Do Trade Associations Matter to Corporate Strategies?

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Abstract

This paper uses textual analysis and plausibly exogenous instruments based on out-of-industry geographic connections and director networks to assess the role of trade associations in forming corporate strategies. Companies are most likely to join trade associations when innovative opportunities have declined, and they are older and larger. Joining associations then induces members to increase profits and markups, improve risk management, find acquisition partners and improve efficiency. To assess mechanisms regarding higher profits, we consider product pricing strategies and high dimensional analysis of market-exclusivity in how firms expand geographically across U.S. states. Overall, we find strong support for the conclusion that associations bring mutually beneficial gains to their members and their industries, and some evidence of an externality in the form of anti-competitive pricing and market-exclusion strategies.

1 Introduction

We estimate that there are 5,114 trade associations nationwide, and among publicly traded firms, 48.5% belong to such associations. Yet despite their prevalence, almost no research in corporate finance has explored the impact of trade associations on decisions and outcomes such as profitability, investments, risk management, and efficiency, and whether any effects are driven by pro-competitive or anti-competitive mechanisms. This paper provides one of the first systematic explorations of these questions. The void of existing literature on this topic is likely due to the absence of data on associations and memberships, reinforced by the fact that association memberships are endogenous decisions. We address these challenges using large-scale web-scraping and textual analysis techniques to build a rich panel of association memberships for industry-focused associations. We then use plausibly exogenous variation in memberships originating from outside a focal firm's industry through director networks and geographic connections. These instruments significantly shift association memberships in a firm-year panel database with rigid firm fixed effects.

The intended role of industry-focused trade associations is to facilitate positive collaboration among industry rivals. Conceptually, collaboration among competitors is well-studied in the field of industrial organization. Unconstrained collaboration results in collusion, where firm rents reach a theoretical maximum and corporate investments are relatively low (see Gutierrez and Philippon (2017) for example). In contrast, no collaboration equates to non-cooperative markets, where competition significantly reduces rents and can both increase corporate efficiency (see Hart (1983) and Giroud and Mueller (2011)) and increase investment (see Aghion et al. (2005)). A market with trade associations is a middle ground of regulated "partial collaboration", where regulators encourage collaboration that improves efficiency and increases investment, but prohibit (perhaps imperfectly) collaboration that is anti-competitive. Theory predicts that the economic impact of allowing cooperation among rivals (and hence trade associations) is likely to be large. Hence filling the void in the literature on this topic is important. We indeed find results that are highly statistically significant and that have large economic magnitudes.

There is a bright-side and a dark-side to how trade associations can improve corporate profits. On the bright side, trade associations are endorsed by regulators because gains in efficiency can bring higher profits while providing relief to consumers via pass-through effects. Also on the bright side, increased investment can increase corporate profits while also increasing desirable product variety for consumers. The dark side is that the efficacy of the regulator to prevent anti-competitive collaboration might be imperfect, as some prohibited activities might be difficult to detect.[1] This can occur even if trade associations themselves do not sanction such activities, as merely providing meeting venues for competitors to interact can facilitate unsanctioned sideline conversations that induce anti-competitive outcomes. Overall, the efficacy of regulators in this complex setting is an empirical question, and hence we conclude our paper with two tests motivated by hypotheses that separate the predictions of the bright and dark sides. These tests (discussed below) are based on product pricing strategies and the exclusivity of geographic expansion strategies.

Overall, regarding corporate finance variables, we find significantly higher efficiency, increased investment (including R&D, CAPX, and acquisitions), improved risk management, and higher profits, markups, and valuations. The first three outcomes validate the bright-side intended role of associations to improve efficiency and investment noted above. Our risk management findings are novel and suggest that joining trade associations also serves as a not-previously-documented operational hedging strategy.[2] Although most of the corporate finance outcomes favor the bright-side positive role in society played by trade associations, which is our main finding, the evidence of increased profits and markups could be consistent with either the bright-side or with potential anti-competitive activities. Providing some evidence of a dark-side externality, we also find higher product prices and geographic expansion patterns with greater exclusivity when firms are more involved with trade associations.

To implement our study, we draw upon multiple data sources to construct a novel firm-year memberships database of industry-specific trade associations. First, we collect information on the universe of U.S. national trade associations from the "Encyclopedia of Associations: National Organizations" published by Gale. Next, we identify firm-specific association memberships using entity-recognition textual analysis methods based on public company

[1] An example is the 6% commission on residential real estate sales, which was reinforced by relatively complex rules on the multiple listing service (MLS). This highly profitable model proliferated for decades, and was only finally broken up by antitrust litigation in 2024.

[2] Examples of operational hedging strategies include geographic diversification (Allayannis et al. (2001)), matching international revenues with the purchase of production inputs (Hoberg and Moon (2017)), vertical acquisitions to reduce supply chain risk (Garfinkel and Hankins (2011)) and using multiple suppliers to reduce supply chain risk (Tomlin (2006)).

names to identify specific firm mentions on the annual websites of trade associations. This is done dynamically within each year using the Wayback Machine from 1999-2022. Finally, to measure firm characteristics and outcomes, we utilize a variety of data sources including Compustat, CRSP, BoardEx, LexisNexis Corporate Affiliations, NielsenIQ, SDC Platinum and data shared with us or made public by other researchers. The result is a rich firm-association-year panel database that allows us to dynamically track firm memberships in associations on a firm-year level over time.

There are two central challenges with this area of research. First, although there is a central database containing information about associations and their characteristics, companies do not report their association memberships to any central database. As noted above, we address this issue by estimating association memberships using company name mentions in association websites. The second challenge is endogeneity. Central concerns are (A) firms do not choose to join associations at random times, but rather they might join them when they are facing specific types of challenges. (B) Additionally, our inferences might be impacted by unobserved omitted variables. We thus consider two instruments for association memberships rooted in firm networks and homophily that mitigate these concerns.

Our first instrument is based on out-of-sector director networks. For each firm, we identify the set of other firms that are (1) connected to the focal firm through a director link either based on overlapping board seats, employment, education, or social clubs, and (2) not in the same industry sector. The managers of connected firms frequently meet socially and can communicate about their business strategies. These networks are likely stronger among managers running similarly-size companies, as social connections are more likely among peers. Our first instrument is simply the extent to which these linked peer-CEO firms are exposed to trade associations, computed as the weighted-average number of association memberships of these connected firms, attributing more importance to spillovers from size peers. Because they are in entirely different sectors, this time varying instrument likely satisfies the exclusion requirement regarding both forms of endogeneity noted above. As business connections are core to trade associations, we also expect this instrument to satisfy the powerful instrument requirement. Indeed we find highly significant results with F-statistics near 80.0, well above the 10.0 threshold for high power.

Our second instrument is similarly-built but based on homophily in geographic networks.

We again seek to identify corporate connections that are both strong and also exogenous to the given firm's business conditions. For each firm, we identify the set of other firms that are (1) within 100 miles of the focal firm and (2) not in the same industry sector. We strengthen this proximity-based measure of connections using the theory of homophily and thus require firms to be roughly the same size, having market capitalizations within $10X$ larger or smaller than the focal firm. As managers are running similar-sized companies in nearby locations, it is likely that these managers network, for example, at local social events and country clubs. Indeed, this instrument also appears powerful with with F-statistics near 30.0. In a separate validation test using business and social connections from Boardex, we find that managers serving firms within a 10x size band and located within 100 miles are indeed highly connected. Because they are in entirely different sectors, this time varying instrument likely also satisfies the exclusion requirement. Our rigid fixed effects further ensure that geography itself is controlled for, a conclusion further reinforced by highly targeted placebo test.

We begin by documenting which firms are most likely to join associations. We use non-causal tests splitting our sample into firms that are association members and firms that are not. We then compare their characteristics including size, age, profitability, growth options, investments, and efficiency. We find that higher profits, a reduction in R&D, along with older age and larger size are important indicators of which firms join associations.

We next examine the impact of joining associations on investment, performance, risk management, and corporate efficiency. We use two instrumental variables models using the two instruments described above along with firm and year fixed effects. We document four main findings regarding corporate strategies and performance. First, joining associations results in higher profits and higher markups (we use markups from both De Loecker et al. (2020) and Pellegrino (2023)). Second, regarding risk management, joining associations reduces both return volatility and earnings volatility. Third, joining associations results in higher Tobin's Q and increased investment in the form of R&D, capital expenditures and acquisitions. Finally, we find that joining associations leads to improved efficiency in the form of COGS, asset turnover, and total factor productivity. Overall, these results are consistent with associations providing significant benefits to member firms and their industries as intended by their regulatory mandates.

To further assess mechanisms for the higher markups we report, we explore product pricing strategies and geographic expansion patterns for association-treated and untreated firms. Regarding product pricing, we use Nielsen scanner data and find some (but not conclusive) evidence of higher prices when firms join more trade associations.

Regarding geographic expansion strategies, we use state-level sales data from Lexis Nexis to explore if firms tend to enter non-overlapping markets when they expand geographically within the U.S. We explore these expansions at the firm-pair level, and consider a high dimensional database of firm-pair-state-year geographic entry decisions. The dark-side thesis predicts that competitor-pairs with plausibly exogenous exposure to associations will enter geographic markets alone but not together (i.e., consistent with anti-competitive exclusionary conduct). For example, firms meeting on the sidelines might exchange quid pro quos where one firm will only enter New York, but the other will only enter Florida, thus creating more profitable less contested markets for both. This test is a "separating test" because the bright-side hypothesis would predict the opposite. For example, trade associations provide education and might present information highlighting opportunities in certain regions during meetings. The consequence is that rivals, both observing the same presentation, would be more likely enter regions together with the same timing, which is indeed diametric-opposite the dark-side predictions.

We use our above-mentioned instruments defined at the firm-pair level to test whether firms with joint high-exposure to associations expand with abnormally high exclusivity. Controlling for endogeneity is important here as there are many economic reasons why firms might expand in unique ways such as first-mover advantages. Our instruments ensure that any differences in expansion patterns are likely caused by trade association proceedings rather than such state variables. We find strong and robust evidence that, when firms are jointly exposed to associations, they expand across states in abnormally exclusive ways.

Our geographic results are consistent with a negative externality in the form of exclusive expansion patterns. We next consider theoretically-motivated cross-sectional tests. Consistent with anti-competitive conduct being more likely when it can be easily maintained, these results are strongest for (1) larger firms, (2) firms facing fewer rivals, and (3) for firms in more concentrated markets. In contrast, our evidence favors bright-side influences for smaller firms and when competition is high, as these firms have strong incentives to pursue efficiency gains. Importantly, our use of instruments indicates that these results are likely due to interactions specifically induced by trade association meetings.

Our study has some limitations. We note that our evidence of exclusionary entry strategies is suggestive, and do not indicate that associations intentionally promote anti-competitive conduct. Unsanctioned sideline conversations among members is more likely as a mechanism given regulatory oversight of association proceedings. We thus believe future research examining meeting proceedings in detail is likely to be fruitful. Moreover, and reinforcing our conclusions regarding a significant bright-side of associations, our findings of improved corporate efficiency, risk management, and investment noted earlier illustrate success in achieving many beneficial stated goals of associations. Although we do not make claims regarding social welfare, which can be complex given that welfare is a function of prices, product variety, and the allocation of goods, we note that gains in efficiency and risk management are typically viewed as welfare enhancing. Such gains should result in both higher profits for firms and also lower prices or higher product quality for consumers.

Our paper makes four contributions to the existing literature. First, we propose novel testable hypotheses regarding conduct, financial risk management and efficiency gains through the lens of collaboration. Second, we make methodological contributions relating to trade association data and the use of exogenous variation in geographic networks at a firm-year level and a firm-pair-year level. Third, we find strong evidence of higher profits and markups as well as novel evidence of improved risk management strategies, acquisitions, and efficiency gains. Finally, we conduct tests of product prices and exclusive geographic expansion strategies that provide novel evidence of potential anti-competitive market strategies.

2 Overview and Related Literature

2.1 Related Literature

The earliest mentions of trade associations in the economics literature date back a full century. For example, Sharfman (1926) outlines the general significance of trade associations, describing them as formal organizations that are, in contrast to cartels, designed to function openly. The associations utilize and improve on the combined industry experience of their members, develop operational standards and practices, and promote operational stability by reducing costs, stimulating demand, managing risks, and providing regulatory protection.

Theoretical models show that information sharing among members can increase consumer welfare (Kirby (1988)), and increase the total surplus under Cournot competition (Vives (1990)). As an example of gains through sharing resources, Bombardini and Trebbi (2012) show that associations lobby regulators as shared representatives of the industry, especially in sectors with higher competition and lower product differentiation.

While the functioning of trade associations does not necessarily lead to illegal cooperation among members, a concern among regulators is that associations can facilitate price agreements and other forms of collusive strategies that reduce competition. Such actions would potentially violate the Sherman Anti-Trust Act (Oliphant (1926)). Yet the empirical literature on collusion within associations is sparse and restricted to industry-specific case studies. For example, cooperation on prices in trade associations is studied in the British coil rope industry (Howe (1973)), Chilean physicians industry (Ale-Chilet and Atal (2020)), U.S. brewing industry (McGahan (1995)), sugar industry (Sugaya and Wolitzky (2018)), and automobile industry (Bertomeu et al. (2021)).

A larger theoretical literature focuses on firm collusion within industries and notes that trade associations could play a facilitating role. This literature studies cartels, and uses trade associations as examples of coordination mechanisms that might sustain the cartels. In a classic study, Stigler (1964) provides a theory of collusion and self-enforcement of cartels, and later Green and Porter (1984) refine the self-enforcement framework. Also in the theoretical studies of Rahman (2014), Sugaya and Wolitzky (2018), and Awaya and Krishna (2020), various degrees of informational exchange and monitoring among members can happen via trade associations, facilitating collusion. Additionally, there is a growing literature on cartels in the international setting (Loderer (1985), Roller and Steen (2006), Harrington and Skrzypacz (2011), Bourveau et al. (2020), Igami and Sugaya (2022)), and on tacit firm coordination (Bernheim and Whinston (1985), Dutta and Madhavan (1997), Dasgupta and Zaldokas (2019), Ferres et al. (2021), and Lehar et al. (2020)). These studies do not require that firms coordinate within trade associations, but they broadly demonstrate theoretical relationships between industry coordination and firm outcomes. We are not aware of existing studies that draw upon plausibly exogenous variation in memberships to comprehensively examine the impact of trade associations on a wide-array of outcomes ranging from profitability, risk management, investment, operating efficiency, and potential anti-competitive exclusionary practices in this important setting.

We also note that collusion in trade associations does not have to be on prices (Marshall and Marx (2014)). In the example of the Sugar Institute, Genesove and Mullin (2001) describe "collusion by rules" as member firms coordinate on business by establishing complex contractual production and distribution restrictions. At the same time, the association members did not openly collude on prices. In a separate theoretical framework, Sugaya and Wolitzky (2018) focus on cartels dividing market shares among the members. In their model, a market-segmentation strategy is possible with the assistance of an intermediary, e.g. in our context, a trade association. In particular, this is possible if members can maintain some secrecy regarding their pricing and sales, which facilitates the design of profitable strategies when entering different markets.

Porter (2005) provides a detailed review on detecting collusion, and highlights an example. New York trash haulers used an association to divide the city geographically, allowing haulers to operate uncontested in their local regions. The association enforced this collusion by punishing violations with arson, violence, forced payments, or exorbitant dues. Although more explicit forms of collusion are consistent with our thesis, we also note that associations can facilitate collusion unintentionally just by holding regular meetings, thus allowing rivals an opportunity to "meet on the side" to discuss mutually beneficial and potentially anti-competitive quid pro quos. In these cases, it is the provision of fully legal ways for competitors to meet that can create an unintended uptick in anti-competitive practices even though this might not be the intent of associations.

2.2 Trade Associations Background

Trade associations are membership organizations comprised of businesses and industry professionals. They can be industry-specific, including members with closely related business activities, as is the case for the American Petroleum Institute. Other associations are more broad and address general business issues, as is the case for the U.S. Chamber of Commerce. In this paper, we focus only on industry-specific associations and limit attention to those that are economically important enough to include publicly listed companies as their members. We identify 3,711 such associations operating from 1999 to 2022.

Most trade associations have a long history and were formed in the late 19th century or in the 20th century. For example, the American Chemistry Council was formed in 1872 and the National Roofing Contractors Association in 1886. The average (median) founding year in our sample is 1967 (1975). 500 out of 3,711 associations in our sample were formed since 1999, the start of our sample. We exclude these since-1999 associations and associations with missing founding years from our analysis to ensure that the set of associations a company could join in our tests is not endogenously influenced by the formation of new associations.

Trade associations operate using a budget that is funded based on membership dues, sponsor donations, and other revenues.[3] Membership dues are usually modest for publicly listed companies, but vary from several thousand to several hundred thousand dollars. The average (median) budget of an association in our data is $4.3 million ($1.1 million), and the budgets are reported for 54.0% of the association-years. Associations with large annual budgets above $100 million include the American Rental Association, American Chemistry Council, and Vinegar Institute.

Trade associations use their budgets to pay for developing and establishing industry standards, providing public advocacy and political representation, providing education, and coordinating activities across their members. For example, in 2005, the Magazine Publishers of America allocated $40 million to a campaign to "promote the benefits of consumer magazines as an advertising medium".[4] An important aspect of coordinating activities among members includes organizing and hosting meetings, conferences, conventions, and educational events. In our sample, 62.2% of associations reported either a"Yes/No" for holding at least one meeting, conference or convention in a given year, with 99.4% of them reporting "Yes" (the remaining 37.8% associations did not report whether or not they have meetings). The high rate of associations hosting frequent events is important in motivating our thesis rooted in sideline meetings among competitors, and our resulting empirical framework especially regarding potential anti-competitive externalities. Association locations are widely-distributed across the U.S. For example, the District of Columbia, Virginia, Illinois, California, New York, Texas, Maryland, Florida, and Ohio each have at least 50 associations.

[3]Matheis M., and Gibbs, B. (2022) Keeping the Right Company When It Comes To Associations. *Oliver Wyman, Insights.* `https://www.oliverwyman.com/our-expertise/insights/2022/apr/keeping-the-right-company-when-it-comes-to-associations.html`.

[4]Elliott S., (2006, January 11) Advertising: Addenda; 2 Trade Associations To Change Agencies, *New York Times.*

Trade associations cover a wide array of industries including all of the Fama-French-12 industries. On average over time, the industries with the highest number of member companies are Business Equipment, Finance, Miscellaneous Category, and Manufacturing. Those with the most combined member total assets are Finance, Business Equipment, Miscellaneous, and Telecommunication. Industry-focused associations typically represent companies operating within a specific industry, a group of related industries, or a particular industry segment. On average, 76.5% of the assets of members of an association in a given year come from a single Fama-French 12 industry, which is in line with our sample of associations indeed being industry-focused.

2.3 Trade Associations and Antitrust Regulation

Both U.S. antitrust regulators, the U.S. Federal Trade Commission (FTC) and the U.S. Department of Justice (DOJ), are aware of the potential for anti-competitive practices in trade associations. Outlining their policies in detail, both agencies drafted a 27-page document providing guidelines on how trade associations can facilitate collaborations among competitors without violating antitrust rules (FTC and DOJ (2000)). Both agencies also indicate related and more abbreviated information on their websites.[5] The guiding principal is that both agencies acknowledge that there exist many activities that competitors can collaborate on that are both mutually beneficial and also pro-competitive. The guidance states:

> *For example, a competitor collaboration may enable participants to offer goods or services that are cheaper, more valuable to consumers, or brought to market faster than would be possible absent the collaboration. A collaboration may allow its participants to better use existing assets, or may provide incentives for them to make output-enhancing investments that would not occur absent the collaboration. The potential efficiencies from competitor collaborations may be achieved through a variety of contractual arrangements including joint ventures, trade or professional associations, licensing arrangements, or strategic alliances.*

[5] U.S. Federal Trade Commission. (n.d.) *Spotlight on Trade Associations* Retrieved April 19, 2022, from `https://www.ftc.gov/advice-guidance/competition-guidance/guide-antitrust-laws/dealings-competitors/spotlight-trade-associations`; U.S. Department of Justice. (n.d.) *Participating in Information Sharing and Trade Associations*, Retrieved April 19, 2022, from `https://www.justice.gov/atr/antitrust-issues-and-your-small-business/participating-information-sharing-and-trade-associations`.

A common theme is that collaborations that enhance efficiency are seen as pro-competitive. These activities can in fact improve consumer welfare, improve product distribution, and ultimately lower product prices. Our thesis includes the prediction that trade associations will generate gains that are pro-competitive and efficiency-improving.

On the other hand, the guidance also specifically references the issue of exclusionary conduct as a risk factor for anti-competitive practices. The document states:

> *In assessing exclusivity when an agreement already is in operation, the Agencies examine whether, to what extent, and in what manner participants actually have continued to compete against each other.*

The DOJ also expresses concern specifically about anti-competitive exclusionary entry into geographical market segments:[6]

> *Section 2 of the Sherman Act makes it unlawful for any person to "monopolize, or attempt to monopolize, or combine or conspire with any other person or persons, to monopolize any part of the trade or commerce among the several states, or with foreign nations."*

Hence our thesis also focuses on the possibility of anti-competitive conduct, and our tests of mechanisms thus look beyond markups alone as we also assess potentially exclusionary strategies relating to how firms expand geographically. In the cases we examine, exclusionary practices would manifest as quid pro quo strategies where rivals mutually agree not to enter one anothers' markets, allowing each to operate in specific market segments uncontested.

3 Data and Methods

3.1 Data

We obtain the universe of U.S. national trade associations from Gale "Encyclopedia of Associations: National Organizations", a series of eBooks listing national organizations from 2004 to 2022. We focus on national organizations due to their economic relevance for the public firms in our sample. The data contains the complete set of association names along with association characteristics including founding years, budgets, locations, industry classi-

[6]U.S. Department of Justice Archives. (2009, May 11) *Competition and Monopoly: Single-Firm Conduct Under Section 2 of the Sherman Act: Chapter 1.*

fications, etc. It is organized in the form of an association-year panel, and, to our knowledge, it is the first and most comprehensive database on national organizations. It includes 36,164 organizations, which we track over time using the unique internal association Gale ID and association names contained in the encyclopedia.

Our study focuses on associations that include firms as members and cater to one or more specific sectors, as our goal is to test hypotheses related to industries, their organization and performance. Thus, from all the entities available in the encyclopedia, we select *Business Associations* in SIC code 8611 or NAICS code 813910. To select industry-focused business associations, we explicitly exclude broad universal-industry associations in the *Chambers of Commerce* encyclopedia section, and we exclude sections containing organizations focused on non-business issues. Appendix A.1 describes all the steps in detail. We estimate that there are 5,114 national trade associations of businesses, 4,162 of which have listed URLs and founding years used in our analysis.

Our goal is to assess membership of U.S. publicly listed firms in industry-focused associations. We use associations' URLs from the encyclopedia and web-scrape their corresponding websites from the Wayback Machine, which contains historical snapshots of websites from the internet archive. We obtain annual snapshots for each available association-year starting 1999 and ending 2022. Our starting year is 1999 as website snapshots are sparse prior to this year. For each identified association name match, we link the firm-year to the association database using the available encyclopedia editions, giving preference to earlier years.

Our approach assumes that companies mentioned on an association's website are members of that association. Thus, we perform a large number of string searches for historical names of publicly listed companies in the associations' websites. The average (median) number of members in an association in a given year is 9 (4). While some associations include only few publicly listed members, others have over 30. We verify that associations with low publicly listed member counts likely also contain private members, by searching the associations' websites for company abbreviations such as "Inc", "Co", "LLC", etc. Overall, 3,711 associations list publicly listed companies as their members, and we retain 3,211 of them formed prior 1999 to mitigate endogenous effects due to the formation of new associations.

We focus on the member firms with economically meaningful above $1 million total assets and sales. Table 1, Panel A shows that on average 48.5% of such firms are mentioned on the association websites in a given year. They amount to 8,624 in total over time. On average a firm belongs to 2.72 associations, with a maximum of 63 associations. We note that our approach may underestimate the true level of association memberships, as associations are not obliged to disclose their members. Yet we find that 93.87% associations do disclose, and they do so in 73.5% of sample years. Although this coverage rate is high, we also note that our use of instrumental variables ensures that our inferences are not due to any strategic reporting incentives.

We use an array of data sources to measure firm policies and build our instruments. We use firm financial information, historical locations of firm headquarters from Compustat, and stock return data from Center for Research in Security Prices (CRSP).[7] We measure corporate director connections using information from BoardEx. We obtain data from LexisNexis Corporate Affiliations to identify geographic state-by-state sales of each firm's subsidiaries and other affiliates; we obtain companies' product prices from NielsenIQ; and we obtain data on M&A transactions from SDC Platinum. Additionally, we use data shared with us or made public by other researchers including Hoberg and Phillips (2010, 2016), İmrohoroğlu and Tüzel (2014), Kogan et al. (2017), De Loecker et al. (2020), Frésard et al. (2020), and Pellegrino (2023).

3.2 Sample Splits by Association Memberships

Summary statistics in Table 1, Panel B demonstrate that the association memberships we construct have novel correlations with firm characteristics and outcomes, by splitting our firm-year panel database into subsamples with above and below median association memberships. The table shows that association members tend to be larger and older firms, and they exhibit significant differences across many different economic outcomes such as profitability, markups, risk, investments, and efficiency. The results suggest that larger and older firms with relatively weaker performance tend to be members of associations.

Yet these results reflect simple correlations, and we note that the observed differences in

[7] Historical location of firms' headquarters is available in Compustat Header History from 2007 onwards. We use the closest and earliest available headquarter ZIP-codes. When historical ZIP-codes are not available, we use the header ones.

characteristics might reflect endogeneity in firm decisions to join associations. For example, association membership could appeal to firms experiencing a decline in sales growth or investment opportunities, especially when such issues might be amenable to improvements via industry coordination. Indeed, a stated goal of associations is to improve efficiency or stimulate output-enhancing investments. Additionally, these differences could be driven by omitted variables. We thus formally study the effects of association membership on firm economic outcomes using an instrumental variables approach discussed below.

3.3 Motivation of Network-Based Instruments

Our network-based instruments are rooted in the foundation of homophily in networks, the tendency of social ties to form among entities with similar characteristics. The instruments exploit spillovers of tendencies to join associations that propagate through social networks of similarly-sized firms operating in different industries, ensuring no exposure to own-industry state variables as needed for identification. We consider spillovers in two settings where social ties and resulting spillovers between firms are likely: (1) when firms have director connections via overlapping boards, other employment, educational links, or memberships in social clubs; (2) when firms are located in close geographic proximity. Intuitively, board members of similar sized firms can network and engage in association knowledge spillovers.

Network and communication-based instruments are well-motivated in this settings because associations themselves are ultimately the means of communication and networking. Hence, networking instruments are likely to be powerful. Homophily enhances power because executives and board members of similarly sized firms are likely to network in common social settings, and they especially likely to do so within the same cities. For example, a focal firm CEO can learn about the strategic benefits of associations over lunch with a nearby local CEO running a similar-sized firm that is from an unrelated industry at a local country club. Because we only consider firms that are in entirely different industries, the instruments cannot be influenced by industry-specific or firm-specific economic state variables that might be relevant to why a given firm might endogenously choose to join associations.

Our two instruments are rooted in director connections and close geographical proximity, which are both settings where firms are likely to network intensively, especially in the presence of size-homophily between firms. We further motivate the relatedness of the two settings, and the relevance of size, by showing that director connections are more likely between firms located in close geographic proximity and between similarly-sized firms. To do so, we use a pairwise networking examination that estimates the following regression equation:

$$\mathrm{C}_{ijt} = \beta_1 \mathrm{D}[0;100]_{ijt} + \beta_2 \mathrm{D}(100;500]_{ijt} + \gamma_1 \mathrm{SizeX}[1;10]_{ijt} + \gamma_2 \mathrm{SizeX}(10;50]_{ijt} + \alpha_{jt} + \theta_t + \varepsilon_{ijt} \quad (1)$$

where C_{ijt} is an indicator for a director connection between firms i and j in year t. D is an indicator for distances between firm-pairs in miles, and $SizeX$ is an indicator for the pairwise size-difference bands. We estimate this equation using a firm-pair-year panel, where both firms in a pair are present in the BoardEx database. Consistent with our network-based instruments, and to ensure no contamination from omitted variables, we exclude all firm-pairs in the same TNIC-2 industries (see Hoberg and Phillips (2010, 2016)) from this calculation, where the TNIC-2 industries are as granular as 2-digit SIC industry groups.[8]

To examine homophily and social networking tests using the above model, we define our dependent variable to be director connections C_{ijt} that are formed via any of the following cases: overlapping boards, other employment current and past links, educational links, and director memberships in social clubs. This approach is consistent with Cohen et al. (2008), Fracassi and Tate (2012), Engelberg et al. (2012), Engelberg et al. (2013), and Schmidt (2015). When building these connections, we include all directors belonging to both executive and supervisory boards.[9] Overlapping boards are cases where two firms share a common director. Other employment links are determined by two distinct directors jointly employed by the same firm in current or prior years. Educational links indicate directors that graduate from the same institution within one year from the same degree program, i.e., (1) undergraduate, (2) master, (3) MBA, (4) PhD, (5) law, (6) medicine, (7) other.

Our first RHS variable of interest is geographic proximity, which we define as being within close geographic proximity at 100 miles following Coval and Moskowitz (2001), Engelberg et al. (2012), and Engelberg et al. (2013). To determine the distance between two firms, we convert ZIP codes of each firm's historical headquarter location into longitude and latitude coordinates, and compute geodesic distance between the resulting coordinates. Our use of

[8]In a later robustness Section 4.7, we additionally exclude vertically related peers based on Frésard et al. (2020) with 10% network granularity. Our results are fully robust.

[9]In BoardEx, such directors are defined by the *Board Position* flag set to "Yes"/"Inside"/"Outside".

historical headquarter locations allows us absorb time-invariant characteristics of a firm-pair and include tight pair fixed effects (α_{jt}) in our regressions. We also use an indicator for a wider geographic radius of (100;500] miles. Intuitively, we expect director employment and social connections to decay with distance and we thus predict $\beta_1 > \beta_2$.

Our second RHS variable is size-homophily. We expect social connections to be more likely among similarly-size firms, as the existing literature motivates stronger social ties among peers sharing similar characteristics (McPherson et al. (2001), Currarini et al. (2009), Pool et al. (2015), Hirshleifer (2020)). We define the size difference between two firms as $SizeX = max\{Size1/Size2, Size2/Size1\}$, where $Size$ is each firm's market equity computed following Fama and French (2001). We set the high "homophily" area to be the zone $[1; 10]$, and expect the director connections to decay with the size and hence $\gamma_1 > \gamma_2$.[10]

Table 2 presents the results for equation (1). The dependent variable in column (1) is an indicator for any of the director connections noted above. Column (2) uses an indicator for connections through overlapping boards only; column (3) uses an indicator for any other connections, setting to zero observations for firm pairs connected via overlapping boards; and column (4) uses an indicator for social connections only, setting to zero observations for any other connections. Across all specifications, the director connections decay with distance and size differences: The estimated coefficient for $D[0; 100]$ is more than twice as large as the coefficient for $D(100; 500]$. Also, the estimated coefficient on $SizeX[1; 10]$ is about 30% larger than that for the outer band $SizeX(10; 50]$. The differences in estimated coefficients are highly statistically significant with F-statistics above 49.

This evidence indicates that close geographic proximity and size homophily are strong indicators of both actual social and professional interactions. This strongly motivates the construction of our instruments as both director connections and close geographic proximity represent settings with stronger social ties among similarly-sized firms. Thus, the transmission of knowledge about the benefits of association memberships is more likely to be shared among these peers. As we only examine knowledge spillovers from firms in different industries, these instruments are likely exogenous to confounders in the focal industry.

[10]Our results are robust to alternative geographic proximity and size thresholds.

3.4 Construction of Instruments

Our two network-based instruments correspond to two different but related settings where similarly-sized firms likely exhibit stronger social ties and thus association spillovers. Both are based on plausibly exogenous connections from unrelated industries.

To construct the first connection-based instrument for each firm i in a given year, we find all other firms $p \in P$ sharing at least one director connection with i, based on all the connection types described in the previous section. We require that i and p are not in the same industry as the focal firm (broadly defined), and thus exclude all firm pairs in the same TNIC-2 industry. For each firm i in a given year, we find the weighted-average number of distinct association memberships of its peers ($p \in P$). Building on the homophily theory, we assign weights that are inversely proportional to the size difference between i and p thus attributing more importance to similar firm. Our instrument has the following form: $\textit{Board connections instrument}_i = \sum_p^P w_{p,i} \times \#\textit{memberships}_p$.

To construct the second geography-based instrument, $\textit{Geographic diffusion instrument}_i$, we require firms i and p to be located within 100 miles. Since geographic distance is an indirect measure of firm connections, we further strenthen it by imposing the size homophily condition, requiring i and p to be within ten times of each other by market capitalization ($SizeX[1;10]$). All other steps are the same as for the board-connections instrument described above. Most notably, as above, we continue to exclude peers that are in the same broad TNIC-2 industry. Panel C of Table 1 summarizes both instruments.

3.5 Regression Specification

In the sections that follow, we estimate standard two-stage IV regression models using our firm-year panel database. The first stage regresses a firm's actual number of distinct association memberships on one of our aforementioned network-based instruments (we will display separate panels for each instrument). The second stage then regresses firm outcomes on the fitted membership values from the first stage. Our two-stage model takes the following form:

$$\mathbf{1^{st}\ Stage:}\ \#\ \text{memberships}_{i,t-1} = \gamma \text{Instrument}_{i,t-1} + \delta X_{i,t-1} + \alpha_i + \theta_t + \eta_{i,t} \tag{2}$$

$$\mathbf{2^{nd}\ Stage:}\ Q_{i,t} = \beta \widehat{\#\ \text{memberships}}_{i,t-1} + \eta X_{i,t-1} + \alpha_i + \theta_t + \varepsilon_{i,t}, \tag{3}$$

where $Instrument_{i,t}$ is either the firms' *Board connections instrument* or its *Geographic diffusion instrument*. The dependent variable $Q_{i,t}$ is a firm-year economic outcome variable, and $X_{i,t-1}$ is a set of controls including firm size and age. We saturate the regressions with year and firm fixed effects and cluster standard errors by firm.

4 Economic Outcomes

In this section, we test our central hypothesis that associations generate gains for their members along a number of important dimensions. In particular, we examine gains in the form of accounting performance, improved risk management, investment opportunities, and corporate efficiency. Because the link between associations and outcomes is endogenous, as previously noted, we use two-stage instrumental variables models to examine these outcomes. Our first instrument is based on observed board connections to out-of-industry peers based on board overlap, employment, or reported social connections. We refer to this instrument as the "board connections instrument". The second is based on local geographic out-of-industry peers and the intensity of association memberships of likely-connected peers. For parsimony, we refer to this instrument as the "geographic diffusion instrument". Both instruments are based only on information from connections in unrelated industries, and more broadly, both address the general concerns of omitted variable bias and reverse causality. We also include rigid firm and year fixed effects throughout.

4.1 Economic Performance

We first examine ex-post outcomes in the form of profitability measured as return on assets, profit margin, sales growth, and markups. The return on assets (ROA) is computed as operating profits scaled by lag of total assets; profit margin is computed as gross profits scaled by sales; sales growth is computed as a log-difference in sales between years $t-1$ and $t+1$; and the markup measures are borrowed from De Loecker et al. (2020) and Pellegrino (2023). All of our two-stage regressions also include controls for firm size, firm age, as well as firm and year fixed effects. Standard errors are clustered by firm.

The results are reported in Table 3. We present results for the board connections instrument in Panel A. The first column displays the results for the first stage of the two-stage model based on equation (2), and illustrates that this instrument is a highly significant predictor of association memberships with a t-statistic above 9.0, indicating the instrument is powerful. Columns (2) to (6) display the second-stage results based on equation (3) for each of the above-mentioned dependent variables. We note that the F-statistic in these models ranges from 69 to 90, well above the threshold of 10.0 used in the literature to indicate powerful instruments. The table shows that instrumented association memberships are a highly significant predictor of profits in the form of ROA and profit margins as well as both measures of markups, with results being significant at the 1% level. These results illustrate that associations likely help their members to increase profits and markups consistent with providing a strong value-proposition for their members. This finding is intuitive and consistent with the significant proliferation of associations in the United States.

We present results for the geographic diffusion instrument in Panel B. The first stage results indicate that the geographic-network implied opportunity set size is a significant predictor of disclosed associations with a t-statistic of nearly 6.0. The table also illustrates that the instrument achieves a F-statistics ranging from 24 to 34, consistent with this second instrument also being powerful. Rows (2) to (6) echo the results in Panel A and document that associations appear to help their members to generate significant economic gains across a wide-ranging set of measures. All five measures are significant at the 1% level.

In the tables and analyses that follow, we further examine the mechanisms through which these gains materialize. The evidence will support the view that gains are likely beneficial not only to members, but also to the industries associations serve more broadly, and in many cases, benefits might accrue to consumers. Yet we will also document some evidence of a potential negative externality in the form of potentially anti-competitive market exclusion strategies later in this paper. We note this evidence here to highlight that the higher markups we report, in particular, are likely the result of two treatment effects from associations, including both mutually beneficial efficiency gains and risk management in addition to some potential rent-seeking externalities that might benefit members at the expense of consumers.

4.2 Evidence of Risk Management

It is natural to expect that associations can help their members to mitigate risk, an outcome that can improve conditions for members, broader industry participants, and consumers alike. We examine ex-post risk-management outcomes in the form of earnings volatility, stock return volatility, and mentions of the word *risk* in the 10K reports. Earnings volatility is computed as standard deviation of quarterly earnings per share over 12 quarters following Hoberg and Prabhala (2009) (we require at least 6 quarters of available data); stock return volatility is computed as the standard deviation of daily stock returns for each firm-year; the number of 10-K mentions of any of the words {risk, uncertain*, unpredictab*, instability, volatil*} is the number of 10-K paragraphs that mention risk scaled by the total number of 10K paragraphs. We use the same two-stage IV framework as in the prior subsection.

The results are reported in Table 4. As before, we present results for the board connections instrument in Panel A and we again note that our instruments satisfy the powerful instrument requirements. Columns (1) to (3) show that instrumented association memberships are a highly significant predictor of risk mitigation in form of lower earnings and stock return volatility, with the estimated coefficients significant at the 1% level. The risk mentions also have a negative estimated coefficient, but it is not statistically significant. These results illustrate that associations help their members to reduce risk.

We present results for the geographic diffusion instrument in Panel B. Rows (1) to (3) echo the results in Panel A and reinforce our conclusion that associations help their members to generate significant risk reductions across a wide-ranging set of measures. Overall the results in this section are consistent with associations providing significant gains in the form of risk-management for their members. As economic agents tend to be risk averse, these risk mitigation gains likely benefit not only members, but also broader industry participants.

4.3 Evidence on Investments

We also hypothesize that associations might help their members to improve their growth opportunities and thus increase investments including capital expenditures, acquisitions, R&D, patenting, and Tobin's Q. For patenting, we use firm's total number of patents filed in a given year based on data from Kogan et al. (2017). We scale CAPX, R&D, and the number of filed patents by lagged total assets. We compute Tobin's Q as firm's market-to-book value of assets, and use an indicator variable for the focal firm being an acquirer in an M&A transaction. We again use the same two-stage IV framework.

Results are reported in Table 5, and we present results for the board connections instrument in Panel A. We again note that our instruments satisfy the powerful instrument requirement. Columns (1) to (5) show that instrumented association memberships predict increases in acquisitions and in innovation including R&D and patenting. The increase in acquisitions is consistent with a positive networking benefit for association members, who form more relationships with lower search costs, resulting in more acquisitions. The increase in innovation indicates that associations likely share novel growth opportunities and technology applications as part of their mandate. Further consistent with a positive effect on growth opportunities and expansion, we also find positive results for Tobins' Q and CAPX.

We present results for the geographic diffusion instrument in Panel B. Rows (1) to (5) echo the results in Panel A for all investment variables, reinforcing our conclusion that associations help their members to identify improved investment opportunities. We abstain from concluding any firm welfare implications given the complex theoretical relationship between investments (such as acquisitions) and consumers. Yet gains in innovation might lead to new products, which can broadly improve welfare.

4.4 Evidence on Efficiency

As noted in Section 2, trade associations often list efficiency gains among their stated goals. Such gains can be important as regulators specifically highlight these gains as pro-competitive, and likely beneficial to firms and consumers alike. In this section, we examine ex-post efficiency outcomes in the form of COGS/sales, Sales/Assets (Asset turnover), and total factor productivity (TFP) as measured by İmrohoroğlu and Tüzel (2014). We use the same framework including two-stage IV models and fixed effects as above.

The results are reported in Table 6. As before, we present results for the board connections instrument in Panel A and we again note that our instruments satisfy the powerful instrument requirements. Columns (1) to (3) show that instrumented association memberships are a highly significant predictor of efficiency gains in the form of lower COGS, higher asset turnover, and higher TFP. All results are significant at the 1% level. These results illustrate that associations likely help their members to cut costs and improve efficiency, supportive of the positive role of associations envisioned by regulators.

We present results for the geographic diffusion instrument in Panel B. Rows (1) to (3) echo the results in Panel A, with results significant at the 1% level. These findings reinforce our conclusion that associations help their members to improve efficiency. Because such gains are often passed onto other firms and consumers at least in part, these gains are consistent with benefits for many industry participants.

4.5 Placebo Test: Geographic or Network Effects?

To further assess the validity of the exclusion requirement regarding our geographic diffusion instrument, we consider a placebo test that assesses whether alternative explanations based on time-varying geographic effects such as agglomeration effects might explain our results. As noted in Section 3.4, this instrument is based on exposure to associations from other local firms that specifically are of similar size, i.e., within a $10X$ size band around the focal firm's market capitalization. Our placebo test is based on the fact that relaxing the homophily condition should result in weak social ties and thus weak results. However, relaxing this condition should not change the measure's exposure to potential time varying agglomeration effects or other purely geographic effects. Hence, this placebo holds fixed geographic radius, and it only relaxes the size homophily of the peers.

To implement this test, we reconstruct our geographic diffusion instrument exactly as described in Section 3.4 with one exception: instead of selecting size-based homophily peers within the $10X$ size band relative to the focal firm, we include firms *outside* the $10X$ size band. All other steps including the selection of out-of-industry peers located within 100 miles from the focal firm remain unchanged. We then rerun the IV models in Tables 3 to 6 using this alternative placebo instrument based on the *outer* size band. It is important to note that because the inner and outer size bands are both located in the same geographic areas, that if our results were driven by time varying agglomeration effects, then the placebo would generate similar results as our baseline results in Panel B of Tables 3 to 6.

Table 7 presents the placebo test results. The first stage estimates in Panel A show that the placebo instrument based on the outer size band has the opposite sign from our baseline. Panel B reports the second stage results, which show weak F-statistics between 2.0 and 8.0, well below levels needed to satisfy the strong instrument condition. Panel B also reports the key instrumented coefficients and their t-statistics in columns (1) and (2). These second-stage coefficients are uniformly insignificant or weakly significant with the estimated coefficients having the opposite signs from the baseline. We also note that the number of observations in these regressions is similar to those in Tables 3 to 6, indicating that the non-results for the placebo are not a result of low power or less data.

To further rule out time-varying effects associated with specific geographies, we repeat our baseline analysis with the exclusion of granular 5-digit ZIP code $\times$ year fixed effects. Appendix A.2, Table A2.1 repeats the baseline estimates from Tables 3 to 6 for both our instruments, replacing year fixed effects with the ZIP code $\times$ year fixed effects. The estimates are similar to the baseline and are highly statistically significant, albeit slightly weaker given the granularity of the fixed effects. Overall, these results affirm that our geography-based instrument captures the effects of homophily-networking among managers of similar-sized firms, and not alternative geographic effects such as agglomeration.

4.6 Network Reflection Considerations

A common challenge associated with network-based instruments is that network transmission can go both ways through the network and peers might be "reflecting" the focal firm. This is known as the "Manski Reflection Problem" (Manksi (2013)). Our instrument is built on the assumption that focal firm f is learning from its peer firms p. To assess whether reflection effects are driving our results, we follow the network econometrics literature, which shows that tests based on "peers of peers" can establish causality (Bramoullé et al. (2009), Cohen-Cole et al. (2014)) and overcome the reflection problem. Intuitively, f would be learning from p_1 what p_1 learned from p_2. In this setting, f and p_2 would not be connected in the social network or homophily region. We modify our instruments to only draw inferences from these peers of peers, and re-estimate our baseline regressions. Since these modified instruments require indirect information transmission from the peers of peers, we expect the results to be weaker. However, if the information is still valuable and this test has power, the results should agree with the baselines.

We construct the modified version of the board connections-based instrument *Board connections instrument, PoP* in two stages. In the first stage, we construct our instrument for each p_1 computing weighted-average association memberships across p_2 just as in the baseline version of the instrument, while imposing an additional condition that each p_2 does not share a director connection with f, it is not located within 100 miles from f, and they are not within $10X$ size band. Thus the peers-of-peers are not direct peers of the focal firm. In the second stage for focal firm f, we compute the weighted-average of the averaged association memberships that p_1 has learned from its peers.

Panel A of Table 8 presents the results for our baseline IV estimation from Tables 3 to 6, but using the modified version of the instrument. The estimates using this instrument agree with the baselines for all the firm outcomes, yet they have slightly lower statistical significance levels than do the baselines as expected. We also construct the corresponding modified version of our geography-based instrument *Geographic diffusion instrument, PoP*, requiring f and p_2 not to be located within 100 miles, not to be within a $10X$ size band, and not share a director connection. Panel B shows that the estimates using this instrument also agree with the baselines for all the firm outcomes except the stock return volatility, and they also have slightly lower statistical significance levels than do the baselines as expected. We conclude that our results are robust to controlling for the Manski reflection problem.

4.7 Further Robustness Tests

We perform an array of additional robustness tests in Appendix A.2. All the tables repeats the baseline estimates in Tables 3 to 6 with the following modifications. First, in Table A2.2 we include granular 3-digit SIC code × year fixed effects, which absorb time-varying industry characteristics. Second, in Table A2.3 we exclude pairs of vertically related peers based on Frésard et al. (2020) with 10% network granularity in construction of both instruments. We do so in addition to excluding horizontally related broad TNIC-2 industry pairs. This further exclusion of the vertical peers helps ensure that the firm-pairs do not share fundamentals, and the transmission of association memberships occurs via networking. Third, in Table A2.4 we explore versions of the geographic diffusion instrument using alternative size and distance thresholds. In Panel A we build this instrument using size peers in $5X$ band located within 50 miles, and in Panel B we use size peers in $15X$ band located within 150 miles.

Additionally, in Table A2.5 we include the size of the firm network as a control variable. *#conn* is defined as the number of firms a focal firm is connected via overlapping boards, current or past employment, education, or social clubs. Explicitly controlling for the number of connections helps rule out that the association memberships simply proxy for the firm network size. Our findings are robust to inclusion of this control, affirming that the effects we documents are likely related to the associations proceedings.

5 Separating Mechanisms

Our results thus far favor the bright-side as trade associations fulfill their intended pro-efficiency agendas and bring positive effects to the industries they serve. We find likely causal evidence of better risk management, increased investment, improved efficiency, and ultimately higher profits. While the first three strongly favor the bright-side interpretation, the evidence of higher profits and markups could also be consistent with potential anti-competitive practices. In this section, we develop specialized mechanism tests that separate predictions for the bright and dark channels. Our first test examines the impact of trade associations on product prices, as the bright side predicts lower prices due to the pass-through effect, and the dark side predicts higher prices due to enhanced market power. Our second test examines how firms expand geographically. The bright side predicts correlated expansion patterns as association members receive correlated education about opportunities through trade associations. The dark side predicts diametric opposite exclusive entry patterns where members collaborate to enter non-overlapping regions to enhance joint market power.

5.1 Nielsen Price Tests

Assessing the potential impact of trade associations on product prices is perhaps the most stark test of the bright-side and dark-side hypotheses. The bright side predicts that improved efficiency will be passed on to consumers resulting in lower prices. The dark side predicts that prices will rise as firms use trade associations to potentially collude on prices. We again emphasize that anti-competitive actions likely are not sanctioned by the trade associations themselves, but might instead arise as a consequence of providing venues for direct competitors to meet on the sidelines. Trade associations also facilitate the transfer of aggregate industry data, and even if the data transferred is not price data, it can nevertheless be used by recipients to engage in less competitive strategies.

We obtain product pricing data from NielsenIQ and directly test the impact of trade associations on product prices. For each product of a given firm, we obtain supermarket-level weekly prices and the numbers of units sold and link them to each firm's Compustat gvkey.[11] If multiple product units are sold in the same package, the product price is the package price divided by the number of units. We then collapse the data to the firm-product-year level, computing the average product price weighted by the number of units. The resulting panel spans 2006-2021, 332 firms, and averages 1,119 products per firm-year.

Table 9 displays the results. As in our previous sections, we use both the board connections instrument and the geographic diffusion instrument in a two-stage instrumental variables model. Our dependent variable is the natural logarithm of the weighted-average price of each product. We include firm, product, and year fixed effects, and standard errors are clustered by firm consistent with our earlier tests. Since association memberships and our instruments are computed on a firm-year level, we adjust standard errors by inversely weighting observations with the firm's yearly number of products.

Panel A displays the results for the board connections instrument, and we find a highly significant first stage coefficient, and a positive and significant (at the 10% level) second stage coefficient, indicating that trade association memberships result in higher product prices. The F-statistic is 12.30, above the desired threshold of 10.0. Panel B displays results for the geographic diffusion instrument. We again find a highly significant first stage coefficient, but this time find the second stage coefficient is positive but insignificant. The F-statistic is 7.74 indicating lower power for this second instrument.

Our evidence on product prices leans toward the possibility of some anti-competitive effects. Yet we note a number of caveats. First, we only find significant results for one of two instruments, making these results suggestive but not definitive. Second, power is limited in this test because our sample only includes 322 firms over 16 years. Third, the sample is also limited to firms that sell tangible products in retail outlets that are included in the Nielsen sample, and these results might not generalize to all industries. Indeed, we remind readers

[11] We are grateful to Varun Sharma for sharing with us a GVKEY-product correspondence.

that our results illustrating bright-side effects such as improved efficiency, risk mitigation, and increased investment are strong. Hence consumer welfare might improve or deteriorate, as the negative effects of marginally higher product prices in this sample might be offset by the positive effects of reduced supply chain risk, improved product features, lower cost, and improved product quality (which might arise from our finding of increased investment).

5.2 Pairwise Exclusive Entry Tests

A second separating test relates to how firms impacted by trade associations expand into new markets. Under the bright-side hypothesis, trade associations present new opportunities to their members via conference presentations by industry experts or by providing industry reports (Varroney (2022)). Since these activities lead many participants to be exposed to the same new information at the same time, as they act on it, we should observe industry participants expanding into new markets in a positively correlated way under the bright-side hypothesis.

In contrast, the dark-side hypothesis predicts the opposite, and that participants might meet on the sidelines to divide markets, thus creating negatively correlated entry patterns. For example, two competitors might agree to one expanding into New York, and the other into Florida. The consequence would be significantly improved market power for both as discussed earlier. Such exclusionary conduct is illegal, as discussed in Section 2, but firms might face a relatively favorable set of costs and benefits to adopting this strategy due to this conduct being difficult to prove. For example, regulators might find it difficult to uniquely explain why firms expanded in different ways due to the myriad of factors firms consider when expanding in general.

Because coordinating entry is easier when there are fewer competitors a given market, we also postulate (and test) that the dark-side hypothesis is more likely to hold when there are fewer rivals and when markets are more concentrated. We also expect that larger firms are more likely to engage in exclusive conduct as they ex-ante have more market power.

We consider two-stage least squares tests of whether expansion patterns by members of the same associations are positively or negatively correlated. The use of instruments would rule out any impact of economic state variables that might sway expansion patterns such as costs of entry and pre-existing supply chains and distribution networks. Any results would be uniquely attributed to the impact of trade associations on firm conduct. Such treatment effects would be the result of either (A) content presented in trade association meetings or periodicals, or (B) sideline meetings by competitors as trade associations facilitate in-person meetings. We thus propose that these are separating tests of the bright versus dark side hypotheses.

We specifically examine how firms and their rivals expand geographically within the United States. This approach is consistent with our trade associations being national associations, and thus serving U.S. markets broadly. We do so using a high-dimensional sample of observed entry decisions at the firm-pair (dyad) $\times$ state $\times$ year level. We use the resulting dyadic panel to examine the extent to which competitor-pair entry decisions are positively or negatively correlated as oppositely predicted by the two hypotheses.

We take several precautions to ensure likely-causal inferences, and to link our findings specifically to associations. First, we saturate our empirical model with high dimensional fixed effects that rule out channels based on unobserved firm or firm-pair, or even firm-pair-state characteristics. We also include state $\times$ year fixed effects to further control for time-varying local economic state variables. Hence our results will focus only on within-firm-state-pair variation, which rules out influence from many economic alternatives. Most importantly, we also use two-stage instrumental variable regressions based on plausibly exogenous variation in association memberships of the firms in the dyad. We thus identify whether associations uniquely increase exclusivity (anti-competitive) or decrease exclusivity (pro-competitive) as firms expand geographically.

5.2.1 Measuring Pairwise Exclusivity

Let i and j denote two firms in a dyad, s denotes a specific state that competitors i and j might enter, and t denotes the year. For example, we model whether and when i and j decide to enter and sell products in Arizona or Minnesota, and if they do so at roughly the same time. We define our dependent variable $Q_{i,j,s,t} = 1$ if both firms i and j are operating in state s in a given year t. If $Q_{i,j,s,t}$ takes a value of one across many markets, it would indicate positively correlated entry patterns consistent with the bright side. $Q_{i,j,s,t}$ otherwise takes a value of zero, indicating that only one of the two firms is selling products in the given state in year t.[12] This is the case of "exclusive" operations in state s in year t. If $Q_{i,j,s,t}$ takes a value of zero across many markets, it would indicate negatively correlated entry patterns that are consistent with exclusive entry induced by trade associations.

We next define our key independent variable, joint association membership for firms i and j ($\#overlaps_{i,j,t-1}$), as the number of associations in which both firms are members in year $t-1$. We then test our hypotheses using the following the two-stage model:

$$\textbf{1}^{\textbf{st}}\ \textbf{Stage:}\ \#\text{overlaps}_{i,j,t-1} = \gamma \text{Instrument}_{i,j,t-1} + \delta X_{i,j,t-1} + \alpha_{\{(i,j)\times s\}} + \theta_{\{s\times t\}} + \mu_{i,j,s,t} \quad (4)$$

$$\textbf{2}^{\textbf{nd}}\ \textbf{Stage:}\ Q_{i,j,s,t} = \beta \widehat{\#\text{overlaps}}_{i,j,t-1} + \eta X_{i,j,t-1} + \alpha_{\{(i,j)\times s\}} + \theta_{\{s\times t\}} + \varepsilon_{i,j,s,t} \quad (5)$$

$Instrument_{i,j,t-1}$ is the product of firm i's and firm j's board connections or geographic diffusion instrument in year $t-1$ (discussed more below). $X_{i,j,t-1}$ is a vector of controls for size and age of the dyad in year $t-1$, which are also defined as products of each variable for firms i and j. $\alpha_{\{(i,j)\times s\}}$ is a rigid high dimensional fixed effect to control for unobservables at the firm-pair $\times$ state level. $\theta_{\{s\times t\}}$ are state $\times$ time fixed effects. To avoid any influence from markets being correlated within dyads, we cluster standard errors at the firm-pair level. Also, because our firm-pair database is symmetric across i and j, we drop any duplicate pairs $\{j, i\}$ when the pair $\{i, j\}$ is already in the database.

We instrument for $\#overlaps_{i,j,t}$ using our homophily-based board connections and geographic diffusion instruments, as explained earlier in Section 3. We define the pairwise version of our instruments as the product of firm i's instrument and firm j's instrument in year t. A high value of this product would indicate both firms in the dyad are highly exposed to associations, and hence this instrument shifts the likelihood that the two firms would have been jointly "treated" by association proceedings. The anti-competitive hypothesis predicts $\beta < 0$. The pro-efficiency hypothesis predicts $\beta > 0$.

We note limitations of our analysis. First, although we can test for the predicted effects of exclusionary conduct, we do not have contractual evidence of exclusion agreements. Second, we do not have evidence of management's unobservable "intent" when they enter new markets, and association proceedings might induce exclusivity through other aspects of association agendas. Yet we are not aware of specific alternative agendas that would promote

[12] We do not include observations in our database if neither i nor j is operating in the given state s in year t, and hence any given observation has a value of $Q_{i,j,s,t}$ that is either one or zero as defined above.

exclusion, as common treatments of efficiency objectives would promote positively correlated actions. Additionally, our rigid fixed effects and instrumental variables ensure that any results are likely causally linked to association memberships specifically. Notwithstanding the noted mitigating factors, future work exploring these limitations remains fruitful.

5.2.2 Geographic Entry into State-Level Markets

We examine state entry patterns and estimate equations (4) and (5) with $Q_{i,j,s,t}$ defined as unity when firms i and j jointly operate in state s in year t. $Q_{i,j,s,t}$ is otherwise set to zero. We note that because we include firm-pair-state fixed effects, our tests focus on within-firm-pair-state variation and hence focus on entry decisions. To assess state-level operating profiles for each firm, we consider data on firm affiliates (subsidiaries, branches, units, plants, facilities, etc.) by LexisNexis Corporate Affiliations. The dataset lists an affiliate's address, sales, and the level of ownership. It allows us to compute the parent firm's sales in a given state, and tag the firm as operating in a given state with annual sales above $1 million.

To ensure our analysis focuses on relevant pairs, we only include firm-pairs in our sample if they are in the same industry. To explore robustness, we report results for industries defined as TNIC-2, TNIC-3, and TNIC-4 industries from Hoberg and Phillips (2016). These text-based industry classifications are as-granular as four digit, three-digit, and two-digit SIC codes, respectively. The resulting firm-pair × state × year databases are large and contain over 10 million valid observations at the most coarse TNIC-2 granularity, and roughly 1.5 million observations at the finer TNIC-4 granularity.

Table 10 displays the baseline results for specifications using the board connections instrument (Panel A) and the geographic diffusion instrument (Panel B). For parsimony, we display the second stage estimates, for all three industry granularities. The first-stage results are presented in Appendix Table A3.1. We uniformly find that first state results are highly significant as our pairwise instruments strongly predict actual pair-level association memberships with very high levels of significance. Our F-statistics are uniformly well above 10.0, indicating that our instruments are powerful. The second stage results in Panel A for the board connections instrument indicate that expansion patterns are more exclusive when firms are exposed to associations, consistent with the dark-side hypothesis. These results are particularly strong at the TNIC-2 and TNIC-3 granularities where there is more statistical power, but become statistically weaker for the TNIC-4 granularity likely due to the smaller sample size. The results in Panel B for the geographic diffusion instrument are less decisive. The estimated coefficients are significantly negative when we include both firm-pair and state-year fixed effects, but become insignificant when we include the more stringent firm-pair × state fixed effects. We conclude that these unconditional tests lean more toward the dark-side hypothesis than the bright-side hypothesis.

5.2.3 Subsamples and State Entry Patterns

We expect the dark-side hypothesis to be stronger when firms are larger, there are fewer competitors, and markets are more concentrated (higher HHIs), as in all of these settings it is easier for firms to engage in collusive agreements. In this section, we re-examine our pairwise state-by-state expansion patterns in subsamples motivated by these extended hypotheses. For these three hypotheses, we form pairwise subsamples by first sorting firm-years on firm size as measured using market capitalization, the number of TNIC competitors, and the TNIC HHI, respectively.

As our database is based on firm-pairs, sorting firms into high and low groups for any characteristic results in four permutations at the pair-level for i and j: $(high, high)$, $(high, low)$, $(low, high)$, and (low, low). We define *High pair* indicator as one if both firms i and j have above median levels of the given variable in the given year, i.e., the $(high, high)$ case. For example, for firm size, *High pair* $= 1$ if both firms in the dyad are large with above-median logarithm of market capitalization. Analogously, *Low pair* $= 1$ if both firms have below median values of the given characteristic, which is the (low, low) case. The residual mixed-pair dyads with one firm having above-median values, and the other having below-median values, the $(high, low)$ and $(low, high)$ cases, take on values of zero for both the *High pair* and *Low pair* indicators. These residual mixed-pair observations thus serve as the baseline group for testing whether the *High pair* or *Low pair* groups exhibit statistically different exclusive entry patterns.

We rerun our baseline second-stage regressions with two additional cross terms (*#overlaps*×*High pair* and *#overlaps*×*Low pair*) and two additional corresponding instruments (*Intrument* × *High pair* and *Intrument* × *Low pair*) in the first-stage. We also include *High pair* and *Low pair* indicators themselves as control variables. This allows us to generate

t-statistics indicating whether the *High pair* group or the *Low pair* group has exclusive entry that is statistically different from the baseline group defined above. Under the dark-side hypothesis, we expect more negative coefficients for instrumented trade associations membership overlaps when firm sizes in a dyad are *High pair*, when the numbers of TNIC competitors are *Low pair*, and when the TNIC HHIs are *High pair*. We only display second-stage results for parsimony as all first-stage regressions have highly significant coefficients.

Table 11 displays results for subsamples based on firm size. Panel A uses the board connections instrument and shows that the instrumented association membership overlaps coefficient is significantly more negative for pairs of large firms. This finding is robust across all three industry granularities and for both sets of fixed effects. We find similar results in Panel B for the geographic diffusion instrument. We conclude that larger firms abnormally expand geographically in exclusive ways when influenced by trade associations. In contrast, both Panels A and B also show that small firm pairs exhibit more positively correlated entry into states, especially for the finer TNIC-4 granularity. This finding suggests that smaller firms are more likely to be influenced by the bright-side, and they tend to jointly take advantage of opportunities discussed in trade association proceedings.

Table 12 displays results for subsamples based on the number of TNIC competitors. We find strong evidence that treatment effects are significantly more negative when both firms face fewer TNIC competitors, especially for the finer TNIC-4 classification. Coefficients are larger and significance levels are higher for TNIC-4, although they remain fully robust at the TNIC-3 level, and are robust for the TNIC-2 classification when the more stringent fixed effects are included. These results are consistent with the dark-side hypothesis being stronger in the presence of fewer competitors, as coordination is more possible when fewer participants need to collaborate. The fact that results are stronger for the TNIC-4 classification is consistent with exclusionary collaborations also being more likely within narrower industry definitions. This is consistent with coordination also being easier when it is based on more homogeneous products that are more likely to be substitutes than complements. We also find some evidence of positively correlated entry for firms facing larger numbers of competitors, especially for the broader TNIC-2 and TNIC-3 classifications. These results are consistent with trade associations facilitating some pro-competitive complementarities, which are attractive to firms in competitive industries.

Table 13 displays results for subsamples based on the TNIC HHI. Relative to our results for the number of competitors and firm size, we find weaker results for HHIs. Yet Panel A shows negative and significant treatment effects for firms with high HHIs for TNIC-2 industries, and Panel B shows similar results for TNIC-4 industries. Both panels also show additional significant coefficients when the more stringent fixed effects are included. These results are overall consistent with the conclusion that firms in more concentrated markets are also more likely to engage in exclusionary conduct, although the link to the number of competitors is stronger than for HHIs. This suggests that the ability to coordinate (likely true when there are fewer competitors) is perhaps a more important consideration than is the presence of a strong market leader within an industry (likely true when HHIs are high). Table 13 also shows some positive coefficients for the low HHI subsamples, suggesting again that the bright-side hypothesis is more likely in more competitive markets.

Our results illustrate some evidence of both the dark and bright side hypotheses, and suggest that either side is more likely in theoretically motivated subsamples. Anti-competitive exclusionary expansion strategies facilitated by trade association meetings are more likely when there is less competition and for larger firms. This allows competitors to operate in less contested non-overlapping markets and to achieve higher profitability. The intuition for these results is well-articulated by the New York trash haulers' example from Porter (2005) discussed earlier in Section 2, where an association-based explicit agreement divided the city among competitors in an exclusionary way. In contrast, pro-competitive expansions are more likely in competitive industries and for smaller firms.

6 Conclusion

To our knowledge, this paper provides the first systematic exploration of trade associations and how they impact U.S. public firm performance, risk management, investment, corporate efficiency, and expansion strategies. The paper also contributes novel and comprehensive association membership data constructed using novel textual analysis techniques.

We hypothesize that trade associations provide two types of benefits to their members. The first is gains in the form of corporate efficiency, risk management and growth options that improve industry conditions. These gains are seen as positive and are welcomed by antitrust regulators. Our evidence indicates a high degree of success on all of these corporate finance dimensions, and illustrates the positive economic role played by associations.

The second is facilitating anti-competitive activities that would result in higher profits. We examine product pricing strategies and potential exclusionary conduct in how firms expand geographically. Although such practices likely are not sanctioned by associations themselves, as they are closely scrutinized by regulators, it might nevertheless arise as competitors might meet on the sidelines during meetings. We find supporting evidence in higher product prices and more exclusive geographic entry patterns when firms are influenced by associations. Consistent with anti-competitive conduct being most prevalent where it is most easily facilitated, these results are particularly strong for larger firms, firms facing fewer rivals, and for firms in more concentrated markets.

As the decision to join an association is endogenous, we use novel instruments based on out-of-industry geographic networks and out-of-industry board connections. Our conclusions, both regarding bright-side impact and dark side externalities, are rigorously established using two-stage instrumental variables models with high dimensional fixed effects.

Key limitations of our study are that we do not have direct contractual evidence of exclusion, and we are unable to detect the intent of firms that are expanding geographically. Yet our use of instruments and rigid high-dimensional fixed effects links our results specifically to association memberships. Future work developing more instruments and further exploring mechanisms remains fruitful.

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Table 1: Summary statistics

Summary statistics are reported for our sample based on annual firm observations from 2000 to 2022. Panel A summarizes corporate membership in national trade associations. *# memberships* denotes a number of distinct national trade associations in which a company is a member in a given year. *Member {0/1}* is an indicator for a company being a member in at least one association in a given year. Panel B summarizes firm characteristics for firms which are members of at least one association in a given year ($Member = 1$) versus non-members ($Member = 0$). t-statistics are based on the standard errors clustered by company. Panel C summarizes instruments for the association membership. The instrument *Board connections instrument* measures association membership spillovers from other firms connected to the focal firm via overlapping boards, current or past employment, education, or social clubs. These other firms belong to different industries from the focal firm, and the instrument is a weighted average of their association membership counts. The weights are inversely proportional to size differences between the other firms and the focal firm. The instrument *Geographic diffusion instrument*, is constructed analogously, but it uses memberships spillovers from closely located firms of similar size. Membership variables and instruments are lagged, and all the variables are winsorized at $1/99^{\text{th}}$ percentile within a year.

Panel A: Membership in trade associations	Mean (1)	Median (2)	SD (3)	Min (4)	Max (5)	Obs (6)
# memberships	2.717	0.000	6.714	0.000	63.000	117,518
Member {0/1}	0.485	0.000	0.500	0.000	1.000	117,518

Panel B: Split of firm characteristics by association membership	*Member = 1*		*Member = 0*		*Test for difference in means*	
	Mean (1)	Obs (2)	Mean (3)	Obs (4)	(1)-(3) (5)	t-stat (6)
ln(Total assets)	7.249	57,029	6.083	60,489	1.166	30.81
ln(Age)	2.724	57,029	2.075	60,489	0.649	45.14
ROA	0.094	57,029	0.031	60,489	0.063	25.39
Profit margin	0.345	57,029	0.235	60,489	0.110	10.51
Sales growth	0.174	57,029	0.215	60,489	-0.042	-7.25
ln(DLEU Markup)	0.315	57,029	0.286	60,489	0.028	7.54
ln(GHL Markup)	0.397	57,029	0.437	60,489	-0.039	-4.53
Earnings volatility	0.085	57,029	0.109	60,489	-0.024	-11.32
Stock returns volatility	2.765	57,029	3.185	60,489	-0.420	-24.69
# Risk mentions/10K size	0.051	57,029	0.056	60,489	-0.005	-11.03
Capex/Total assets$_{t-1}$	0.048	57,029	0.044	60,489	0.004	5.11
Acquisition {0/1}	0.168	57,029	0.099	60,489	0.069	21.95
R&D/Total assets$_{t-1}$	0.037	57,029	0.047	60,489	-0.010	-7.73
# Patents/Total assets$_{t-1}$	0.007	57,029	0.005	60,489	0.002	5.75
Tobin's Q	1.526	57,029	1.579	60,489	-0.053	-2.39
COGS/Sales	0.655	57,029	0.765	60,489	-0.110	-10.51
Asset turnover	0.906	57,029	0.708	60,489	0.198	15.41
Total factor productivity	-0.283	57,029	-0.383	60,489	0.100	9.91

Panel C: Instruments	Mean	Median	SD	Min	Max	Obs
Board connections instrument	4.399	2.797	5.000	0.000	42.707	83,669
Geographic diffusion instrument	3.345	2.084	3.959	0.000	34.705	64,229

Table 2: Firm connections and homophily

The table presents the regression estimation results of equation (1) using a firm-pair-year panel. In column (1), the dependent variable *Any firm connection 0/1* is an indicator for the firm-pair sharing a connection via overlapping boards, current or past employment, education, or social clubs. In column (2), the dependent variable *Overlapping directors 0/1* is an indicator for the firm-pair sharing a connection via overlapping boards only. In column (3), the dependent variable *All other connections 0/1* is an indicator for the firm-pair sharing a connection via current or past employment, education, or social clubs; it is set to zero for the pairs connected via overlapping boards or not connected. In column (4), the dependent variable *Social clubs 0/1* is an indicator for the firm-pair sharing a connection via social clubs; it is set to zero the pairs connected via overlapping boards or not connected. $D[0,100]$ and $D(100,500]$ are indicators for respective intervals of distance in miles between firms, and $SizeX[0;10]$ and $SizeX(10;50]$ are indicators for respective intervals of size differences. All the regressions include firm-pair and year fixed effects. Standard errors are clustered by firm-pair. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels.

	Any firm connections {0/1} (1)	Overlapping boards {0/1} (2)	All other connections {0/1} (3)	Social clubs {0/1} (4)
Distance [0;100]	4.2370***	0.2440***	3.9930***	1.3918***
	(68.33)	(22.39)	(65.42)	(44.01)
Distance (100;500]	1.1544***	0.0382***	1.1162***	0.2895***
	(30.71)	(7.92)	(29.95)	(16.47)
SizeX [0;10]	0.3590***	0.0309***	0.3280***	0.1225***
	(21.21)	(16.12)	(19.48)	(14.38)
SizeX (10;50]	0.2286***	0.0140***	0.2146***	0.0864***
	(17.01)	(9.98)	(16.02)	(12.44)
Pair F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
R-squared	105,670,864	105,670,864	105,670,864	105,670,864
Observations	0.55	0.53	0.54	0.47
F-statistic, $\beta_{D[0;100]} = \beta_{D(100;500]}$	2,057.57	321.80	1,843.31	1,026.13
F-statistic, $\gamma_{SizeX[1;10]} = \gamma_{SizeX(10;50]}$	161.50	168.09	123.24	49.01
SD_Y	25.7980	3.2540	25.6211	12.7595
Mean_Y	7.1693	0.1060	7.0633	1.6555

Table 3: Firm profitability, sales growth, markups and association membership

The table presents the instrumental variables estimation results of equations (2) and (3) using the firm-year panel data. In Panel A, the instrument *Board connections instrument* measures association membership spillovers from other firms connected to the focal firm via overlapping boards, current or past employment, education, or social clubs. These other firms belong to different industries from the focal firm, and the instrument is a weighted average of their association membership counts. The weights are inversely proportional to size differences between the other firms and the focal firm. In Panel B, the instrument *Geographic diffusion instrument*, is constructed analogously, but it uses memberships spillovers from closely located firms of similar size. In both panels, column (1) presents the first-stage results, where the dependent variable (*# memberships*) is the number of distinct associations in which a firm is a member in a given year. Columns (2)-(6) display the second-stage regression results. The dependent variables are: *ROA* (return on assets) computed as operating income scaled by lag of total assets; *Profit margin* computed as sales net of cost of goods sold scaled by sales; *Sales growth* computed as a natural logarithm of a ratio of total sales in year $t+1$ over total sales in year $t-1$; *ln(DLEU Markup)* is from De Loecker et al. (2020); and *ln(GHL Markup)* is from Pellegrino (2023). All the regressions include the natural logarithms of firm total assets and age as control variables, and firm and year fixed effects. The instruments and the control variables are lagged, and all the variables are winsorized at $1/99^{\text{th}}$ percentiles within a year. Standard errors are clustered by firm. F-statistic corresponds to Kleibergen and Paap (2006) Wald test for weak instruments. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels.

Panel A: Board connections instrument	1^{st} *stage*	2^{nd} *stage estimates*				
	# memberships	ROA	Profit margin	Sales growth	ln(DLEU Markup)	ln(GHL Markup)
	(1)	(2)	(3)	(4)	(5)	(6)
Board connections instrument	0.2946***					
	(9.22)					
$\widehat{\#\text{ memberships}}$		0.0127***	0.0238***	0.0354***	0.0115***	0.0190***
		(6.52)	(4.98)	(6.52)	(5.70)	(4.18)
ln(Total assets)	0.1215**	-0.0079***	-0.0138*	-0.2654***	0.0242***	-0.0068
	(2.05)	(-3.29)	(-1.87)	(-29.23)	(12.03)	(-1.30)
ln(Age)	0.4500***	-0.0017	-0.0135	-0.1298***	0.0010	-0.0205***
	(6.00)	(-0.65)	(-1.38)	(-12.35)	(0.42)	(-2.97)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	87,270	83,901	87,270	71,939	69,412	45,938
F-statistic		83.68	85.06	90.28	87.03	69.95
$\beta_{\widehat{\#\text{memb}}} \times \sigma_{\widehat{\#\text{memb}}}$		0.0206	0.0385	0.0573	0.0186	0.0307
SD_Y		0.1948	1.0426	0.5558	0.2073	0.4653
Mean_Y		0.0633	0.2884	0.1933	0.3007	0.4153

Panel B: Geographic diffusion instrument	1^{st} *stage*	2^{nd} *stage estimates*				
	# memberships	ROA	Profit margin	Sales growth	ln(DLEU Markup)	ln(GHL Markup)
	(1)	(2)	(3)	(4)	(5)	(6)
Geographic diffusion instrument	0.1873***					
	(5.69)					
$\widehat{\#\text{ memberships}}$		0.0166***	0.0354***	0.0464***	0.0126***	0.0277***
		(4.64)	(4.25)	(4.57)	(3.44)	(3.20)
ln(Total assets)	0.2582***	-0.0089***	-0.0174**	-0.2719***	0.0249***	-0.0162**
	(4.39)	(-3.16)	(-2.00)	(-26.50)	(10.56)	(-2.54)
ln(Age)	0.4502***	-0.0020	-0.0207*	-0.1493***	-0.0014	-0.0253***
	(5.31)	(-0.60)	(-1.81)	(-11.43)	(-0.49)	(-2.95)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74,658	71,572	74,658	59,812	57,991	38,428
F-statistic		32.44	32.32	34.61	33.72	24.22
$\beta_{\widehat{\#\text{memb}}} \times \sigma_{\widehat{\#\text{memb}}}$		0.0273	0.0582	0.0762	0.0207	0.0455
SD_Y		0.1948	1.0426	0.5558	0.2073	0.4653
Mean_Y		0.0633	0.2884	0.1933	0.3007	0.4153

Table 4: Firm risk and association membership

The table presents the second-stage instrumental variables estimation results of equation (3) using the firm-year panel data. In Panel A, the instrument *Board connections instrument* measures association membership spillovers from other firms connected to the focal firm via overlapping boards, current or past employment, education, or social clubs. These other firms belong to different industries from the focal firm, and the instrument is a weighted average of their association membership counts. The weights are inversely proportional to size differences between the other firms and the focal firm. In Panel B, the instrument *Geographic diffusion instrument*, is constructed analogously, but it uses memberships spillovers from closely located firms of similar size. The dependent variables are: *Earnings volatility* computed as standard deviation of quarterly earnings per share over 12 quarters following Hoberg and Prabhala (2009) requiring at least 6 quarters of data available; *Stock returns volatility* computed as standard deviation of firm daily stock returns within a company-year; *# Risk mentions/10K size* is the number of paragraphs in which a company mentions one of the words {risk, uncertain*, unpredictab*, instability, volatil*} in its 10K report, scaled by the total number of paragraphs in the report. All the regressions include the natural logarithms of firm total assets and age as control variables, and firm and year fixed effects. The instruments and the control variables are lagged. Standard errors are clustered by firm. F-statistic corresponds to Kleibergen and Paap (2006) Wald test for weak instruments. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels.

Panel A: Board connections instrument	2^{nd} *stage estimates*		
	Earnings volatility	Stock returns volatility	# Risk mentions/ 10K size
	(1)	(2)	(3)
$\widehat{\#\text{ memberships}}$	-0.0069***	-0.0363***	-0.0001
	(-4.60)	(-3.67)	(-0.69)
ln(Total assets)	0.0006	-0.0614***	0.0011***
	(0.23)	(-4.83)	(5.30)
ln(Age)	0.0066**	-0.1648***	-0.0013***
	(2.14)	(-9.69)	(-5.22)
Year F.E.	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes
Observations	76,843	86,751	80,832
F-statistic	91.47	85.14	89.53
$\beta_{\widehat{\#\text{memb}}} \times \sigma_{\widehat{\#\text{memb}}}$	-0.0111	-0.0589	-0.0002
SD_Y	0.1769	1.5264	0.0147
Mean_Y	0.0969	2.9758	0.0258

Panel B: Geographic diffusion instrument	2^{nd} *stage estimates*		
	Earnings volatility	Stock returns volatility	# Risk mentions/ 10K size
	(1)	(2)	(3)
$\widehat{\#\text{ memberships}}$	-0.0078***	-0.0584***	-0.0001
	(-3.30)	(-3.34)	(-0.55)
ln(Total assets)	0.0029	-0.0546***	0.0011***
	(1.05)	(-3.82)	(4.93)
ln(Age)	0.0048	-0.1859***	-0.0014***
	(1.36)	(-9.51)	(-4.84)
Year F.E.	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes
Observations	64,232	74,002	67,764
F-statistic	35.45	31.88	36.38
$\beta_{\widehat{\#\text{memb}}} \times \sigma_{\widehat{\#\text{memb}}}$	-0.0129	-0.0960	-0.0002
SD_Y	0.1769	1.5264	0.0147
Mean_Y	0.0969	2.9758	0.0258

Table 5: Firm investments and association membership

The table presents the second-stage instrumental variables estimation results of equation (3) using the firm-year panel data. In Panel A, the instrument *Board connections instrument* measures association membership spillovers from other firms connected to the focal firm via overlapping boards, current or past employment, education, or social clubs. These other firms belong to different industries from the focal firm, and the instrument is a weighted average of their association membership counts. The weights are inversely proportional to size differences between the other firms and the focal firm. In Panel B, the instrument *Geographic diffusion instrument*, is constructed analogously, but it uses memberships spillovers from closely located firms of similar size. The dependent variables are: *Capex/Total assets*$_{t-1}$ is the firm's annual capital expenditures scaled by a lag of total assets; *Acquisition {0/1}* an indicator for a company that acquired any stake in another company in a given year based on SDC Platinum database; *R&D/Total assets*$_{t-1}$ is the firm's annual research and development expenses scaled by a lag of total assets; *# Patents/Total assets*$_{t-1}$ is the firm's total number of patents filed in a given year based on data from Kogan et al. (2017) available until 2020, scaled by a lag of total assets; *Tobin's Q* is the firm market value of assets scaled by its book of assets. All the regressions include the natural logarithms of firm total assets and age as control variables, and firm and year fixed effects. The instruments and the control variables are lagged. Standard errors are clustered by firm. F-statistic corresponds to Kleibergen and Paap (2006) Wald test for weak instruments. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels.

Panel A: Board connections instrument	*2^{nd} stage estimates*				
	Capex/Total assets$_{t-1}$	Acquisition {0/1}	R&D/Total assets$_{t-1}$	# Patents/Total assets$_{t-1}$	Tobin's Q
	(1)	(2)	(3)	(4)	(5)
$\widehat{\#\text{ memberships}}$	0.0075***	0.0349***	0.0039***	0.0009***	0.2564***
	(7.71)	(7.65)	(6.72)	(4.28)	(7.90)
ln(Total assets)	-0.0131***	-0.0412***	-0.0215***	-0.0045***	-0.4493***
	(-15.30)	(-10.58)	(-21.25)	(-12.35)	(-18.35)
ln(Age)	-0.0135***	-0.0320***	-0.0015*	-0.0027***	-0.2965***
	(-12.06)	(-5.98)	(-1.72)	(-6.99)	(-9.55)
Year F.E.	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes
Observations	85,097	87,270	87,270	80,312	86,856
F-statistic	83.68	85.06	85.06	93.14	82.57
$\beta_{\widehat{\#\text{memb}}} \times \sigma_{\widehat{\#\text{memb}}}$	0.0122	0.0566	0.0064	0.0014	0.4157
SD_Y	0.0662	0.3390	0.0955	0.0227	1.6229
Mean_Y	0.0460	0.1325	0.0422	0.0059	1.5531

Panel B: Geographic diffusion instrument	*2^{nd} stage estimates*				
	Capex/Total assets$_{t-1}$	Acquisition {0/1}	R&D/Total assets$_{t-1}$	# Patents/Total assets$_{t-1}$	Tobin's Q
	(1)	(2)	(3)	(4)	(5)
$\widehat{\#\text{ memberships}}$	0.0093***	0.0453***	0.0056***	0.0009***	0.3354***
	(5.06)	(4.81)	(4.99)	(3.51)	(5.07)
ln(Total assets)	-0.0133***	-0.0448***	-0.0238***	-0.0044***	-0.4845***
	(-13.14)	(-8.91)	(-20.85)	(-11.09)	(-14.42)
ln(Age)	-0.0155***	-0.0338***	-0.0018	-0.0031***	-0.3379***
	(-9.94)	(-4.62)	(-1.59)	(-6.96)	(-7.17)
Year F.E.	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes
Observations	72,856	74,658	74,658	67,751	74,242
F-statistic	30.94	32.32	32.32	37.01	31.89
$\beta_{\widehat{\#\text{memb}}} \times \sigma_{\widehat{\#\text{memb}}}$	0.0153	0.0744	0.0092	0.0015	0.5511
SD_Y	0.0662	0.3390	0.0955	0.0227	1.6229
Mean_Y	0.0460	0.1325	0.0422	0.0059	1.5531

Table 6: Firm efficiency and association membership

The table presents the second-stage instrumental variables estimation results of equation (3) using the firm-year panel data. In Panel A, the instrument *Board connections instrument* measures association membership spillovers from other firms connected to the focal firm via overlapping boards, current or past employment, education, or social clubs. These other firms belong to different industries from the focal firm, and the instrument is a weighted average of their association membership counts. The weights are inversely proportional to size differences between the other firms and the focal firm. In Panel B, the instrument *Geographic diffusion instrument*, is constructed analogously, but it uses memberships spillovers spillovers from closely located firms of similar size. The dependent variables are: *COGS/Total sales* computed as cost of goods sold scaled by sales; *Asset turnover* computed as sales scaled by average of contemporaneous and lagged total assets; and *TFP* borrowed from İmrohoroğlu and Tüzel (2014) up to the last well-populated year of 2019. All the regressions include the natural logarithms of firm total assets and age as control variables, and firm and year fixed effects. The instruments and the control variables are lagged. Standard errors are clustered by firm. F-statistic corresponds to Kleibergen and Paap (2006) Wald test for weak instruments. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels.

Panel A: Board connections instrument	2^{nd} *stage estimates*		
	COGS/Total sales	Asset turnover	Total factor productivity
	(1)	(2)	(3)
$\widehat{\# \text{ memberships}}$	-0.0238***	0.0234***	0.0513***
	(-4.98)	(5.60)	(6.36)
ln(Total assets)	0.0138*	-0.1840***	0.0678***
	(1.87)	(-24.53)	(6.21)
ln(Age)	0.0135	0.0604***	-0.1042***
	(1.38)	(9.20)	(-7.76)
Year F.E.	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes
Observations	87,270	87,270	40,020
F-statistic	85.06	85.06	70.48
$\beta_{\widehat{\#\text{memb}}} \times \sigma_{\widehat{\#\text{memb}}}$	-0.0385	0.0379	0.0832
SD_Y	1.0426	0.7533	0.5271
Mean_Y	0.7116	0.8097	-0.3232

Panel B: Geographic diffusion instrument	2^{nd} *stage estimates*		
	COGS/Total sales	Asset turnover	Total factor productivity
	(1)	(2)	(3)
$\widehat{\# \text{ memberships}}$	-0.0354***	0.0247***	0.0714***
	(-4.25)	(3.71)	(3.73)
ln(Total assets)	0.0174**	-0.1766***	0.0444***
	(2.00)	(-24.97)	(3.05)
ln(Age)	0.0207*	0.0626***	-0.1073***
	(1.81)	(8.58)	(-5.26)
Year F.E.	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes
Observations	74,658	74,658	33,424
F-statistic	32.32	32.32	21.78
$\beta_{\widehat{\#\text{memb}}} \times \sigma_{\widehat{\#\text{memb}}}$	-0.0582	0.0406	0.1174
SD_Y	1.0426	0.7533	0.5271
Mean_Y	0.7116	0.8097	-0.3232

Table 7: Placebo test: Geographic or network effects

The table repeats regressions from Tables 3-6 using a placebo version of *Geographic diffusion instrument*. The placebo instrument is constructed using membership spillovers from other firms located in the same $[0;100]$ miles radius from the focal firm, but with above $10X$ size difference. As in the baseline version of the instrument, we still consider firms which do not share industry with the focal firm, and we inverse-weight the measure by the size differences. All the specifications include the same set of control variables and fixed effects as in the baselines.

Geographic diffusion instrument, placebo with $SizeX > 10$ and $[0;100]$ miles radius				
1st stage estimates	$\beta_{\text{Geo diff instr}, > 10X}$ (1)	t-stat (2)	Observations (3)	
# memberships	-0.0356***	(-2.81)	74,246	
2nd stage estimates	$\beta_{\widehat{\#\text{memb}}}$ (1)	t-stat (2)	Observations (3)	F-stat (4)
Profitability, sales growth, and markups				
ROA	-0.0384**	(-2.24)	71,187	6.87
Profit margin	0.0208	(0.72)	74,246	7.88
Sales growth	-0.0359	(-1.01)	59,444	7.45
ln(DLEU Markup)	0.0026	(0.28)	57,637	6.60
ln(GHL Markup)	-0.0151	(-0.62)	38,337	3.57
Risk management				
Earnings volatility	-0.0089	(-0.73)	63,847	7.23
Stock returns volatility	0.1784**	(2.03)	73,583	7.62
# Risk mentions/10K size	0.0009	(0.74)	67,375	6.69
Investments				
Capex/Total assets$_{t-1}$	-0.0060	(-1.48)	72,495	7.66
Acquisition {0/1}	-0.0379	(-1.38)	74,246	7.88
R&D/Total assets$_{t-1}$	0.0018	(0.67)	74,246	7.88
# Patents/Total assets$_{t-1}$	-0.0024	(-1.51)	67,349	7.17
Tobin's Q	-0.1285	(-1.32)	73,833	7.99
Efficiency				
COGS/Sales	-0.0208	(-0.72)	74,246	7.88
Asset turnover	0.0105	(0.45)	74,246	7.88
Total factor productivity	-0.0823	(-1.13)	33,341	1.99

Table 8: Reflection: Learning from peers of peers

The table repeats the regressions from Tables 3-6 using instruments constructed based on the peers of peers to the focal firms. To perform a clean test of the Manski (1993) reflection problem, the peers of peers of each focal firm exclude any firms that are direct peers of the focal firm itself based on firm board connections, 100 miles radius locations, or $10X$ size band. In Panel A, *Board connections instrument, PoP* is the modified version of the connection-based instrument, and in Panel B *Geographic diffusion instrument, PoP* is the modified version of the geography-based instrument.

Panel A: Board connections instrument based on peers of peers				
1st stage estimates	$\beta_{\text{Board conn instr, PoP}}$ (1)	t-stat (2)	Observations (3)	
# memberships	0.1461***	(5.05)	67,218	
2nd stage estimates	$\beta_{\widehat{\#\text{memb}}}$ (1)	t-stat (2)	Observations (3)	F-stat (4)
Profitability, sales growth, and markups				
ROA	0.0392***	(4.44)	64,345	23.78
Profit margin	0.0551***	(3.68)	67,218	25.53
Sales growth	0.0874***	(3.95)	55,281	23.42
ln(DLEU Markup)	0.0172***	(3.10)	52,093	17.77
ln(GHL Markup)	0.0501**	(2.20)	33,937	8.31
Risk management				
Earnings volatility	-0.0184***	(-3.68)	58,453	23.97
Stock returns volatility	-0.2416***	(-4.43)	66,877	25.21
# Risk mentions/10K size	-0.0011**	(-2.49)	63,160	25.13
Investments				
Capex/Total assets$_{t-1}$	0.0160***	(4.74)	65,932	26.29
Acquisition {0/1}	0.0964***	(4.68)	67,218	25.53
R&D/Total assets$_{t-1}$	0.0045***	(3.34)	67,218	25.53
# Patents/Total assets$_{t-1}$	0.0008	(1.58)	60,783	24.01
Tobin's Q	0.4007***	(4.75)	66,851	26.59
Efficiency				
COGS/Sales	-0.0551***	(-3.68)	67,218	25.53
Asset turnover	0.0509***	(3.97)	67,218	25.53
Total factor productivity	0.1248***	(3.19)	30,312	12.94
Panel B: Geographic diffusion instrument based on peers of peers				
1st stage estimates	$\beta_{\text{Geo diff instr, PoP}}$ (1)	t-stat (2)	Observations (3)	
# memberships	0.0813***	(5.35)	66,900	
2nd stage estimates	$\beta_{\widehat{\#\text{memb}}}$ (1)	t-stat (2)	Observations (3)	F-stat (4)
Profitability, sales growth, and markups				
ROA	0.0095***	(3.33)	64,032	27.49
Profit margin	0.0296***	(3.97)	66,900	28.65
Sales growth	0.0177**	(2.04)	55,010	25.50
ln(DLEU Markup)	0.0052**	(1.99)	51,850	23.43
ln(GHL Markup)	0.0103	(1.60)	33,817	17.29
Risk management				
Earnings volatility	0.0028	(0.84)	58,187	26.29
Stock returns volatility	-0.0237	(-1.54)	66,555	28.47
# Risk mentions/10K size	-0.0001	(-0.28)	62,854	26.58
Investments				
Capex/Total assets$_{t-1}$	0.0025***	(3.07)	65,579	29.34
Acquisition {0/1}	0.0247***	(3.05)	66,900	28.65
R&D/Total assets$_{t-1}$	0.0031***	(3.75)	66,900	28.65
# Patents/Total assets$_{t-1}$	0.0010***	(2.97)	60,522	27.05
Tobin's Q	0.1378***	(3.98)	66,533	29.11
Efficiency				
COGS/Sales	-0.0296***	(-3.97)	66,900	28.65
Asset turnover	0.0246***	(3.02)	66,900	28.65
Total factor productivity	0.0280**	(2.26)	30,156	16.84

Table 9: Firm product prices and association membership

The table presents the instrumental variables estimation results using the firm-product-year panel data. In Panel A, the instrument *Board connections instrument* measures association membership spillovers from other firms connected to the focal firm via overlapping boards, current or past employment, education, or social clubs. These other firms belong to different industries from the focal firm, and the instrument is a weighted average of their association membership counts. The weights are inversely proportional to size differences between the other firms and the focal firm. In Panel B, the instrument *Geographic diffusion instrument*, is constructed analogously, but it uses memberships spillovers spillovers from closely located firms of similar size. In both panels, column (1) presents the first-stage results, where the dependent variable (*# memberships*) is the number of distinct associations in which a firm is a member in a given year. Column (2) displays the second-stage regression results, where the dependent variable ($\ln(\overline{Price}_w)$) is the natural logarithm of the weighted-average price of each product, with weights proportionate to the number of sold units. The instruments and the control variables are lagged. Standard errors are adjusted by inversely weighting observations with the firm's yearly number of products, and are clustered by firm. F-statistic corresponds to Kleibergen and Paap (2006) Wald test for weak instruments. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels.

Panel A: Board connections instrument	# memberships (1)	$\ln(\overline{Price}_w)$ (2)
Board connections instrument	0.4711***	
	(3.51)	
$\widehat{\#\ \text{memberships}}$		0.0156*
		(1.78)
ln(Total assets)	1.0341	0.0020
	(1.26)	(0.06)
ln(Age)	1.7859***	-0.1075**
	(2.87)	(-2.59)
Year F.E.	Yes	Yes
Firm F.E.	Yes	Yes
Product F.E.	Yes	Yes
Observations	1,834,187	1,834,166
F-statistic		12.30

Panel B: Geographic diffusion instrument	# memberships (1)	$\ln(\overline{Price}_w)$ (2)
Geographic diffusion instrument	0.3008***	
	(2.78)	
$\widehat{\#\ \text{memberships}}$		0.0044
		(0.50)
ln(Total assets)	1.8080	0.0291
	(1.61)	(0.85)
ln(Age)	1.5824**	-0.0817*
	(2.12)	(-1.89)
Year F.E.	Yes	Yes
Firm F.E.	Yes	Yes
Product F.E.	Yes	Yes
Observations	1,644,186	1,644,167
F-statistic		7.74

Table 10: Geographic entry into state-level markets and association memberships

The table presents the instrumental variables estimation results using the firm pair-state-year panel data. It shows the second-stage estimates of equation (5). The first stage estimating equation (4) is reported in Appendix Table A3.1. The dependent variable is *Same state* $\{0/1\}_{ij}$ is an indicator variable for both firms i and j having above $1m sales in a given state in a given year. TNIC-2, 3, and 4 are Hoberg and Phillips (2010, 2016) industries. The control variables include the products of total assets and age for the firm pair, an indicator for whether the firms belong to the same SIC code as granular as the corresponding to the TNIC industry (i.e., SIC 3 for TNIC-3), and the TNIC product similarity scores. All the controls are lagged. Standard errors are clustered by firm-pair. F-statistic corresponds to Kleibergen and Paap (2006) Wald test for weak instruments. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels. The estimated coefficients are multiplied by 100 for readability.

Panel A: Board connections instrument	2^{nd} *stage estimates. Dependent variable: Same state* $\{0/1\}_{ij}$					
	TNIC-2		TNIC-3		TNIC-4	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\#\text{overlaps}}_{ij}$	-0.0505***	-0.0274***	-0.0580***	-0.0320***	-0.0485***	-0.0150
	(-9.39)	(-4.76)	(-6.37)	(-3.52)	(-3.72)	(-1.23)
ln(Total assets)$_{ij}$	0.0008***	0.0012***	0.0009***	0.0013***	0.0010***	0.0014***
	(25.74)	(36.96)	(15.17)	(22.21)	(8.38)	(12.55)
ln(Age)$_{ij}$	-0.0010***	-0.0009***	-0.0005**	-0.0002	-0.0002	-0.0002
	(-6.37)	(-5.43)	(-1.99)	(-0.85)	(-0.75)	(-0.53)
Same SIC code $\{0/1\}_{ij}$	-0.0042***	-0.0096***	-0.0041***	-0.0072***	-0.0028***	-0.0042***
	(-5.90)	(-12.87)	(-5.22)	(-9.59)	(-3.00)	(-4.66)
Product similarity$_{ij}$	0.0145***	-0.0088**	0.0137***	-0.0181***	-0.0035	-0.0289***
	(3.76)	(-2.22)	(2.60)	(-3.50)	(-0.44)	(-3.73)
Year × State F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm pair$_{ij}$ F.E.	Yes	No	Yes	No	Yes	No
Firm pair$_{ij}$ × State F.E.	No	Yes	No	Yes	No	Yes
Observations	13,668,504	12,146,479	5,802,943	5,192,677	2,208,002	1,979,046
F-statistic	360.36	349.82	127.02	122.86	40.56	38.90
SD_Y	0.2481	0.2481	0.2413	0.2413	0.2174	0.2174
$Mean_Y$	0.0659	0.0659	0.0621	0.0621	0.0497	0.0497

Panel B: Geographic diffusion instrument	2^{nd} *stage estimates. Dependent variable: Same state* $\{0/1\}_{ij}$					
	TNIC-2		TNIC-3		TNIC-4	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\#\text{overlaps}}_{ij}$	-0.0266***	0.0020	-0.0305**	-0.0078	-0.0280*	-0.0082
	(-3.26)	(0.23)	(-2.56)	(-0.64)	(-1.87)	(-0.56)
ln(Total assets)$_{ij}$	0.0008***	0.0011***	0.0009***	0.0011***	0.0011***	0.0014***
	(20.57)	(27.93)	(13.15)	(16.88)	(7.60)	(9.86)
ln(Age)$_{ij}$	-0.0016***	-0.0013***	-0.0010***	-0.0003	-0.0006	-0.0001
	(-7.55)	(-5.65)	(-3.36)	(-1.05)	(-1.50)	(-0.14)
Same SIC code $\{0/1\}_{ij}$	-0.0009	-0.0074***	-0.0036***	-0.0077***	-0.0029*	-0.0047***
	(-0.98)	(-7.44)	(-3.37)	(-6.94)	(-1.89)	(-2.96)
Product similarity$_{ij}$	0.0180***	-0.0023	0.0227***	-0.0092	0.0070	-0.0227**
	(3.78)	(-0.46)	(3.36)	(-1.35)	(0.65)	(-2.09)
Year × State F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm pair$_{ij}$ F.E.	Yes	No	Yes	No	Yes	No
Firm pair$_{ij}$ × State F.E.	No	Yes	No	Yes	No	Yes
Observations	9,658,981	8,427,361	3,883,384	3,409,904	1,337,948	1,180,981
F-statistic	142.08	144.36	59.40	62.21	26.30	27.13
SD_Y	0.2481	0.2481	0.2413	0.2413	0.2174	0.2174
$Mean_Y$	0.0659	0.0659	0.0621	0.0621	0.0497	0.0497

Table 11: State entry patterns, firm size, and association memberships

The table presents the second-stage estimates which are based on an expanded version of the model in Table 10. The first stage, not reported for parsimony, regresses $\#overlaps_{ij}$ and its interactions with two indicator variables ($High\ pair_{ij}$ and $Low\ pair_{ij}$) on the instrument and the corresponding instrument interactions with the two indicator variables, controls and fixed effects. $High\ pair_{ij}$ is an indicator for both firms in the pair having above median size (measured using market capitalization), and $Low\ pair_{ij}$ is an indicator for both firms having below median size. The baseline hold-out group is thus all firm pairs with mixed size (one above and one below median). The second stage reported in this table then regresses the indicator for both firms having above \$1m sales in the same state ($Same\ state\ \{0/1\}_{ij}$) on the predicted values of $\#overlaps_{ij}$ and its interactions, along with the same set of controls and fixed effects. Standard errors are clustered by firm-pair. F-statistic corresponds to the Kleibergen and Paap (2006) Wald test for weak instruments. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels. The estimated coefficients are multiplied by 100 for readability.

Panel A: Board connections instrument	*2^{nd} stage estimates. Dependent variable: Same state $\{0/1\}_{ij}$*					
	TNIC-2		TNIC-3		TNIC-4	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\#\text{overlaps}}_{ij}$	-0.0365***	0.0162	-0.0412***	0.0392**	-0.0439**	0.0372**
	(-3.78)	(1.54)	(-2.65)	(2.41)	(-2.26)	(2.00)
$\widehat{\#\text{overlaps} \times \text{High pair}}_{ij}$	-0.0115**	-0.0373***	-0.0128	-0.0548***	-0.0013	-0.0420***
	(-1.99)	(-5.76)	(-1.38)	(-5.44)	(-0.11)	(-3.42)
$\widehat{\#\text{overlaps} \times \text{Low pair}}_{ij}$	0.0331**	0.0299**	0.0217	0.0953***	0.0496	0.1585***
	(2.31)	(2.28)	(0.83)	(3.74)	(1.04)	(3.21)
High pair$_{ij}$	0.0049***	0.0101***	0.0037*	0.0136***	-0.0012	0.0075***
	(3.96)	(7.43)	(1.71)	(5.77)	(-0.50)	(3.14)
Low pair$_{ij}$	-0.0002	-0.0005	0.0020	-0.0038*	-0.0009	-0.0069**
	(-0.17)	(-0.43)	(0.89)	(-1.76)	(-0.29)	(-2.30)
ln(Total assets)$_{ij}$	0.0008***	0.0011***	0.0009***	0.0011***	0.0010***	0.0012***
	(20.67)	(28.53)	(12.64)	(16.21)	(8.06)	(10.64)
ln(Age)$_{ij}$	-0.0011***	-0.0013***	-0.0006**	-0.0009***	-0.0003	-0.0006*
	(-6.01)	(-6.80)	(-2.21)	(-3.34)	(-0.95)	(-1.78)
Same SIC code $\{0/1\}_{ij}$	-0.0041***	-0.0095***	-0.0041***	-0.0074***	-0.0029***	-0.0048***
	(-5.88)	(-12.80)	(-5.35)	(-9.88)	(-3.09)	(-5.05)
Product similarity$_{ij}$	0.0127***	-0.0124***	0.0122**	-0.0232***	-0.0036	-0.0288***
	(3.25)	(-3.09)	(2.30)	(-4.43)	(-0.46)	(-3.66)
Year × State F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm pair$_{ij}$ F.E.	Yes	No	Yes	No	Yes	No
Firm pair$_{ij}$ × State F.E.	No	Yes	No	Yes	No	Yes
Observations	13,668,504	12,146,479	5,802,943	5,192,677	2,208,002	1,979,046
F-statistic	75.88	81.97	25.98	29.39	10.90	13.39

Panel B: Geographic diffusion instrument	*2^{nd} stage estimates. Dependent variable: Same state $\{0/1\}_{ij}$*					
	TNIC-2		TNIC-3		TNIC-4	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\#\text{overlaps}}_{ij}$	0.0076	0.0792***	0.0203	0.1018**	0.0138	0.1019**
	(0.41)	(3.45)	(0.62)	(2.45)	(0.51)	(2.30)
$\widehat{\#\text{overlaps} \times \text{High pair}}_{ij}$	-0.0281***	-0.0627***	-0.0408*	-0.0873***	-0.0348	-0.0928**
	(-2.63)	(-4.53)	(-1.91)	(-3.04)	(-1.54)	(-2.57)
$\widehat{\#\text{overlaps} \times \text{Low pair}}_{ij}$	0.0264*	0.0235*	0.0385**	0.0520**	0.1624**	0.2766***
	(1.91)	(1.70)	(2.08)	(2.51)	(2.19)	(2.68)
High pair$_{ij}$	0.0097***	0.0174***	0.0123**	0.0234***	0.0078	0.0206**
	(4.08)	(5.56)	(2.42)	(3.36)	(1.56)	(2.50)
Low pair$_{ij}$	-0.0009	-0.0014	-0.0017	-0.0023	-0.0101*	-0.0186**
	(-0.73)	(-1.09)	(-0.88)	(-1.08)	(-1.67)	(-2.12)
ln(Total assets)$_{ij}$	0.0007***	0.0009***	0.0008***	0.0009***	0.0010***	0.0011***
	(12.85)	(14.93)	(7.79)	(7.80)	(6.40)	(5.58)
ln(Age)$_{ij}$	-0.0020***	-0.0022***	-0.0015***	-0.0014***	-0.0009**	-0.0009*
	(-6.19)	(-5.84)	(-3.33)	(-2.61)	(-2.09)	(-1.70)
Same SIC code $\{0/1\}_{ij}$	-0.0008	-0.0074***	-0.0040***	-0.0087***	-0.0044***	-0.0074***
	(-0.90)	(-7.14)	(-3.75)	(-7.04)	(-2.59)	(-3.64)
Product similarity$_{ij}$	0.0145***	-0.0086	0.0167**	-0.0202**	0.0065	-0.0241**
	(2.87)	(-1.57)	(2.22)	(-2.45)	(0.61)	(-2.01)
Year × State F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm pair$_{ij}$ F.E.	Yes	No	Yes	No	Yes	No
Firm pair$_{ij}$ × State F.E.	No	Yes	No	Yes	No	Yes
Observations	9,658,981	8,427,361	3,883,384	3,409,904	1,337,948	1,180,981
F-statistic	17.97	19.91	4.93	6.66	5.54	5.26

Table 12: State entry patterns, number of competitors, and association memberships

The table presents the second-stage estimates which are based on an expanded version of the model in Table 10. The first stage, not reported for parsimony, regresses $\#overlaps_{ij}$ and its interactions with two indicator variables ($High\ pair_{ij}$ and $Low\ pair_{ij}$) on the instrument and the corresponding instrument interactions with the two indicator variables, controls and fixed effects. $High\ pair_{ij}$ is an indicator for both firms in the pair having above median number of TNIC competitors, and $Low\ pair_{ij}$ is an indicator for both firms having below median number of TNIC competitors. The baseline hold-out group is thus all firm pairs with mixed number of competitors (one above and one below median). The second stage reported in this table then regresses the indicator for both firms having above \$1m sales in the same state ($Same\ state\ \{0/1\}_{ij}$) on the predicted values of $\#overlaps_{ij}$ and its interactions, along with the same set of controls and fixed effects. Standard errors are clustered by firm-pair. F-statistic corresponds to the Kleibergen and Paap (2006) Wald test for weak instruments. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels. The estimated coefficients are multiplied by 100 for readability.

Panel A: Board connections instrument	2^{nd} *stage estimates. Dependent variable: Same state* $\{0/1\}_{ij}$					
	TNIC-2		TNIC-3		TNIC-4	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\#\text{overlaps}}_{ij}$	-0.0567***	-0.0384***	-0.0610***	-0.0292***	-0.0479***	-0.0160
	(-9.85)	(-6.16)	(-6.14)	(-2.83)	(-3.48)	(-1.26)
$\widehat{\#\text{overlaps} \times \text{High pair}}_{ij}$	0.0129***	0.0267***	0.0353***	0.0497***	-0.0031	0.0030
	(4.74)	(9.04)	(7.22)	(9.78)	(-0.63)	(0.67)
$\widehat{\#\text{overlaps} \times \text{Low pair}}_{ij}$	-0.0012	-0.0063**	-0.0201***	-0.0421***	-0.0237***	-0.0349***
	(-0.43)	(-2.11)	(-3.45)	(-6.95)	(-4.14)	(-6.40)
High pair$_{ij}$	0.0020***	-0.0012**	-0.0040***	-0.0037***	0.0013**	0.0024***
	(4.48)	(-2.56)	(-5.27)	(-5.36)	(2.53)	(4.75)
Low pair$_{ij}$	-0.0050***	0.0007	0.0018	0.0077***	0.0017*	0.0014
	(-7.45)	(0.97)	(1.39)	(6.32)	(1.67)	(1.52)
ln(Total assets)$_{ij}$	0.0008***	0.0012***	0.0009***	0.0013***	0.0010***	0.0015***
	(25.20)	(37.12)	(14.49)	(20.54)	(8.10)	(12.10)
ln(Age)$_{ij}$	-0.0008***	-0.0007***	-0.0003	0.0001	-0.0003	-0.0003
	(-5.64)	(-4.47)	(-1.11)	(0.54)	(-0.77)	(-0.76)
Same SIC code $\{0/1\}_{ij}$	-0.0046***	-0.0097***	-0.0042***	-0.0074***	-0.0032***	-0.0048***
	(-6.45)	(-12.75)	(-5.14)	(-9.16)	(-3.38)	(-5.35)
Product similarity$_{ij}$	0.0063	-0.0117***	0.0187***	-0.0118**	-0.0060	-0.0380***
	(1.60)	(-2.90)	(3.45)	(-2.15)	(-0.66)	(-4.41)
Year × State F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm pair$_{ij}$ F.E.	Yes	No	Yes	No	Yes	No
Firm pair$_{ij}$ × State F.E.	No	Yes	No	Yes	No	Yes
Observations	13,668,504	12,146,479	5,802,943	5,192,677	2,208,002	1,979,046
F-statistic	119.57	117.56	41.22	40.08	12.18	11.73

Panel B: Geographic diffusion instrument	2^{nd} *stage estimates. Dependent variable: Same state* $\{0/1\}_{ij}$					
	TNIC-2		TNIC-3		TNIC-4	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\#\text{overlaps}}_{ij}$	-0.0274***	-0.0059	-0.0409***	-0.0252*	-0.0192	0.0043
	(-3.14)	(-0.62)	(-3.18)	(-1.90)	(-1.33)	(0.30)
$\widehat{\#\text{overlaps} \times \text{High pair}}_{ij}$	0.0021	0.0114***	0.0275***	0.0440***	0.0002	0.0061
	(0.55)	(2.75)	(3.98)	(6.10)	(0.04)	(1.24)
$\widehat{\#\text{overlaps} \times \text{Low pair}}_{ij}$	0.0049	0.0037	-0.0195***	-0.0279***	-0.0305***	-0.0454***
	(1.35)	(0.97)	(-2.62)	(-3.63)	(-2.70)	(-4.09)
High pair$_{ij}$	0.0040***	0.0011*	0.0003	-0.0004	-0.0001	-0.0003
	(6.37)	(1.65)	(0.22)	(-0.32)	(-0.13)	(-0.36)
Low pair$_{ij}$	-0.0078***	-0.0035***	-0.0046***	0.0004	0.0059**	0.0108***
	(-8.96)	(-4.02)	(-2.66)	(0.24)	(2.24)	(4.55)
ln(Total assets)$_{ij}$	0.0008***	0.0011***	0.0009***	0.0012***	0.0011***	0.0014***
	(19.66)	(27.99)	(12.62)	(16.35)	(7.54)	(9.47)
ln(Age)$_{ij}$	-0.0016***	-0.0012***	-0.0007**	0.0001	-0.0004	0.0002
	(-7.43)	(-5.35)	(-2.22)	(0.33)	(-1.00)	(0.40)
Same SIC code $\{0/1\}_{ij}$	-0.0015	-0.0077***	-0.0036***	-0.0076***	-0.0034**	-0.0055***
	(-1.56)	(-7.68)	(-3.18)	(-6.53)	(-2.33)	(-3.69)
Product similarity$_{ij}$	0.0061	-0.0080	0.0207***	-0.0098	0.0098	-0.0204*
	(1.27)	(-1.61)	(2.89)	(-1.35)	(0.83)	(-1.71)
Year × State F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm pair$_{ij}$ F.E.	Yes	No	Yes	No	Yes	No
Firm pair$_{ij}$ × State F.E.	No	Yes	No	Yes	No	Yes
Observations	9,658,981	8,427,361	3,883,384	3,409,904	1,337,948	1,180,981
F-statistic	46.66	48.36	17.78	18.22	8.75	8.83

Table 13: State entry patterns, HHI, and association memberships

The table presents the second-stage estimates which are based on an expanded version of the model in Table 10. The first stage, not reported for parsimony, regresses $\#overlaps_{ij}$ and its interactions with two indicator variables ($High\ pair_{ij}$ and $Low\ pair_{ij}$) on the instrument and the corresponding instrument interactions with the two indicator variables, controls and fixed effects. $High\ pair_{ij}$ is an indicator for both firms in the pair having above median sales-based HHI in the firm's TNIC industry, and $Low\ pair_{ij}$ is an indicator for both firms having below median HHI. The baseline hold-out group is thus all firm pairs with mixed HHI (one above and one below median). The second stage reported in this table then regresses the indicator for both firms having above \$1m sales in the same state ($Same\ state\ \{0/1\}_{ij}$) on the predicted values of $\#overlaps_{ij}$ and its interactions, along with the same set of controls and fixed effects. Standard errors are clustered by firm-pair. F-statistic corresponds to the Kleibergen and Paap (2006) Wald test for weak instruments. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels. The estimated coefficients are multiplied by 100 for readability.

Panel A: Board connections instrument	2^{nd} *stage estimates. Dependent variable: Same state* $\{0/1\}_{ij}$					
	TNIC-2		TNIC-3		TNIC-4	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\#\text{overlaps}}_{ij}$	-0.0526***	-0.0358***	-0.0600***	-0.0357***	-0.0451***	-0.0110
	(-9.88)	(-6.27)	(-6.41)	(-3.75)	(-3.40)	(-0.91)
$\widehat{\#\text{overlaps} \times \text{High pair}}_{ij}$	-0.0053**	-0.0174***	-0.0040	-0.0212***	-0.0196***	-0.0217***
	(-2.25)	(-6.68)	(-0.94)	(-4.41)	(-3.22)	(-4.08)
$\widehat{\#\text{overlaps} \times \text{Low pair}}_{ij}$	0.0044*	0.0188***	0.0041	0.0139***	-0.0018	-0.0039
	(1.93)	(7.67)	(1.53)	(5.02)	(-0.55)	(-1.49)
High pair$_{ij}$	-0.0006	0.0030***	0.0005	0.0013*	0.0006	-0.0027***
	(-1.22)	(6.00)	(0.69)	(1.70)	(0.85)	(-4.30)
Low pair$_{ij}$	0.0004	0.0015***	0.0004	0.0038***	0.0012***	0.0043***
	(1.15)	(4.19)	(1.02)	(9.01)	(2.61)	(10.64)
ln(Total assets)$_{ij}$	0.0008***	0.0012***	0.0009***	0.0013***	0.0010***	0.0014***
	(25.93)	(37.48)	(15.27)	(22.08)	(8.22)	(12.26)
ln(Age)$_{ij}$	-0.0009***	-0.0008***	-0.0004*	-0.0001	-0.0002	-0.0001
	(-6.14)	(-4.78)	(-1.88)	(-0.37)	(-0.68)	(-0.18)
Same SIC code $\{0/1\}_{ij}$	-0.0041***	-0.0093***	-0.0040***	-0.0067***	-0.0029***	-0.0044***
	(-5.73)	(-12.12)	(-5.07)	(-8.74)	(-3.16)	(-4.97)
Product similarity$_{ij}$	0.0115***	-0.0166***	0.0119**	-0.0285***	-0.0062	-0.0404***
	(2.95)	(-4.15)	(2.23)	(-5.37)	(-0.73)	(-4.99)
Year × State F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm pair$_{ij}$ F.E.	Yes	No	Yes	No	Yes	No
Firm pair$_{ij}$ × State F.E.	No	Yes	No	Yes	No	Yes
Observations	13,668,504	12,146,479	5,802,943	5,192,677	2,208,002	1,979,046
F-statistic	127.80	122.94	43.87	41.60	11.76	11.42
Panel B: Geographic diffusion instrument	2^{nd} *stage estimates. Dependent variable: Same state* $\{0/1\}_{ij}$					
	TNIC-2		TNIC-3		TNIC-4	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\#\text{overlaps}}_{ij}$	-0.0278***	-0.0101	-0.0321***	-0.0092	-0.0216	-0.0004
	(-3.51)	(-1.21)	(-2.59)	(-0.75)	(-1.58)	(-0.03)
$\widehat{\#\text{overlaps} \times \text{High pair}}_{ij}$	0.0047	-0.0085***	0.0022	-0.0127**	-0.0234**	-0.0247***
	(1.63)	(-2.74)	(0.45)	(-2.27)	(-2.43)	(-2.81)
$\widehat{\#\text{overlaps} \times \text{Low pair}}_{ij}$	0.0014	0.0160***	0.0018	0.0052	-0.0002	-0.0043
	(0.46)	(4.69)	(0.42)	(1.32)	(-0.04)	(-1.28)
High pair$_{ij}$	-0.0031***	0.0017**	-0.0014	0.0010	0.0018	-0.0010
	(-4.81)	(2.57)	(-1.24)	(0.93)	(1.20)	(-0.76)
Low pair$_{ij}$	-0.0003	0.0002	-0.0004	0.0046***	0.0010	0.0055***
	(-0.61)	(0.43)	(-0.56)	(6.61)	(1.40)	(8.06)
ln(Total assets)$_{ij}$	0.0008***	0.0011***	0.0009***	0.0011***	0.0011***	0.0014***
	(20.84)	(28.81)	(13.27)	(16.99)	(7.71)	(9.73)
ln(Age)$_{ij}$	-0.0016***	-0.0011***	-0.0010***	-0.0002	-0.0006	0.0000
	(-7.74)	(-5.17)	(-3.43)	(-0.74)	(-1.46)	(0.09)
Same SIC code $\{0/1\}_{ij}$	-0.0010	-0.0072***	-0.0036***	-0.0072***	-0.0030**	-0.0048***
	(-1.07)	(-7.19)	(-3.36)	(-6.43)	(-2.04)	(-3.19)
Product similarity$_{ij}$	0.0162***	-0.0071	0.0222***	-0.0196***	0.0040	-0.0344***
	(3.38)	(-1.43)	(3.28)	(-2.87)	(0.35)	(-3.05)
Year × State F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm pair$_{ij}$ F.E.	Yes	No	Yes	No	Yes	No
Firm pair$_{ij}$ × State F.E.	No	Yes	No	Yes	No	Yes
Observations	9,658,981	8,427,361	3,883,384	3,409,904	1,337,948	1,180,981
F-statistic	52.82	53.93	21.10	22.18	8.45	8.85

A Appendices

A.1 Constructing the Association Membership Panel

A.1.1 Association-Year Panel Based on the Encyclopedia of Associations

We obtain data on the U.S. national trade associations from the Encyclopedia of Associations: National Organizations. The encyclopedia provides a panel of national organization-years over 2004 to 2022. For the years 2008 and 2009, the encyclopedia has two editions; and for each of these years we use the latest edition.

We track associations over time using the internal encyclopedia organization ID number and organization name. We preprocess the names by retaining only alphanumeric characters, removing articles "the" and "an" at the start of the string, removing "and" conjunction as well as acronyms which are frequently listed in brackets at the end of the string. We do not use names with below five non-space characters, which are 0.3% of the sample. Finally, we form an association Global ID by grouping entities that share the encyclopedia ID or the name at any point throughout the available years. This procedure results in 36,164 unique organizations.

The encyclopedia enables us to select a relevant set of the organizations, since it includes both SIC and NAICS codes and categorizes associations into functional groups. Thus, we select 5,815 national business associations classified as *Business Associations* by either primary or secondary SIC code 8611 or NAICS code 813910.[13] Since our goal is to retain industry-focused associations, we explicitly exclude *Chambers of Commerce and Trade and Tourism Organizations*, which constitute only 2.36% of the national business associations. We exclude these chambers of commerce if they are classified as such at any point throughout the sample. We also exclude associations likely focused exclusively on non-business issues such as *Cultural Organizations*, *Educational Organizations*, *Hobby and Avocational Organizations*, *Legal, Governmental, Public Administration*, *Public Affairs Organizations*, *Social Welfare Organizations*, etc. Each of these sections accounts for less than 2% of the business associations, and they are excluded only if they do not belong to other sections devoted to business activities.

[13]For example, another large group is *Professional Organizations* with SIC code 8621 and NAICS code 813920. It includes organizations with individual rather than corporate memberships.

As a result, we retain business associations in the following encyclopedia sections: *Trade, Business, and Commercial Organizations*, *Environmental and Agricultural Organizations*, *Engineering, Technological, and Natural and Social Sciences Organizations*, and *Health and Medical Organizations*. Together, these sections represent 88.05% of the business association-years, with *Trade, Business, and Commercial Organizations* being the largest, accounting for about 76.10% of the retained sections. The associations are retained if they satisfy these criteria at any point throughout the sample, after excluding the chambers of commerce. The filtering procedure results in 5,114 associations.

In a small number of cases (0.3% of the sample) association Global ID refers to multiple organizations in the encyclopedia. For these Global ID-encyclopedia years, to remove the duplicates, we retain organizations in that year classified as industry focused-associations of businesses, have non-missing value of the founding year, non-missing URL information, larger budgets, and larger number of staff. In 11.7% of Global IDs, same association refers to multiple values of the founding year across different editions. We manually verified that this mostly happens to updates and corrections in the encyclopedia over time. In these cases, for a given Global ID, we select the minimum founding year. To avoid endogenous formation of associations, we retain the associations formed before 1999, which is the start of the association membership data, as it is explained below. To be able to apply this filter, we retain 4,515 associations with non-missing founding years.

To identify company memberships in associations, we rely on association websites, as it is described below in Section A.1.3. To web scrape associations' websites, we obtain the list of URLs for the associations in our sample listed in the encyclopedia. We standardize the URLs to the unified format, e.g. `api.org` or `nbda.com`, and exclude URLs referring to specific pages within a domain. Further, we retain the domains likely belonging to the associations by removing the domains of social media and other platforms hosting pages of multiple associations (e.g., `linkedin.com`, `Facebook.com`, `opencorporates.com`). We use the combination of regular expressions and manual checks to additionally remove associations with government-owned domains (e.g., `.gov`, `albany.net`), and educational institutions (`.edu`). In our sample, there are 4,162 associations with identified domains.

A.1.2 Collecting Association Websites

Next, we construct a panel of memberships for publicly listed U.S. companies in these national industry-focused business associations. To do so, we first web scrape annual historical versions of the associations' websites from the Wayback Machine Internet Archive, and then we look up member company names in the website text of each association's website.

Our sample starts in 1999, which is the earliest year of sufficient quality website snapshots are available, and our sample ends in 2022. To keep data collection manageable, for each website-year snapshot, we collect all pages within the website up to three layers of URL depth (pages appearing with no more than three forward slashes in their URL) and up to 200 pages. These simplifications are for efficiency and scalability as the Wayback Machine only allows 15 requests per minute. We consider snapshots to be valid if the combined size of the website pages extracted, when saved in .TXT format, exceed 5kB in a given year, and if the file size does not drop below 10% of sizes of the surrounding snapshots in $[-2, 2]$ year window (this avoids corrupted snapshots where the full website was not saved). We are able to collect an unbalanced panel of valid yearly snapshots for over 99% associations in our sample. We link each snapshot-year association to the association database using the available encyclopedia editions, giving preference to earlier years.[14]

For each association, we keep the sample years from the earliest until the latest valid website snapshot. The resulting panel is unbalanced with 13.0% missing association-year snapshots. When a period of missing snapshots lasts up to two years, we carry-forward the latest available valid snapshot, which assumes temporary noise in snapshot quality. Filling in such "donut holes" of up to two years reduces the intermediate missing years to 7.3%. Our results are not sensitive to these parameters and are robust to filling in longer donut holes using the carry-forward approach. In the next section, we use the text of the websites to determine association membership by publicly listed firms.

[14] In about 0.2% cases, multiple websites are associated with the same association-year. Prioritizing non-missing snapshots eliminates these duplicates.

A.1.3 Membership of Firms in Trade Associations

To determine the membership of firms in trade associations, we assume that if a company name was mentioned on the association's website in a given year, the company is a member of the association in that year. We utilize names of publicly listed firms from the Center for Research in Security Prices (CRSP) and the WRDS SEC Analytics Suite. Both sources contain historical names of companies corresponding to unique firm identifiers (GVKEY and PERMNO) mapped to specific dates. We include all names of firms with above $1m in assets and sales, based on the CRSP-Compustat Merged database.

To perform the lookup procedure, we pre-process names by retaining only alphanumeric characters, removing common endings referring to corporate forms and geographic states, removing the article "the", and the conjunction "and". We additionally standardize references to frequently occurring corporate forms such as "Company" and "Co", "Incorporated", "Inc", and others, and references to the United States, both in firm names and in website texts. To reduce false matches, we include all names that, after pre-processing, contain at least five non-space characters and that have at least one space in the name. To account for potential differences in spacing in the writing of the names, we remove all spaces from both names and web text, and then perform the lookup procedure using these compressed strings. For each name, we look up versions with and without removing the standardized corporate endings, as longer strings yield more precise matches. To ensure high accuracy, after these lookups, we manually verify that the matched strings likely refer to the intended company names, and that they do not reference something else in the website text.

Since some associations list few publicly listed members, we verify that such associations include other private members as well (to ensure that the association is generally listing members) by searching the website text for frequent endings of private firm names such as "Inc", "Co", "LLC", etc. We count the combined occurrences of these frequent endings and the number of publicly listed firm names, and require these combined counts to be at least five for a given association in a given year. This ensures the publicly listed name matches we find are part of a general list of members provided by the association. Overall, the complete look up procedure results in 3,711 companies being members of 8,624 national industry-focused trade associations.

A.2 Additional Robustness Tests

Table A2.1: Robustness: Including ZIP code × year fixed effects

The table presents the instrumental variables estimation results of equations (2) and (3) using the firm-year panel data. It repeats regressions from Tables 3-6 with the inclusion of 5-digit ZIP-code × year fixed effects instead of year fixed effects. All the other specification details are the same as in the baseline. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels.

Panel A: Board connections instrument

1st stage estimates	$\beta_{\text{Board conn instr}}$ (1)	t-stat (2)	Observations (3)
# memberships	0.2586***	(6.55)	54,827

2nd stage estimates	$\beta_{\widehat{\#\text{memb}}}$ (1)	t-stat (2)	Observations (3)	F-stat (4)
Profitability, sales growth, and markups				
ROA	0.0141***	(4.32)	51,632	43.51
Profit margin	0.0234***	(2.73)	54,827	42.89
Sales growth	0.0328***	(3.49)	43,223	40.79
ln(DLEU Markup)	0.0127***	(3.89)	41,975	38.78
ln(GHL Markup)	0.0249***	(2.80)	26,725	23.73
Risk management				
Earnings volatility	-0.0088***	(-2.91)	47,594	41.52
Stock returns volatility	-0.0367**	(-2.37)	54,447	43.04
# Risk mentions/10K size	-0.0001	(-0.49)	51,856	43.02
Investments				
Capex/Total assets$_{t-1}$	0.0090***	(5.32)	53,484	40.87
Acquisition {0/1}	0.0389***	(4.89)	54,827	42.89
R&D/Total assets$_{t-1}$	0.0061***	(5.04)	54,827	42.89
# Patents/Total assets$_{t-1}$	0.0010***	(2.95)	50,436	43.08
Tobin's Q	0.2616***	(5.29)	54,443	40.20
Efficiency				
COGS/Sales	-0.0234***	(-2.73)	54,827	42.89
Asset turnover	0.0344***	(4.20)	54,827	42.89
Total factor productivity	0.0694***	(3.74)	21,033	23.21

Table A2.1 continues on the next page.

Table A2.1 continues on the next page.

Panel B: Geographic diffusion instrument

1st stage estimates	$\beta_{\text{Geo diff instr}}$ (1)	t-stat (2)	Observations (3)	
# memberships	0.1696***	(3.97)	56,693	
2nd stage estimates	$\beta_{\widehat{\#\text{memb}}}$ (1)	t-stat (2)	Observations (3)	F-stat (4)
Profitability, sales growth, and markups				
ROA	0.0188***	(3.08)	53,491	15.72
Profit margin	0.0357***	(2.67)	56,693	15.74
Sales growth	0.0574***	(2.92)	43,424	14.09
ln(DLEU Markup)	0.0159***	(2.76)	43,061	14.59
ln(GHL Markup)	0.0299**	(2.29)	28,018	9.57
Risk management				
Earnings volatility	-0.0116**	(-2.56)	48,451	15.23
Stock returns volatility	-0.0724***	(-2.62)	56,116	15.50
# Risk mentions/10K size	-0.0002	(-0.54)	51,941	17.47
Investments				
Capex/Total assets$_{t-1}$	0.0137***	(3.47)	55,149	14.61
Acquisition {0/1}	0.0672***	(3.44)	56,693	15.74
R&D/Total assets$_{t-1}$	0.0086***	(3.50)	56,693	15.74
# Patents/Total assets$_{t-1}$	0.0014***	(2.59)	52,037	16.66
Tobin's Q	0.3349***	(3.39)	56,291	15.68
Efficiency				
COGS/Sales	-0.0357***	(-2.67)	56,693	15.74
Asset turnover	0.0466***	(3.14)	56,693	15.74
Total factor productivity	0.1018**	(2.39)	21,746	7.92

Table A2.2: Robustness: Including 3-digit SIC code × year fixed effects

The table presents the instrumental variables estimation results of equations (2) and (3) using the firm-year panel data. It repeats regressions from Tables 3-6 with the inclusion of 3-digit SIC-code × year fixed effects instead of year fixed effects. All the other specification details are the same as in the baseline. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels.

Panel A: Board connections instrument				
1st stage estimates	$\beta_{\text{Board conn instr}}$ (1)	t-stat (2)	Observations (3)	
# memberships	0.2844***	(9.52)	86,506	
2nd stage estimates	$\beta_{\widehat{\#\text{memb}}}$ (1)	t-stat (2)	Observations (3)	F-stat (4)
Profitability, sales growth, and markups				
ROA	0.0114***	(6.24)	83,130	89.36
Profit margin	0.0247***	(4.76)	86,506	90.64
Sales growth	0.0353***	(6.17)	71,156	92.01
ln(DLEU Markup)	0.0113***	(5.51)	68,740	87.49
ln(GHL Markup)	0.0196***	(3.78)	45,294	67.25
Risk management				
Earnings volatility	-0.0065***	(-4.18)	76,148	92.15
Stock returns volatility	-0.0473***	(-5.39)	85,977	89.96
# Risk mentions/10K size	-0.0001	(-0.76)	80,074	93.12
Investments				
Capex/Total assets$_{t-1}$	0.0059***	(7.43)	84,333	89.85
Acquisition {0/1}	0.0326***	(7.45)	86,506	90.64
R&D/Total assets$_{t-1}$	0.0040***	(6.24)	86,506	90.64
# Patents/Total assets$_{t-1}$	0.0008***	(3.51)	79,617	94.53
Tobin's Q	0.2338***	(7.86)	86,092	88.63
Efficiency				
COGS/Sales	-0.0247***	(-4.76)	86,506	90.64
Asset turnover	0.0209***	(5.03)	86,506	90.64
Total factor productivity	0.0525***	(6.15)	39,515	67.17

Panel B: Geographic diffusion instrument				
1st stage estimates	$\beta_{\text{Geo diff instr}}$ (1)	t-stat (2)	Observations (3)	
# memberships	0.1839***	(6.02)	73,839	
2nd stage estimates	$\beta_{\widehat{\#\text{memb}}}$ (1)	t-stat (2)	Observations (3)	F-stat (4)
Profitability, sales growth, and markups				
ROA	0.0140***	(4.47)	70,744	36.74
Profit margin	0.0353***	(4.23)	73,839	36.20
Sales growth	0.0433***	(4.18)	58,960	35.58
ln(DLEU Markup)	0.0122***	(3.36)	57,265	36.18
ln(GHL Markup)	0.0260***	(2.94)	37,759	25.31
Risk management				
Earnings volatility	-0.0067***	(-2.77)	63,471	37.24
Stock returns volatility	-0.0682***	(-4.18)	73,183	35.48
# Risk mentions/10K size	-0.0001	(-0.39)	66,986	41.66
Investments				
Capex/Total assets$_{t-1}$	0.0076***	(5.08)	72,035	35.01
Acquisition {0/1}	0.0432***	(4.83)	73,839	36.20
R&D/Total assets$_{t-1}$	0.0058***	(4.96)	73,839	36.20
# Patents/Total assets$_{t-1}$	0.0009***	(2.98)	67,007	39.13
Tobin's Q	0.3077***	(5.31)	73,422	36.98
Efficiency				
COGS/Sales	-0.0353***	(-4.23)	73,839	36.20
Asset turnover	0.0266***	(3.94)	73,839	36.20
Total factor productivity	0.0736***	(3.71)	32,970	22.89

Table A2.3: Robustness: Excluding vertically related pairs

The table presents the instrumental variables estimation results of equations (2) and (3) using the firm-year panel data. It repeats regressions from Tables 3-6 with the exclusion of vertically related firm-pairs when constructing both instruments, *Board connections instrument* and *Geographic diffusion instrument*. We exclude vertically related peers based on Frésard et al. (2020) with 10% network granularity in addition to already excluding broad TNIC-2 industry pairs as we do in the baselines. All the other specification details are the same as in the baseline. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels.

Panel A: Board connections instrument

1st stage estimates	$\beta_{\text{Board conn instr}}$ (1)	t-stat (2)	Observations (3)
# memberships	0.2645***	(8.39)	87,222

2nd stage estimates	$\beta_{\widehat{\#\text{memb}}}$ (1)	t-stat (2)	Observations (3)	F-stat (4)
Profitability, sales growth, and markups				
ROA	0.0137***	(6.15)	83,853	69.02
Profit margin	0.0263***	(4.90)	87,222	70.44
Sales growth	0.0348***	(5.92)	71,905	75.58
ln(DLEU Markup)	0.0129***	(5.67)	69,376	72.53
ln(GHL Markup)	0.0222***	(4.21)	45,911	55.03
Risk management				
Earnings volatility	-0.0076***	(-4.60)	76,804	76.62
Stock returns volatility	-0.0416***	(-3.73)	86,705	70.70
# Risk mentions/10K size	-0.0001	(-0.75)	80,790	74.82
Investments				
Capex/Total assets$_{t-1}$	0.0079***	(7.09)	85,050	69.03
Acquisition {0/1}	0.0354***	(7.03)	87,222	70.44
R&D/Total assets$_{t-1}$	0.0040***	(6.23)	87,222	70.44
# Patents/Total assets$_{t-1}$	0.0009***	(4.36)	80,274	78.24
Tobin's Q	0.2711***	(7.29)	86,808	68.07
Efficiency				
COGS/Sales	-0.0263***	(-4.90)	87,222	70.44
Asset turnover	0.0220***	(4.95)	87,222	70.44
Total factor productivity	0.0560***	(5.82)	39,995	54.61

Panel B: Geographic diffusion instrument

1st stage estimates	$\beta_{\text{Geo diff instr}}$ (1)	t-stat (2)	Observations (3)
# memberships	0.1726***	(5.53)	74,528

2nd stage estimates	$\beta_{\widehat{\#\text{memb}}}$ (1)	t-stat (2)	Observations (3)	F-stat (4)
Profitability, sales growth, and markups				
ROA	0.0160***	(4.46)	71,442	30.71
Profit margin	0.0342***	(4.11)	74,528	30.61
Sales growth	0.0451***	(4.25)	59,701	32.10
ln(DLEU Markup)	0.0122***	(3.33)	57,878	31.61
ln(GHL Markup)	0.0274***	(2.97)	38,374	20.28
Risk management				
Earnings volatility	-0.0088***	(-3.58)	64,117	33.45
Stock returns volatility	-0.0642***	(-3.52)	73,872	29.94
# Risk mentions/10K size	-0.0001	(-0.29)	67,640	34.33
Investments				
Capex/Total assets$_{t-1}$	0.0095***	(4.93)	72,734	29.17
Acquisition {0/1}	0.0461***	(4.90)	74,528	30.61
R&D/Total assets$_{t-1}$	0.0054***	(4.89)	74,528	30.61
# Patents/Total assets$_{t-1}$	0.0008***	(3.04)	67,633	34.85
Tobin's Q	0.3255***	(4.92)	74,112	30.15
Efficiency				
COGS/Sales	-0.0342***	(-4.11)	74,528	30.61
Asset turnover	0.0242***	(3.51)	74,528	30.61
Total factor productivity	0.0684***	(3.51)	33,359	18.83

Table A2.4: Robustness: Alternative distance and size thresholds

The table presents the instrumental variables estimation results of equations (2) and (3) using the firm-year panel data. It repeats regressions from Tables 3-6 for *Geographic diffusion instrument* constructed using alternative distance and size threshold. In Panel A, the instrument is constructed using firms from other industries in $5X$ size band located within 50 miles. In Panel B, the instrument is constructed using firms from other industries in $15X$ size band located within 150 miles. All the other specification details are the same as in the baseline. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels.

Panel A: Geographic diffusion instrument with $SizeX < 5$ and $[0;50]$ miles radius

1st stage estimates	$\beta_{\text{Geo diff instr, alt}}$ (1)	t-stat (2)	Observations (3)
# memberships	0.1366***	(4.89)	72,375

2nd stage estimates	$\beta_{\widehat{\#\text{memb}}}$ (1)	t-stat (2)	Observations (3)	F-stat (4)
Profitability, sales growth, and markups				
ROA	0.0158***	(3.92)	69,296	23.98
Profit margin	0.0366***	(3.72)	72,375	23.90
Sales growth	0.0446***	(3.82)	57,819	25.33
ln(DLEU Markup)	0.0131***	(3.16)	56,066	23.28
ln(GHL Markup)	0.0277***	(2.69)	37,610	16.16
Risk management				
Earnings volatility	-0.0081***	(-2.94)	62,206	25.32
Stock returns volatility	-0.0556***	(-2.91)	71,776	23.59
# Risk mentions/10K size	-0.0002	(-0.73)	65,772	27.42
Investments				
Capex/Total assets$_{t-1}$	0.0090***	(4.44)	70,717	22.94
Acquisition {0/1}	0.0459***	(4.37)	72,375	23.90
R&D/Total assets$_{t-1}$	0.0056***	(4.43)	72,375	23.90
# Patents/Total assets$_{t-1}$	0.0011***	(3.37)	65,682	26.43
Tobin's Q	0.3130***	(4.30)	71,980	22.88
Efficiency				
COGS/Sales	-0.0366***	(-3.72)	72,375	23.90
Asset turnover	0.0225***	(3.06)	72,375	23.90
Total factor productivity	0.0715***	(3.10)	32,652	14.72

Panel B: Geographic diffusion instrument with $SizeX < 15$ and $[0;150]$ miles radius

1st stage estimates	$\beta_{\text{Geo diff instr, alt}}$ (1)	t-stat (2)	Observations (3)
# memberships	0.2687***	(6.56)	75,180

2nd stage estimates	$\beta_{\widehat{\#\text{memb}}}$ (1)	t-stat (2)	Observations (3)	F-stat (4)
Profitability, sales growth, and markups				
ROA	0.0144***	(5.20)	72,089	42.92
Profit margin	0.0278***	(4.50)	75,180	43.05
Sales growth	0.0385***	(4.96)	60,258	45.95
ln(DLEU Markup)	0.0117***	(4.03)	58,417	45.23
ln(GHL Markup)	0.0231***	(3.74)	38,594	36.53
Risk management				
Earnings volatility	-0.0062***	(-3.37)	64,689	47.47
Stock returns volatility	-0.0457***	(-3.50)	74,516	42.68
# Risk mentions/10K size	-0.0001	(-0.37)	68,246	49.00
Investments				
Capex/Total assets$_{t-1}$	0.0081***	(5.73)	73,341	41.77
Acquisition {0/1}	0.0388***	(5.41)	75,180	43.05
R&D/Total assets$_{t-1}$	0.0051***	(5.68)	75,180	43.05
# Patents/Total assets$_{t-1}$	0.0008***	(3.93)	68,211	49.14
Tobin's Q	0.2948***	(5.75)	74,764	42.00
Efficiency				
COGS/Sales	-0.0278***	(-4.50)	75,180	43.05
Asset turnover	0.0240***	(4.50)	75,180	43.05
Total factor productivity	0.0571***	(4.65)	33,582	35.97

Table A2.5: Robustness: Controlling for numbers of connections

The table presents the instrumental variables estimation results of equations (2) and (3) using the firm-year panel data. It repeats regressions from Tables 3-6 with an additional control variable measuring the number of firm connections to firms in other industries in year $t-1$. In both Panels A and B, *#conn* is the number of firm connections via overlapping boards, current and past employment, education, and social clubs.

Panel A: Board connections instrument						
1st stage estimates	$\beta_{\text{Board conn instr}}$ (1)	t-stat (2)	$\beta_{\#\text{conn}}$ (3)	t-stat (4)	Observations (5)	
# memberships	0.2955***	(9.35)	0.0010***	(2.81)	83,669	
2nd stage estimates	$\beta_{\widehat{\#\text{memb}}}$ (1)	t-stat (2)	$\beta_{\#\text{conn}}$ (3)	t-stat (4)	Observations (5)	F-stat (6)
Profitability, sales growth, and markups						
ROA	0.0132***	(6.65)	-0.0001***	(-5.15)	80,464	86.02
Profit margin	0.0236***	(4.97)	-0.0001***	(-3.11)	83,669	87.39
Sales growth	0.0358***	(6.50)	-0.0000	(-1.08)	71,888	88.69
ln(DLEU Markup)	0.0115***	(5.66)	-0.0000	(-0.41)	69,350	85.02
ln(GHL Markup)	0.0196***	(4.23)	-0.0001***	(-2.98)	45,915	68.38
Risk management						
Earnings volatility	-0.0072***	(-4.72)	0.0000***	(3.32)	76,788	89.69
Stock returns volatility	-0.0362***	(-3.60)	0.0002***	(3.08)	83,219	87.51
# Risk mentions/10K size	-0.0001	(-0.75)	0.0000	(1.44)	80,782	87.76
Investments						
Capex/Total assets$_{t-1}$	0.0077***	(7.82)	-0.0000**	(-2.53)	81,521	86.17
Acquisition {0/1}	0.0351***	(7.59)	-0.0001***	(-4.26)	83,669	87.39
R&D/Total assets$_{t-1}$	0.0037***	(6.55)	0.0000***	(3.02)	83,669	87.39
# Patents/Total assets$_{t-1}$	0.0008***	(4.13)	0.0000**	(2.08)	80,239	91.32
Tobin's Q	0.2523***	(7.98)	-0.0004***	(-2.74)	83,282	84.88
Efficiency						
COGS/Sales	-0.0236***	(-4.97)	0.0001***	(3.11)	83,669	87.39
Asset turnover	0.0231***	(5.62)	0.0000	(0.01)	83,669	87.39
Total factor productivity	0.0527***	(6.34)	-0.0002***	(-4.49)	40,001	69.03

Panel B: Geographic diffusion instrument						
1st stage estimates	$\beta_{\text{Geo diff instr}}$ (1)	t-stat (2)	$\beta_{\#\text{conn}}$ (3)	t-stat (4)	Observations (5)	
# memberships	0.2026***	(5.56)	0.0011***	(2.61)	63,698	
2nd stage estimates	$\beta_{\widehat{\#\text{memb}}}$ (1)	t-stat (2)	$\beta_{\#\text{conn}}$ (3)	t-stat (4)	Observations (5)	F-stat (6)
Profitability, sales growth, and markups						
ROA	0.0153***	(4.40)	-0.0001***	(-4.10)	60,982	31.03
Profit margin	0.0314***	(3.95)	-0.0001**	(-2.46)	63,698	30.88
Sales growth	0.0407***	(4.25)	-0.0001	(-1.10)	55,111	32.07
ln(DLEU Markup)	0.0097***	(2.92)	-0.0000	(-0.25)	51,932	30.39
ln(GHL Markup)	0.0226***	(2.86)	-0.0001***	(-2.83)	33,888	23.00
Risk management						
Earnings volatility	-0.0065***	(-2.83)	0.0000***	(2.70)	58,288	32.31
Stock returns volatility	-0.0433***	(-2.69)	0.0001	(1.43)	63,378	30.48
# Risk mentions/10K size	-0.0001	(-0.49)	0.0000	(1.54)	62,953	33.22
Investments						
Capex/Total assets$_{t-1}$	0.0087***	(4.93)	-0.0000**	(-2.38)	62,387	29.52
Acquisition {0/1}	0.0455***	(4.64)	-0.0001***	(-3.72)	63,698	30.88
R&D/Total assets$_{t-1}$	0.0050***	(4.76)	0.0000**	(2.19)	63,698	30.88
# Patents/Total assets$_{t-1}$	0.0009***	(3.34)	0.0000*	(1.72)	60,611	33.23
Tobin's Q	0.3152***	(4.91)	-0.0004**	(-2.19)	63,355	30.48
Efficiency						
COGS/Sales	-0.0314***	(-3.95)	0.0001**	(2.46)	63,698	30.88
Asset turnover	0.0219***	(3.44)	-0.0000	(-0.14)	63,698	30.88
Total factor productivity	0.0684***	(3.56)	-0.0002***	(-3.43)	30,200	20.11

A.3 Additional Pairwise Panel Results

Table A3.1: Geographic entry into state-level markets and association memberships, 1st-stage estimates

The table presents the first-stage instrumental variables estimation results of equation (4). In Panel A, the instrument *Board connections instrument*$_{ij}$ is the product of the corresponding instruments for firms i and j. In Panel B, the instrument is *Geographic diffusion instrument*$_{ij}$ computed analogously. The depended variable *# overlaps*$_{ij}$ counts the number of the distinct associations in this both firm i and j are members in a given year. TNIC-2, 3, and 4 are Hoberg and Phillips (2010, 2016) industries. The control variables include the products of total assets and age for the firm pair, an indicator for whether the firms belong to the same SIC code as granular as the corresponding to the TNIC industry (i.e., SIC 3 for TNIC-3), and the TNIC product similarity scores. All the controls are lagged. Standard errors are clustered by firm-pair. F-statistic corresponds to Kleibergen and Paap (2006) Wald test for weak instruments. The symbols ***,**,* denote statistical significance at 1%, 5%, and 10% levels. The estimated coefficients are multiplied by 100 for readability.

Panel A: Board connections instrument	*1st stage estimates. Dependent variable: # overlaps*$_{ij}$					
	TNIC-2		TNIC-3		TNIC-4	
	(1)	(2)	(3)	(4)	(5)	(6)
Director connections instrument$_{ij}$	0.0009***	0.0009***	0.0008***	0.0008***	0.0009***	0.0009***
	(18.98)	(18.70)	(11.27)	(11.08)	(6.37)	(6.24)
ln(Total assets)$_{ij}$	0.0021***	0.0020***	0.0028***	0.0027***	0.0045***	0.0045***
	(12.25)	(11.89)	(8.25)	(8.21)	(5.69)	(5.72)
ln(Age)$_{ij}$	0.0160***	0.0160***	0.0145***	0.0145***	0.0102***	0.0100***
	(18.37)	(18.74)	(10.33)	(10.65)	(3.85)	(3.85)
Same SIC code $\{0/1\}_{ij}$	-0.0158***	-0.0148***	-0.0112*	-0.0096*	-0.0057	-0.0058
	(-3.48)	(-3.39)	(-1.89)	(-1.74)	(-0.74)	(-0.80)
Product similarity$_{ij}$	0.0933***	0.0806***	0.0947**	0.0914**	-0.0110	0.0062
	(3.72)	(3.38)	(2.52)	(2.57)	(-0.16)	(0.09)
Year × State F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm pair$_{ij}$ F.E.	Yes	No	Yes	No	Yes	No
Firm pair$_{ij}$ × State F.E.	No	Yes	No	Yes	No	Yes
Observations	13,668,504	12,146,479	5,802,943	5,192,677	2,208,002	1,979,046

Panel B: Geographic diffusion instrument	*1st stage estimates. Dependent variable: # overlaps*$_{ij}$					
	TNIC-2		TNIC-3		TNIC-4	
	(1)	(2)	(3)	(4)	(5)	(6)
Geographic diffusion instrument$_{ij}$	0.0009***	0.0009***	0.0009***	0.0009***	0.0010***	0.0010***
	(11.92)	(12.02)	(7.71)	(7.89)	(5.13)	(5.21)
ln(Total assets)$_{ij}$	0.0023***	0.0022***	0.0030***	0.0029***	0.0062***	0.0061***
	(11.91)	(11.48)	(7.83)	(7.65)	(6.20)	(6.16)
ln(Age)$_{ij}$	0.0179***	0.0177***	0.0150***	0.0153***	0.0075**	0.0080**
	(16.15)	(16.47)	(8.07)	(8.52)	(2.01)	(2.18)
Same SIC code $\{0/1\}_{ij}$	-0.0121*	-0.0102*	-0.0065	-0.0043	-0.0047	-0.0035
	(-1.95)	(-1.74)	(-0.80)	(-0.56)	(-0.38)	(-0.29)
Product similarity$_{ij}$	0.1120***	0.1031***	0.1514***	0.1466***	-0.0699	-0.0409
	(3.47)	(3.35)	(2.91)	(2.98)	(-0.67)	(-0.41)
Year × State F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm pair$_{ij}$ F.E.	Yes	No	Yes	No	Yes	No
Firm pair$_{ij}$ × State F.E.	No	Yes	No	Yes	No	Yes
Observations	9,658,981	8,427,361	3,883,384	3,409,904	1,337,948	1,180,981