[23] Our results stay consistent with the Model 1 multilevel results and are subject to the same caveat. In Model 3 of Table 4, we change the year effects from random to fixed effects and see the network effects increase slightly from 6.10% to 6.24%, but produce a lower effect compared to the estimate from the Shapley Value

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[22] https://www.rdocumentation.org/packages/lme4/versions/1.1-26/topics/lmer.

[23] https://www.rdocumentation.org/packages/MCMCglmm/versions/2.29/topics/MCMCglmm; https://cran.r-project.org/web/packages/MCMCglmm/index.html; Results are essentially the same using the MLwinN software.

(because Shapley Value is not sensitive to the choice of either the nesting of effects or the type of effects, fixed vs. random).

In Models 4 and 5 of Table 4, we show results using nested ANOVA and, along the lines of McGahan and Porter (1997), consider two paths to arrive at the full model. First, we introduce the effects in the following order: year, industry, corporate parent, business segment, and network. Then, we follow the following sequence: year, corporate parent, industry, business segment, and network. The contribution of network effects in both models is lower still at 3.39%. At the same time, as we pointed out earlier, these estimates are sensitive to entry order. For example, if we enter network after industry and before corporate parent in the sequence, the variance explained by the network increases to 24.8%.

8 | SELECTION ISSUES IN NETWORKS

Although the main purpose of this or any variance decomposition study is not to establish causality *per se*, comparability and sampling may be an issue in our use of networks.[24] A critical conceptual issue arises when comparing networks to business, industry, and year effects. Being in a business segment, in an industry, and in a certain year are all required by definition for a corporate parent to exist or follow naturally from the fact that the corporate parent exists in the first place. However, the very fact that a corporate parent exists would not necessarily make it a part of a network. Being part of a network is not *required* to operate in a certain business segment, industry, or year in the definitional sense. Even though selection into certain businesses or industries may be nonrandom, this may seem less of an issue in existing variance decomposition studies because the results of prior work are limited only to corporate parents that choose to do business in a particular industry (i.e., the intrinsic comparison is not with firms that do not choose to operate in a certain business or industry). However, our sample contains firms that, for whatever reason, select or do not select into networks.[25] We deal with this issue of selection in four broad ways, namely, subsetting data based on network membership (size), employing coarsened exact matching (CEM), examining the influence of industry and diversification profiles, and evaluating the interactions between network membership and other regressors.

8.1 | Data subsetting

Selection into networks may make comparing firms with and without membership in a network community like comparing apples to oranges. To account for this fact, we restrict the estimation sample to exclude observations pertaining to "isolate" firms which did not form any alliances at any point in time during our sampling period. In order to do so, we subset the data to include only those observations for which any identified network has more than one member firm. We run our Shapley Value variance decomposition analysis on this subsample and find consistent results (Table 5; Model 1).

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[24] The nature of the nominal or network membership approach exacerbates the selection problem, but the issue would remain unchanged even when we use a continuous measure.

[25] For example, only 2,318 firms were assigned to a network out of 8,926 firms in the sample. In contrast, every single one of the 8,926 firms were assigned to at least a business or an industry and a year by definition.

TABLE 5 Robustness checks using data subsetting

Components	Model 1: Network (>1 firm)	Model 2: Network (>2 firms)	Model 3: Network (>5 firms)	Model 4: Network (>10 firms)	Model 5: Network (>20 firms)	Model 6: CEM samples (4,304 treatment obs. & 7,021 matched control obs.)
Business segment	29.75%	29.69%	29.70%	29.68%	29.24%	35.46%
Corporate parent	9.62%	9.52%	9.52%	9.51%	9.46%	15.02%
Industry	5.65%	5.77%	5.75%	5.70%	5.87%	5.50%
Year	0.98%	0.97%	0.95%	0.94%	0.91%	0.30%
Residual	43.97%	44.18%	44.19%	44.28%	44.70%	29.42%
Network	10.04%	9.89%	9.89%	9.89%	9.82%	14.29%

Moreover, we generate four additional subsamples after imposing more severe restrictions for the network membership. We use the criteria that each observation belongs to a network community with more than 2, 3, 10, and 20 member firms, respectively, to create four distinct sample partitions. The different subsamples attempt to capture different underlying networking intensities. As shown in Models 2–5 of Table 5, the results from the Shapley Value method hold in these subsamples as well.

8.2 | Coarsened exact matching

In a second approach, to make firms with and without membership in a network community comparable, we consider alliance formation by a firm in a year as a *treatment* and no alliance formation as a *control* group. We use a nonparametric approach, namely, coarsened exact matching (CEM) to create matched controls for the treated observations, using an exhaustive list of COMPUSTAT-based firm- and industry-level dimensions for each year. The detailed list makes the matching criteria more stringent.[26] We next use the sample with only matched treatment and controls to conduct variance decomposition analyses. Our results remain consistent (Table 5; Model 6).

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[26] Our firm-level variables include firm size measured as logged value of assets (AT), current ratio as current assets (ACT) divided by current liabilities (LCT), solvency ratio as long-term debt (DLTT) divided by assets (AT), normalized capital expenditures as capital expenditures (CAPX) divided by assets (AT), normalized short-term investments as cash and short-term investments (CHE) divided by assets (AT), normalized invested capital as invested capital (ICAPT/AT) divided by assets (AT), normalized intangible assets as intangible assets (INTAN/AT) divided by assets (AT), normalized R&D expense as R&D expense (XRD) divided by assets (AT), normalized selling expense as selling, general and administrative expense (XSGA) divided by assets (AT), slack as sales (SALE) divided by the sum of inventory (INVT) and fixed assets (PPENT), country of incorporation together with state (FIC-STATE), and industry (NAICS2). Our industry-level controls included average sales, average R&D, and average slack in an industry. We dichotomize each of the continuous variables into top and non-top categories based on the 85th percentile.

8.3 | Industry type and diversification profile

In our main analysis, we discussed the importance of unrestricted network effects. We now attempt to tease out graphically the potential “interactions” arising due to the influence of other sources of variance on the network effects. A corporate parent’s membership in certain industries or the industries in which business segments operate may differentially determine membership in a network community compared to those in other industries, in turn affecting the strength of network effects.

8.3.1 | Network effects and industry type

To analyze how network effects differ by industry, following McGahan and Porter (1997), based on one-digit SIC, we consider six main sectors, namely, agriculture, fishing, forestry, and mining (SICs 0 and 1), manufacturing (SICs 2 and 3), transportation (SIC 4), wholesale trade (SIC 5), lodging and entertainment services (SIC 7), and services (SIC 8). For each of these six economic sectors, we repeat the analyses on subsamples comprising of network communities having *m* or more members, with *m* varying from *1* (broad subsample) to *10* (the sample containing only the largest network communities) to examine the percentage of total variance in business segment profitability that networks explain.

Figure 2 (left panel) represents the variance decomposition estimates of network membership from subsamples using the Shapley Value method. In fact, as can be seen in Figure 2 (left panel), network effects differ based on different economic sectors. At the same time, networks matter because the effects persist and have above-zero values in each of these sectors. For example, in the lodging and entertainment services sector, as the minimum number of members in a network increases from one to two, network effects increase and then decline as members increase to three. But after that, the network effects stay generally stable for network

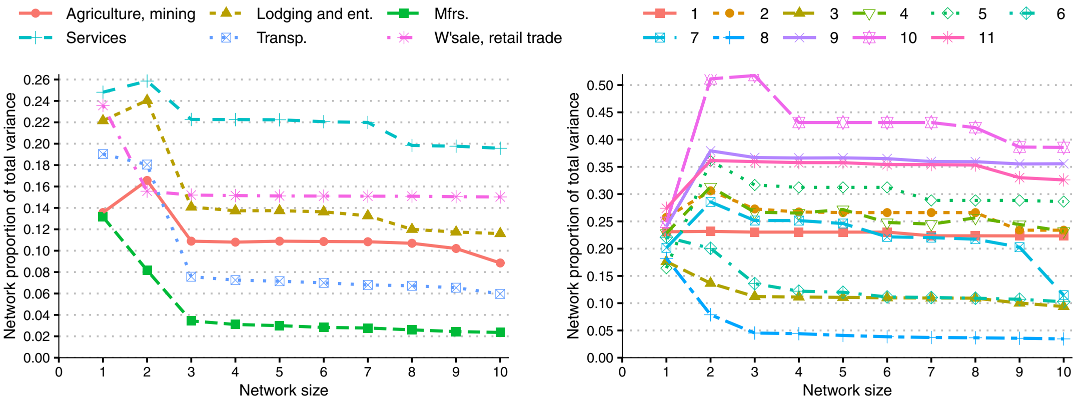

FIGURE 2 Proportion of variance explained by network effects as minimum number of corporate parents which network communities span increases within each economic sector (left panel) and within each high-technology industry in the manufacturing sector (right panel; 1—aircraft, space vehicles, guided missiles, and parts; 2—motor vehicle bodies and parts; 3—chemicals and associated products; 4—computer and office equipment; 5—household audio and audiovisual appliances; 6—medical, surgical, and dental apparatus; 7—petroleum refining and associated products; 8—pharmaceutical drugs; 9—electronic components, semiconductors, and peripherals; 10—telecommunications apparatus; and 11—Laboratory instruments and measuring and controlling apparatuses)

communities having between three and seven members, and show a downward trend for networks with more than seven members, suggesting some influence of network size within the sector. In contrast, network effects stay generally stable as the minimum number of members within a network community increases to two and above in the wholesale trade sector. In the manufacturing sector, network effects decline as the minimum network size increases from one to three and remain relatively stable after that. Across all sectors, membership in a network community explains the largest share of variance in the services sector and the lowest within the manufacturing sector.

To further parse out the variance explained by networks within the manufacturing sector, in Figure 2 (right panel), we next examine the influence of 11 high-technology manufacturing industries based on Schilling and Phelps (2007): aircraft, space vehicles, guided missiles and parts (SICs 3,721, 3,724, 3,728, 3,761, 3,764, and 3,769), motor vehicle bodies and parts (SICs 3,711, 3,713, and 3,714), chemicals and associated products (SICs 281-, 282-, 285-, 286-, 287-, 288-, and 289-), computer and office equipment (SICs 3,571, 3,572, 3,575, and 3,577), household audio and audiovisual appliances (SICs 365-), medical, surgical, and dental apparatus (SICs 3,841, 3,842, 3,843, 3,844, and 3,845); petroleum refining and associated products (SICs 2,911, 2,951, 2,952, 2,992, and 2,999), pharmaceutical drugs (SICs 2,833, 2,834, 2,835, and 2,836), electronic components, semiconductors, and peripherals (SICs 367-), telecommunications apparatus (SICs 366-), and laboratory instruments and measuring and controlling apparatuses (SICs 382-). As regards high-technology industries, network membership explains the highest proportion of variance in the telecommunications equipment industry followed by electronic components, semiconductors, and peripherals. Network effects are the lowest in the pharmaceutical industry. Although network effects depend on network size in high-tech industries such as telecommunications equipment and petroleum refining and affiliated products, they remain relatively stable in industries such as electronic components manufacturing as the minimum membership increases to two or more. Overall, while network effects remain relevant across all industries, they are considerably influenced by network size and industry type.

Similarly, corporate parents with different diversification profiles, or for that matter network communities with different diversification profiles, may exhibit different relationship between networks and their share of performance variance. We next discuss how diversification influences network effects.

8.3.2 | Network effects and corporate parent diversification

Specifically, we examine how the importance of networks in explaining the total variance in business segment profitability changes with corporate parent size determined by the number of its business segments. In order to analyze this relationship, we rerun the analyses on subsamples that contain corporate parents having z or more business segments, with z varying from *1* (the baseline full sample) to *10* (the sample containing the largest corporate parents).

Next, to examine the effect of *related* diversification on the linkage between network membership and business segment profitability, we estimate the proportion of variance explained by network membership on subsamples that include corporate parents with businesses in z_1 or more SIC 4-digit industries within the corresponding SIC 2-digit sector, with z_1 varying from *1* (the simple model) to *10* (the model with most related diversification). To evaluate the influence of *unrelated* diversification on network membership effects, we estimate the network effects on

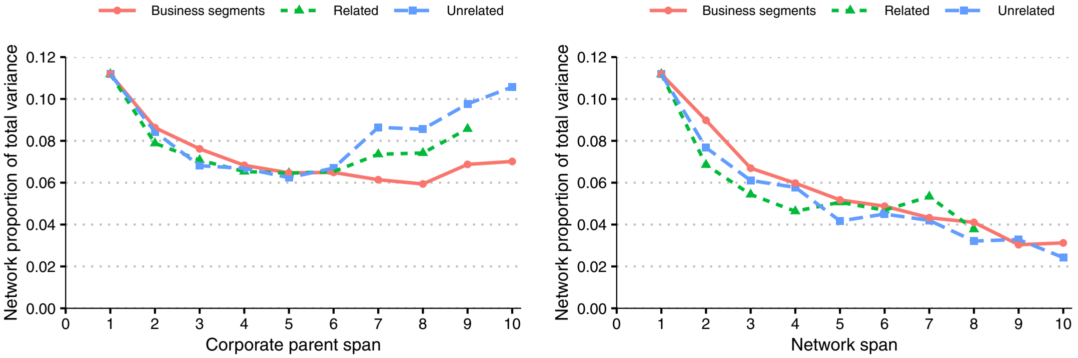

FIGURE 3 Proportion of variance explained by network effects as minimum number of business segments/industries which corporate parents span (left panel) and which network communities span (right panel) increase

subsamples containing corporate parents with businesses in z_2 or more two-digit SIC sectors, with z_2 varying from *1* (the simple model) to *10* (the model with most unrelated diversification).

In Figure 3 (left panel), we plot estimates of network effects from subsamples using the Shapley Value variance decomposition method. As the minimum number of business segments in a corporate parent increases from one to four, network effects decline. But after that, the network effects stay generally stable for corporate parents that manage between four and eight business segments and show an upward trend for corporate parents with more than eight segments, suggesting some influence of the corporate parent. As regards related diversification, the share of variance in business segment profitability explained by network membership declines as the industries z_1 in which corporate parents have businesses increase from one to three, stays roughly stable between three and six industries, and again increases when the corporate parent conducts business in more than six industries within the same two-digit SIC sector. When a corporate parent has businesses in unrelated industries, the effect of network membership declines as the number of industries z_2 increases from one to three, remains stable between three and six, and increases as the number of unrelated industries increases beyond six. Interestingly, while the patterns across related and unrelated diversification are similar until presence in six industries, the increase beyond six industries when they are unrelated is greater than when they are related, suggesting that the homogenizing effect of the corporate parent helps network effects more across unrelated industries possibly through the superior handling of diversity.

8.3.3 | Network effects and network diversification

We next evaluate how the strength of network effects in explaining the total variance in business segment profitability changes with network size determined by the number of business segments within a network normalized by the number of corporate parents. To study this relationship, we re-estimate the results on subsamples with network communities having z' or more business segments per corporate parent, with z' varying from *1* (the baseline sample) to *10* (the sample containing networks with the largest corporate parents).

We then assess the influence of *related* diversification on the network membership effects. Specifically, we estimate the share of variance explained by network membership on subsamples with network communities whose members' conduct businesses in z'_1 or more SIC four-digit industries within the corresponding SIC two-digit sector normalized by the number of corporate parent members in a network community, with z_1' varying from *1* (the simple model) to *10* (the model with the most related diversification in a network community). To examine the impact of *unrelated* diversification on network membership effects, we estimate the network effects on subsamples comprising of network communities with their members' businesses in z_2' or more 2-digit SIC sectors normalized by the number of corporate parent members in a network community, with z_2' varying from *1* to 10.

Figure 3 (right panel) shows the variance decomposition estimates of network membership depending on the network diversification profile. As the number of business segments (per corporate parent) in a network community increases, network effects decline. Similarly, the importance of network effects decreases when either related or unrelated diversification increases within a network community. An interesting difference between the influences of corporate diversification profile (left panel) and network diversification profile is that the network effects *decline* in the case of increases in both unrelated and related diversification within a network community. In contrast, network effects *strengthen* in the case of both related and unrelated diversification of a corporate parent, with unrelated diversification exerting the maximum positive influence beyond six 2-digit SIC sectors. A plausible explanation could be that within a firm boundary, a corporate group might exert an integrating influence on business segments, enhancing knowledge sharing. As a result, the benefits of diversity are better managed, and diversification and the network acts in a mutually beneficial manner. However, network boundaries may not be as unifying as corporate parent boundaries, and knowledge sharing may therefore become problematic when diversification increases within a network community.

8.3.4 | Interaction with known variance sources

We adopt interactions to account for the possibility that a firm's decisions about which alliance relations to enter into and in turn, about which network to be a member of, may be influenced by industry effects (e.g., industry norms), corporate parent effects (e.g., corporate policy), and business segments effects (e.g., business unit manager decisions). In fact, the interaction approach may be another potential way to address the selection concern by embracing the possibility of network selection across industries, corporates, and businesses, that is, level at which the decisions about network membership are made. Is it a corporate-level decision (Alphabet not collaborating with Apple) or a business unit decision (operating system businesses across the two firms not collaborating with one another) or an industry-based decision?[27] Not only may the interactions bring clarity regarding the origins of networks but also help situate our contribution within the existing stream of variance decomposition studies focused on industry, corporate parent, and business segments, answering whether any of the three effects become more prominent under the influence of network membership, and vice versa.

In Model 1 of Table 6, we interact network with industries, corporate parents, and business segments, respectively. The first-order effect of network now goes down to 4.74%. The interaction between network and industries explains 16.19% of the performance variance, and the corporate parents' interaction contributes to 5.94%. Business segments interactions contribute to 21.30% of the explained variance. We next introduce the yearly interactions in Model 2 of Table 6. Yearly interactions explain 11.62% of the explained variance. The fact that a large share of

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[27] Theoretically, decisions about network membership can be made at any of the three levels: industry, corporate parent, and business segment (units; e.g., Wassmer, Dussauge, & Planellas, 2010).

TABLE 6 Robustness checks using interactions

Components	Main model: Shapley value	Model 1: Shapley value with interactions	Model 2: Shapley value with interactions	Model 3: Shapley value with interactions (supervised machine learning)
Business segment	31.51%	12.73%	12.03%	25.91%
Corporate parent	10.60%	5.73%	3.23%	6.51%
Industry	3.32%	1.56%	1.20%	2.36%
Year	1.30%	1.19%	0.31%	0.28%
Residual	42.09%	30.62%	8.19%	7.18%
Network	11.19%	4.74%	2.80%	5.61%
Network × Industry		16.19%	15.25%	–
Network × Corporate parent		5.94%	5.39%	–
Network × Business segment		21.30%	17.77%	–
Network × Year			11.62%	14.74%
Corporate parent × Year			14.50%	25.58%
Industry × Year			7.71%	11.84%

network effects are driven by industry factors may suggest that network selection is industry specific. This seems consistent with the empirical reality that alliances are especially needed in industries where resources and expertise are widely distributed (e.g., biotech and software). Corporate parents and business segments also exert influence in determining network effects. Overall, the variance explained by network effects seems to be influenced by whether the industry is collaborative or competitive in general (e.g., Thatchenkery & Katila, 2021; Zaheer & Usai, 2004) and also by corporate parents and business segments.

8.3.5 | Machine-learning based interactions

Using machine learning, we attempt to select the *relevant* interactions for our model for predictive purposes. In this vein, following Vanneste and Gulati (2021), we use the LASSO (least absolute shrinkage and selection operator) estimator, a supervised machine learning method (Tibshirani, 1996). Given their theoretical implications, we always retain the main sources of variance, namely, business segment, corporate parent, industries, years, and network.

LASSO estimation requires conversion of categorical variables into binary variables but fails to account for the groups (e.g., industry, corporate parent) underlying these binary variables. To overcome this limitation, we employ Group LASSO which, in the penalty function, uses the

Euclidean norm of the coefficients related to the binary variables belonging to a group (Bakin, 1999). Specifically, Group LASSO addresses the issue of selecting group and the individual binary variable at the same time, that is, bi-level selection (Breheny & Huang, 2009, 2015). To implement Group LASSO, we used the *cv.grpreg* function of the *grpreg R* package.[28]

Since our sample has categorical variables with numerous categories, we need to generate too many binary variables (237,171 dummies),[29] making the computation using this machine learning algorithm computationally intensive. Hence, we follow the following sampling procedure. We first keep the firms belonging to the top 20 largest network communities (membership >160 firms). This step provides 24,806 observations, with 1,491 firms from 1,880 network communities across 3,542 industries. We then randomly select a subsample with 15% of the firms belonging to these communities, which generates 3,720 observations with 20,431 dummy coded features (grouped factors). We next utilize this randomly generated subsample to explore the important interaction effects using Group LASSO. Over a grid of values for the tuning parameter lambda, we then perform a 10-fold cross-validation with grouped covariates. The model at the highest value of lambda, which is within one standard error of the minimum mean cross-validated error, suggested an interaction between network and year (14.74%), corporate parent and year (25.58%), and industry and year (11.84%), respectively. We show this result in Model 3 of Table 6. Here, the network in terms of first-order effects, explains 5.61% variance in profitability. The other interactions discussed earlier seem to be less relevant for predictive modeling.

Overall, the big question we focus on is how much variance in performance is explained by network membership. To understand better the influence of selection effects in network membership, we explore interactions between networks and the three well-known sources of variance, namely, industry, corporate parent, and business segment. In the presence of these interactions, the first-order effect of network membership is lower, suggesting the possibility that the interactions themselves may provide rich insights. Our main model without any interactions suggests that network membership is related to performance outcomes, explaining approximately 11% of the variance, *after* holding constant (i.e., setting aside) the values of the other existing sources of variance, thus reflecting unconditional or unrestricted effects. The interaction terms tell us that we cannot fairly ignore the presence of other sources of variance when evaluating the relationship between network membership and performance outcomes. It is important to note that in the presence of interactions, the main effects of network membership become first-order or conditional effects which capture the network effect for the cases in which the moderator's value is zero.

9 | UPDATED TIME WINDOWS

We take special care to ensure that our study remains as comparable as possible to prior work, including the sampling period from 1979 to 1996. While engaging in purely replication-based research with networks as an added factor may be relevant to scholarship, not extending the time period of the study by bringing the analysis to the present may be a missed opportunity in two ways. First, by detecting temporal trends, it can help us better understand whether network

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[28] https://pbreheny.github.io/grpreg/.

[29] At its best, even a paid software like Stata/MP (6+ core) can handle only 65,532 independent variables, and the maximum number of columns allowed in the dataset is 120,000). https://www.stata.com/products/which-stata-is-right-for-me/.

effects remain stable or have strengthened over time. Second, SDC alliance data coverage may not be ideal until about 1990 (Schilling, 2009).[30] Thus, a concern may arise about whether the network effects we estimated up to 1996 are driven by the sparseness of the network data.

For additional robustness checks, we conduct analyses with four *consecutive* time windows, namely,[31] 1979–1985,[32] 1986–1996,[33] 1997–2007,[34] and 2008–2018, and report the results in Table 7. As shown in the table, networks explain 11.16% of variance in performance from 1979 to 1985. The share of variance explained by networks in the three consecutive 10-year windows is 12.77%, 10.97%, and 4.27%, respectively (i.e., ranging from 4.27% to 12.77%, Table 7).

Additionally, updating the time windows used in prior work, we use the following *cumulative* time windows: 1979–1985 (repeated for ease of reference), 1979–1996 (main model repeated for ease of reference), 1979–2007, and 1979–2018. The network in these windows explains, respectively, 11.16, 11.19, 11.05, and 7.93% of the variance,[35] further validating our main findings (i.e., 11.19% for 1979–1996). Furthermore, we run the analyses for the most recent period (from 1997 onwards), using the following *cumulative* time windows: 1997–2007 (repeated for ease of reference), and 1997–2018. As Table 7 shows, the network explains 10.97 and 7.44% of the variance respectively during these time frames.

10 | TYPES OF ALLIANCES

A possibility remains that our main results are influenced by certain types of alliances which are less “involved,” such as licensing and distribution. Similarly, joint ventures involve equity ownership and may be fundamentally different from any other alliance relationship. The same alliance can involve multiple alliance types. For example, an alliance can entail both licensing and R&D. In Table 8, we adopt a stringent stance and eliminate observations containing any alliance that *also* involved licensing (Model 1), distribution (marketing; Model 2), and joint ventures (Model 3), separately and additionally by dropping the observations involving any of these alliance types (Model 4). Our results hold. Next, we drop from our sample any observations that involve *only* licensing (Model 5), distribution (marketing; Model 6), and joint ventures (Model 7), separately and also by dropping the observations involving any of these alliance types (Model 8). Our results remain robust.

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[30] According to SDC manuals, alliance data availability starts from 1988, and onward. We found alliances starting from 1985 and sparseness before 1985 in that only a handful of alliances were reported. At the same time, scholars have pointed out that the SDC alliance data is spotty until 1990 (e.g., Anand & Khanna, 2000; Schilling, 2009).

[31] Additional data collection from the COMPUSTAT and the SDC database used the same steps as described earlier for the initial data collection in Sections 4.1 and 4.2.

[32] Ideally, we should have started at 1975 for a 10-year interval but COMPUSTAT manual mentions that pre 1979 business segments data is not present in the database. https://wrds-www.wharton.upenn.edu/pages/support/support-articles/compustat/segments/business-segment-finding-data-prior-1979-and-industry-codes-sic-and-naics-prior-1990/. In our downloaded data, even though observations are present since June 1976, one of the variables (either the identifiable assets or the operating profit) was missing for the most part throughout the pre-1979 period. The 1985 cutoff is based on our observation that alliance data was sparse before that year.

[33] As discussed earlier, the new NAICS classification started in 1997, and the new accounting standard came into effect after 1997.

[34] The Great Recession started from December 2007.

[35] We note that for the same firm, network membership over a longer time window can potentially change to greater extent, given the dynamic nature of alliance relationships, even while its industry remains fixed. This results in greater variation in the network in contrast to industry, relatively speaking, over longer time frames.

TABLE 7 Robustness checks using different time windows

	Consecutive windows				Cumulative windows 1979				Cumulative windows 1997	
Components	**1979–1985**	**1986–1996**	**1997–2007**	**2008–2018**	**1979–1985**	**1979–1996**	**1979–2007**	**1979–2018**	**1997–2007**	**1997–2018**
Business segment	41.94%	30.72%	31.09%	30.03%	41.94%	31.51%	29.41%	21.72%	31.09%	21.05%
Corporate parent	11.05%	12.97%	15.37%	17.30%	11.05%	10.60%	11.48%	8.68%	15.37%	9.36%
Industry	5.65%	3.67%	1.99%	1.72%	5.65%	3.32%	1.79%	1.47%	1.99%	1.53%
Year	1.44%	0.25%	0.14%	0.06%	1.44%	1.30%	0.67%	0.36%	0.14%	0.10%
Residual	28.77%	39.62%	40.44%	46.62%	28.77%	42.09%	45.60%	59.85%	40.44%	60.52%
Network	11.16%	12.77%	10.97%	4.27%	11.16%	11.19%	11.05%	7.93%	10.97%	7.44%

TABLE 8 Robustness checks after removing certain alliance types

	Dropping alliances that *also* include				Dropping alliances that *only* include			
Components	**Licensing (1)**	**Distribution (marketing) (2)**	**Joint ventures (3)**	**Any of these three types (4)**	**Licensing (5)**	**Distribution (marketing) (6)**	**Joint ventures (7)**	**Any of these three types (8)**
Business segment	31.35%	31.32%	31.41%	31.03%	31.50%	31.51%	31.41%	31.44%
Corporate parent	10.33%	10.39%	10.43%	9.96%	10.60%	10.56%	10.48%	10.49%
Industry	3.31%	3.31%	3.32%	3.30%	3.31%	3.32%	3.30%	3.31%
Year	1.32%	1.32%	1.34%	1.36%	1.30%	1.30%	1.31%	1.32%
Residual	42.14%	42.47%	42.69%	43.56%	42.10%	42.11%	41.66%	42.21%
Network	11.55%	11.19%	10.82%	10.78%	11.19%	11.20%	11.85%	11.23%

11 | DISCUSSION

The key purpose of this article is to understand how the variance in business segment profitability is explained by the alliance network in which the firm is embedded. We discussed that including networks as a relevant determinant in examining firm performance variance generates a more comprehensive picture of the sources of firm profitability. Traditional empirical work analyzing the variance components of firm profitability has treated industry, corporate parent, year, and business segment as relevant origins of performance but have mostly viewed firms as atomistic, autonomous entities. However, consistent with seminal theorizing on strategic networks, we find that variance in performance is also attributable in part to their network membership.

We find that the network to which the firms belong explain roughly 11% of the variance in business segment profitability, underscoring a salient complement to conventional empirical models of variance decomposition. Our interaction analyses (Table 6, Model 1) reveal implications for both industrial organization scholars, whose key focus is on industries, and resource-based view scholars, whose main area of interest is firms. More specifically, for scholars focused on the industry, we find that the inclusion of network–industry interaction effects (16.19%) become considerably more influential than the industry effects alone (1.56%). This empirically validates the argumentation in prior literature that the effects of different sources of variance may be interdependent (e.g., McGahan & Porter, 2002), suggesting that the performance benefits of a firm's industry membership are also influenced by its network membership. Additionally, for resource-based view scholars, we find the network–corporate interaction is also relevant (5.94%), but the magnitude is smaller. Overall, this suggests that the variance in business segment profitability may also be contingently determined by the corporate parent and network membership.

A limitation of this study would be the potential biases and data quality issues in the SDC alliance dataset, despite our use of expanded time windows. To the extent that only relationships that are driven by corporate level (or, for that matter, industry, or business segment) decisions dominate the SDC data, the errors may be nonrandom. We believe this is less likely to be the case because as discussed earlier, a main advantage of the SDC database for our empirical context is that it reports alliances across the *widest* range of SIC codes, compared to any other database, i.e., SDC reported at least one alliance across almost all of the four-digit SIC codes (Schilling, 2009). However, questions remain, providing fertile avenues for future research.

Similarly, the COMPUSTAT dataset only accounts for public firms. A fruitful direction for future research would be to reevaluate how the various sources of profitability have changed over time using a more comprehensive and updated dataset containing both public and private firms and their alliances. Future work could reevaluate whether some effects have lost their potency over time and conversely whether others have become more salient. Our analyses using different time windows (Table 7) using the 1979–2018 period suggest that the importance of the industry effects appears to diminish when longer time periods are considered. Conversely, the salience of the corporate parent effect increases, compared to the industry effect, in the case of expanded time periods. The dominance of corporate parent effects over industry is consistent with Vanneste (2017). These findings suggest that the structure of the economy may be evolving to make industry boundaries more porous and fluid, and possibly also that synergies deployable via corporate strategy have become stronger. An example of the latter may be the role of proprietary capabilities in information and communication technologies which might be increasingly utilized by corporations across industries to increase the corporate parent effect and reduce that of the industry. Another possible research direction would be to examine whether the relative importance of different sources of variance change depending on the country context and government (e.g., Furman, 2000).

Our work has implications for managers. Keeping an eye on the external environment for strategy formulation, managers have traditionally paid attention to both the industry or industries in which their firms operate and looked inward within the firm to leverage value from its unique resources. However, an equally important approach would be to keep in mind the value-creating potential of alliance networks in the managerial quest for competitive advantage. Additionally, taken to its extreme, networks may become more relevant in the digital era in which the industry boundaries are blurring (Raskino & Waller, 2016). In fact, in such cases the ecosystem can be understood as complementing firm membership in networks (Adner & Kapoor, 2010; Nohria & Garcia-Pont, 1991).

Furthermore, in this study, while we consider a broad range of alliance network relations including joint ventures, R&D, marketing, and licensing, there may be additional relevant interfirm networks that we leave out, such as board interlocks. Unfortunately, BoardEx data is only available from 1997, and the data before 1999 are sparse (Engelberg, Gao, & Parsons, 2013), thus falling outside the bounds of the time period considered in this article. Future research could include the board network, and potentially other networks such as the financing network as well, to tease out possibly additional network effects in explaining business segment profitability.

In conclusion, we add a new dimension to extant variance decomposition studies by introducing an important determinant of firm performance, namely the network. Studies glossing over the contribution of the firm's alliance network to business segment profitability therefore provide only a partial explanation of the origins of firm performance. By bringing the network perspective into variance decomposition work we provide a more complete picture of the sources of variance in business segment profitability. Networks do matter, both directly and by influencing industry and corporate parent effects on business-segment profitability.

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DATA AVAILABILITY STATEMENT

Data subject to third party restrictions

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